The U.S. shale oil boom, the oil export ban, and the economy: A general equilibrium analysis

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Abstract

This paper examines the U.S. shale oil boom in a two-country DSGE model with a rich representation of crude oil and refined products and a crude oil export ban in the U.S. The model shows that the shale boom leads to a decline in oil and fuel prices, and a dramatic fall in U.S. imports of light oil. Additionally, the shale boom leads to a 1 percent increase in U.S. GDP and a significant improvement in the oil trade balance. We show that the export ban was a binding constraint, primarily from 2014 to 2015, and would likely have remained a binding constraint thereafter had the policy not been removed at the end of 2015. While the ban distorted oil prices, the refining sector and trade balances, we find that it had a negligible impact on fuel prices and the macroeconomy.

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

JEL Codes: F41, Q43, Q38.

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1 Introduction

The recent boom in U.S. crude oil production has been one of the most significant events in oil markets. 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 the dynamics of global oil markets. From 2010 to 2015, U.S. crude production increased from 5.5 million barrels per day (mb/d) to 9.6 mb/d, and imports of crude oil fell almost 2 mb/d.

An important facet of the boom, beyond its magnitude, is that oil produced from shale deposits is predominately of one type of oil: light crude. While crude oil is often assumed to be a homogeneous product, its characteristics can actually differ along several dimensions. The different types of crude oil are imperfect substitutes for each other in the refining process, and refining sectors in various countries have tended to specialize in processing certain types of oil. This is particularly true of the U.S. refining sector, which has a distinct comparative advantage in processing heavier crude oils relative to the rest of the world. The mismatch of increased light crude supply versus heavier refining capacity in the U.S. has important implications for the use and trade of various types of crude oil. These implications were potentially magnified during a large part of the boom due to the U.S. export ban on crude oil, a policy which had been put in place after the 1973 oil embargo and which was in effect until the end of 2015.

In light of these issues, we develop a two-country, dynamic stochastic general equilibrium (DSGE) model to investigate the quantitative impacts of the shale boom on both the upstream and downstream oil industry as well as trade in crude oil and fuel. Given the sizeable increase in U.S. oil production, we also use our model to investigate the effects of the boom on broader macroeconomic aggregates.

In our model, the two countries represent the U.S. and the rest of the world. Both countries produce oil, a non-oil good and refined petroleum products (fuel). Oil is only used to produce fuel, while fuel is consumed by households and also used as an input to produce the non-oil good. The non-oil good is used for consumption and investment in both countries. An internationally traded bond allows for the possibility of trade imbalances. The model also includes several novel features to allow us to adequately discuss the effects of the shale boom: heterogeneous oil types that are imperfect substitutes into the refining process, heterogeneous refining sectors in both countries, and a potentially binding export ban on crude oil in the U.S. 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 boom as a series of positive productivity shocks that replicate the increase in U.S. light crude production from 2010 to 2015 and then illustrate the impacts of those shocks in the DSGE model. We find that our model can match several important aspects of U.S. oil-related data during the boom. U.S. refiners increase their use of light oil but much of the new production simply crowds out imports of light oil. The decline in imports generates a major improvement in the U.S. crude oil trade balance by about one percentage point (as a share of GDP). The decline in light crude oil imports is large enough to make the export ban a binding constraint in the model for several years. The ban distorted light crude oil prices in the U.S. relative to the rest of the world and relative to other grades of crude oil. This discount provides a cost-advantage to U.S. refiners who over-process light crude oil and take market share from refiners elsewhere.

Although the oil sector is a small part of the U.S. economy at the start of the boom, the production increase is large enough to boost the level of U.S. GDP by 1 percent. This boost is due in part to increased household consumption of fuel and the non-oil good. While the oil trade balance improves significantly, we find only a slight deterioration in the non-oil balance.\(^1\)

To investigate the role of the export ban in driving our results, we consider an alternative model that ignores the constraint. In this free trade setting, the shale boom leads the U.S. to become a net exporter of light crude oil.\(^2\) We find the distorting effects of the ban were primarily concentrated in oil prices and the refining sectors. Fuel prices and most macro aggregates are essentially unchanged relative to the model that takes the ban into account. The results show that the ban was a binding constraint on the economy, particularly in 2014 and 2015, and would very likely have remained a binding constraint thereafter if the policy had not been removed at the end of 2015.

Our model fits into the DSGE literature with oil, which includes works such as Backus and Crucini (2000) \([4]\), who look at the impact of oil supply shocks on terms of trade, trade flows, and output; Bodenstein et al. (2011) \([16]\) who study the relationship between oil prices and the trade balance; Nakov and Nuno (2013) \([46]\) who model the oil market as a dominant supplier and a competitive fringe; and papers that consider optimal monetary policy in the face of oil shocks, such as Bodenstein et al. (2008) \([15]\) and Plante (2014) \([48]\).\(^3\)

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\(^{1}\)The non-oil balance would deteriorate to a much greater extent if we had assumed financial autarky. In that case, trade must balance each period and the change in the non-oil balance must be of similar magnitude but of opposite direction to the oil balance.

\(^{2}\)This finding is consistent with recent data where the U.S. has been exporting more than 1 million barrels per day of oil.

Our work also has connections with the international real business cycle literature, see for example Backus et al. (1992) [5], Backus et al. (1994) [6], Crucini and Kahn (1996) [25]. We contribute to this literature by being the first to introduce a distinction between different types of oil in a DSGE model, the first to model the refining sector and the first to explore the impact of the U.S. crude oil export ban in such a modeling framework.

Our paper is also related to studies analyzing trade in oil markets and the crude oil export ban. Farrokhi (2017) [30] develops a static, multi-country general equilibrium model with a detailed refinery sector and examines how changes in oil markets affect oil prices and trade flows across the world. He then uses his framework to evaluate the removal of the U.S. crude oil export ban. Langer et al. (2016) [40] also analyze the lifting of the export ban, but use a numerical, partial equilibrium model of the refining sector.

A line of empirical research examines crude price differentials between U.S. and international benchmarks emerging as a result of the oil boom (see for example, Agerton and Upton (2017) [3] and McRae (2017) [43]). Borenstein and Kellogg (2014) [21] investigate the shale boom-induced differential in domestic and international oil prices and show that this differential did not pass through to fuel prices. Our work complements these studies by analyzing developments in oil and fuel prices resulting from the shale oil boom using a DSGE model where oil trade is constrained by an export ban.

We provide a quantitative estimate of the impact of the shale boom on U.S. GDP. To the best of our knowledge, there are no papers with directly comparable results for the U.S., but there are studies that analyze the GDP effects of resource booms in other countries. Bjornland and Thorsrud (2015) [11] show, with a dynamic factor model, that a boom in the resource sector increases GDP in Norway and Australia. Bayoumi and Muehleisen (2006) [13], using the IMF’s Global Economic Model, find that a 50 percent increase in Canadian oil production gives rise to a 0.56 percent increase in GDP.

There are also several recent papers analyzing the global and local economic implications of the U.S. shale oil boom. Using a DSGE model, Manescu and Nuno (2015) [42] find that the shale boom resulted in a 0.2 percent increase in the GDP of oil importers. Mohaddes and Raissi (2016) [45], with a VAR model, show that the shale boom increased global GDP by 0.16 to 0.37 percent. Feyrer et al. (2016) [31], Gilje et al. (2016) [34], Allcott and Keniston (2017) [2], and Bjornland and Zhulanova (2018) [12] investigate local implications and find positive spillovers from the shale boom to regional economies.

4A number of non-academic studies discuss the impact of U.S. trade policy relating to crude oil, including Ebinger and Greenley (2014) [27], EIA (2014) [50], Vidas et al. (2014) [53], IHS (2014) [35], IHS (2015) [36], Brown et al. (2014) [24] present a good background analysis of the oil export ban, Bordoff and Houser (2015) [20] summarize several other reports on the issue, and Brown et al. (2014) [23] and Medlock (2015) [44] provide more academic analyses of the export ban.
The rest of the paper is organized as follows. We present background information and data in Section 2. Our general model framework is presented in Section 3. Section 4 provides the calibration, results are discussed in Section 5 and we conclude in Section 6.

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 refined products, and refiner use of different types of oil. Using these 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 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.

Density is one of the more important measures used to distinguish between different types of crude oil. The American Petroleum Institute gravity (API gravity) is a commonly used measure of a crude oil’s density with values ranging from 10 to 70. A higher API gravity indicates lower density. Oils with higher API gravities are known as light oils; those with low API gravities are known as heavy. 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.

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 sweet crude oil, with an API near 40 and a relatively low sulfur content. Other examples of light, sweet 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 sour 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. It has an API and sulfur content in between the lights and Maya, and is similar in quality to Dubai, an important benchmark outside the U.S.

The latter require less processing and are therefore preferred to sour oils. Generally speaking, 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: Characteristics of various crude oils

Light oils tend to be preferred by refiners as they require less processing to produce larger amounts of gasoline and diesel. However, a refinery can profitably process heavy crude oils and produce lighter, high-value products if it invests in certain capital, such as cokers. The refineries that have invested in this capital tend to be very large, complex refineries, and the U.S. has a preponderance of such refineries relative to the rest of the world.

Prices of similar quality oils tend to remain fairly close to each other.\textsuperscript{6} Light oils often sell at a premium to medium and heavy crudes, though, because they require less processing. As quality differences become more pronounced, so do the price differences between the oils. For example, if we consider the price of light, medium and heavy crude on 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.

Not surprisingly, the relative prices of different oils also 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 from 1997 to 2010 for the price ratios of LLS to Brent, LLS to Mars and LLS to Maya. We then considered the coefficient of variation of these three relative oil prices as a function of how different each pair was in terms of API gravity. We observed that the more pronounced the quality differences, the higher the coefficient of variation.\textsuperscript{7}

\textsuperscript{6}Factors such as transportation bottlenecks can occasionally cause prices of similar quality oils to deviate substantially from each other. An example of this in recent years is the price of WTI.

\textsuperscript{7}A similar pattern emerges when looking at other crude oils, for example, if one uses the Asian benchmarks Tapis, Dubai and Duri crudes instead of LLS, Mars and Maya.
2.2 Crude oil production

We rely on production data from the 2017 version of Eni’s World Oil and Gas Review [28]. It provides a breakdown of crude oil production into several different types. The 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 2016. 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.

Data on crude production by type are available from other sources, such as DrillingInfo and the Energy Information Administration, but they either have a limited time series or limited coverage. The EIA monthly production data by API gravity for the U.S. only starts in 2015, EIA (2015) [51] only provides annual data for 2010 to 2013, and a significant portion of U.S. crude production is unclassified in DrillingInfo data.

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.

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 4.4 mb/d in the U.S., more than tripling its 2010 level. Outside the U.S., increased production was from medium and heavy crudes, with declines in light crude production.

2.3 U.S. exports and imports: crude oil and refined products

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 to 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 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.

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8A 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.
Table 2.1: Crude oil production by type, mb/d

<table>
<thead>
<tr>
<th></th>
<th>U.S.</th>
<th>Rest of the world</th>
<th>Total world</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Light</td>
<td>Medium</td>
<td>Heavy</td>
</tr>
<tr>
<td>2000</td>
<td>2.1</td>
<td>2.9</td>
<td>0.8</td>
</tr>
<tr>
<td>2005</td>
<td>1.7</td>
<td>2.8</td>
<td>0.7</td>
</tr>
<tr>
<td>2010</td>
<td>2.1</td>
<td>2.8</td>
<td>0.6</td>
</tr>
<tr>
<td>2011</td>
<td>2.6</td>
<td>2.5</td>
<td>0.6</td>
</tr>
<tr>
<td>2012</td>
<td>3.5</td>
<td>2.4</td>
<td>0.6</td>
</tr>
<tr>
<td>2013</td>
<td>4.5</td>
<td>2.4</td>
<td>0.6</td>
</tr>
<tr>
<td>2014</td>
<td>5.9</td>
<td>2.4</td>
<td>0.6</td>
</tr>
<tr>
<td>2015</td>
<td>6.5</td>
<td>2.5</td>
<td>0.6</td>
</tr>
<tr>
<td>2016</td>
<td>5.9</td>
<td>2.5</td>
<td>0.6</td>
</tr>
</tbody>
</table>

However, there have been 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. light crude production that year.

Table 2.2: U.S. crude oil and refined products exports and imports, mb/d

<table>
<thead>
<tr>
<th>U.S. crude imports</th>
<th>U.S. crude exports</th>
<th>U.S. refined products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>Medium</td>
<td>Heavy</td>
</tr>
<tr>
<td>2000</td>
<td>2.2</td>
<td>4.6</td>
</tr>
<tr>
<td>2005</td>
<td>2.3</td>
<td>4.3</td>
</tr>
<tr>
<td>2010</td>
<td>2.1</td>
<td>3.3</td>
</tr>
<tr>
<td>2011</td>
<td>1.7</td>
<td>3.3</td>
</tr>
<tr>
<td>2012</td>
<td>1.4</td>
<td>3.1</td>
</tr>
<tr>
<td>2013</td>
<td>0.9</td>
<td>3.0</td>
</tr>
<tr>
<td>2014</td>
<td>0.6</td>
<td>2.7</td>
</tr>
<tr>
<td>2015</td>
<td>0.6</td>
<td>2.6</td>
</tr>
<tr>
<td>2016</td>
<td>0.9</td>
<td>2.6</td>
</tr>
</tbody>
</table>

The middle block 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 100,000 b/d. Exports picked up noticeably starting in 2014, however, and have continued increasing every year since.

Until December 2015, there was a federal ban on crude oil exports whose motivation dated back to the 1973 oil embargo. Despite the ban, exporting oil was possible under certain circumstances. The most relevant exemption was the possibility to export crude oil to Canada.\textsuperscript{9} This could be done so long as the oil was not re-exported from Canada. This

\textsuperscript{9}Another exemption regarded exports of Alaskan crude oil. However, exports from Alaska have been
exemption was used heavily in both 2014 and 2015. The EIA crude oil export data show that, on average, the U.S. shipped about 95% and 92% of its exported oil to Canada in 2014 and 2015, respectively. This share fell to 61% in 2016, though, well below the 2014 and 2015 shares.

The rightmost column of Table 2.2 shows net imports of U.S. refined products. Over the course of the shale boom there was a significant increase in the production of refined products. As the export ban did not apply to refined petroleum products, exports of products increased significantly and by 2011 the United States had become a net exporter.

2.4 Refiner inputs by type of oil

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,

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

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

As mentioned previously, the EIA does not provide a breakdown of 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.\(^{10}\) Given this, we assume that all U.S. exports of crude oil from 2010 to 2016 were light. This has the effect of lowering our estimate for U.S. refiner use of light crude oil, particularly from 2014 to 2016.

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 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 negligible since 2000. More details can be found in Bausell et al. (2001) \cite{9}, Kumins (2005) \cite{39} and Van Vactor (1995) \cite{52}.

\(^{10}\)See Çakır Melek and Ojeda (2017) \cite{26} for more details.
of oil being processed by U.S. refiners each day.

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

<table>
<thead>
<tr>
<th>Year</th>
<th>U.S. refiner inputs</th>
<th>ROW refiner inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Light</td>
<td>Medium</td>
</tr>
<tr>
<td>2010</td>
<td>4.2</td>
<td>6.1</td>
</tr>
<tr>
<td>2011</td>
<td>4.2</td>
<td>5.8</td>
</tr>
<tr>
<td>2012</td>
<td>4.9</td>
<td>5.6</td>
</tr>
<tr>
<td>2013</td>
<td>5.3</td>
<td>5.3</td>
</tr>
<tr>
<td>2014</td>
<td>6.1</td>
<td>5.1</td>
</tr>
<tr>
<td>2015</td>
<td>6.6</td>
<td>5.1</td>
</tr>
<tr>
<td>2016</td>
<td>6.3</td>
<td>5.1</td>
</tr>
</tbody>
</table>

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. For example, in 2010, the U.S. alone processed more than 40 percent of the world’s heavy crude oil. On the other hand, the U.S. processed about 18 percent of the world’s light crude, and only around 15 percent of the world’s medium crude. The over-weighting of the U.S. refining sector in terms of how much heavy crude oil it processes reflects the fact that the U.S. has a number of very large, complex refineries that are able to efficiently process heavy crude oils.

It is possible to quantitatively compare how complex the U.S. refinery sector is relative to the rest of the world by making use of the Nelson complexity index (NCI), a measure commonly used in the industry to compare complexity of refineries. The simplest possible refinery has an NCI of 1 while the largest and most complex refineries can have scores of over 15. The highest score known to us is Valero’s St. Charles refinery on the Gulf Coast, with a self-reported complexity index of 17.1. According to the Eni data, the complexity index for North America as a whole (U.S. and Canada) was 11.5 in 2010 relative to an index of 7.8 for the rest of the world. The U.S. accounts for about 90 percent of the capacity in North America.

2.5 Summary: changes since 2010

There have been 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. have changed from 2010 to 2015.

11See Johnston 1996 [37] for more details.
The impact of the new technology on production is immediately obvious. Light production increased by 4.4 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 2.4 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 significant drop in imports. One possibility is that light oil may have 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 1.3 mb/d higher in 2015 than in 2010. U.S. refiners processed about 31 percent of the increase, with the crude being imported from other countries.

Table 2.4: Change in select U.S. data from 2010 to 2015, mb/d

<table>
<thead>
<tr>
<th></th>
<th>Production</th>
<th>Imports</th>
<th>Exports</th>
<th>Refiner inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>4.4</td>
<td>-1.5</td>
<td>0.4</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td>(204)</td>
<td>(-73)</td>
<td>(1017)</td>
<td>(57)</td>
</tr>
<tr>
<td>Medium</td>
<td>-0.3</td>
<td>-0.8</td>
<td>-1.0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-9)</td>
<td>(-23)</td>
<td></td>
<td>(-17)</td>
</tr>
<tr>
<td>Heavy</td>
<td>0.02</td>
<td>0.4</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3)</td>
<td>(12)</td>
<td></td>
<td>(11)</td>
</tr>
<tr>
<td>Total</td>
<td>4.1</td>
<td>-1.9</td>
<td>0.4</td>
<td>1.8</td>
</tr>
<tr>
<td></td>
<td>(75)</td>
<td>(-20)</td>
<td>(1017)</td>
<td>(13)</td>
</tr>
</tbody>
</table>

Note: % changes from 2010 to 2015 are presented in parentheses.

Motivated by these facts, the next section presents our theoretical framework used to evaluate the impact of the U.S. shale oil boom.
3 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). 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 and comes in three types: light, medium or heavy crude. Production of refined products requires capital, labor, and a composite of the three types of crude oil. The household consumption bundle is a composite of refined products and the non-oil good. The non-oil good is produced using capital, labor, and refined products. The model includes an internationally traded, non-state contingent bond so that trade need not balance each period.

3.1 Households

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

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

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

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

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 the goods are imperfect substitutes, and the weights reflect how consumption expenditures are allocated across these goods.

The budget constraint for the household in country 1 is given by

\[
c_{1,t}^a + P_{1,t}^c c_{1,t}^c + \sum_{j} P_{j,t}^i c_{1,t}^j + \sum_{j} p_{b,t}^j B_{1,t+1} = \sum_{j} W_{j,t}^i n_{1,t}^j + \sum_{j} R_{j,t}^i K_{1,t}^j + \sum_{j} \Pi_{j,t}^i + B_{1,t} + T_{1,t}, \tag{3.2}
\]

\[12\text{See Backus and Crucini (2000) [4], Backus et al. (1992) [5], Backus et al. (1994) [6], Crucini and Kahn (1996) [25], etc. for more details on this framework.}\]
where $j$ indexes across sectors. Except for the $\Phi_{b,t}$ term, which we discuss shortly, each country has analogous variables in their respective budget constraint. Given this, we keep the subscript $i$ in the rest of the section.

We assume good $a$ is the numeraire and $p^f_{i,t}$ denotes the relative price of good $f$ in country $i$. The wage rate and rental rate of capital in sectors $j = a, f$ are given by $W^j_i$ and $R^j_i$, respectively. Households own the firms operating in the economy and hence receive profits from all sectors: $\Pi^a_{i,t}$, $\Pi^f_{i,t}$, and $\Pi^o_{i,t}$. Profits from the oil sector are given by $\Pi^o_{i,t} = \sum_k \Pi^ok_{i,t}$ where the three types of oil are denoted by $k = h, l$ or $m$ for heavy, light and medium crude, respectively.

Lump-sum taxes to the government are denoted as $T_{i,t}$. They are used to finance a fixed amount of government spending, $G_i$, which absorbs some of the non-oil good. Government spending is incorporated in the model solely to help match GDP-shares for consumption and investment.

The non-oil good is used for investment in physical capital, hence the relative price of the investment good is equal to 1. Investment augments the capital stock $K^j_{i,t+1}$, according to the following law of motion

$$K^j_{i,t+1} = (1 - \delta)K^j_{i,t} + I^j_{i,t} - \Phi \left( \frac{I^j_{i,t}}{K^j_{i,t}} \right) K^j_{i,t}$$  \tag{3.3}

where $I^j_{i,t}$ denotes investment in sector $j$, and $\delta$ is the depreciation rate. Physical capital formation is subject to adjustment costs as in Baxter and Crucini (1995) [10]. The costs are governed by a quadratic investment adjustment cost function, $\Phi (\cdot)$, which takes the following form

$$\Phi \left( \frac{I^j_{i,t}}{K^j_{i,t}} \right) = \frac{1}{2\delta\phi_i} \left( \frac{I^j_{i,t}}{K^j_{i,t}} - \delta \right)^2,$$

where $\phi_i > 0$ governs the elasticity of investment-capital ratio with respect to Tobin’s $q$. Adjustment costs are incorporated to slow investment responses to shocks.

The model includes a one-period, non-state contingent bond that is internationally traded, $B_{i,t}$. The price of the bond at time $t$ is given by $p^b_t$ and the bond pays off one unit of the non-oil good at time $t + 1$, similar to Baxter and Crucini (1995) [10]. To ensure stationarity of the debt-level, we follow Bodenstein et al. (2011) [16] and assume that households in country 1 pay a small intermediation fee, $\Phi_{b,t}$. Similar to that paper, the functional form is given by

$$\Phi_{b,t} = \exp \left( -\phi_b \left( B_{1,t+1}/y^a_{1,t} \right) \right),$$

where $\phi_b$ is a parameter that controls how sensitive the intermediation costs are to changes
in debt levels.

Finally, household activities exhaust total hours available:

$$\bar{L}_i - L_{i,t} - n_{i,t} - n_{i,t}^f = 0,$$

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

In every period $t$, the household maximizes its utility function 3.1 with respect to consumption, labor supply, investment, bond holdings and end-of-period capital stock subject to its budget constraint 3.2, the laws of motion for capital 3.3, and the time constraint 3.4. Prices, wages and intermediation costs are taken as given.

### 3.2 Firms and production

Each country produces three goods: crude oil, refined products, and a non-oil good. Production is done 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) [7]. We continue to denote the three oil types by $k = h, l$ or $m$.

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

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

where

$$C_{i,t}^{ok} = \left( \frac{y_{i,t}^{ok}}{z_{i,t}^{ok}} \right)^{1+1 \over \eta} \eta^{-1}_{i},$$

denotes the production costs, representing the quantity of the non-oil good needed to produce a given amount of oil. These costs can be considered as (non-energy) inputs needed to produce oil, such as rigs, etc.; $y_{i,t}^{ok}$ 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 decrease with higher productivity. The firm sells its output to refineries at a price of $p_{i,t}^{ok}$.
Profit maximization implies

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

where \( \eta_{k}^{i} \) is country \( i \)'s elasticity of supply for type \( k \) oil. This suggests that the higher the elasticity of supply, the lower the output-elasticity of the marginal cost of producing 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 CES of a capital-labor composite, itself a Cobb-Douglas function, and a composite of the three types of oil,

\[
y_{f}^{i,t} = \left[ w_{f}^{i} \left( z_{f}^{i} (n_{f}^{i,t})^{\chi_{f}^{i}} (K_{f}^{i,t})^{1-\chi_{f}^{i}} \right)^{-\rho_{f}^{i}} + (1 - w_{f}^{i})G(o_{fl}^{i,t}, o_{fm}^{i,t}, o_{fh}^{i,t})^{-\rho_{oil}^{i}} \right]^{\frac{1}{1-\rho_{oil}^{i}}} \tag{3.5}
\]

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 \( w_{f}^{i} \) governs the share of value-added in gross output in country \( i \), and \( \chi_{f}^{i} \) governs the labor share in value-added in country \( i \), with \( 0 < w_{f}^{i}, \chi_{f}^{i} < 1 \). The elasticity of substitution between the capital-labor composite and the oil composite is \( \frac{1}{1+\rho_{oil}^{i}} \). Hence, we allow for the possibility that the cost-shares and productivity levels vary across countries, and the fact that it is hard to substitute between oil and other inputs when it comes to producing fuel.

The function \( G(\cdot) \) is a constant returns to scale CES aggregate of the three types of oil inputs, \( o_{fl}^{i,t}, o_{fm}^{i,t}, o_{fh}^{i,t} \). 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 work with the following nested-CES function:

\[
G(o_{fl}^{i,t}, o_{fm}^{i,t}, o_{fh}^{i,t}) = \left[ w_{o}^{i} (o_{fh}^{i})^{-\rho_{oil}^{i}} + (1 - w_{o}^{i}) \left( \omega_{o}^{i} (o_{fl}^{i,t})^{-\rho_{oil}^{i}} + (1 - \omega_{o}^{i}) (o_{fm}^{i,t})^{-\rho_{oil}^{i}} \right) \right]^{\frac{1}{1-\rho_{oil}^{i}}} \tag{3.6}
\]

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 $\frac{1}{1+\rho_{oil}}$, and the elasticity of substitution between light oil and medium oil is $\frac{1}{1+\eta_{oil}}$.

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 we illustrated that the relative price of light crude to medium is much less volatile 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.

The representative producer of refined products in each country chooses $n_{i,t}^f$, $K_{i,t}^f$, $o_{i,t}^{fl}$, $o_{i,t}^{fm}$, and $o_{i,t}^{fh}$ to maximize profits

$$\Pi_{i,t}^f = p_{i,t}^f y_{i,t}^f - W_{i,t}^f n_{i,t}^f - R_{i,t}^f K_{i,t}^f - p_{i,t}^{ol} o_{i,t}^{fl} - p_{i,t}^{om} o_{i,t}^{fm} - p_{i,t}^{oh} o_{i,t}^{fh},$$

subject to equations 3.5 and 3.6. In solving this problem, the producer takes as given the wage $W_{i,t}^f$, the rental price of capital $R_{i,t}^f$, and the prices of light, medium and heavy oil $p_{i,t}^{ol}, p_{i,t}^{om}, p_{i,t}^{oh}$. The representative firm sells its output to households and non-oil good producers at a price $p_{i,t}^f$.

### 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 the 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

$$y_{i,t}^a = \left[ w_{i}^a \left( z_{i,t}^a (n_{i,t}^a)^{\chi_{i}^a} (K_{i,t}^a)^{1-\chi_{i}^a})^{-\rho} + (1 - w_{i}^a)(m_{i,t}^f)^{-\rho} \right) \right]^{\frac{1}{1-\rho}},$$

where $z_{i,t}^a$ represents a stochastic process for the evolution of productivity, $n_{i,t}^a, K_{i,t}^a$ denote labor and capital inputs, and $m_{i,t}^f$ is the input of refined products. The parameter $\chi_{i}^a$ controls the share of labor in non-oil sector’s value-added in country $i$, $w_{i}^a$ controls the relative use of the capital-labor composite and refined products in the sector, and $\frac{1}{1+\rho}$ is the elasticity of substitution between the capital-labor composite and refined products. The firm chooses

---

13 The higher volatility of the relative price of light to heavy oil could also be due to differences in the volatility of supply shocks to medium or heavy crude. Data limitations prevent us from investigating this possibility.

14 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.
\[ n_{i,t}^a, K_{i,t}^a, \text{ and } m_{i,t}^f \] to maximize profits

\[ \Pi_{i,t}^a = y_{i,t}^a - W_{i,t}^a n_{i,t}^a - R_{i,t}^a K_{i,t}^a - p_{i,t}^f m_{i,t}^f, \]

subject to equation 3.7. The producer sells its output to households and oil producers.

### 3.3 Market clearing

A competitive equilibrium for the world economy requires market clearing for all goods, i.e. that production of each good must equal the total use of that good. In the oil market, \( \forall k = h, l, m \), we have

\[ y_{1,t}^{ok} + y_{2,t}^{ok} = a_{1,t}^k + o_{2,t}^k. \]

For the fuel and the non-oil good markets, market clearing equations are respectively given by

\[ y_{1,t}^f + y_{2,t}^f = c_{1,t}^f + c_{2,t}^f + m_{1,t}^f + m_{2,t}^f, \]

\[ \sum_{i=1,2} y_{i,t}^a = \sum_{i=1,2} c_{i,t}^a + \sum_{i=1,2} \sum_{j=a,f} f_{i,t}^j + \sum_{i=1,2} \sum_{k=h,l,m} C_{i,t}^k + \sum_{i=1,2} G_i. \]

Finally, the bond market clears when

\[ B_{1,t} = -B_{2,t}. \]

All goods are traded freely and no trade costs are assumed, so both purchasing power parity (PPP) and law of one price hold. That is, \( p_{1,t}^{ok} = p_{2,t}^{ok}, \forall k = h, l, m \), and \( p_{1,t}^f = p_{2,t}^f \).

### 3.4 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

\[ a_{1,t}^k - y_{1,t}^{ok} \geq 0, \quad (3.8) \]

for \( k = h, m, l \).\(^{15}\)

One important point is that modeling heterogeneous oil types is crucial if one wants to

\(^{15}\)Further mathematical details about how we set up the export ban can be found in the Appendix C.
discuss the implications of the ban over the time frame we consider. Assuming a single, homogeneous oil would lead to a situation where U.S. net oil imports are so large that the ban would not be a binding constraint, even with the large production increases seen during the shale boom. With heterogeneous oil types, it is only necessary for net oil imports of a particular type to fall to zero for the ban to become a binding constraint.

We point out several other important facets of this constraint using the case of light oil as an example. First, if the constraint binds, then part of the oil market in the U.S. becomes segmented from the rest of the world. This would create 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. For example, the ability of refiners to substitute away from using other oils towards light oil has implications for when the constraint binds 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) [33] OccBin toolkit for Dynare, allowing us to examine the possibility that the export ban could bind for some period of time. The length of time is endogenously determined by the shocks that hit the economy and the structure of the economy.

4 Calibration and solution method

4.1 Calibration

We solve the model numerically, which requires us to calibrate the model.\footnote{We use the Dynare software package developed by Adjemian et al. (2011) [1] to solve our model.} Our model is calibrated at an annual frequency. Country 1 represents the U.S. while country 2 represents the rest of the world.

We choose the starting values for a number of the model’s variables and calibrate some parameters to match certain moments of the data. Where possible, we calibrate an initial steady state to match data from 2010, as this is the year before oil production in the U.S. started booming. In certain cases, the steady state is chosen to match time-series averages of the data. A number of parameters and starting values are then determined implicitly through the steady state equations. Finally, the parameters for the shock processes, along with several model parameters, are calibrated using simulated method of moments. Appendix A contains a complete description of the data series used in the calibration.

A select set of the starting values and moments used in the model calibration are presented in Table 4.1. Appendix B provides the full description of the starting values, moments and
parameter settings in the calibration. A discussion of the moment-matching exercise is deferred until later.

Several parameters related to preferences, capital accumulation and production functions are calibrated to be equal across countries. The discount factor $\beta$ is set to 0.96. The depreciation rate of capital, $\delta$, is set to 0.10. The curvature parameter determining the household’s coefficient of relative risk aversion, $\gamma$, is set at $-1$, as in Backus and Crucini (2000) [4] or Backus, Kehoe and Kydland (1994) [6]. The elasticity of substitution between refined petroleum products and the non-oil good consumption, given by $1 + \rho$, is set at 0.20. This produces a low price elasticity of demand for refined products, with a value that is within the range of the literature. Following Bodenstein et al. (2011) [16], we constrain this elasticity to be equal for households and firms in both countries. The elasticity of supply of oil is set to $0.13$, consistent with Bornstein et al. (2017) [22]. This ensures that oil supply is fairly inelastic in response to price changes, a key feature of the data.

Without loss of generality, we normalize U.S. GDP to 1, which allows us to calibrate several variables in terms of GDP ratios. The total time available in the U.S., $\bar{L}_1$ is normalized to 1. The share of world GDP due to the U.S. was 17% in 2010 and the U.S. population share was 4.5%, based on UN data. We use these facts to calibrate ROW GDP and the total time available in ROW, $\bar{L}_2$. For both the U.S. and ROW, we assume an average time allocation of $2/3$ to leisure. The share of government spending in GDP is set to 19.3%, the average U.S. share over 2000-2009, for both the U.S. and ROW. We set the initial debt level to zero, so that trade balances in the steady state. The parameter $\phi_b$ is set to 0.001, as in

Table 4.1: Calibration

<table>
<thead>
<tr>
<th>Description</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c^f_1 = 0.022$</td>
<td>U.S. household fuel use</td>
</tr>
<tr>
<td>$y^f_1 = 0.995 (c^f_1 + m^f_1)$</td>
<td>U.S. fuel production</td>
</tr>
<tr>
<td>$y^f_2 = 0.35 y^f_1$</td>
<td>U.S. total oil production</td>
</tr>
<tr>
<td>$y^o_1/y^o_2 = 1.06$</td>
<td>Rel. price of light to medium crude</td>
</tr>
<tr>
<td>$y^o_1 + y^o_2 = .83$</td>
<td>Size of ROW economy</td>
</tr>
<tr>
<td>$\bar{L}_1 = 2/3$</td>
<td>U.S. time allocated to leisure</td>
</tr>
</tbody>
</table>

Shared parameters

<table>
<thead>
<tr>
<th>Description</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta = 0.96$</td>
<td>Discount factor</td>
</tr>
<tr>
<td>$\delta = 0.10$</td>
<td>Depreciation rate of capital</td>
</tr>
<tr>
<td>$\rho = 4$</td>
<td>Elas. of sub. for fuel (0.2)</td>
</tr>
<tr>
<td>$\eta^{oil} = -0.72$</td>
<td>Elas. of sub. for $a^f, a^m$ (3.6)</td>
</tr>
<tr>
<td>$\eta^h = 0.13$</td>
<td>Elas. of oil supply for $k = l, m, h$</td>
</tr>
</tbody>
</table>

Other parameters

<table>
<thead>
<tr>
<th>Description</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^f_1 = 0.164$</td>
<td>Labor share in U.S. refining</td>
</tr>
<tr>
<td>$\chi^f_2 = 0.060$</td>
<td>Labor share in U.S. non-oil sector</td>
</tr>
</tbody>
</table>

For example, see the discussion in Baumeister and Hamilton (2016) [8].
Bodenstein et al. (2017) [19].

The relative price of fuel, \( p_f \), is also normalized to 1. We set \( c_1^f \) equal to 2.2% of U.S. GDP, based on data from the BEA for household spending on gasoline and heating oil in 2010. Non-household petroleum spending in the U.S., \( m_1^f \), is set to 2.2% of GDP, based on BEA and EIA data.

The calibration for household and firm petroleum use in ROW is obtained using data from several sources. The World Input Output Database provides data on spending by firms on “coke and refined petroleum products” as an intermediate input and also final consumption of the good by households for 40 countries.\(^{18}\) The EIA provides data on world consumption of petroleum and other liquids by region and end-use sector. Finally, Exxon 2016 Energy Outlook [29] provides data on world oil use by end-use sector. Based on our calculations using different sources, we assume a value of 0.50 for the ratio of household to firm use of petroleum for 2010, allowing us to pin down steady state values of household use and firm use of refined products for the ROW.

We rely on data from the World Input Output Database to calibrate the labor share of value-added in the non-oil sector, given by \( \chi_1^a \) and \( \chi_2^a \). The database 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 countries. We use this data to generate a time series for the labor share of total value-added in each country and take an average 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, we find the share of global GDP for each country, excluding the U.S., and use these shares to weight each country’s average labor share. We then sum the weighted labor shares to get our estimate for the ROW, \( \chi_2^a = 0.55 \).

U.S. refined products production equaled 99.5% of total domestic refined products consumption in 2010, which we use to set \( y_1^f \). The total volume of crude oil processed by U.S. refiners that year was about 93.6% of total U.S. refinery production.\(^{19}\) To determine the shares of each type of oil processed in the U.S. refineries, we use the estimates presented in subsection 2.4. These shares determine the starting values for \( o_{k1}^f \) for \( k = l, m, h \). Data on refinery gains for the ROW that come from the EIA and IEA are used to pin down total ROW fuel production, \( y_2^f \).

We set total U.S. oil production to match the fact that U.S. production in 2010, in mb/d, was 35% of U.S. refinery output of fuel. The U.S. share in global oil production in 2010 was 0.073, which determines total ROW oil production. The steady state values of light, medium,


\(^{19}\)This is due to a volumetric expansion that occurs when crude oil is processed into refined petroleum products.
and heavy oil production for both the U.S. and ROW are set to match the shares of each type of oil in total production, based on Eni data presented in subsection 2.2.

Oil price data are used to set two moments in the model, the relative price of light oil to medium and the relative price of light oil to heavy. As a proxy for light, medium and heavy oil prices, we consider LLS, Dubai and Maya prices, respectively.\textsuperscript{20} 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 the U.S. for 2010, 77.4\%, to determine the weight \( w^f_1 \). For the labor share of value-added in the refining sector, \( \chi^f_1 \) and \( \chi^f_2 \), we rely on data from the World Input Output Database. 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.), and covers about 75\% of global refining capacity. We generate a time series for the labor share of value-added for each country and calculate the average over 2000 – 2009. The value we find for the U.S. is 0.164. To get the ROW labor share, we used data from the Oil&Gas Journal on refining capacity in 2010 to find the share of refining capacity in each country out of the total excluding the U.S. We use these shares to weight each country’s labor share and sum across these countries to get our estimate for the ROW, 0.297. This implies that U.S. refining sector is more capital intensive than the ROW.

\subsection*{4.2 Moment-matching exercise}

The parameters governing the autoregressive processes for the productivity shocks are not determined by the deterministic steady state. We also need to calibrate the capital adjustment cost parameter, given by \( \phi \), the elasticities of substitution across different oil inputs, given by \( \eta^{oil} \) and \( \rho^{oil} \), as well as the elasticity of substitution between value-added and oil in the refining production function, given by \( \rho^f \). To calibrate these parameters, we use simulated method of moments, a standard technique in the business cycle literature, to have the model match several time-series properties of the data.

We use data on U.S. and ROW real GDP as well as U.S. and ROW crude oil production to help guide the calibration of the shocks, and use data on U.S. real private fixed investment to guide the calibration of the capital adjustment cost parameter. The ROW GDP series is an index of the trade-weighted average of GDP series for 39 countries from the Database

\textsuperscript{20}Due to data limitations, we use Dubai, not Mars, for medium oil prices in our calibration. They both have similar API gravity, and the coefficient of variations for LLS to Mars price ratio and LLS to Dubai price ratio are roughly the same, 0.055 and 0.056 over 1997-2016, respectively.
of Global Economic Indicators.\textsuperscript{21} Data on U.S. investment is based on the BEA. 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 use annual data for the investment spending. Then, we take the log of the annual series.

As we do not explicitly model trends in economic variables, oil or otherwise, we de-trend the data using a one-sided HP filter. For the oil production and refiner input series we filter the entire sample from 1973 to 2016. For the GDP and investment series, we start the filter in 1981, as this is the first year for which we have an annual average for ROW GDP.

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. Having a longer time series on oil production by type would have allowed us to do otherwise.

This leaves a total of 8 parameters that need to be calibrated for the shocks. We choose 8 moments from the de-trended data to calibrate them: the first-order autocorrelations and the volatilities of each data series. Our goal in the exercise is to calibrate the shock parameters so as to have the model-simulated data match these moments in the actual 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. The oil production series starts in 1986 as this follows the collapse of OPEC production cuts around that time.

We jointly estimate those 8 parameters with the capital adjustment cost parameter and the elasticities. We constrain the cost parameter and the elasticities to be equal across countries, so there are a total of four that need to be calibrated. We use four moments in the data as targets for the calibration: the volatility of U.S. real private fixed investment, the correlation between (real) light and medium oil prices, the correlation between (real) light and heavy oil prices, and the volatility of total crude oil inputs to U.S. refiners. We have chosen to match these moments as the parameters in the model play a key role in determining the values of those moments in model-simulated data. For the oil price data, we use annual price data on LLS, Dubai and Maya crude oils from 1991 to 2016. We start in 1991 as this is the first year for which we have regular price data on heavy crude oil (Maya). The refiner input series is obtained from the EIA. As with the GDP, investment, and oil production series, we filter the data using a one-sided HP filter, and then calculate

\textsuperscript{21}See Grossman et al. (2014) \textsuperscript{32} for more details.
The results of the moment matching exercise for the shock parameters are presented in Table 4.2. The moments are reported in Table 4.3, which compares the properties of the model to actual data. The model does a good job in matching the targeted moments. It closely replicates the observed volatilities of U.S. and ROW oil supply and GDP, and the observed volatilities of U.S. investment and total crude oil inputs to U.S. refiners.

The model’s ability to match several non-targeted moments varies. The model does match the observed correlation between medium and heavy crude prices, but its ability to match oil price volatilities is weaker. However, the model can still account for 57 to 67 percent of the volatilities. We note that other works that use a similar modeling framework, such as Bodenstein et al. (2011) [16], also have trouble matching oil price volatility at business cycle frequencies.

Our exercise leads to an elasticity between light and medium ($\frac{1}{1+\eta_{oil}}$) of 3.6. The elasticity between heavy and the composite of light-medium crude ($\frac{1}{1+\rho_{oil}}$) is 2. Light and medium oil are more substitutable with each other than with heavy oil, in line with our intuition. The value for the elasticity between value-added and oil is 0.20, a low value in line with our intuition, i.e. it is very difficult to substitute between oil and other inputs in the production of refined petroleum products.

### 5 Results

Our goal is to investigate the effects of the U.S. shale oil boom on the global oil markets and the broader economy. We model the shale oil boom as an exogenous shock that lowers the cost of producing light oil in the U.S., i.e. positive shocks to $z_{oil}^t$. In order to generate a path for the shocks, we conduct the following exercise. We have data on the annual percent change in U.S. light oil production from 2010 to 2015. We numerically solve for the values of the productivity shocks that would generate the same percentage changes in the model. We then feed these shocks into the model and analyze how various variables respond to the increased in light oil production. Given that the export ban was in place for most of the

<table>
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<th>Shock type</th>
<th>AR(1) coefficient</th>
<th>Volatility</th>
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<tr>
<td>Technology (U.S.)</td>
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<td>.0055</td>
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<tr>
<td>Technology (ROW)</td>
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<td>.0061</td>
</tr>
<tr>
<td>Oil supply (U.S.)</td>
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<td>.0278</td>
</tr>
<tr>
<td>Oil supply (ROW)</td>
<td>.736</td>
<td>.0327</td>
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**Table 4.2:** Calibration of shock parameters
boom, our baseline model incorporates the ban. To highlight the potential implications of the ban, we also consider an alternative model that ignores the constraint, i.e. a free trade model.

We find that the shale boom had significant impacts not only on oil market variables, but also on U.S. macro variables. The export ban was a binding constraint, particularly in 2014 and 2015, and likely would have remained a binding constraint thereafter given the expected path of oil production.\footnote{Data, such as disaggregated U.S. crude imports and the light oil price differential between the U.S. and the ROW, support this conclusion. Further details can be found in the Appendix E and in Çakır Melek and Ojeda (2017) \cite{26}.} We find that the ban distorted a number of economic outcomes, particularly those related to oil prices, the refining sector, and trade balances. It had a minimal impact on fuel prices and most macro aggregates.

### 5.1 Oil market impacts

Given the large number of oil market variables in the model, we choose to focus on a subset of the results that are of particular interest and importance. The impulse responses for those variables are shown in Figure 5.1.\footnote{A full set of responses are available upon request.} Units are percentage deviations of each variable from its starting point, calibrated in most cases to line up with 2010 data. The dashed lines show the responses with the ban and the solid lines show the responses with free trade.

The top left panel of Figure 5.1 shows the path of U.S. light oil production, which by
Table 5.1: Percent changes from 2010 to 2015: Model vs. Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Data</th>
<th>Model</th>
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<tr>
<td>U.S. light oil production</td>
<td>204</td>
<td>204</td>
</tr>
<tr>
<td>U.S. total oil production</td>
<td>75</td>
<td>78</td>
</tr>
<tr>
<td>U.S. light oil prices</td>
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<td>-28</td>
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<tr>
<td>U.S. light oil imports (net)</td>
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</tr>
<tr>
<td>U.S. light refiner inputs</td>
<td>57</td>
<td>55</td>
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</table>

Note: Annual data for real LLS and Brent oil prices are considered for the U.S. and the ROW light oil prices, respectively.

default lines up with the data. Total U.S. production rises by around 78 percent by 2015. The rise in U.S. oil production induces a small decline of about 2 percent in oil production outside the U.S., resulting in about a 4 percent increase in world oil production by 2015.

The increased light oil production lowers the price of light oil in the U.S. and the ROW. When the ban is in place, the price of light crude oil in the U.S. becomes artificially cheap relative not only to light crude oil in the ROW, but also compared to other grades of crude oil. The model predicts a decline of about 28 percent in U.S. light oil prices, compared to a 20 percent decline in the free trade model. Likewise, the decline in the relative price of light to both medium and heavy crudes is more than 5 percentage points greater than in the case of free trade. The price distortions generated by the ban have only minor implications for crude production levels due to low oil supply elasticity, as can be seen in Figure 5.1.

With exports prohibited, refiners must be incentivized to absorb the excess supply when the export ban binds. The discounts that emerge between light oil in the U.S. and the rest of world, as well as against other grades of crude, provide the needed incentive. This cost advantage leads U.S. refiners to over-process light crude oil and take market share from refiners elsewhere. Moreover, as light oil is a substitute for medium oil, the use of medium crude by U.S. refiners declines by 16.5 percent.

The increase in light oil production and the increase in domestic light oil inputs to U.S. refiners leads to a sharp decline in imports of light crude. In fact, our model suggests that the supply increase is large enough to make the U.S. a net exporter of light crude oil when exports are allowed. We also find that imports and use of medium and heavy crudes by U.S. refiners decline, as there is substitution away from medium and heavy crudes towards light crude.

Given that crude oil is only used in the refining sector to produce fuel and that it accounts for a bulk of the cost of producing fuel, fuel prices fall by around 14 percent both in the US
Figure 5.1: Impulse responses to a light oil productivity shock
U.S. refiners produce significantly more refined petroleum product when the ban binds, about 7 percent. However, world fuel production is essentially the same whether there is an export ban or not. Extra production from the U.S. simply crowds out ROW fuel production.

In Table 5.1, we focus on how several variables changed from 2010 to 2015 in the data, and compare those changes with the changes predicted by the model. By default, U.S. light oil production in the model grows by exactly the same amount as the data. The increase in total oil production predicted by the model is about 3 percentage points higher than in the actual data, due to a larger decline in medium crude oil production in the data relative to the model. The model generates a smaller decline in U.S. light oil prices and a larger light oil price differential between the U.S. and the ROW compared to the data. We find the fall in net oil imports and increase in U.S. light refiner inputs in the model are very close to changes in the data. Overall, the model does a good job in explaining some of the changes seen in the data despite the fact that we only relied on a single shock to generate these changes.

The differential between domestic and ROW light oil prices does not pass through to fuel prices, as in Borenstein and Kellogg (2014) [21].
5.2 Macroeconomic impacts

Figure 5.2 plots a select number of responses for U.S. macroeconomic aggregates. We find that the shale boom had significant effects on the broader economy. Cheaper fuel prices due to the shale boom increase household fuel consumption by about 3.6 percent. Although not presented in the figures, lower fuel prices also boost firm fuel use and lead to increases in non-oil output. Driven by a higher marginal product of capital, U.S. aggregate investment increases. Aggregate consumption also rises by about 0.7 percent. While the oil sector was less than 1.5 percent of U.S. GDP in 2010, its dramatic expansion due to the shale boom boosts the level of U.S. GDP 1 percent higher in 2015 versus 2010. The export ban has no discernable effects on these variables.

The increase in oil production and the resulting decline in oil imports lead to an improvement in the U.S. oil balance. The U.S. oil trade balance as a share of GDP goes up from a deficit of 2 percent in 2010 to a deficit of 1 percent in 2015, very close to what we observe in the data. During the shale boom, the non-oil balance deteriorates slightly by 0.5 percentage points, as a share of GDP. Our assumption that there is an internationally traded bond plays a large role in the response of the non-oil balance. If we had financial autarky, the non-oil balance would have deteriorated significantly, as it would need to mirror the improvement in the oil balance. We find that the crude export ban does have an impact on trade balances. While the oil trade balance improves slightly more under free trade than with the ban, the ban’s impact on fuel trade balance is more significant. The U.S. produces more fuel with the export ban and becomes a net exporter of refined products by 2014 in the model. Without the ban, however, the U.S. would have remained a net importer of fuel.

5.3 Additional results

5.3.1 Longer-term increase in light oil supply

The experiments presented so far assume U.S. light crude production increases until 2015 and thereafter declines at a pace determined by the persistence of the productivity shocks. However, forecasts from around 2015 pointed to further increases in U.S. shale production in years to come. To consider this, we ran an alternative exercise making use of the EIA’s forecast from the 2016 Annual Energy Outlook for light (tight) oil production from 2016 to 2020. Under this scenario, our model predicts the export ban would have remained a binding constraint through 2020. The distortions in the refining sector would have been amplified but the ban’s macroeconomic implications would have remained modest. A fuller set of results can be found in Appendix D.
5.3.2 Alternative U.S. refinery calibration

Finally, we investigate the importance of U.S. refineries being geared towards processing heavy crude relative to the rest of the world in driving our results. In our baseline calibration, the distribution parameters controlling the relative use of different types of oil in the refining sector are set such that the U.S. crude mix is 28.6 percent light and 29.9 percent heavy. We consider a counterfactual calibration where the U.S. crude mix is set to 38.6 percent light and 19.9 percent heavy, i.e. a reduced mismatch between increased light oil production and U.S. refining capacity. In this case, we find that the export ban only binds in 2015, and then only slightly. Hence, properly calibrating the refining sectors to match the U.S. refinery sector’s specialization in heavy crude is important in explaining the distortions the export ban created in the oil and refining sectors.

6 Conclusion

In this paper we study the effects of the U.S. shale oil boom on oil markets and the broader economy through the lens of a two country DSGE model. Our model includes heterogeneous refining sectors, different types of crude oil and a potentially binding export ban on crude oil in the U.S. These novel features allow us to take into account the fact that shale oil production is primarily light crude while the U.S. refining sector has a comparative advantage in processing heavier crude oils relative to the ROW.

We model the shale boom as a series of productivity shocks that boosts U.S. light oil production as in the data from 2010 to 2015. We find that our model successfully generates an increase in U.S. refiner use of light oil, a dramatic decline in U.S. light oil imports and a significant improvement in the U.S. crude oil trade balance as in the data. Our model suggests that the shale boom also boosted fuel and non-oil consumption, and increased the level of U.S. GDP by one percent.

We find that the export ban was a binding constraint, particularly in 2014 and 2015, and likely would have remained a binding constraint thereafter had it not been removed at the end of 2015. The impact of the ban appears limited to oil prices, the refining sector and trade balances, however, with negligible impacts on fuel prices or U.S. GDP.

We believe a number of avenues exist for future research on the topics of the shale boom, the export ban and oil price differentials. One potentially interesting extension would be to estimate the DSGE model to identify the impacts of various shocks over time. Another would be to consider a more geographically disaggregated model for the U.S. that would allow one to explore the implications of oil price differentials within the U.S. We leave these
for future research.
References


APPENDIX

A Data sources

The following series are available from Bloomberg:

- **Brent crude price**: Bloomberg European Dated Brent Forties Oseberg Ekofisk (BFOE) price. (Bloomberg ID: EUCRBRDT).

- **Dubai crude price**: Bloomberg Arabian Gulf Dubai Fateh crude oil spot price. (Bloomberg ID: PGCRDUBA).

- **Louisiana Light Sweet crude price**: Bloomberg light Louisiana sweet crude oil spot price. (Bloomberg ID: USCRLLSS).

- **Mars crude price**: Bloomberg Deepwater Sour Mars Blend crude oil spot price. (Bloomberg ID: USCRMARS).

- **Maya crude price**: Bloomberg Latin America Maya crude oil spot price to U.S. (Bloomberg ID: LACRMAUS).

The following series are available from the U.S. Energy Information Administration:

- **U.S. crude oil exports**: Annual data in thousands of barrels per day. Total exports and exports to Canada.

- **U.S. crude oil imports by API gravity**: Annual data in millions of barrels per day. Data is broken into seven bins: API gravity 20 or less, 20.1 to 25.0, 25.1 to 30, 30.1 to 35.0, 35.1 to 40.0, 40.1 to 45.0, and 45.1 and above. We define heavy imports as those of API gravity 25.0 and below, medium as 25.1 to 35.0, and light as 35.1 and above.

- **U.S. crude oil input to refiners**: Annual data in millions of barrels per day. EIA series name is U.S. refinery and blender net input of crude oil.

- **U.S. refinery processing gains**: Annual data in millions of barrels per day.

- **U.S. refinery production**: Sum of U.S. crude oil input to refineries, refinery processing gain and petroleum products adjustment series found in Table 4a of the Short-term Energy Outlook.

- **U.S. total spending on fuel**: Annual, nominal series in billions of dollars. This series is calculated as total spending on petroleum excluding LPG. Series is from Table ET1 of the State Energy Data 2015: Prices and Expenditures report.

- **Cost-share of crude oil in fuel production**: Monthly data from the Gasoline and Diesel Fuel Update report. We take a simple average of the cost-share for gasoline and diesel (excluding taxes).

- **U.S. consumption of refined products**: Annual series in millions of barrels per day. Calculated as total consumption excluding hydrocarbon gas liquids, ethanol and biodiesel.
Consumption of biodiesel estimated as the difference between renewables and oxygenate production and fuel ethanol production. All series from Table 4a of the Short-term Energy Outlook.

**Net imports of refined products:** Annual series in millions of barrels per day. Calculated as total consumption of refined products minus U.S. refinery production.

The following series are from the Bureau of Economic Analysis:

- **U.S. real GDP:** Quarterly data in chained, 2009 dollars.
- **U.S. nominal GDP:** Annual, billions of dollars.
- **U.S. real investment:** Annual data in chained, 2009 dollars.
- **U.S. government spending:** Annual nominal data for U.S. government consumption expenditures and investment (federal, state and local).
- **U.S. household spending on fuel:** Annual, nominal series in billions of dollars. Sum of Personal Consumption Expenditures on “gasoline motor vehicle fuels, lubricants and fluids” and “fuel oil and other fuels.”
- **U.S. oil trade balance:** Constructed using annual series on imports and exports of crude oil, in millions of dollars.
- **U.S. fuel trade balance:** Constructed using annual series on imports and exports of “fuel oil” and “other petroleum products,” in millions of dollars.

Data available from other sources:

- **U.S. crude oil production by API gravity:** Annual series in thousands of barrels per day. Data is available for ultra light and light crude oil, three types of medium crude and heavy crude. Source: World Oil and Gas Review 2017, Eni.
- **World crude oil production by API gravity:** Annual series in thousands of barrels per day. Data is available for light, medium and heavy crude production. Source: World Oil and Gas Review 2017, Eni.
- **U.S. firm spending on fuel:** Annual, nominal series in billions of dollars. Calculated as total spending on fuel minus household spending. Source: Authors’ calculations.
- **Refining capacity by country:** Annual series for crude distillation capacity (atmospheric), in barrels per day. Data source: 2010 Worldwide Refining Survey, Oil&Gas Journal.
- **World refinery processing gains:** Annual data in millions of barrels per day. Data source: International Energy Agency.
- **Labor compensation and value-added:** Annual, nominal series for the petroleum and coal sector, and the total economy. Available for 40 countries, including the U.S. Source:
World Input Output Database.

**U.S. share of world GDP:** Annual series. U.S. share of PPP-adjusted world GDP. Data source: International Monetary Fund.


**Rest-of-world fuel use:** Data are for 2010 and comes from the Energy Information Administration’s International Energy Outlook 2014 and Exxon’s 2016 Energy Outlook.
B Full model calibration

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<th>Description</th>
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Table B.1: Baseline Calibration: Targets
**Shared parameters**

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<th>Description</th>
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</tbody>
</table>

**Table B.2:** Baseline Calibration: Parameter values
C 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. We have abstracted from trade costs in the problem, which could be done if one wanted to introduce a constant spread between crude oil prices in the U.S. and the ROW reflecting various transportation costs.

C.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 $p_{11,t}^o$ or imported from country 2 at $p_{2,t}^o$. The oil distributor chooses output and imports of type $k$ crude oil to maximize the present discounted value of cash flow

$$E_0 \sum_{t=0}^{\infty} \beta^t \lambda_{1,t} \left\{ p_{11,t}^o o_{1,t}^f - p_{11,t}^k y_{1,t}^o - p_{2,t}^o o_{1,t}^m \right\}$$

subject to

$$o_{1,t}^f = y_{1,t}^o + o_{1,t}^m$$

$$o_{1,t}^m \geq 0$$

where $o_{1,t}^m$ is the import of type $k$ crude oil, $o_{1,t}^f$ is type $k$ crude oil demand by the refineries.\(^{25}\)

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, $k = l, m, h$, from becoming negative, i.e. crude oil exports are impossible. For instance, in the case of light oil the constraint would translate into $o_{1,t}^{fl} - y_{1,t}^{ol} \geq 0$. As both refiner use of light oil and production of light oil are choice variables in the model, the timing and extent to which the constraint binds is endogenous and affected by the calibration of the model. For instance, 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 $\psi_{t}^k$ be the multiplier on the inequality constraint for type $k$ crude oil. The first order

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\(^{25}\)Note that $\lambda_{i,t}$ is the lagrange multiplier on the household’s budget constraint in country $i$. **
conditions for the distributor’s optimization problem are then given by

\[ p_{1,t}^k = p_{11,t}^k \]

implying the spot price and the retail price of type \( k \) crude oil are the same, and

\[ p_{2,t}^k = p_{1,t}^k + \frac{\psi_t^k}{\lambda_{1,t}} \]

and

\[ \psi_t^k o_{1,t}^{mk} = 0. \]

In the case where the ban does not bind, \( \psi_t^k \) equals zero and the price of type \( k \) oil in the U.S., \( p_{1,t}^k \), will be equal to the cost of importing the marginal barrel of type \( k \) oil from country 2. The market clearing condition for type \( k \) oil will be given by

\[ y_{1,t}^o + y_{2,t}^o = o_{1,t}^{f,k} + o_{2,t}^{f,k}. \]

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 the world, implying that \( o_{1,t}^{f,k} = y_{1,t}^o \) and \( o_{2,t}^{f,k} = y_{2,t}^o \).

The distributor’s problem in country 2 is simply to choose output of type \( k \) crude oil to maximize

\[ E_0 \sum_{t=0}^{\infty} \beta^t \lambda_{2,t} \left\{ p_{2,t}^{o,k} o_{2,t}^{f,k} - p_{22,t}^{o,k} (y_{2,t}^o - o_{1,t}^{m,k}) \right\} \]

subject to

\[ o_{2,t}^{f,k} = y_{2,t}^o - o_{1,t}^{m,k}. \]

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

\[ p_{2,t}^o = p_{22,t}^o. \]
C.2 Solution method

It is useful to briefly map our model conditions into the notation used in Guerrieri and Iacoviello (2015) [33]. In our model, country 1’s crude oil imports are subject to an occasionally binding constraint, \( \sigma_{1,lt}^{mk} \geq 0 \) for \( k = l, m, h \). The complementary slackness condition implies that \( \psi_t^k = 0 \) when the constraint is slack. When the constraint binds, \( \sigma_{1,lt}^{mk} = 0 \).

The conditions in the reference regime, \( M1 \), encompass \( \psi_t^k = 0 \), and the function \( g \) captures \( \sigma_{1,lt}^{mk} \geq 0 \). The conditions in alternative regime, \( M2 \), encompass the case when \( \sigma_{1,lt}^{mk} = 0 \) and the function \( h \) captures \( \psi_t^k > 0 \).
D Longer-term increase in U.S. light oil supply

Our experiments presented in the paper match U.S. light crude production up until 2015. After that, the path of production is assumed to decline at a pace determined by the persistence of the productivity shocks. However, forecasts as of late 2015 pointed to further increases in U.S. shale production in years to come. In this section, we investigate how incorporating a more persistent increase in U.S. light oil supply matching these forecasts affects our results.

To capture expectations of shale production beyond 2015, we use the EIA’s forecast for light (tight) oil production from 2016 to 2020, found in their 2016 Annual Energy Outlook (AEO) report. This version of the AEO was put together at the end of 2015 and, therefore, presents forecasts that would have been made using information available before the ban was lifted. We derive a set of shocks that ensure U.S. light crude production grows at the pace seen in those forecasts.

Figures D.1 and D.2 show the main set of results under this experiment. As the EIA forecasted continued increases in U.S. light oil production, the model predicts the export ban would have been a binding constraint through 2020, leading to a persistent gap between U.S. and foreign light oil prices. U.S. light oil prices are 10 percentage points lower than they would be without the ban. U.S. refiners significantly ramp up their use of light oil, and due to the persistent cost advantage, increase output more than 10 percent, at the expense of refiners elsewhere.

We find that the ban’s macroeconomic implications remain modest. The oil balance as a share of GDP deteriorates by about 0.5 percentage points compared to the no ban scenario. The fuel balance, on the other hand, becomes positive by 2014 and improves significantly at more than 0.3 percent of GDP by 2020. As the impact of the ban on fuel prices is negligible, U.S. household fuel consumption does not change much. The persistent increase in light oil production leads to nearly a 2 percent increase in the level of U.S. GDP by 2020 and the export ban slightly amplifies that magnitude.
Figure D.1: Impulse responses when production follows the EIA forecasts through 2020

Note: Units are percent deviations from the steady state.
Figure D.2: Impulse responses when production follows the EIA forecasts through 2020

Note: Units are percent deviations from the steady state.
E 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 evidence from the data to see whether the model prediction is consistent with the data.

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 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 of the model if the export ban was binding at some point in time. First, an unusually large spread should develop between light oil in the U.S. and outside the U.S. Second, the model predicts that imports of light oil should become zero. Finally, and related to the second, if the ban is a binding constraint, it could prevent exports of light crude oil.

First, we turn to 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. 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 measure of foreign light oil prices.

Figure E.1 plots the real price spread between LLS and Brent. Starting in late 2013, we see that the price spread between LLS and Brent turned negative and declined to unusually low levels compared to where it was in previous years. This continued through some of 2015. After the ban was removed, the price spread has generally remained close to levels seen in the years before 2013, and has never again fallen to the abnormal levels seen in late 2013 and early 2014.

A review of Table 2.2 suggests that the second prediction of the model does not appear to hold in the data. At no point in time did imports of “light” crude oil become zero. However, the EIA import data allows us to consider more disaggregated slices of the crude import data for light oil, which are shown in the left panel of Figure E.2. 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.

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26We 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 focus on light crude oil.
We point out here that our modeling decision to define “light” oil as API gravity 35 and above is driven by data limitations for the production data. It is known from other analysis that most U.S. shale oil actually has API of 40 and above.\(^{27}\) 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 of very light crude approach zero first, followed by those slightly below.

Finally, we are 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 the right panel of Figure E.2. 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.

\(^{27}\)EIA (2015) [51].
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 use this loophole to export crude to Canada and indirectly back out Canadian imports of oil from another country. The dashed red line shows that exports of crude to Canada did indeed start increasing in 2013 through 2015, but fell after the ban was lifted. Since this loophole was not heavily used at any point before 2013, this suggests that the ban had likely become binding. 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.