# A Macroeconomic Analysis of Lifting the U.S. Crude Oil Export Ban*


Nida Çakır Melek†

Michael Plante‡

Mine K. Yücel§


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**Abstract**

This paper examines the effects of the U.S. shale oil boom in a two-country DSGE model where countries produce crude oil, refined oil products, and a non-oil good. The model incorporates different types of crude oil that are imperfect substitutes for each other as inputs into the refining sector. The model is calibrated to match oil market and macroeconomic data for the U.S. and the rest of the world (ROW). We investigate the implications of a significant increase in U.S. light crude oil production similar to the shale oil boom. Consistent with the data, our model predicts that light oil prices decline, U.S. imports of light oil fall dramatically, and light oil crowds out the use of medium crude by U.S. refiners. In addition, fuel prices fall and U.S. GDP rises modestly. We then use our model to examine the potential implications of the former U.S. crude oil export ban. The model predicts that the ban was a binding constraint from 2013 to 2015. We find that the distortions introduced by the policy are greatest in the refining sector. Light oil prices become artificially low in the U.S., and U.S. refineries produce inefficiently high amount of refined products, but the impact on refined product prices and GDP are negligible.



**Keywords:** DSGE, oil, trade, fuel prices, export ban.

**JEL Codes:** F41, Q43, Q38.


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†Federal Reserve Bank of Kansas City, nida.cakirmelek@kc.frb.org.

‡Federal Reserve Bank of Dallas, michael.plante@dal.frb.org.

§Federal Reserve Bank of Dallas, mine.k.yucel@dal.frb.org.

# 1 Introduction

One of the more dramatic events in oil markets has been the recent boom in U.S. crude oil production. Often referred to as the shale boom, the large increase in oil production brought about by the application of horizontal drilling and hydraulic fracturing has changed the nation's energy landscape and global oil markets in a very short time. U.S. crude oil production increased 4 million barrels per day (mb/d) from 2010 to 2015, a 72 percent increase, and imports of crude oil fell 1.9 mb/d, a 20 percent decline.

An important facet of the shale boom is that the crude oil produced from shale plays tends to be of a very specific type. To the general observer, oil is a homogenous commodity. In reality, oils produced in different parts of the world can have very different characteristics. For example, some oils are very dense while others are not. The former are referred to as heavy crudes, the latter as light oils and everything in between as medium crudes. The oil produced from shale areas is predominantly light crude oil.

Oil can be processed into refined petroleum products independent of type but the different oils are imperfect substitutes for each other as inputs in the refining process. There is also specialization of refinery capacity across countries. In particular, the U.S. refining sector processes a relatively large amount of heavy crude oil as a proportion of total refining capacity vis-a-vis the rest of the world. As a result, the large, unexpected increase in U.S. light oil production generated a significant discussion over how or whether the oil could be processed by U.S. refiners given the mis-match of increased light crude inputs versus heavier refining capacity. This issue was particularly relevant until the end of 2015 because of the U.S. export ban on crude oil, a policy that had been put in place after the 1973 oil embargo.

With these issues in mind, we investigate the impact of the shale oil boom on the upstream and downstream energy industry and the broader economy using a dynamic stochastic general equilibrium (DSGE) model. In our model, the world economy consists of two countries, the U.S. and the rest of the world (ROW). Both countries produce oil, a non-oil good and refined petroleum products. Oil comes in three types, light, medium and heavy, and they are imperfect substitutes as inputs into the refining process. We calibrate our model to match a variety of macroeconomic and oil market data, and take into account important differences in the refining sectors of the U.S. and the rest of the world.

We model the U.S. shale oil boom as a series of positive productivity shocks that increase U.S. light crude oil production, and then illustrate the general equilibrium repercussions. Our model predicts that the production boom causes light oil prices and fuel prices to fall, and backs out a significant portion of imported light crude oil. U.S. refiners process more light oil at the expense of other types. These features are consistent with the data. We also find that the light oil supply increase has a modest impact on U.S. GDP.

We then use our model to investigate the distortionary effects of the U.S. crude oil export ban. We find that the ban binds from 2013 to 2015. When the ban binds, we find that the policy primarily distorts the price of crude oil in the U.S. and refining sectors in both the U.S. and the rest of the world. The price of light oil becomes artificially low in the U.S., which provides a cost advantage to the U.S. refining sector. As a result, the U.S. processes more light oil than it would otherwise, and gains market share at the expense of the rest of the world. We find that the impact on refined fuel prices is negligible, as there was no ban on refined petroleum products trade. The impact on U.S. GDP is slight, due in part to the upstream and downstream sectors being relatively minor components of U.S. GDP.

Then, we examine the data to see if there is evidence that the export ban may have been binding at some point in time, using two different approaches. First, we look to see if the model's predictions about the export ban's effects appear in the data. We do find some evidence in line with these predictions. For example, the domestic price of light crude oil in the U.S. was unusually low compared to the international benchmark starting in late 2013. Data also show that U.S. crude oil exports continued increasing in 2016, despite lower production levels. Finally, we explore to what extent certain loopholes in the export ban policy were used to circumvent the ban. The data show that one such loophole, the ability to export to Canada, was used in 2014 and 2015 to a much larger extent than before. We conclude that the export ban was likely binding to some degree in 2014 and 2015.

Our model fits into the DSGE literature focused on oil, which includes works such as Backus and Crucini (2000) [1], Leduc and Sill (2007) [28], Bodenstein et. al. (2011) [8], Nakov and Nuno (2013) [32], and Plante (2014) [33]. Our work also has connections with the international real business cycle literature, see for example Backus et al. (1992) [2], Backus et al. (1994) [3], Crucini and Kahn (1996) [13]. To the best of our knowledge, we contribute to this literature by being the first to model the refining sector in a DSGE model, the first to introduce a distinction between different types of oil and the first to explore the U.S. crude oil export ban in this modeling framework.

There are several recent papers analyzing the U.S. shale oil boom and its effects on global oil prices, the global economy and the energy industry. Manescu and Nuno (2015) [29], in a general equilibrium model of OPEC and a competitive fringe, show that the price decline due to increased supply was already incorporated into market prices for crude oil, and resulted in an additional increase of 0.2 percent of GDP for oil importers. Using a VAR model, Mohaddes and Raissi (2016) [31] show that the oil supply shock increased global GDP by 0.16 to 0.37 percentage points. Walls and Zheng (2016) [39] show that the shale boom has made refiners sensitive to oil price changes and that their profitability rises 3 percent in response to a 1 percent fall in oil prices. A study by Kang et. al. (2016) [23] finds that positive U.S. oil supply shock had a positive effect on stock returns. Kilian (2016, 2017) ( [24], [25]) argues that the U.S. shale oil boom had an insignificant effect on the global oil market, and increased U.S. GDP by a miniscule 0.1 percentage points.

There are a number of recent non-academic studies by national and international organizations discussing the impact of free trade policy relating to U.S. crude oil.[1] A Congressional Research Service report by Brown et al. (2014) [11] has a good background analysis of the oil export ban. Bordoff and Houser (2015) [9] summarize several other reports on the issue. A somewhat more academic analysis can be found in

[1]Ebinger and Greenley (2014) [15], EIA (2014) [35], Vidas et.al. (2014) [38], IHS (2014) [21], IHS (2015) [22], etc. These studies are typically qualitative in nature or rely on simple models in order to evaluate the impact. Overall, they argue that free trade would increase the price of domestic crude oil, hence could result in higher production and lower price of gasoline, benefiting consumers. The estimated decline in domestic gasoline prices change from 1.5 cents to 13 cents in these studies.

and Brown et al. (2014) [10] and Medlock (2015) [30]. Langer et al. (2016) [27] analyze the lifting of the export ban with a numerical, partial equilibrium model. They find that U.S. sweet crude exports expand significantly and the sweet oil-importing ROW gains from not having to invest in refinery capacity.

Farrokhi (2016) [18] studies how local changes in oil markets affect oil prices and trade flows across the world. After presenting a detailed model of refinery costs, including various types of oil inputs, transport costs, and differing refinery technology, he embeds the estimated model of refinery sourcing into a multi-country general equilibrium model which also incorporates refinery product demand. There is global trade in oil and refined products, and the model is calibrated using data from 110 refiners across 33 countries. With some counterfactual experiments, he shows that if the crude oil export ban had been lifted during the shale boom, U.S. crude oil prices would have risen by 4.7 percent, U.S. refinery profits would have fallen by 6.6 percent, and refined product prices would have risen by 0.1 percent. He also finds that the gains from trade for the U.S. are much larger than in the standard trade models of manufactured goods trade.

The rest of the paper is organized as follows. We present the background information and data in Section 2. Our general model framework is presented in Section 3. Section 4 provides the calibration, and results are discussed in Section 5. We introduce crude oil export ban and examine its implications in Section 6, and conclude in Section 7.

# 2 Data

Our goal in this section is to review some key data to gauge how the shale boom has affected the oil market. To this end, we introduce data on crude oil production by type, U.S. imports and exports of crude oil and refiner use of different types of oil. Using this data, we show the breakdown of production in the U.S. and the rest of the world, characterize the extent to which refiners in the U.S. are specialized in processing different types of oil and document how the data have changed in general since the onset of the shale boom.

## 2.1 Introduction to crude oil quality

Although crude oil is generally viewed as a homogenous commodity, crude oils vary across a number of dimensions. These include density, sulfur content, and contamination with other elements, such as certain metals.

The density of a crude oil is one of the more important measures used to distinguish between different types of oil. The American Petroleum Institute gravity (API gravity) is a commonly used measure of a crude oil's density. A higher API gravity indicates less density and gravity values range from 10 to 70. Oils with higher API gravities are known as light oils, those with low API gravities are known as heavy. Light oils tend to be preferred by refiners as they require less processing to produce larger amounts of gasoline and diesel. As a result, light oils often sell at a premium to medium and heavy crudes.

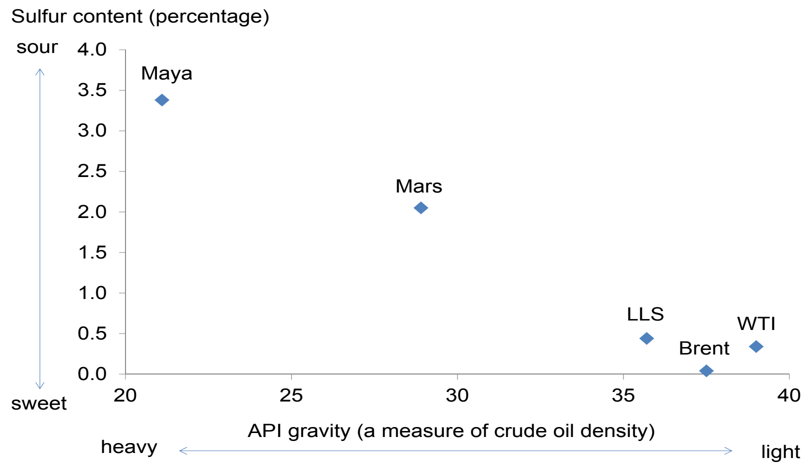
Sulfur content is another important characteristic that distinguishes crude oils. Oils with high sulfur content are referred to as sour while those with low sulfur content are sweet. The latter require less processing and are therefore preferred to sour oils. There is a correlation between a crude's API gravity and the amount of sulfur present in the oil. Although not always the case, lighter oils often have lower sulfur content, especially when compared to heavy crudes.

Figure 2.1 shows how some important crude oil benchmarks vary in terms of their API gravity and sulfur content. West Texas Intermediate, the benchmark crude oil for the U.S., is an important example of a light crude oil, with an API near 40 and a relatively low sulfur content. Other examples of light oils include Louisiana Light Sweet (LLS) and Brent, which is an important benchmark outside the U.S. Maya crude, produced in Mexico, is an example of a heavy crude, a dense oil with a low API near 20 and a very high sulfur content relative to other crude oils. Mars is a medium crude produced in the U.S. Gulf of Mexico, and has an API and sulfur content in between the lights and Maya.

Prices of similar quality oils tend to remain fairly close to each other.[2] As quality differences become more pronounced, so do the price differences between the oils. For

[2] Factors such as transportation bottlenecks can cause prices of similar quality oils to deviate substantially from each other. An example of this in recent years is the price of WTI.

**Figure 2.1:** Characteristics of various crude oils




SOURCES: Bloomberg; Platts.

example, if we consider the price of light, medium and heavy crude in the U.S. Gulf Coast we see that the price of LLS has, on average, been about 12 percent higher than Mars crude oil since 1997, when data became available for Mars, and 27 percent more expensive than Maya.

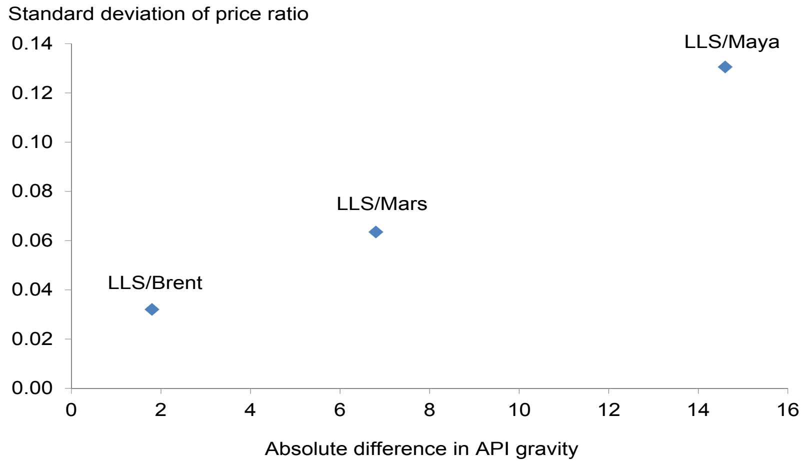
We have also found that the relative prices of different oils tend to be more volatile as the quality differences become more pronounced. Using the Gulf Coast as an example again, we constructed a monthly time series for the price ratios of LLS to Brent, LLS to Mars and LLS to Maya. The data run from 1997 to 2016. Figure 2.2 plots the standard deviation of the relative oil prices as a function of how different each pair is in terms of API gravity. While this chart only considers three relative prices, a similar pattern emerges when looking at other crude oils.[3]

## 2.2 Crude production data

We rely on production data from the 2016 version of Eni's World Oil and Gas Review [16]. It provides a breakdown of crude oil production into several different types. The

[3]For example, a similar pattern is found if one uses the Asian benchmarks Tapis, Dubai and Duri crudes instead of LLS, Mars and Maya.

**Figure 2.2:** Volatility of relative oil prices




SOURCES: Bloomberg; Platts.

Note: Data is monthly and the sample was from 1997 to 2010.

breakdown covers world output and production in a number of countries, including the U.S. The data are available for a select number of years, including 2000, 2005 and from 2010 to 2015. Although this is a limited time series, it covers years when oil production in the U.S. boomed due to horizontal drilling and hydraulic fracking and does provide a snapshot of U.S. production before the boom.

Other sources of data on crude production by type are available but, unfortunately, they either have a limited time series or limited coverage. For example, the Energy Information Administration has recently started releasing monthly production data by API gravity for the U.S. but the data only start in 2015. EIA (2015) [36] provides annual data but only for 2010 - 2013. We also constructed a longer time series for U.S. production using data from DrillingInfo and several other sources. However, this method produces a time series that often leaves a large portion of production unclassified because of limited API gravity information. Neither source provides information for countries outside the U.S. As a result, we did not use these data for this paper.

We define different categories of crude oil using API gravity as our metric. We would have preferred to further expand the categorization to include sulfur content but could not because of data limitations. Following Eni, we define heavy crude oil as oil with an API less than 26, medium from 26 up to 35, and light crude oil with an API of 35 and above. Using these definitions, it is possible to construct a series for the U.S. and the rest of the world (ROW) for oil production by type.[4]

Table 2.1 shows the production data in millions of barrels per day (mb/d). One feature of the shale boom is that new production is primarily light oil. By 2015, light production had increased by more than 4 mb/d in the U.S. Outside the U.S., increased production was from medium and heavy crudes, with declines in light crude production. The table also provides some information on the relative importance of the different crude oil types. In 2010, more than half of the world's crude oil was medium. Another 30 percent was light and the remainder was heavy crude oil.

**Table 2.1:** Crude oil production by type, mb/d

| | **U.S.** | | | **Rest of the world** | | | **Total world** | | |
|---|---|---|---|---|---|---|---|---|---|
| | Light | Medium | Heavy | Light | Medium | Heavy | Light | Medium | Heavy |
| 2000 | 2.1 | 2.9 | 0.8 | 20.0 | 34.9 | 7.6 | 22.1 | 37.8 | 8.4 |
| 2005 | 1.7 | 2.8 | 0.7 | 19.8 | 40.2 | 9.4 | 21.5 | 43.0 | 10.1 |
| 2010 | 2.1 | 2.7 | 0.6 | 20.6 | 39.2 | 9.8 | 22.8 | 41.9 | 10.4 |
| 2011 | 2.6 | 2.5 | 0.6 | 19.7 | 40.9 | 9.8 | 22.3 | 43.4 | 10.4 |
| 2012 | 3.5 | 2.4 | 0.6 | 20.1 | 41.4 | 9.6 | 23.6 | 43.8 | 10.2 |
| 2013 | 4.6 | 2.3 | 0.6 | 19.6 | 40.9 | 9.7 | 24.2 | 43.2 | 10.3 |
| 2014 | 5.7 | 2.4 | 0.6 | 19.0 | 41.5 | 9.9 | 24.7 | 44.0 | 10.5 |
| 2015 | 6.3 | 2.5 | 0.6 | 19.1 | 42.1 | 10.8 | 25.4 | 44.6 | 11.4 |

## 2.3 U.S. crude imports and exports

The EIA provides disaggregated data on U.S. crude imports by API gravity, which allows us to categorize imports into light, medium or heavy. Annual data go back until

[4]A small amount of world crude oil production, less than 1 percent of the total for most years, was unclassified by Eni. We distribute the unclassified amount equally between light, medium and heavy crude oil.

1978. An extensive time series is available for annual crude exports but the EIA does not provide a breakdown by type. Given our interest in the shale boom, we focus on the more recent data available for both imports and exports.

The left portion of Table 2.2 shows the import data by type for 2000, 2005 and 2010 to 2016. We note that the U.S. has been and continues to be a major importer of crude oil. However, there have been some dramatic shifts in the quantity and types of oil being imported. Since the shale boom, imports of light oil have fallen substantially and imports of medium have declined. Imports of heavy crude have increased about 10 percent since 2010 and are up substantially since 2000. We note that imports of light oil picked up again in 2016, concurrent with the decline in U.S. crude production that year.

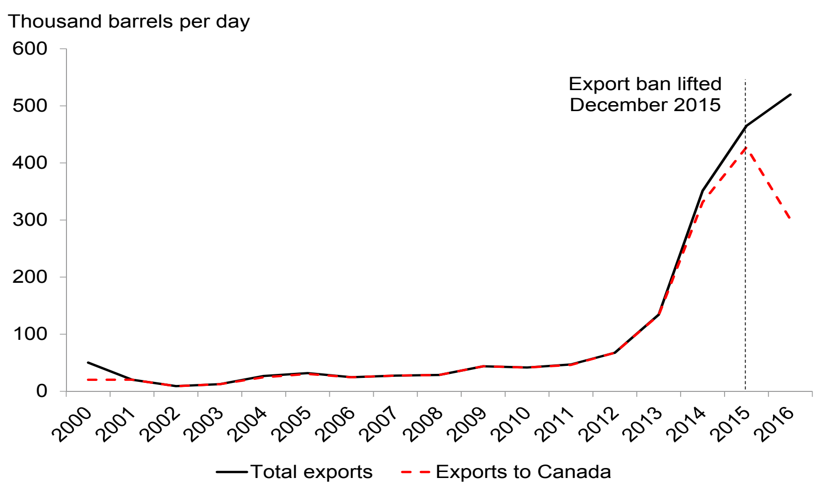
**Table 2.2:** U.S. imports and exports of crude oil, mb/d

| | **U.S. crude imports** | | | **U.S. crude exports** |
|---|---|---|---|---|
| | Light | Medium | Heavy | Total |
| 2000 | 2.2 | 4.6 | 2.3 | 0.05 |
| 2005 | 2.3 | 4.3 | 3.5 | 0.03 |
| 2010 | 2.1 | 3.3 | 3.8 | 0.04 |
| 2011 | 1.7 | 3.3 | 4.0 | 0.05 |
| 2012 | 1.4 | 3.1 | 4.0 | 0.07 |
| 2013 | 0.9 | 3.0 | 3.9 | 0.13 |
| 2014 | 0.6 | 2.7 | 4.1 | 0.35 |
| 2015 | 0.6 | 2.6 | 4.2 | 0.47 |
| 2016 | 0.9 | 2.6 | 4.4 | 0.52 |

The rightmost column of Table 2.2 shows the data for U.S. crude exports. From 2000 to 2013, the U.S. exported a trivial amount of crude oil, typically under 100 kb/d. Exports picked up noticeably starting in 2014, however, and have continued increasing every year since. The increase in exports in 2014 and 2015 might seem at odds with the U.S. policy of prohibiting exports of crude oil that was in place at the time. A short discussion on the policy will help provide some context for this.

Until December 2015, there was a federal ban on crude oil exports whose motivation dated back to the 1973 oil embargo. Although labeled a ban, exporting oil was possible under certain circumstances. The most relevant exemption for recent export data was the possibility to export crude oil to Canada.[5] This could be done so long as the oil was not re-exported from Canada. This exemption was used heavily in both 2014 and 2015, with EIA export data showing that most U.S. exports of crude oil went to Canada. This can be seen in figure 2.3.

**Figure 2.3:** U.S. crude oil exports



SOURCE: Energy Information Administration.

## 2.4 Refiner inputs

We next construct an estimate of how much oil of each type is being processed by refiners in the U.S. and ROW. Our estimate of U.S. refiner inputs by type is given by the following,

$$\text{Input}_t^j = \text{Production}_t^j + \text{Imports}_t^j - \text{Exports}_t^j,$$

[5]Another exemption regarded exports of Alaskan crude oil. However, exports from Alaska have been negligible since 2000. More details can be found in Bausell et al. (2001) [6], Kumins (2005) [26] and Van Vactor (1995) [37].

where each variable is for the U.S. and the types are indexed by $j = l, m, h$. The production data comes from Eni, while the import and export data are from the EIA.

As mentioned previously, the EIA does not provide a breakdown of the export data by type of oil. For most of the years considered, exports were relatively small and could be ignored without significantly affecting our estimates. This is not true for 2014 and 2015, however. Data available from Canada, along with analysis from several other sources, suggest that most, if not all, of the oil exported to Canada was of the light variety. Given this, we assume that all U.S. exports of crude oil from 2010 to 2015 were light. This has the effect of lowering our estimate for U.S. refiner use of light crude oil, particularly in 2014 and 2015.

The estimate for ROW is then constructed by calculating the difference between world oil production of type $j$ and U.S. refiner use of type $j$. We note that it would be preferable to account for crude oil inventory changes when making this calculation. However, we are unaware of any data that would allow us to break inventory changes into the respective types, even in the U.S. Outside of the U.S, data are also limited regarding overall crude oil inventory changes. We do note, however, that changes in crude oil inventories in the U.S. from year to be year, at least, tend to be very small when compared to the other flow data we are interested in. For example, crude inventories changed by +.02 mb/d, - .01 mb/d and + .1 mb/d in 2010, 2011 and 2012, respectively. These are fairly small compared to the amount of oil being processed by U.S. refiners each day.

Table 2.3 shows our estimates for refining inputs. As can be seen in the table, the U.S. refinery sector is geared towards processing heavy crude oil relative to the rest of the world. This can also be seen in Figure 2.4, where we plot 2010 data for illustrative purposes. In that year, the U.S. alone processed more than 40 percent of the world's heavy crude oil. On the other hand, the U.S. processed 18.4 percent of the world's light crude, and only 14.6 percent of the world's medium crude. This is consistent with the refinery complexity ratio data. The higher the refinery complexity ratio, the more efficient the sector is at processing heavier oils. The data show that the U.S. complexity ratio is 69 compared to a 43 average for the rest of the world which is 43.[6]

[6] The complexity ratio for European refiners is 34, while the complexity ratio is 17 for Middle

**Table 2.3:** Refiner inputs by type, U.S. and rest of the world, mb/d

| | U.S. refiner inputs | | | ROW refiner inputs | | |
|---|---|---|---|---|---|---|
| | Light | Medium | Heavy | Light | Medium | Heavy |
| 2000 | 4.3 | 7.5 | 3.1 | 17.8 | 30.4 | 5.3 |
| 2005 | 4.0 | 7.1 | 4.2 | 17.5 | 36.0 | 5.9 |
| 2010 | 4.2 | 6.1 | 4.4 | 18.6 | 35.9 | 6.0 |
| 2011 | 4.2 | 5.7 | 4.6 | 18.0 | 37.6 | 5.8 |
| 2012 | 4.9 | 5.5 | 4.5 | 18.7 | 38.3 | 5.7 |
| 2013 | 5.3 | 5.3 | 4.5 | 18.9 | 37.9 | 5.8 |
| 2014 | 5.9 | 5.1 | 4.7 | 18.8 | 38.8 | 5.9 |
| 2015 | 6.4 | 5.1 | 4.8 | 19.0 | 39.5 | 6.6 |

## 2.5 Changes since 2010

There have been some dramatic changes not only in U.S. oil production but also in crude imports, exports and refining data since the start of the shale boom. We take stock of these in Table 2.4 by comparing how select data for the U.S. has changed from 2010 to 2015.

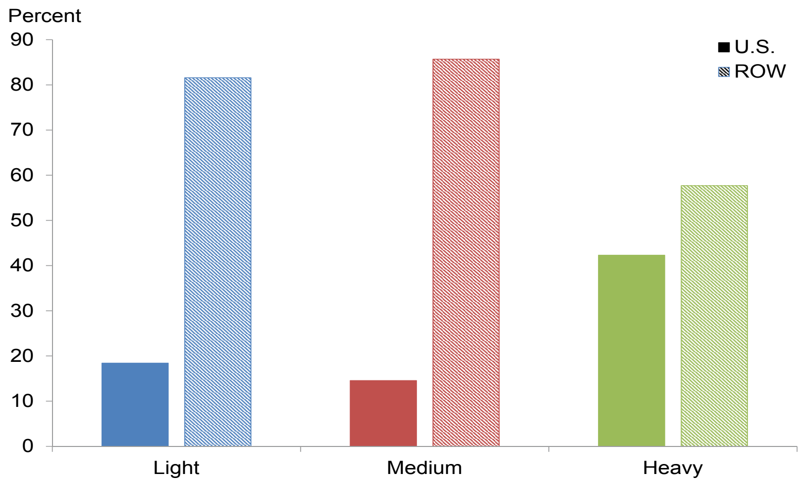
The impact of the new technology on production is immediately obvious. Light production increased by more than 4 mb/d over the 5 year period. Production of other types was relatively flat, with production of medium crudes down slightly and heavy crude production essentially unchanged.

Refiner use of light oil also increased substantially, with U.S. refiners processing an additional 2.2 mb/d in 2015 vs. 2010. The increase was insufficient to absorb all new U.S. light production. As a result, imports of light oil from other countries dropped sharply. There was also an increase in exports, primarily to Canada, especially in 2015.

One feature of the data that does not receive much attention concerns imports and refiners' use of medium crude oil. U.S. refiners reduced their use of medium crudes by 1 mb/d, leading to a sharp drop in imports. One possibility is that light oil may have

Eastern refiners.

**Figure 2.4:** Refining shares by type of oil, U.S. and the ROW




SOURCE: Author's calculations.

crowded out medium oil. We will return to this point later when discussing results from our theoretical model.

Finally, U.S. refiners have continued increasing their usage of heavy crude oil over these years. Based on the Eni data, world production of heavy crude was about 1 mb/d higher in 2015 than in 2010. U.S. refiners processed about half of the increase, with the crude being imported from other countries.

**Table 2.4:** Change in select data from 2010 to 2015, mb/d

| | Production | Imports | Exports | Refiner inputs |
|---|---|---|---|---|
| Light | 4.2 | -1.5 | 0.4 | 2.2 |
| Medium | -0.2 | -0.8 | | -1.0 |
| Heavy | 0.0 | 0.4 | | 0.5 |
| Total | 4.0 | -1.9 | 0.4 | 1.7 |

# 3 Baseline Model

The world economy is represented by a dynamic stochastic general equilibrium model that consists of two countries, the U.S. and the rest of the world (ROW).[7] We refer to the U.S. as country 1 and ROW as country 2. Both countries produce three goods: crude oil, refined oil products, and a non-oil good. Their preferences and technologies have the same functional forms. Crude oil is produced using the non-oil good as an input. Production of refined products requires capital, labor, and a composite of three types of crude oil. The household consumption bundle is a composite of refined products and the non-oil good. Finally, the non-oil good is produced using capital, labor, and refined products.

## 3.1 Households

The utility of a typical household in country $i$, $i = 1, 2$, is characterized by

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{(c_{i,t}^{\mu_i} L_{i,t}^{1-\mu_i})^\gamma}{\gamma}, \tag{3.1}$$

where $c_{i,t}$ and $L_{i,t}$ are aggregate consumption and leisure, respectively. The parameter $0 < \beta < 1$ denotes the discount factor, $\mu_i$ governs the time spent in the workplace, and $\gamma$ governs the intertemporal elasticity of substitution. We assume that crude oil is not directly consumed by households, but is used only in the production of refined products (fuel). The variable $c$ measures aggregate consumption and is a composite of the non-oil good, good $a$, and refined products, good $f$, which are combined via an Armington aggregator with weights $w_i$ and $(1 - w_i)$ as follows

$$c_{i,t} = [w_i(c_{i,t}^a)^{-\rho} + (1 - w_i)(c_{i,t}^f)^{-\rho}]^{\frac{-1}{\rho}},$$

where $\frac{1}{1+\rho}$ is the elasticity of substitution between $c_{i,t}^a$ and $c_{i,t}^f$. The aggregator function captures the idea that these goods are imperfect substitutes, and the weights reflect how consumption expenditures are allocated across these goods.

[7] See Backus and Crucini (2000) [1], Backus et al. (1992) [2], Backus et al. (1994) [3], Crucini and Kahn (1996) [13], etc. for more details on this framework.

The household faces a budget constraint in period $t$ stating that the combined expenditure on consumption and investment must equal income:

$$c_{i,t}^{a}+p_{i,t}^{f}c_{i,t}^{f}+I_{i,t}^{a}+I_{i,t}^{f}=W_{i,t}^{a}n_{i,t}^{a}+W_{i,t}^{f}n_{i,t}^{f}+R_{i,t}^{a}K_{i,t}^{a}+R_{i,t}^{f}K_{i,t}^{f}+\Pi_{i,t}^{a}+\Pi_{i,t}^{f}+\Pi_{i,t}^{o}. \quad (3.2)$$

We assume good $a$ is the numeraire and $p_{i,t}^{f}$ denotes the relative price of good $f$ in country $i$. Moreover, the relative price of the investment goods is equal to that of the non-oil good. $W_i^j$ is the wage rate and $R_i^j$ is the rental rate of capital in sector $j$, $j=a,f$, in country $i$. Households own the firms operating in the economy, hence receive profits from all sectors: $\Pi_{i,t}^{a}$, $\Pi_{i,t}^{f}$, and $\Pi_{i,t}^{o}$, where $\Pi_{i,t}^{o}=\Pi_{i,t}^{oL}+\Pi_{i,t}^{oM}+\Pi_{i,t}^{oH}$ where $L$ (light), $M$ (medium), $H$ (heavy) denote the three types of crude oil.

Investment in physical capital augments the capital stock $K_{i,t+1}^{j}$, $j=a,f$, according to the following laws of motion

$$K_{i,t+1}^{f} = (1-\delta)K_{i,t}^{f}+I_{i,t}^{f}-\Phi\left(\frac{I_{i,t}^{f}}{K_{i,t}^{f}}\right)K_{i,t}^{f} \quad (3.3)$$

$$K_{i,t+1}^{a} = (1-\delta)K_{i,t}^{a}+I_{i,t}^{a}-\Phi\left(\frac{I_{i,t}^{a}}{K_{i,t}^{a}}\right)K_{i,t}^{a}, \quad (3.4)$$

where $I_{i,t}^{j}$ denotes investment in sector $j=a,f$, and $\delta$ is the depreciation rate. Physical capital formation is subject to adjustment costs as in Baxter and Crucini (1995) [7] and Christiano, Eichenbaum and Evans (2005) [12]. Costs are governed by a quadratic investment adjustment cost function, $\Phi\left(\cdot\right)$, which takes the following form

$$\Phi\left(\frac{I_{i,t}^{j}}{K_{i,t}^{j}}\right)=\frac{1}{2\delta\phi_i}\left(\frac{I_{i,t}^{j}}{K_{i,t}^{j}}-\upsilon\right)^{2},$$

where $j=a,f$. $\phi_i>0$ governs the elasticity of investment-capital ratio with respect to Tobin's $q$, and $\upsilon$ denotes the steady state investment-capital ratio. Adjustment costs are incorporated to slow investment responses to shocks.

Finally, household's activities exhaust total hours available:

$$\bar{L}_i-L_{i,t}-n_{i,t}^{a}-n_{i,t}^{f}=0, \quad (3.5)$$

where $\bar{L}_i$ is the total amount of time available for work and leisure in country $i$.

Each household earns labor income, capital income, and receives profits. In every period t, the household maximizes the utility function 3.1 with respect to consumption, labor supply, investment, and end-of-period capital stock subject to its budget constraint 3.2, the laws of motion for capital 3.3 and 3.4, and the time constraint 3.5. In doing so, prices and wages are taken as given.

## 3.2 Firms and Production

Each country produces three goods, crude oil, refined products, and a non-oil good, by perfectly competitive firms.

### 3.2.1 Crude Oil Production (Light, Medium, Heavy)

Each type of crude oil is produced by a representative profit-maximizing firm in country $i = 1, 2$. Oil production costs are in terms of the non-oil good and are an increasing function of oil production as in Balke, Plante, and Yucel (2015) [4]. In what follows, we denote the types of oil by $k =$ H, M or L.

The oil producing firm chooses its oil production to maximize profits:

$$\Pi_{i,t}^{ok} = p_{i,t}^{ok} y_{i,t}^{ok} - C_{i,t}^{k},$$

where

$$C_{i,t}^{k} = \frac{\left(\frac{y_{i,t}^{ok}}{z_{i,t}^{ok}}\right)^{1+\frac{1}{\eta_i^k}}}{1+\frac{1}{\eta_i^k}}$$

denotes the production costs. These production costs can be considered as expenditures on any non-oil good that can be used to produce oil, such as rigs. $y_{i,t}^{ok}$ is production of oil type $k$ and $z_{i,t}^{ok}$ represents a stochastic process for the evolution of productivity. Marginal costs increase with production increases, reflecting the difficulty of producing an additional unit of oil as oil production increases, and decreases with higher productivity. The firm sells its output to refineries at a price of $p_{i,t}^{ok}$. Profit maximization implies

$$p_{i,t}^{ok} = (z_{i,t}^{ok})^{-1} \left(\frac{y_{i,t}^{ok}}{z_{i,t}^{ok}}\right)^{\frac{1}{\eta_i^k}},$$

where $\eta_i^k$ is country $i$'s elasticity of supply for type $k$ oil. This suggests that the higher the elasticity of supply, the lower the marginal cost of producing a given amount of oil.

### 3.2.2 Refined Products Production

For the refining sector, we work with a production function in five inputs and restrict our attention to the class of constant elasticity of substitution production technologies. This type of production function is relatively simple and parsimonious, and gives a specification that allows for different elasticities of substitution across inputs.

We assume that the production function is a constant returns to scale Cobb-Douglas function of a capital-labor composite, itself a Cobb-Douglas function, and a composite of the three types of oil,

$$y^f_{i,t} = z^f_i \left[ (n^f_{i,t})^{\chi^f_i} (K^f_{i,t})^{1-\chi^f_i} \right]^{\alpha^f_i} G(o^f_{L_{i,t}}, o^f_{M_{i,t}}, o^f_{H_{i,t}})^{1-\alpha^f_i} \tag{3.6}$$

where $z^f_i$ represents productivity in the sector, and $n^f_{i,t}, K^f_{i,t}$ denote labor and capital inputs. The parameter $\alpha^f_i$ is the share of value-added in gross output in country $i$, and $\chi^f_i$ is the labor share in value-added in country $i$, with $0 < \alpha^f_i, \chi^f_i < 1$. We allow for the possibility that the cost-shares and productivity levels vary across countries.

The function $G(\cdot)$ is a constant returns to scale CES aggregate of the three types of oil inputs, $o^f_{L_{i,t}}, o^f_{M_{i,t}}, o^f_{H_{i,t}}$. Using a CES aggregator allows us to introduce the idea that the oils are imperfect substitutes for each other in a relatively parsimonious way. It also helps us capture differences in how much oil is being consumed by the refining sector of each country.

We choose to work with the following nested-CES function:

$$G(o^f_{L_{i,t}}, o^f_{M_{i,t}}, o^f_{H_{i,t}}) = \left[ w^o_i (o^f_{H_{i,t}})^{-\rho^{oil}_i} + (1-w^o_i) \left( \omega^o_i (o^f_{L_{i,t}})^{-\eta^{oil}_i} + (1-\omega^o_i)(o^f_{M_{i,t}})^{-\eta^{oil}_i} \right)^{\frac{\rho^{oil}_i}{\eta^{oil}_i}} \right]^{\frac{1}{-\rho^{oil}_i}}, \tag{3.7}$$

where light and medium crudes form their own composite. The $w^o_i$ and $\omega^o_i$ terms are distribution parameters that control the relative use of the different types of oil in the sector. The elasticity of substitution between light oil (or medium oil) and heavy oil is $\frac{1}{1+\rho^{oil}_i}$, and the elasticity of substitution between light oil and medium oil is $\frac{1}{1+\eta^{oil}_i}$.

The use of this composite allows us to take a stand on whether light and medium crudes are more or less substitutable with each other than with heavy crude oil. This is motivated by the discussion in section 2, where it was shown that the relative price of light crude to medium is much less variable over time than the relative price of light to heavy. As we show later, allowing the elasticity to be different between light and medium vs. heavy will let us model this feature of the data.[8]

The representative producer of refined products in each country chooses $n^f_{i,t}$, $K^f_{i,t}$, $o^f_{L_{i,t}}$, $o^f_{M_{i,t}}$, and $o^f_{H_{i,t}}$ to maximize profits

$$\Pi^f_{i,t} = p^f_{i,t} y^f_{i,t} - W^f_{i,t} n^f_{i,t} - R^f_{i,t} K^f_{i,t} - p^{oL}_{i,t} o^f_{L_{i,t}} - p^{oM}_{i,t} o^f_{M_{i,t}} - p^{oH}_{i,t} o^f_{H_{i,t}}$$

subject to equations 3.6 and 3.7. In solving this problem, the producer takes as given the wage $W^f_{i,t}$, the rental price of capital $R^f_{i,t}$, and the prices of light, medium and heavy oil $p^{oL}_{i,t}, p^{oM}_{i,t}, p^{oH}_{i,t}$. The representative firm sells its output to households and non-oil good producers at a price $p^f_{i,t}$.

### 3.2.3 Non-oil Good Production

Finally, a representative firm hires labor and rents capital from the household and purchases refined products from refineries to produce non-oil good. In doing so, it uses a constant returns to scale technology that combines a capital-labor composite with refined products. The production function is

$$y^a_{i,t} = \left[ w^a_i \left( z^a_{i,t} (n^a_{i,t})^{\chi^a_i} (K^a_{i,t})^{1-\chi^a_i} \right)^{-\rho^a_i} + (1 - w^a_i)(m^f_{i,t})^{-\rho^a_i} \right]^{\frac{1}{-\rho^a_i}} \tag{3.8}$$

where $z^a_{i,t}$ represents a stochastic process for the evolution of productivity, $n^a_{i,t}, K^a_{i,t}$ denote labor and capital inputs, and $m^f_{i,t}$ is the input of refined products. The parameter $\chi^a_i$ controls the share of labor in non-oil sector's value-added in country $i$, $w^a_i$ controls the relative use of capital-labor composite and refined products in the sector, and $\frac{1}{1+\rho^a_i}$ is the elasticity of substitution between capital-labor composite and refined products. The firm chooses $n^a_{i,t}, K^a_{i,t}$, and $m^f_{i,t}$ to maximize profits

$$\Pi^a_{i,t} = y^a_{i,t} - W^a_{i,t} n^a_{i,t} - R^a_{i,t} K^a_{i,t} - p^f_{i,t} m^f_{i,t},$$

subject to equation 3.8. The producer sells its output to households and oil producers.

[8]Another signal that the two are more substitutable is that the prices of light and medium are typically much closer to each other than they are to heavy crude oil. The processing of heavy crude oil also generally requires some very specific pieces of machinery, such as cokers, which are not required to process light crude oils.

### 3.3 Market Clearing

A competitive equilibrium for the world economy requires market clearing for all the goods, i.e. that production of each good must equal the total use of that good,

$$y_{1,t}^{oL} + y_{2,t}^{oL} = o_{L_{1,t}}^{f} + o_{L_{2,t}}^{f}, \tag{3.9}$$

$$y_{1,t}^{oM} + y_{2,t}^{oM} = o_{M_{1,t}}^{f} + o_{M_{2,t}}^{f}, \tag{3.10}$$

$$y_{1,t}^{oH} + y_{2,t}^{oH} = o_{H_{1,t}}^{f} + o_{H_{2,t}}^{f}, \tag{3.11}$$

$$y_{1,t}^{f} + y_{2,t}^{f} = c_{1,t}^{f} + c_{2,t}^{f} + m_{1,t}^{f} + m_{2,t}^{f}, \tag{3.12}$$

$$y_{1,t}^{a} + y_{2,t}^{a} = c_{1,t}^{a} + c_{2,t}^{a} + I_{1,t}^{a} + I_{2,t}^{a} + I_{1,t}^{f} + I_{2,t}^{f} + C_{1,t}^{L} + C_{2,t}^{L} + C_{1,t}^{M} + C_{2,t}^{M} + C_{1,t}^{H} + C_{2,t}^{H}. \tag{3.13}$$

All the goods can be traded freely and no trade costs are assumed, so purchasing power parity (PPP) holds:

$$\begin{aligned} p_{1,t}^{oL} &= p_{2,t}^{oL}, \\ p_{1,t}^{oM} &= p_{2,t}^{oM}, \\ p_{1,t}^{oH} &= p_{2,t}^{oH}, \\ p_{1,t}^{f} &= p_{2,t}^{f}. \end{aligned}$$

# 4 Calibration and solution method

### 4.1 Calibration

We solve the model numerically, as it is impossible to solve analytically due to its complexity. This in turn requires us to calibrate the model. The model is calibrated at an annual frequency. We choose our parameter values such that the deterministic steady state for the endogenous variables replicates certain time series averages of the actual economy.

Our main data sources are the U.S. Energy Information Administration, Oil and Gas Journal, the International Energy Agency, the Bureau of Labor Statistics, the Bureau of Economic Analysis, the International Monetary Fund, the United Nations, Bloomberg, World Input Output Database (WIOD), and Eni's 2016 World Oil and

**Table 4.1:** Preference parameter values

| Description | Symbol | Parameter value |
|---|---|---|
| Discount factor | $\beta$ | 0.96 |
| Intertemporal substitution | $1/(1-\gamma)$ | 0.50 |
| Elasticity of substitution $c^a$, $c^f$ | $1/(1+\rho)$ | 0.20 |

Gas Review. In our calibration, country 1 represents the U.S. and country 2 represents the rest of the world. Where possible we have the model match data from 2010. The year 2010 is chosen because it is before oil production in the U.S. started booming in 2011.

Several preference parameters are calibrated to be equal across countries, Table 4.1. The discount factor $\beta$ is 0.96. The elasticity of substitution between products and non-oil goods (good $f$ and good $a$), $\frac{1}{1+\rho}$, is set at 0.20, pinning down the price elasticity of demand for refined products on the household side. This value is within the range of the literature for short-run price elasticities of demand for refined products.[9] The curvature parameter determining the household's coefficient relative risk aversion, $\gamma$, is set at $-1$, as in Backus and Crucini (2000) [1] or Backus, Kehoe and Kydland (1994) [3].

We assume an average time allocation of $\frac{2}{3}$ to leisure. Without loss of generality, we can normalize U.S. GDP in the deterministic steady state to unity, $GDP_1 = 1$, which allows us to calibrate several variables in terms of GDP-ratios. The price of fuel is also normalized to 1, $p_1^f = 1$. We set $c_1^f$ equal to 2.2 percent of GDP, based on data from the BEA for household spending on gasoline and heating oil in 2010. Based on 2010 data from the BEA and the EIA, we also set the the share of non-household petroleum spending to nominal GDP, $m_1^f$, to 2.2 percent.

The average ratio of refined products production to refined products consumption in the U.S. for 2010, 0.965, helps us pin down the steady state value for refined products production, $y_1^f$. Then, using the average ratio of total crude oil production to total refined products production in the U.S., 0.35, we can obtain the steady state value of total crude oil production. The steady state values of light, medium, and heavy oil

[9] See the discussion in Baumeister and Hamilton (2016) [5], for example.

production are set to match the shares of each type of oil in total production, based on Eni data. The total volume of crude oil processed by U.S. refiners is set using EIA data which shows that the ratio of total U.S. crude oil inputs to refineries and crude oil production in 2010 was 2.675. To determine the shares of each type of oil processed in the U.S. refineries, we use the estimates presented in subsection 2.4.

As a proxy for light, medium and heavy oil prices, we consider LLS, Dubai and Maya prices, respectively. We construct annual averages for relative oil prices using monthly data from Bloomberg, and set the steady state price ratios to their 2010 averages.

We match the average cost share of crude oil in gasoline and diesel prices in 2010, 77.4 percent, to obtain the share of crude oil in gross output of the refined products sector, $(1-\alpha_1^f)$.

For the labor share of value-added in the refining sector, we rely on data from the World Input Output Database.[10] This database provides annual data on labor compensation and value-added in the petroleum and coal products sector for 38 countries (including the U.S.). The time series run from 1995 to 2011 for most of the countries. We use these data to generate a time series for the labor share of value-added for each country. Then, for each country we obtain the average labor share over $2000-2009$. The value for the U.S. is obtained as 0.164, representing the parameter $\chi_1^f$. To get the labor share of value-added in the refining sector for the ROW, i.e. $\chi_2^f$, we also use data from the Oil&Gas Journal on refining capacity in 2010 to account for the different size of the refining sector across countries. The countries included in the WIOD data cover about 75 percent of global refining capacity. We first find the share of refining capacity in each country out of the total excluding the U.S., and use these shares to weight each country's labor-share. We then sum across these countries to get our estimate for the ROW. We set an annual depreciation rate of 10 percent, and obtain the steady state value of $k_1^f$ using the FOC for capital stock. Then, investment in refining at the steady state would be $\delta k_1^f$.

For the refining sector, we also need to calibrate the distribution parameters for the oil aggregator, which requires elasticities of substitution across different oil inputs. Calibrating the elasticities is somewhat involved. As we do not have a long time

[10] See Timmer et al. (2015) [34] for details.

series on refiner crude inputs by oil type, we can not use a standard procedure of estimating the elasticities using regressions based on FOCs. Instead, we turn to a common procedure used in the Real Business Cycle literature, where we pin down the values of $\eta_1^{oil}$ and $\rho_1^{oil}$ so that simulated data from the model matches up with some of the features of real world data. Specifically, we focus on two moments: the ratio of the volatility of the relative price of light crude to medium over the volatility of (real) light oil prices, and a similar ratio calculated using the volatility of the relative price of light crude oil to heavy.

To do this, we use annual price data on LLS, Dubai and Maya crude oils. Dubai is chosen as a benchmark for medium crude oil as Mars only became available in 1997, which is a very limited sample when using annual data. We de-trend the series using a one-sided HP filter and then calculate the volatilities of the relative prices along with the inflation-adjusted series for LLS. We then simulate the model and set the elasticities so that the model-simulated data matches the moments from the actual data. This exercise sets the elasticity between light and medium ($\eta^{oil}$) at 5.35 and the elasticity between heavy and composite ($\rho^{oil}$) at 3.23.[11]

Given the elasticities and the FOCs for oil inputs, the relative oil prices and the oil inputs at the steady state help us determine the share of light oil, $\omega_1^o$, and the share of heavy oil, $w_1^o$, in producing refined products. Then, heavy, medium and light oil prices at the steady state can be found using the FOCs and the steady state relative oil prices.

The elasticity of supply for crude oil is set to 0.20. This ensures that supply of all types of all is fairly inelastic in response to price changes, a key feature of the data.

The elasticity of substitution between the capital-labor composite and refined products in the non-oil sector is set equal to the price elasticity of demand for refined products on the household side, $\frac{1}{1+\rho_i^a} = \frac{1}{1+\rho}$, $i = 1, 2$, in both countries. The value of $y_1^a$ then can be obtained using the resource constraint for country 1, which helps us determine $w_1^a$. Finally, we need to calibrate the parameter that controls the share of labor in non-oil sector's value-added, $\chi_1^a$. We again rely on data from the World Input Output

[11]We also find that $\eta^{oil}$ is greater than $\rho^{oil}$ when using annual data for Mars instead of Dubai, and also if we use quarterly price data to provide the moments.

Database, which provides annual data on labor compensation and total value-added for 40 countries (including the U.S.), with the time series running from 1995 to 2011 for most of the countries. First, we use this data to generate a time series for the labor share of total value-added in each country. Then, for each country we get the average labor share over $2000 - 2009$. The value for the U.S. is obtained as $\chi_1^a = 0.60$. To get the labor share of total value-added for the ROW, i.e. $\chi_2^a$, we also use data from the IMF on GDP in 2010 to account for different size of GDP across countries. We first find the share of GDP in each country out of the global GDP excluding the U.S., and use these shares to weight each country's labor-share. We then sum the weighted labor shares to get our estimate for the ROW, $\chi_2^a = 0.55$.

In line with Christiano, Eichenbaum and Evans (2005), we set $\phi_1 = 4$. The values for the rest of the parameters and the steady state values for the rest of the U.S. variables are obtained from the steady state model. Parameters for the U.S. are presented in the top panel of Table 4.2.

Taking the calibration of the U.S. economy as given, we continue calibrating the ROW. First, based on Eni data for 2010 we set the U.S. share in global oil production as 0.073. We also obtain the shares of light, medium, and heavy oil production in total ROW oil production for 2010. They help us determine the steady state values of light, medium, and heavy oil supply in the ROW. Crude oil inputs to refiners in the ROW are then obtained from the oil market clearing condition.

We calculate $y_2^f$ by making use of data on refinery gains from the EIA and IEA. Given total crude oil inputs data for the ROW, we assume refined production in the ROW is a sum of total crude oil inputs in the ROW and refinery gains in the ROW. Then, we calculate $\frac{o_2^f}{y_2^f}$, which is 0.983 for 2010. At the steady state, we set $y_2^f = \frac{o_{L_2}^f + o_{M_2}^f + o_{H_2}^f}{0.983}$. Continuing with the parameters of the refining sector, the elasticities of substitution across different oil inputs are set equal to the elasticities in the U.S. refining sector. As PPP holds, prices of all the goods are equal across countries at the steady state. Then, we can determine the share of light oil, $\omega_2^o$, the share of heavy oil, $w_2^o$, and the share of oil composite, $(1 - \alpha_2^f)$, in producing refined products.

The share of global GDP due to the U.S. was 17 percent in 2010 and the U.S. population share was 4.5 percent, based on UN data, allowing us to obtain GDP

**Table 4.2:** Baseline Calibration

| **Calibration for the U.S.** | | |
|---|---|---|
| **Description** | **Symbol** | **Parameter value** |
| Depreciation rate of capital | $\delta$ | 0.10 |
| Labor and capital's share in refining production | $\alpha_1^f$ | $(1-0.774)$ |
| Labor's share in refining value-added | $\chi_1^f$ | 0.164 |
| Elasticity of substitution between $L$ and $M$ | $\eta_1^{oil}$ | 5.35 |
| Elasticity of substitution between $H$ and $M(orL)$ | $\rho_1^{oil}$ | 3.23 |
| Share of $L$ in refining production | $\omega_1^o$ | 0.497 |
| Share of $H$ in refining production | $w_1^o$ | 0.294 |
| Elasticity of $k = L, M, H$ supply | $\eta_1^k$ | 0.20 |
| Elasticity of substitution in non-oil production | $1/(1+\rho_1^a)$ | 0.20 |
| Labor's share in non-oil production | $\chi_1^a$ | 0.60 |
| Refined product's share in non-oil production | $(1-w_1^a)$ | $5.1050e-09$ |
| Elasticity of investment-capital ratio w.r.to Tobin's $q$ | $\phi_1$ | 4 |
| Non-oil consumption intensity in $c_1$ | $w_1$ | $3.1632e-08$ |
| Share of time spent in the workplace | $\mu_1$ | 0.378 |
| **Calibration for the ROW** | | |
| Labor and capital's share in refining production | $\alpha_2^f$ | 0.1697 |
| Labor's share in refining value-added | $\chi_2^f$ | 0.297 |
| Elasticity of substitution between $L$ and $M$ | $\eta_2^{oil}$ | $\eta_1^{oil}$ |
| Elasticity of substitution between $H$ and $M(orL)$ | $\rho_2^{oil}$ | $\rho_1^{oil}$ |
| Share of $L$ in refining production | $\omega_2^o$ | 0.484 |
| Share of $H$ in refining production | $w_2^o$ | 0.216 |
| Elasticity of $k = L, M, H$ supply | $\eta_2^k$ | $\eta_1^k$ |
| Elasticity of substitution in non-oil production | $1/(1+\rho_2^a)$ | $1/(1+\rho_1^a)$ |
| Labor's share in non-oil production | $\chi_2^a$ | 0.55 |
| Refined product's share in non-oil production | $(1-w_2^a)$ | $6.0810e-09$ |
| Elasticity of investment-capital ratio w.r.to Tobin's $q$ | $\phi_2$ | $\phi_1$ |
| Non-oil consumption intensity in $c_1$ | $w_2$ | $1.2534e-09$ |
| Share of time spent in the workplace | $\mu_2$ | 0.3926 |

and time available for work and leisure in ROW. The household and firm petroleum consumption ratio for 2010 is obtained using data from several sources. WIOD provides data on "coke and refined petroleum products" by firms as an intermediate input and also final consumption of the good by households for 40 countries. The EIA provides data on world consumption of petroleum and other liquids by region and end-use sector. Finally, Exxon 2016 Energy Outlook [17] provides data on world oil use by end-use sector. Based on our calculations using different sources, we assume a ratio of 0.50 for the ratio of household use of petroleum to firm use for 2010, allowing us to pin down steady state values of household use and firm use of refined products for the ROW. Elasticities of oil supply are equal to the U.S. elasticities. The value of $y_2^a$ then follows from the resource constraint for country 2, which helps us determine $w_2^a$. Moreover, we assume $\phi_2 = \phi_1$. The rest of the parameters are calibrated using the remaining of the equilibrium conditions at the steady state.

## 4.2 Calibrating the shocks

The parameters governing the autoregressive processes for the productivity shocks are not determined by the deterministic steady state. We use simulated method of moments, a standard technique in the business cycle literature, to match several moments in the data and calibrate these parameters.

We use data on U.S. and ROW real GDP as well as U.S. and ROW crude oil production for the moment matching exercise. The ROW GDP series is an index of the trade-weighted average of GDP series for 40 countries from the Database of Global Economic Indicators.[12] Data on U.S. and ROW oil production are based on the EIA World Crude Oil Production Including Lease Condensate series. We would have preferred to use time series data on oil production by type but we do not have a sufficiently long time series available, even for the U.S. We average the monthly and quarterly observations for oil production and GDP, respectively, to produce an annual time series and then take the log of the annual series.

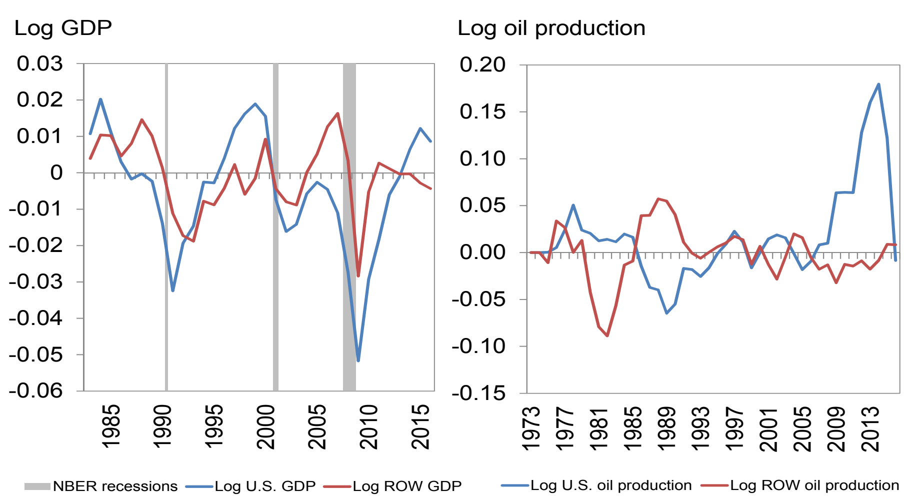
As we do not explicitly model trends in economic variables, oil or otherwise, we

[12]See Grossman et al. (2014) [19] for more details.

de-trend the data using a one-sided HP filter. For the oil production series we filter the entire sample from 1973 to 2016. For the GDP series, we start the filter in 1981, as this is the first year for which we have an annual average for ROW GDP.

The left and right panels of Figure 4.1 plot the de-trended data series for GDP and oil production, respectively. The gray bars in the GDP figure denote NBER recessions. We note that the GDP series picks up the Great Recession, U.S. recessions in the early 1990s and early 2000s, and the above trend growth in the ROW GDP in the mid-2000s due to the BRICs. The de-trended oil production series clearly show the impact of the shale boom and subsequent production decline in the U.S., as well as the long period from 2005 to 2013 where production outside the U.S. remained range-bound between about 68 to 70 million barrels per day.

**Figure 4.1:** De-trended GDP and oil production, U.S. vs. the ROW




SOURCES: Bureau of Economic Analysis; Database of Global Economic Indicators; Energy Information Administration; authors' calculations.

In our calibration exercise, we constrain the autocorrelations and volatilities of the productivity shocks for different oil types to be equal, although they can differ between the U.S. and ROW. Ideally, we would prefer to allow these to be different across types within countries but we do not have a sufficiently long time series to do this. This leaves a total of 8 parameters that need to be calibrated for the shocks.

**Table 4.3:** Calibration of shock parameters

| Shock | AR(1) coefficient | Volatility |
|---|---|---|
| Technology (U.S.) | .613 | .0086 |
| Technology (ROW) | .367 | .0075 |
| Oil supply (U.S.) | .696 | .0258 |
| Oil supply (ROW) | .731 | .0324 |

**Table 4.4:** Properties of key variables, Data vs Model

| | **Data** | | **Model** | |
|---|---|---|---|---|
| Variable | Autocorrelation | Volatility | Autocorrelation | Volatility |
| U.S. oil production (total) | 0.698 | 0.03 | 0.698 | 0.03 |
| ROW oil production (total) | 0.737 | 0.024 | 0.735 | 0.024 |
| U.S. GDP | 0.714 | 0.016 | 0.713 | 0.016 |
| ROW GDP | 0.495 | 0.011 | 0.496 | 0.011 |

We choose 8 moments from the de-trended data for our purposes: the first-order autocorrelations and the volatilities. Our goal in the exercise is to calibrate the shock parameters so as to have the model simulated data match these moments in the data. We trim the sample to run from 1986 to 2010. We remove data after 2010 to remove the influence of the shale boom, as we want to treat that as the "shock" in our DSGE model. We start in 1986 to start our oil production series following the collapse of OPEC production cuts around that time.

Table 4.3 shows the calibration of the shock parameters as a result of our moment matching exercise. Table 4.4 compares the properties of the data to those of the simulated data from the model. In addition to the four variables we purposely try to match, the table provides information on refiner runs (total oil inputs into the U.S. refining sector) and the price of light oil. We see the model is able to successfully match the moments we have targeted, both for GDP and the oil production series.

# 5 Results

We model the shale oil boom as an exogenous shock that lowers the cost of producing light oil in the U.S., i.e. a positive shock to $z^{oL}_{1,t}$. In order to generate a path for the shocks, we conduct the following exercise. We have data on the percent change in U.S. light oil production from 2010 onwards. We numerically solve for the values of the productivity shocks in the model that would generate the same percentage changes in U.S. light oil production as seen in the data. We do this to match the data in $2011 - 2014$.[13] We then feed these shocks into the model and analyze how various variables respond to the increased light oil production.

Given the large number of variables in the model, we choose to focus on a subset of the results of particular interest and importance. Figures 5.1 - 5.3 plot the responses of those variables. We note that units are percentage deviations of each variable from its starting point. These are calibrated in most cases to line up with 2010 data.

Figure 5.1 focuses on a number of oil market variables. We discuss the results moving from left to right, top to bottom. The top left panel shows the path of U.S. light oil production, which by default lines up with the data. Overall, total U.S. production rises by more than 60 percent by 2014, slightly higher than the actual data. Oil production outside the U.S. falls by a small amount, and total oil production rises by more than 2 percent.

Turning to prices, we find that the increased supply is enough to push down the price of light oil by more than 10 percent by 2014. The price of light oil outside the U.S. falls by the same amount, as there is free trade. The bottom two panels show that the relative price of light crude to other grades of crude declines, i.e. the price of light crude falls by more than medium and heavy. This is in line with the fact that the different types of crude oil are imperfect substitutes for each other, and that the supply increase is solely in light crude oil.

Figure 5.2 plots imports of light and medium crude oil, as well as refiner inputs

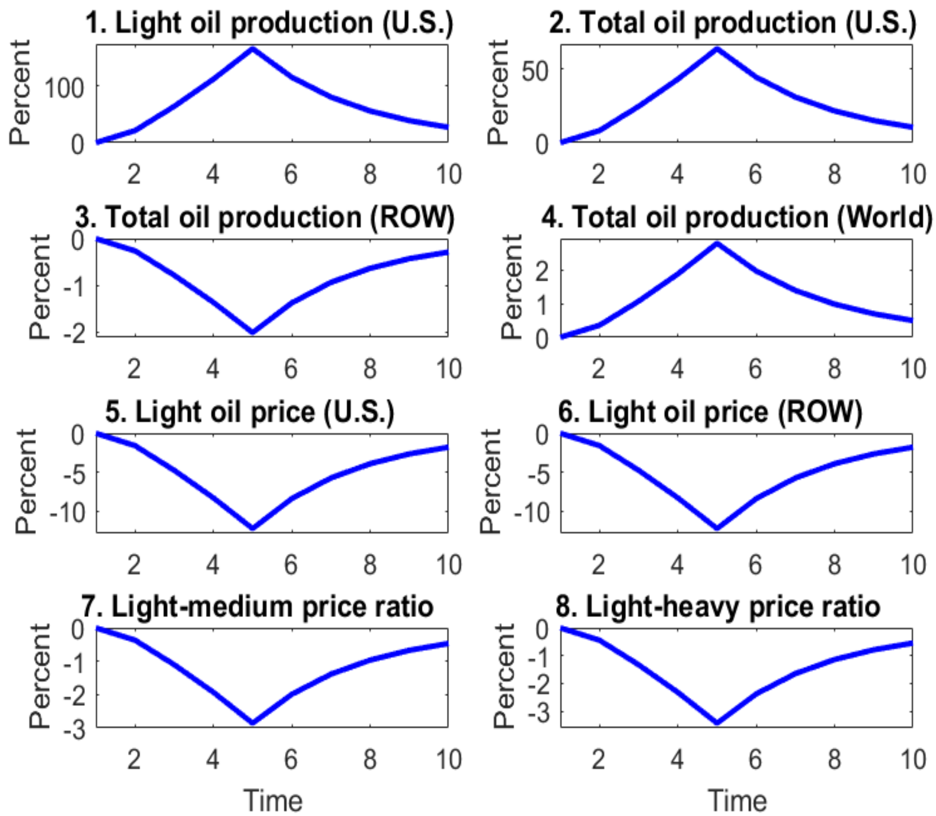
[13] 2014 is the end date as the sharp decline in the price of oil late in 2014 significantly reduced drilling for oil in the U.S., affecting production levels in 2015. Therefore, some of the production change that year is arguably not exogenous.

by type of oil for the U.S. and ROW. The model predicts that the supply increase is large enough to make the U.S. a net exporter of light crude oil by 2014. Imports of medium crude also decline. As the price of light oil relative to other grades has declined, refiners in both the U.S. and the ROW process more light crude oil. We note that the increase in use of light oil by U.S. refiners is not enough to fully make use of all the new production; hence we see a sharp decline in imports of light crude.

The top panel of figure 5.3 plots two other variables related to the refining sector. We find that production of refined petroleum products in the U.S. rises by about a percentage point by the peak of the shock. The top right panel plots the relative price of fuel to light oil prices. We find that this rises by several percentage points, providing an economic incentive for refiners to process more light oil to produce fuel.

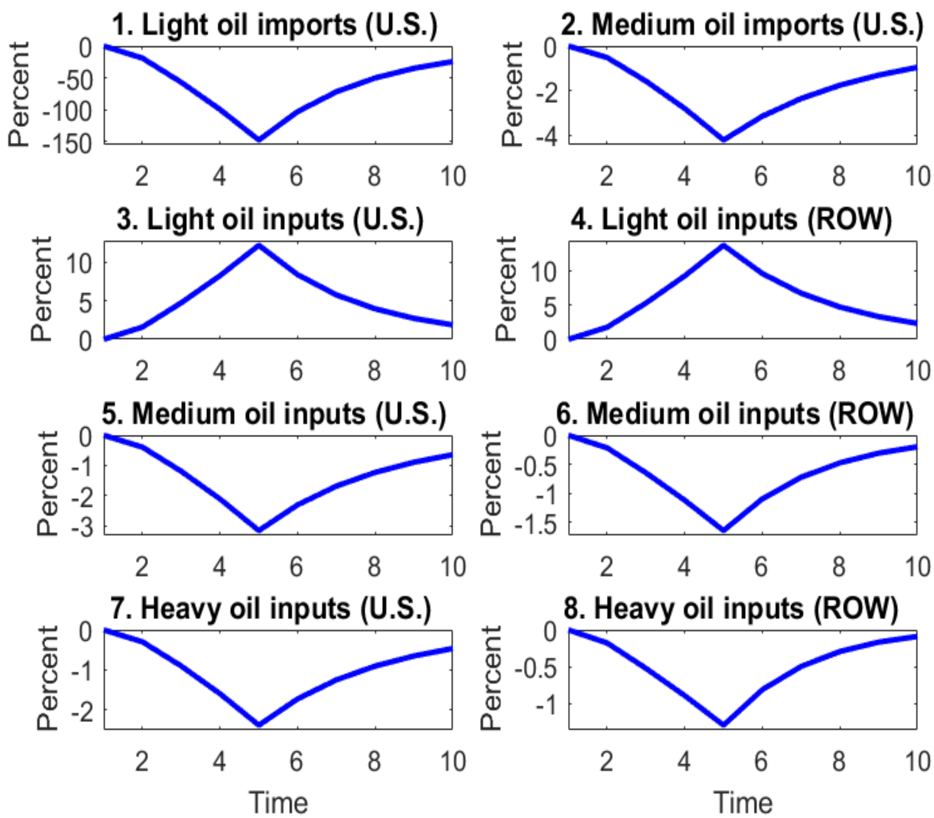
The bottom panel plots the response of the U.S. GDP and fuel prices. We find that the increase in light oil production boosts U.S. GDP by 0.8 percent in 2014 vs 2010 levels. This may seem small in light of the 60 percent increase in total U.S. crude oil production entailed by the shock. However, the oil sector in the U.S. is small compared to the broader economy. We find that fuel prices drop by 8 percent by 2014. As the decline in fuel prices is less than the decrease in light oil prices, the crack spread increases.

**Figure 5.1:** Impulse responses from the model



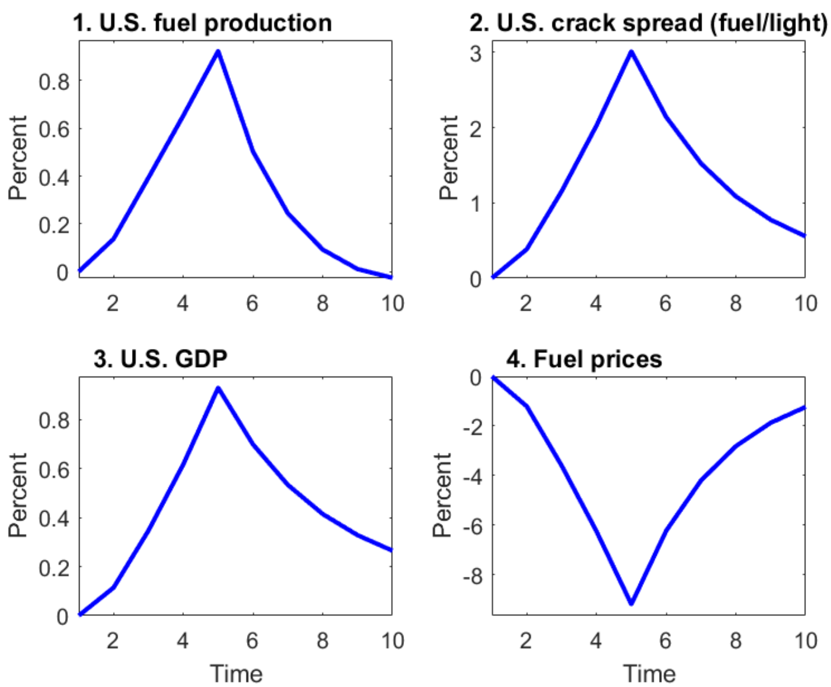

Note: Units are percent deviations from the steady state.

**Figure 5.2:** Impulse responses from the model




Note: Units are percent deviations from the steady state.

**Figure 5.3:** Impulse responses from the model




Note: Units are percent deviations from the steady state.

# 6 The Impact of Crude Oil Export Ban

In our general framework presented in Section 3, there are no restrictions on trade and purchasing power parity holds for all goods. We now extend the baseline model to incorporate the U.S. crude oil export ban. The export ban is modeled as an exogenously given constraint that prevents (net) imports of all types of crude oil in the U.S. from becoming negative, i.e. exports are impossible. At its most basic level, this means having inequality constraints in the model, one for each type of oil. These constraints are given by

$$o^{f}_{k_{1,t}} - y^{ok}_{1,t} \geq 0 \tag{6.1}$$

for $k = H, M, L$. Further mathematical details about setting up the export ban can be found in the Appendix A.

We point out several important facets of this constraint. We use the case of light oil as an example but these facets apply equally to other types of crude oil. First, if the constraint binds, then part of the oil market in the U.S. becomes segmented from the rest of the world. This generates a wedge between domestic light oil prices and foreign light oil prices. Second, the constraint itself is endogenous, in the sense that both refiner use of light oil and production of light oil are endogenous variables. Therefore, the ability of refiners to substitute away from other oils towards light oil has implications for when the constraint might bind and what kind of price differentials it is likely to generate.

To solve the model with inequality constraints, we use the Guerrieri and Iacoviello (2015) [20] OccBin toolkit for Dynare, allowing us to examine the possibility that the export ban could bind for some period of time. The length of the time is endogenously determined by the shocks that hit the economy and the structure of the economy.

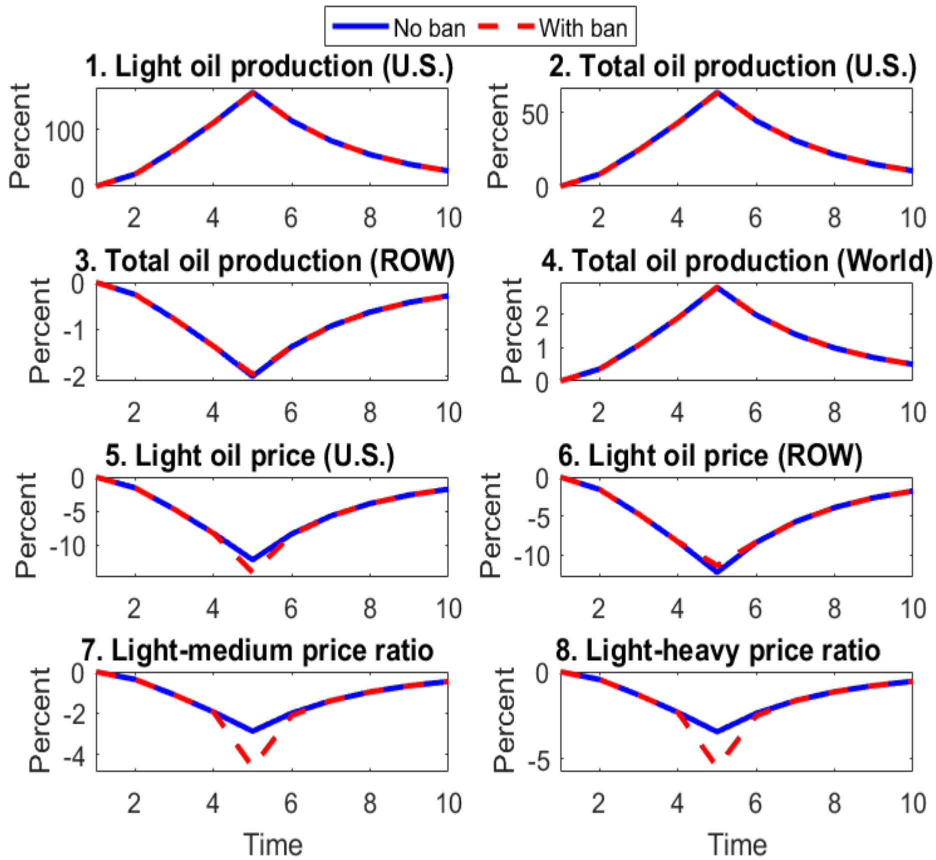
Our goal is to investigate the effects of higher U.S. light oil production on the oil markets and the broader economy under the U.S. oil export ban. Our experiment is as follows. We start from the initial steady state and feed in a series of positive light oil supply shocks in the U.S. country 1 over 4 years. The shocks exactly replicate the path of U.S. light oil production from 2011 to 2014.

Figures 6.1 to 6.3 compare the impulse responses for the free trade scenario to the case where the export ban is taken into account. The blue lines are the free trade base case, and the dashed-red lines are with the ban in place.

We first turn to the most basic question: was the ban binding? Our model says yes, primarily in 2014 but also to a very small extent in 2013 and 2015. This can be seen in the top left panel of figure 6.2. We find that the ban distorts a number of economic outcomes, although these are primarily concentrated in the oil and refining sectors. The price of light crude oil in the U.S. becomes artificially cheap, relative not only to light oil outside the U.S. but also to other grades of crude oil. This price discount boosts the crack spread for refiners in the U.S. compared to those outside of the country. This price differential leads to a significantly higher jump in the use of light oil by U.S. refiners, and to a jump in the amount of refined petroleum products produced by the U.S.

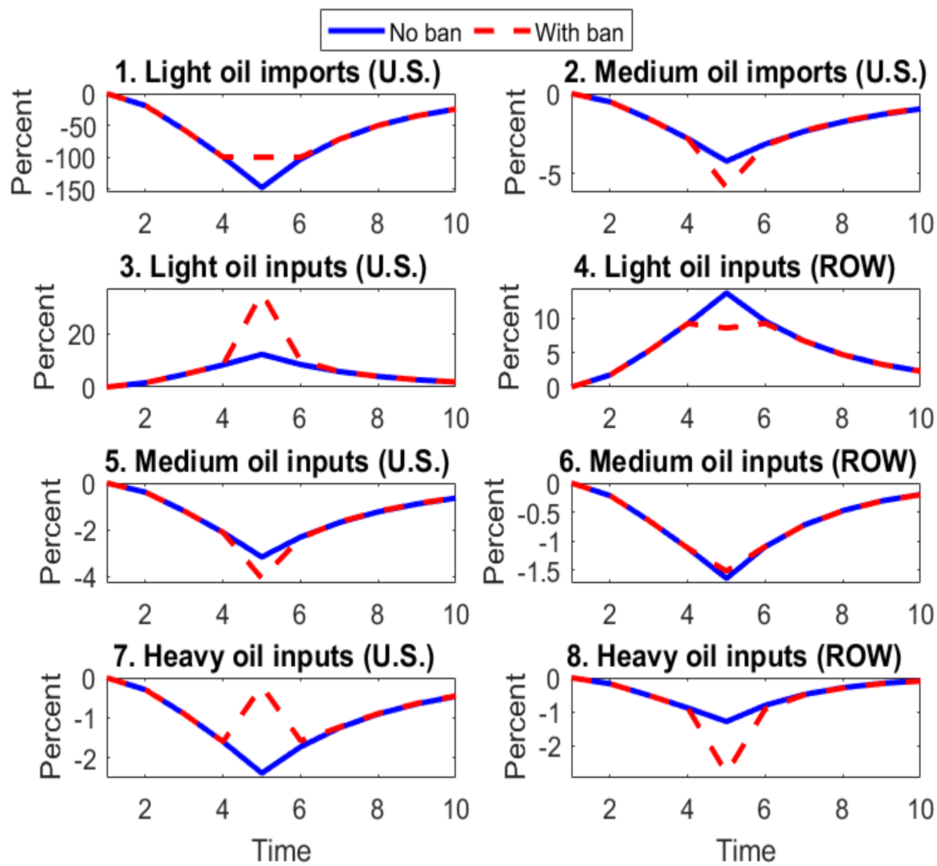
While the distortions in the refining sector appear large, the spillovers to the other parts of the economy appear fairly small. The price discount in light crude oil that appears is not sufficiently large enough to distort oil production by an extreme amount. And, since refined petroleum products are not subject to any ban, the increased production by U.S. refiners primarily comes at the expense of refiners in ROW, who get crowded out of the market. As a result, the impact on fuel prices is negligible and so is the impact on U.S. GDP.

**Figure 6.1:** Impulse responses from the model



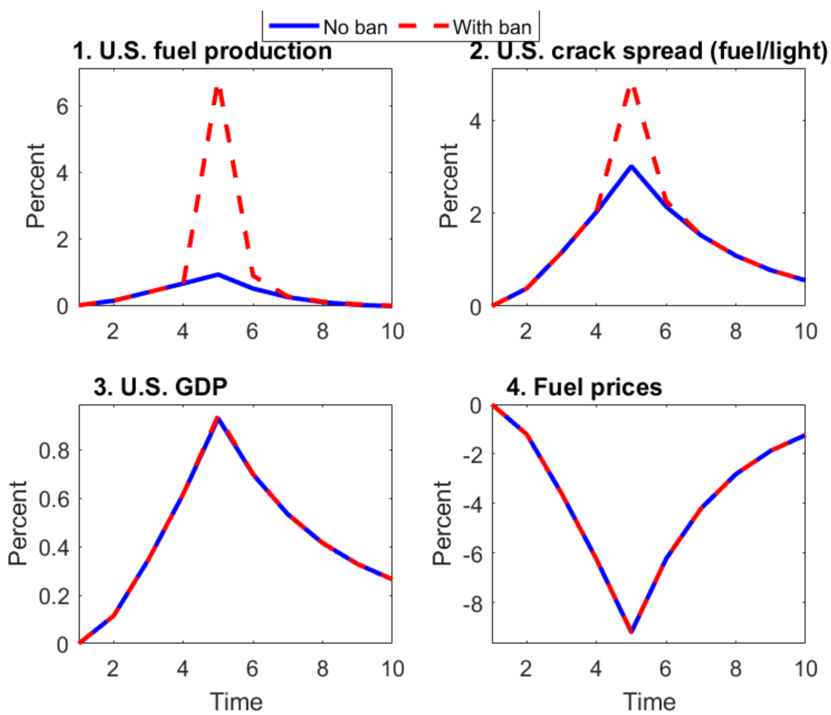

Note: Units are percent deviations from the steady state. Blue lines: free trade (no ban), dashed-red: with the export ban.

**Figure 6.2:** Impulse responses from the model




Note: Units are percent deviations from the steady state. Blue lines: free trade (no ban), dashed-red: with the export ban.

**Figure 6.3:** Impulse responses from the model




Note: Units are percent deviations from the steady state. Blue lines: free trade (no ban), dashed-red: with the export ban.

## Was the ban binding in reality?

According to our model, the export ban on crude oil was a binding constraint from 2013 to 2015. We now try to review the evidence from the data to see whether the model prediction is consistent with the data itself.[14]

We approach this question in two ways. First, we consider several predictions from the model that can be checked in the data. We focus primarily on variables that are very closely connected to the market for light crude oil. Second, we take advantage of the fact that the U.S. crude oil export ban had several loopholes. These loopholes could act as release valves for pressure that might arise in the market if the ban became a binding constraint.

We focus on three predictions our model makes about what we should see in the data if the export ban was binding at some point in time. First, the model predicts that imports of light oil should become zero. Second, and related to the first, if the ban is a binding constraint, it could actually prevent exports of light crude oil. Finally, an unusually large spread should develop between light oil in the U.S. and outside the U.S.

A review of table 2.2 suggests that the first prediction of the model does not appear to hold in the data. At no point in time did exports of "light" crude oil become zero, or even approach anything close to zero. However, we can take a deeper look at the data. The EIA import data allows us to consider more disaggregated slices of the crude import data for light oil, which are shown in figure 6.4. When we look at the import data for crude oil with API gravity higher than 40, we see that these imports did, indeed, fall to near zero for several years.

We point out here that our modeling decision to define "light" oil as API gravity 35 and above is driven due to data constraints for the production data. It is known from other analysis that most U.S. shale oil actually has API of 40 and above.[15]. When viewed from this context, it seems natural that the first crude oils that would get crowded out are those of relatively high API gravity. And indeed, we see that imports

[14] Çakır Melek (2017) [14] analyzes oil market data for the same time period and argues that the ban distorted oil flows during the shale boom.

[15] EIA (2015) [36]

of very light crude approach zero first followed by those slightly below.

Turning to the second prediction, we are actually able to make firm statements about whether the ban constrained exports because the ban was removed at the end of 2015 and we now have export data for 2016. We plot this data in figure 2.3. The black line shows total crude exports, and it shows that U.S. crude exports increased in 2016 compared to 2015, despite the fact that U.S. crude production actually declined that year.

The export ban policy had a loophole in it that allowed for exports of crude oil to Canada, so long as the crude oil was to be processed in Canada and the fuels used for domestic consumption therein. In other words, if the desire to export crude oil was large enough, it was possible to try and use this loophole to export crude to Canada and indirectly back out Canadian imports of oil from another country. The dashed red line shows those numbers. We see that exports of crude to Canada did indeed start increasing in 2013 through 2015. Since this loophole was not heavily used at any point before this time, this is very suggestive that the ban had become binding in some sense.

Finally, we turn towards the prediction that light crude oil in the U.S. should sell at a discount to light oil outside the U.S. if the ban binds.[16] Using West Texas Intermediate crude prices may be problematic as the interior of the U.S. faced some logistical constraints that affected prices of WTI relative to other benchmarks. Given this, we instead use Louisiana Light Sweet (LLS) as our light oil price. This is a light crude oil similar in nature to WTI but is priced in the Gulf Coast of the U.S. We use Brent crude for our measures of foreign light oil prices.

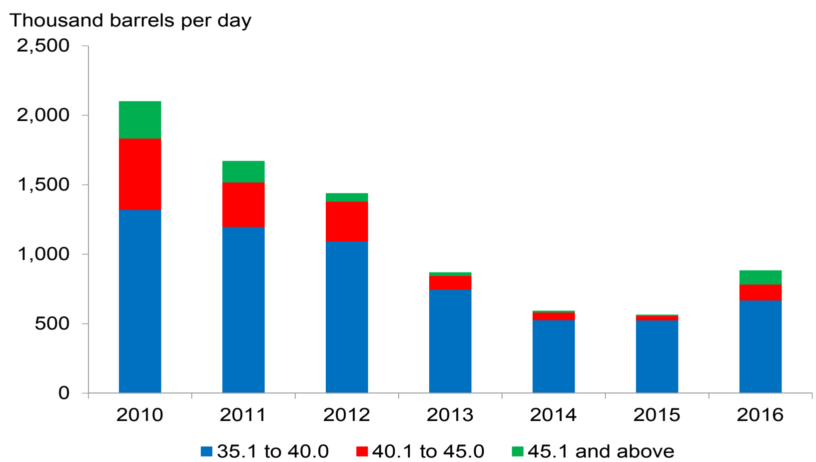
Figure 6.5 plots the relative price of LLS to Brent. Starting in late 2013, we see that the relative price of LLS to Brent declined to unusually low levels compared to where it was in previous years. This continued through much of 2015. After the ban was removed, the relative price has generally remained close to levels seen in the years before 2013, and has never fallen to the abnormal levels seen in late 2013 and early

[16]We do not consider the predictions regarding the price of light relative to medium and heavy as there were changes in the supply of both those types of crude outside the U.S. that would have impacted their prices. Since we have not modeled those changes in supply, we feel it is best to focus on light crude oil.

2014.

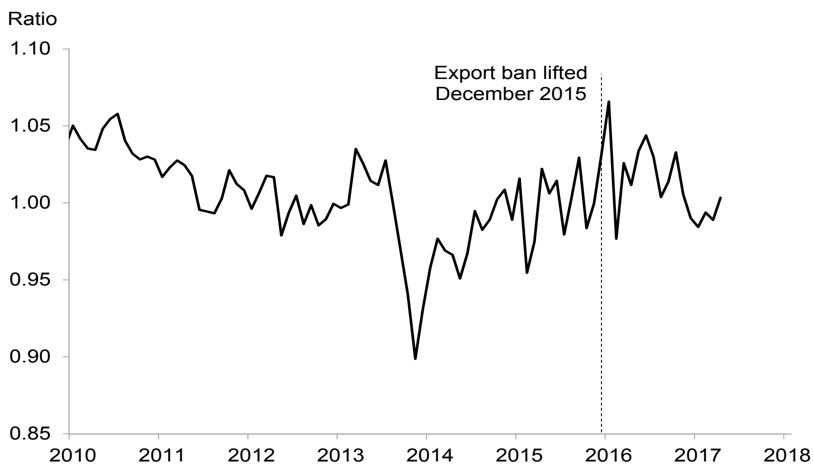
Overall, we believe the evidence presented here is very suggestive that the crude oil export ban became a binding constraint sometime in 2013 and remained a constraint through 2015.

**Figure 6.4:** U.S. imports of light crude oil by API gravity.




SOURCE: Energy Information Administration.

**Figure 6.5:** Relative price of Louisiana Light Sweet to Brent crude oil.




SOURCE: Bloomberg.

# 7 Conclusion

In this paper we introduce a two-country DSGE model that incorporates a refining sector and different types of crude oil. The model is used to consider the impacts of the shale oil boom and the U.S. crude oil export ban on both the oil and refining sectors, as well as the broader economy. The introduction of different types of crude oil, which are modeled as imperfect substitutes as inputs to the refining process, allows us to take into account the fact that oil produced from shale plays is primarily light crude oil and that refining sectors in the U.S. and the rest of the world specialize in processing different types of oil.

Under a free trade scenario, we find that a light oil boom of the same magnitude as the shale boom in the U.S. reduces light oil prices by more than 10 percent, increases U.S.' use of light crude at the expense of other types, and makes the U.S. a net exporter of light crude oil. It also lowers fuel prices by about 8 percent and modestly increases GDP.

Taking the export ban into account, our model predicts that the ban was binding in 2013 through 2015. The impact of the ban was primarily concentrated in the energy sector, especially the refining sector. Light oil prices were artificially low in the U.S. relative to the rest of the world, and refiners in the U.S. processed more light oil than they would have otherwise. The impact of the ban on GDP and fuel prices was negligible.

# References


[1] Backus, D. K., and Crucini, M. J., 2000, "Oil prices and the terms of trade," Journal of International Economics, Vol. 50, 185-213

[2] Backus, D. K., Kehoe, P. J., and Kydland, F. E., 1992, "International Real Business Cycles," Journal of Political Economy, Vol. 100, No. 4, 745-775

[3] Backus, D. K., Kehoe, P. J., and Kydland, F. E., 1994, "Dynamics of the Trade Balance and the Terms of Trade: The J-Curve?" The American Economic Review, Vol. 84, No. 1, 84-103

[4] Balke, N. S., Plante, M.D. and Yucel, M. K., 2015, "Fuel Subsidies, the Oil Market and the World Economy," The Energy Journal, Vol. 36(S), 99-127

[5] Baumeister, C., and Hamilton, J., 2015, "Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks," Working paper

[6] Bausell Jr., C. W., Rusco, F. W., and Walls, W. D., 2001, "Lifting the Alaskan Oil Export Ban: An Intervention Analysis," The Energy Journal, Vol. 22, No. 4, 81-94

[7] Baxter, M., and Crucini, M. J., 1995, "Business cycles and the asset structure of foreign trade," International Economic Review, Vol. 36, No. 4, 821-854

[8] Bodenstein, M., Erceg, C. J., and Guerrieri, L., 2011, "Oil Shocks and External Adjustment," Journal of International Economics, Vol. 83, No. 2, 168-184

[9] Bordoff, J., and Houser, T., 2015, "Navigating the U.S. Oil Export Debate," Columbia SIPA Center on Global Energy Policy, January 2015

[10] Brown, S.A., Mason, C., Krupnick, A., and Mares, J., 2014, "Crude Behavior: How Lifting the Export Ban Reduces Gasoline Prices in the United States," Resources for the Future Issue Brief, March 2014

[11] Brown, P., Pirog, R., Vann, A., Fergusson, I., Ratner, M., and Ramseur, J., 2014, "U.S. Crude Oil Export Policy: Background and Considerations," Congressional Research Service, March 2014

[12] Christiano, L. J., Eichenbaum, M., and Evans, C.L., 2005, "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," Journal of Political Economy, Vol. 113, No. 1, 1-45

[13] Crucini, M. J. and Kahn, J., 1996, "Tariffs and Aggregate Economic Activity: Lessons from the Great Depression," Journal of Monetary Economics, Vol. 38, 427-467

[14] Çakır Melek, Nida, 2017. "Lifting the U.S. Crude Oil Export Ban: Prospects for Increasing Oil Market Efficiency," Federal Reserve Bank of Kansas City, Economic Review, Forthcoming.

[15] Ebinger, C.K., and Greenley, H., 2014. "Changing Markets: Economic Opportunities from Lifting the U.S. Ban on Crude Oil Exports," Brookings Institution, September 2014

[16] Eni, 2016. "Eni World Oil and Gas Review 2016"

[17] Exxon, 2016. "Exxon 2016 Energy Outlook"

[18] Farrokhi, F., 2016, "Global Sourcing in Oil Markets," Purdue University Dissertation, August 2016

[19] Grossman, V., Mack, A., and Martinez-Garcia, E., 2014, "A New Database of Global Economic Indicators," Journal of Economic and Social Measurement, Vol. 39, No. 3, 163-197

[20] Guerrieri, L., and Iacoviello, M., 2015, "Occbin: A Toolkit to Solve Models with Occasionally Binding Constraints Easily," Journal of Monetary Economics, Vol. 70, March, 22-38

[21] IHS, 2014, "U.S. Crude Oil Export Decision: Assessing the Impact of the Export Ban and Free Trade on the Economy"

[22] IHS, 2015, "Unleashing the Supply Chain: Assessing the Economic Impact of a U.S. Crude Oil Free Trade Policy"

[23] Kang, W., Ratti, R., and Vespignani, J., 2016, "The impact of oil price shocks on the U.S. stock market: A note on the roles of U.S. and non-U.S. oil production," Economics Letters, Vol. 145, 176-181

[24] Kilian, L., 2016, "The Impact of the Shale Oil Revolution on U.S. Oil and Gasoline Prices," Review of Environmental Economics and Policy, Vol. 10, No. 2, 185-205

[25] Kilian, L., 2017, "How the Tight Oil Boom Has Changed Oil and Gasoline Markets," CEPR Discussion Paper No. DP11876

[26] Kumins, Larry, 2005, "West Coast and Alaska Oil Exports," Congressional Research Service, May 2005

[27] Langer, L., Huppmann, D., and Holz, F., 2016, "Lifting the US Crude Oil Export Ban: A Numerical Partial Equilibrium Analysis," Energy Policy, Vol. 97, 258-266

[28] Leduc, S., and Sill, K., 2007, "Monetary Policy, Oil Shocks, and TFP: Accounting for the Decline in U.S. Volatility," Review of Economic Dynamics, Vol. 10, No. 4, 595-614

[29] Manescu, C., and Nuno, G., 2015, "Quantitative effects of the shale oil revolution," Energy Policy 86 (2015): 855-866

[30] Medlock, K., 2015, "To Life or Not to Lift? The U.S. Crude Oil Export Ban: Implications for Price and Energy Security," Rice Universitys Baker Institute for Public Policy, Center for Energy Studies, March 2015

[31] Mohaddes, K., and Raissi, M., 2016, "The U.S. Oil Supply Revolution and the Global Economy," Globalization and Monetary Policy Institute Working Paper, No. 263

[32] Nakov, A., and Nuno, G., 2013, "Saudi Arabia and the Oil Market," Economic Journal, Royal Economic Society, Vol. 123, No. 12, 1333-1362

[33] Plante, M., 2014, "How Should Monetary Policy Respond to Changes in the Relative Price of Oil? Considering Supply and Demand Shocks," Journal of Economic Dynamics and Control, Vol. 44(C), 1-19

[34] Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J., 2015, "An Illustrated User Guide to the World Input-Output Database: the Case of Global Automotive Production," Review of International Economics, 23, 575-605

[35] U.S. Energy Information Administration, 2014, "What Drives U.S. Gasoline Prices?"

[36] U.S. Energy Information Administration, 2015, "U.S. Crude Oil Production to 2025: Updated Projection of Crude Types."

[37] Van Vactor, S. A., 1995, "Time to end the Alaskan Oil Export Ban," Policy Analysis, 227, Cato Institute

[38] Vidas, H., Tallett, M., OConnor, T., Freyman, D., Pepper, W., Adams, B., Nguyen, T., Hugman, R., and Bock, A., 2014, "The Impacts of U.S. Crude Oil Exports on Domestic Crude Oil Production, GDP, Employment, Trade and Consumer Costs," ICF International and EnSys Energy submission to the American Petroleum Institute, March 2014

[39] Walls, W. D., Zheng, X., 2016, "Shale oil boom and the profitability of US petroleum refiners," OPEC Energy Review, Vol. 40, 337353

# APPENDIX

# A Modeling the export ban

We address the U.S. oil export ban in the model as follows. We assume that crude oil is distributed by perfectly competitive firms, called distributors of crude oil. A distributor's problem is a tool for us to model an export ban on crude oil, which will be introduced into the distributor's problem as an inequality constraint. Moreover, we assume that there are iceberg trade costs for shipping crude oil. Adding trade costs allows the model to generate a small, positive spread between crude oil prices in the U.S. and the ROW. This is a feature of the data due to the costs of importing the marginal barrel of oil into the U.S. To match this feature of the data we work with a simple form of iceberg trade costs. If country 1 imports $o^m_{1,t}$ units of crude oil, then $\tau_{o2} o^m_{1,t}$ units will be lost in transit, where $\tau_{o2} > 0$ is the iceberg cost of moving crude oil from country 2 to country 1. We assume there is no cost of moving crude oil within country 1 or country 2. This form of trade costs implies that crude oil imports are given by $o^m_{1,t} = \frac{o^f_{1,t} - y^o_{1,t}}{1-\tau_{o2}}$.

## A.1 Distributors of crude oil

A perfectly competitive distributor purchases crude oil in domestic spot market or imports it, and then re-sells it to refined products producers (refineries) costlessly. In country 1, crude oil of type $k$ can be purchased in the domestic spot market at price $p^{ok}_{11,t}$ or imported from country 2 at $p^{ok}_{2,t}$. The oil distributor chooses output and imports of type $k$ crude oil to maximize the present discounted value of cash flow

$$E_0 \sum_{t=0}^{\infty} \beta^t \lambda_{1,t} \left\{ p^{ok}_{1,t} o^f_{k_{1,t}} - p^{ok}_{11,t} y^{ok}_{1,t} - p^{ok}_2 o^m_{k_{1,t}} \right\}$$

subject to

$$o^f_{k_{1,t}} = y^{ok}_{1,t} + (1-\tau_{o2})\, o^m_{k_{1,t}}$$

$$o^m_{k_{1,t}} \geq 0$$

where $o^m_{k_{1,t}}$ is the import of type $k$ crude oil, $o^f_{k_{1,t}}$ is type $k$ crude oil demand by the refineries, and $\tau_{o2}$ is the parameter determining the cost of importing crude oil from country 2.[17]

So, the crude oil export ban in country 1 (U.S.) is modeled as an inequality constraint that prevents (net) imports of all types of crude oil, $k = L, M, H$, in country 1 from becoming negative, i.e. crude oil exports are impossible. For instance, consider the case of light oil, then the constraint would translate into $\frac{o^f_{L_{1,t}} - y^{oL}_{1,t}}{(1-\tau_{o2})} \geq 0$. As both refiner use of light oil and production of light oil are chosen by the distributor, the constraint is endogenous. Therefore, the ability of refiners to substitute away from other types of oils towards light oil has implications for how strongly the constraint will bind and what kind of price differentials it is likely to generate.

Let $\psi^k_t$ be the multiplier on the inequality constraint for tyke $k$ crude oil. The first order conditions for the distributor's optimization problem are then given by

$$p^{ok}_{1,t} = p^{ok}_{11,t}$$

implying the spot price and the retail price of type $k$ crude oil are the same, and

$$p^{ok}_{2,t} = (1 - \tau_{o2})\, p^{ok}_{1,t} + \frac{\psi^k_t}{\lambda_{1,t}},$$

and

$$\psi^k_t o^m_{k_{1,t}} = 0.$$

In the case where the ban does not bind, $\psi^k_t$ equals zero and the price of type $k$ oil in the U.S., $p^{ok}_{1,t}$, will be equal to the cost of importing the marginal barrel of type $k$ oil from country 2. Due to shipping costs, there is a small, positive gap between type $k$ crude prices in the U.S. and ROW. Moreover, the type $k$ oil market clearing condition in this case will be given by

$$y^{ok}_{1,t} + y^{ok}_{2,t} - \tau_{o2} o^m_{k_{1,t}} = o^f_{k_{1,t}} + o^f_{k_{2,t}}.$$

However, when the ban binds, a gap is introduced between domestic and foreign type $k$ crude prices, and type $k$ crude oil market becomes segmented from the rest of

[17] Note that $\lambda_{i,t}$ is the lagrange multiplier on the household's budget constraint in country $i$.

the world, implying that $o^f_{k_{1,t}} = y^{ok}_{1,t}$ and $o^f_{k_{2,t}} = y^{ok}_{2,t}$.

The distributor's problem in country 2 is simply to choose output of type $k$ crude oil to maximize

$$E_0 \sum_{t=0}^{\infty} \beta^t \lambda_{2,t} \left\{ p^{ok}_{2,t} o^f_{k_{2,t}} - p^{ok}_{22,t} \left( y^{ok}_{2,t} - o^m_{k_{1,t}} \right) \right\}$$

subject to

$$o^f_{k_{2,t}} = y^{ok}_{2,t} - o^m_{k_{1,t}}.$$

The first order condition for the distributor's optimization problem is given by

$$p^{ok}_{2,t} = p^{ok}_{22,t}.$$

In our benchmark simulations of the model with the export ban, we assumed $\tau_{o2} = 0$.

**Solution method**

It is useful to briefly map our model conditions into the notation used in Guerrieri and Iacoviello (2015) [20]. In our model, country 1's crude oil exports are subject to an occasionally binding constraint, $o^m_{k_{1,t}} \geq 0$ for $k = L, M, H$. The complementary slackness condition implies that $\psi^k_t = 0$ when the constraint is slack. When the constraint binds, $o^m_{k_{1,t}} = 0$. The conditions in the reference regime, $M1$, encompass $\psi^k_t = 0$, and the function $g$ captures $o^m_{k_{1,t}} \geq 0$. The conditions in alternative regime, $M2$, encompass the case when $o^m_{k_{1,t}} = 0$ and the function $h$ captures $\psi^k_t > 0$.