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Resource Booms and the Macroeconomy: The Case of U.S. Shale Oil*

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Abstract

We examine the implications of the U.S. shale oil boom for the U.S. economy, trade balances, and the global oil market. Using comprehensive data on different types of crude oil, and a two-country general equilibrium model with heterogenous oil and refined products, we show that the shale boom boosted U.S. real GDP by 1 percent and improved the oil trade balance as a share of GDP by more than 1 percentage points from 2010 to 2015. The boom led to a decline in oil and fuel prices, and a dramatic fall in U.S. light oil imports. In addition, we find that the crude oil export ban, which was in place during a large part of this boom, was a binding constraint, and would likely have remained a binding constraint thereafter had the policy not been removed at the end of 2015.

Keywords: oil, trade, DSGE, shale, fuel prices, export ban.
JEL Codes: F41, Q33, Q38, Q43.

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1 Introduction

Technological advances in horizontal drilling and hydraulic fracturing have led to an unprecedented increase in U.S. oil production. Often referred to as the shale or fracking revolution, the boom in U.S. oil production has renewed interest in the long-standing question on the link between resource booms and economic performance. There are several recent papers focusing on the local or regional implications of the U.S. shale boom, suggesting positive economic effects (see, for example, Feyrer et al. (2017) [23], Allcott and Keniston (2018) [2]). However, little is known about the implications of this boom for the U.S. aggregate economy and trade. In this paper, we study the importance and implications of the U.S. oil boom for the U.S. economy, trade balances, and the global oil market in a dynamic stochastic general equilibrium model of the world economy that takes into account unique characteristics of the U.S. experience: a large increase in production of a certain type of crude oil with an oil export ban in place.

Oil has often not been explicitly modeled in many leading macro and international trade models, partly because the share of oil in aggregate production is small and primary commodities overall account for a modest fraction of global trade. However, recent research, indicating emerging interest with further insights, has shown that shocks to sectors that are economically small, such as oil and gas, but feature complementarities with other inputs of production can have disproportionate aggregate effects (Baqaee and Farhi (2018) [7]) and that trade in primary commodities is important with notably large gains from trade compared to gains from trade in standard models (Farrokhi (2018) [22] and Fally and Sayre (2018) [21]).

The relatively few general equilibrium models that do feature oil generally assume that oil is a homogenous good. This is a strong assumption since the characteristics of oil can differ across several dimensions, one of which is density. A key feature of the recent U.S. oil boom is that oil produced from shale deposits via the application of horizontal drilling and hydraulic fracturing is predominantly one type of oil: light crude. Different types of crude oil are imperfect substitutes for each other in the refining process and refining sectors tend to specialize in processing certain types of oil. The U.S. refining sector is specialized in processing heavier crude oils relative to the rest of the world. This mismatch of increased supply of light oil and existing refining capacity for heavier oil in the U.S. has important implications for the use and trade of various types of crude oil. These implications were potentially exacerbated by the U.S. export ban on crude oil, a policy which was in effect until the end of 2015.

To assess the implications of the U.S. light oil boom quantitatively, we make two contributions to the literature. First, we introduce two sources of heterogeneity into a general equilibrium model with endogenous oil prices. The first source of heterogeneity arises from the different types of oil produced that are imperfect substitutes into the refining process. The second one stems from the difference between refineries in the U.S. and the rest of the world (ROW). Our model also features a potentially binding export ban on U.S. crude oil. Second, we assemble a comprehensive data set that contains information on crude oil quality in order to build our model on solid microeconomic foundations. These data inform the building of our model in three ways. First, we compile a set of facts about the global oil market. Second, we obtain micro estimates of three key model parameters related to the refining sector using simulated method of moments: the elasticities of substitution across different oil types and the elasticity of substitution between oil and other factors of production. Third, we carefully calibrate the remaining model parameters targeting a set of first and second order moments for oil-related and macro variables. One key point to highlight is the importance of examining detailed oil data and introducing heterogeneity in crude oil types and in refining technology. If we were to only use aggregate data and pool different types of crude oil into one single oil sector, we would not be able to assess the implications of the shale oil boom for trade in different types of oil, relative prices of oil, and specialization of the refining sector. In addition, examining the distortionary effects of the crude export ban would not be possible. When different oil types are aggregated, we find that macroeconomic effects of the oil boom would also be smaller.

An essential initial step for this analysis is to assemble global oil market data at a disaggregated level. Using various sources, we gather data on production and prices of different types of crude oil as well as trade flows and refiner use of different types of oil. We document that from 2010 to 2015 U.S. light oil production more than tripled, while production increases outside the U.S. were from medium and heavy crudes. In addition, the U.S. refiners' use of light oil increased substantially from 2010 to 2015. Meanwhile, their medium crude use declined and heavy crude use increased. We document dramatic shifts in the quantity and types of oil being imported as well: U.S. light oil imports dropped sharply, medium oil imports declined and heavy oil imports increased since the shale boom. With the increased total crude inputs to U.S. refineries, refined products production and exports increased substantially, as the export ban did not apply to refined petroleum products. These facts help justify the features of our model.

Our two-country (U.S. and ROW) general equilibrium model with heterogeneities and an export ban has the following additional features. An internationally traded bond allows for the possibility of trade imbalances. In addition to oil and refined products (fuel), both countries produce a non-oil good.[1] The non-oil good is used to produce oil and for consumption and investment which is costly to adjust. 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. We model the shale boom as a series of positive technology shocks that replicate the increase in U.S. light crude production from 2010 to 2015 and then illustrate the general equilibrium outcomes.

Our main findings can be summarized as follows. First, we find that the shale oil boom boosted U.S. real GDP by 1 percent from 2010 to 2015 which accounts for about one tenth of actual GDP growth over this period. This suggests that the boom has contributed to the recovery from the Great Recession. The boom also had sizable effects on trade flows and the upstream and downstream oil sectors. In addition, the U.S. crude oil export ban was a binding constraint with distortions primarily in trade flows and upstream and downstream sectors and a negligible effect on U.S. real GDP.

Second, our model can match several important aspects of U.S. oil market data during the boom despite relying on a single shock, a light oil technology shock. The increase in light oil supply causes light oil prices and fuel prices to fall. 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. oil trade balance, by more than one percentage point (as a share of GDP), in line with the data. The decline in light crude oil imports is large enough to make the export ban a binding constraint in the model for several years. Properly modeling and calibrating the refinery sector is key to this result, as it is driven by the fact that the U.S. refinery sector is specialized in processing heavy crude relative to the rest of the world.[2] The ban distorts light crude oil prices in the U.S. relative to the rest of the world and relative to other types 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.

Cheaper fuel prices boost household consumption and firm fuel use and increase both non-oil output and aggregate consumption, suggesting positive spillovers to the aggregate economy. While the oil trade balance improves significantly, we find only a slight deterioration in the non-oil trade balance.[3]

[1] To optimize our model's tractability and ensure transparency of its insights, we assume that the non-oil good is homogenous.

[2] In section 6, we consider a counterfactual exercise where the U.S. refinery sector processes more light oil and less heavy oil, which lessens the mismatch between increased light oil production and the sector's ability to process that oil. In that case, we find that the export ban is not binding.

[3] 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.

Third, using a counterfactual exercise, we show that had there been no ban during the shale boom from 2010 to 2015, domestic light oil prices would have been higher and the U.S. would have become a net exporter of light crude oil consistent with the recent data.[4] As ROW refiners are specialized in processing light crude relative to the U.S., the ROW would have processed the increased light oil supply and gained market share. The U.S., thereby, would have become a net importer of fuel. The increase in global fuel supply and the decline in fuel prices, however, would have been similar as there was no ban on refined products. With the size of the decline in fuel prices essentially unchanged relative to the baseline model that takes the ban into account, the responses of most macro aggregates, such as real GDP or aggregate consumption, would have been similar to the baseline model. In other words, the distortionary effects of the ban seem to be primarily concentrated in oil prices, refining sectors, and trade flows. The results also suggest that the ban was a binding constraint particularly in 2014 and 2015, and would very likely have remained a binding constraint thereafter had the policy not been removed at the end of 2015.

1.1 Related literature

Our paper is unique in analyzing the implications of the U.S. oil boom for the U.S. economy, trade, and the global oil market taking into account specific characteristics of the U.S. experience. Our attempt is important for several reasons. First, the ongoing structural change in the global oil market with the emergence of the U.S. as a major oil producer via technological advances in unconventional production (the broad application of horizontal drilling and hydraulic fracturing) warrants further examination. Second, understanding the implications of a resource boom for a large advanced economy can shed more light on the natural resource abundance and the macroeconomy debate. Third, oil shocks can have significant aggregate implications. That said, our work draws from a large literature regarding resources and commodities, and our model and calibration approach is similar to a number of other papers aimed at quantifying the effect of oil shocks and policy changes on various economic outcomes.

On the theoretical side, our paper relates to work analyzing the effects of oil price fluctuations on the economy and the mechanisms through which oil shocks operate using general equilibrium models.[5] The model developed in this paper is closely related to Bodenstein et al. (2011) [12] with some key differences regarding the distinction between different types

[4] For example, the U.S. exported about 1.2 million barrels per day of crude oil on average in 2017.

[5] Examples of this type of work include Kim and Loungani (1992) [34], Backus and Crucini (2000) [5], Leduc and Sill (2004) [32], and Nakov and Nuno (2013) [38].

of oil, oil production and refining.[6] Careful modeling of oil production and refining are key theoretical contributions of our paper allowing a granular analysis of the oil market. Both the specifics of upstream and downstream oil sectors and a worldwide equilibrium analysis must come together to address oil-related, macro, and trade implications of the U.S. shale oil boom. In that context, our paper also complements two recent studies, Farrokhi (2018) [22] and Fally and Sayre (2018) [21], who use detailed data on commodities and incorporate oil and other primary commodities into multi-country models of trade to address the role of commodities in trade.[7] Farrokhi (2018) [22], for example, employs a detailed refinery sector in his static, multi-country general equilibrium model, and also examines the implications of the U.S. crude export ban.[8]

The shale revolution has motivated several recent papers to investigate local or regional implications of the shale boom, suggesting positive spillovers from the boom to regional economies (for example Gilje et al. (2016) [28], Feyrer et al. (2017) [23]).[9] In addition, a line of empirical research examines crude price differentials between U.S. and international benchmarks emerging as a result of the U.S. oil boom.[10] [11] Our paper complements these studies by investigating the implications of the shale oil boom for the U.S. aggregate economy and the global oil market using a DSGE model.

More broadly, our work relates to an extensive literature focusing on the consequences of resource booms. Earlier studies in this literature generally use macroeconomic cross-country data, mostly for developing countries with a large dependence on resource production, and many suggest an adverse impact on economic growth.[12] Recent studies offer further useful insights on the impact of natural resources on economic performance by exploring different mechanisms, using better identification strategies, or employing higher quality micro data. For example, Bjornland and Thorsrud (2016) [11] highlight the importance of the source of windfall gains -volume versus price changes- when analyzing the relationship between

[6] Oil price is determined endogenously while oil supply is exogenous in Bodenstein et al. (2011) [12].

[7] Both studies find significantly larger gains from trade compared to benchmark trade models due in part to some specific features of primary commodities such as low price elasticities of demand and supply, and low elasticity of substitution.

[8] Langer et al. (2016) [31] also analyze the lifting of the export ban, but use a numerical, partial equilibrium model of the refining sector.

[9] Mohaddes and Raissi (2018) [37] investigate global macroeconomic consequences of declining oil prices due to the U.S. oil revolution, while Manescu and Nuno (2015) [35] examine oil price and oil-importer GDP implications of expected U.S. oil supply increases under different scenarios. Baumeister and Kilian [14] discuss the potential impact of the rise of the shale oil sector on the transmission of oil price shocks to the U.S. economy.

[10] See for example, Agerton and Upton (2017) [3] and Borenstein and Kellogg (2014) [14].

[11] Kilian (2016) [30] also examines how the oil boom has affected the evolution of crude oil and gasoline prices.

[12] See van der Ploeg (2011) [42] for a survey of the literature.

a booming resource sector and the rest of the economy. Focusing on two advanced small open economies, Norway and Australia who are commodity exporters, as their case studies, they show that a resource boom driven by increasing resource activity can have substantial productivity spillovers on non-resource sectors and stimulate the economy.[13] By the same token, using new microdata, Allcott and Keniston (2018) [2] examine the local effects of oil and gas booms in the U.S. since the 1960s and find no evidence for a Dutch Disease mechanism. Motivated by the fast-paced technological progress turning the United States into a major oil producer in a short period of time, we contribute to this literature by studying the implications of a resource boom stemming from a resource (technology) shock for a large advanced economy. We show that the oil boom contributed importantly to economic activity despite the U.S. being a net-importer of oil with the resource (oil) sector representing a relatively smaller share of the aggregate economy.

The remainder of the paper is organized as follows. Section 2 presents data. Section 3 develops the model. Section 4 presents the calibration of the baseline model. Baseline results are discussed in Section 5 and additional results are presented in Section 6. We conclude in Section 7.

2 Data

Our goal in this section is to document some key facts about the global oil market which will motivate our key assumptions in the model. To this end, we gather and examine comprehensive data on prices of different crude types, 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 U.S. shale oil boom.[14]

[13] On the other hand, exploring the price channel, i.e. windfall income stemming from changes in commodity prices, Charnavoki and Dolado (2014) [17] find a Dutch disease effect for the case of Canada, another advanced small open commodity-exporting economy.

[14] Hydraulic fracturing and horizontal drilling were first applied to natural gas areas and have led to a boom in the production of both natural gas and natural gas liquids (NGLs), such as propane and ethane. Ethane, in particular, is an important feedstock to the U.S. petrochemical sector, and increased ethane production has led to an investment boom in the U.S. petrochemical sector. The NGL production boom and its implications for the petrochemical sector is an interesting question but requires jointly modeling the shale oil boom and the shale gas boom. We leave this for future research as this would require adding a natural gas sector and a petrochemical sector to the model.

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. Although not always the case, light oils typically 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 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. for sour crude oils.

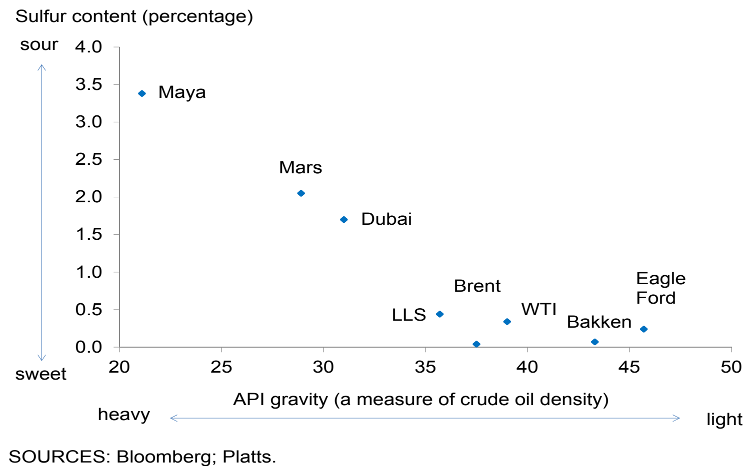
Shale oil produced in the U.S. generally has low sulfur levels and an API gravity greater than 40 (EIA (2015) [41]). While there is no benchmark crude oil for U.S. shale production, Platts, a price reporting agency, does assess the price of two specific grades of shale: Bakken in North Dakota and Eagle Ford in Texas. Figure 2.1 also shows the respective API gravity and sulfur content of these two grades of shale.

The prices of crude oils with similar API gravities and sulfur content tend to remain close to each other.[15] Price differentials between any given pair of crude oils are usually an increasing function of how different the two crude oils are in terms of API gravity and sulfur content.[16] In addition, light, sweet crude oils tend to be preferred by refiners for several reasons, and therefore have higher prices than other crude oils. First, they have low sulfur content, hence require less processing than a high sulfur crude oil. Second, a given amount of

[15] Factors such as storage constraints and 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 relative to Brent.

[16] See Giulietti et al. (2015) [24] for an analysis using 32 different crude oils.

Figure 2.1: Characteristics of various crude oils



light crude oil will generally produce more gasoline and diesel -high-value refined products- than a heavy crude oil. However, a refinery can also profitably process heavy, sour 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. Gulf Coast has a preponderance of such refineries relative to the rest of the world.

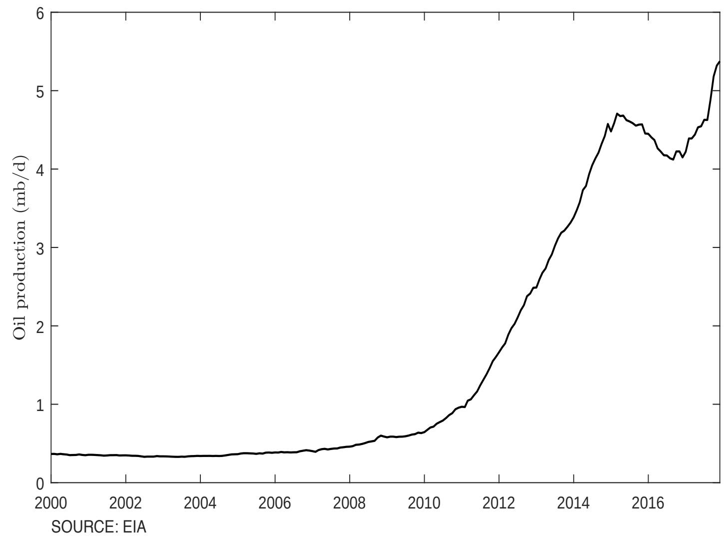
Using monthly time series price data from Bloomberg, we look at the price of light, medium and heavy crude on the U.S. Gulf Coast as an example. We find that the price of LLS has, on average, been about 12 percent higher than Mars crude oil and 27 percent more expensive than Maya. We also find that the relative prices of different oil types tend to be more volatile, the further apart the two are in terms of their API gravity and sulfur content.[17]

2.2 Crude oil production

Data on monthly U.S. shale oil production are available from the U.S. Energy Information Administration starting in the year 2000. Figure 2.2 presents the time series through the end of 2017. It clearly shows that the boom in shale oil production began after 2010, with

[17] 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. 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.

Figure 2.2: U.S. shale oil production



only modest production increases seen before that time. Following broader applications of horizontal drilling and hydraulic fracturing, production grew rapidly from 2010 to 2015, when low oil prices curtailed activity in many shale areas.

In order to investigate how the increase in U.S. shale oil production has changed the dynamics of the global oil market and inform our theoretical model introduced later, we compile data on crude oil production by type for both the U.S. and the rest of the world from the 2017 version of Eni's World Oil and Gas Review [19]. Collecting consistent, global time series data on different crude types is a challenging task. The Eni data does cover the years when oil production in the U.S. boomed due to horizontal drilling and hydraulic fracking and provide a good snapshot of the changes in U.S. and global oil production.[18] It provides a breakdown of crude oil production into several different types covering 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.

We define different categories of crude oil using API gravity as our metric.[19] Following Eni, we define heavy crude oil as oil with an API less than 26, medium from 26 up to 35,

[18] We considered using other sources for data on crude production by type, 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) [41] only provides annual data for 2010 to 2013. Moreover, a significant portion of U.S. crude production is unclassified in *DrillingInfo* data.

[19] We would have preferred to further expand our categorization to include sulfur content but could not because of data limitations.

and light crude oil with an API of 35 and above.[20] Using these definitions, it is possible to construct a consistent series for the U.S. and the rest of the world (ROW) oil production by type.[21]

Table 2.1 shows the production data in millions of barrels per day (mb/d). One feature of the U.S. oil 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.

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	20.1	34.9	7.6	22.2	37.8	8.4
2005	1.7	2.8	0.7	19.9	40.3	9.5	21.6	43.0	10.1
2010	2.1	2.8	0.6	20.8	38.8	9.9	23.0	41.6	10.4
2011	2.6	2.5	0.6	19.7	40.2	10.0	22.3	42.7	10.5
2012	3.5	2.4	0.6	20.1	41.0	9.8	23.6	43.4	10.4
2013	4.5	2.4	0.6	19.6	40.5	10.1	24.2	42.9	10.7
2014	5.9	2.4	0.6	19.0	41.4	10.2	24.8	43.8	10.9
2015	6.5	2.5	0.6	19.1	42.0	11.1	25.6	44.5	11.7
2016	5.9	2.5	0.6	19.3	42.6	10.9	25.2	45.1	11.4

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 and heavy. Annual data go back to 1978. An extensive time series is available for annual crude exports as well, but the EIA does not provide a breakdown by crude 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.

[20] As mentioned earlier, shale oil generally has an API gravity greater than 40. So, it would be preferable to have an additional group that matches the characteristics of shale oil better than including it in a bucket that begins at 35 API gravity. However, the Eni production data does not allow us to create such a category. Nor do we have price data for such a group, which would be required to calibrate our model's refining sector. As a result, we choose to use the categorization explained in the text, with the understanding that it is an approximation to the reality that we would like to model.

[21] 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.

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.[22] 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

	U.S. crude imports			**U.S. crude exports**	**U.S. refined products**
	Light	Medium	Heavy	Total	Net imports
2000	2.2	4.6	2.3	0.05	0.87
2005	2.3	4.3	3.5	0.03	2.00
2010	2.1	3.3	3.8	0.04	0.08
2011	1.7	3.3	4.0	0.05	-0.35
2012	1.4	3.1	4.0	0.07	-1.00
2013	0.9	3.0	3.9	0.13	-1.13
2014	0.6	2.7	4.1	0.35	-1.49
2015	0.6	2.6	4.2	0.47	-1.51
2016	0.9	2.6	4.4	0.52	-1.48

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.[23] 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. 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 petroleum products increased significantly and by 2011 the United States had become a net exporter.

[22] The EIA's import data allow us to break down the light crude group into further sub-groups with API gravity greater than 35. When we look at these sub-groups, we find that the U.S. imports of crude with API 45.1 and higher dropped to near zero by 2013, and that the imports of crude with API from 40.1 to 45 dropped to very low levels by 2014.

[23] 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) [9].

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

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

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. 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 want to highlight two points regarding our calculations. First, we are unaware of any inventory data that would allow us to break inventory changes into the respective crude types, even in the U.S.[24] We do note, however, that changes in U.S. crude oil inventories from year to year tend to be very small when compared to the amount of oil being processed by U.S. refiners each day. For example, the annual changes in U.S. oil inventories from 2010 to 2015 were generally below 0.10 mb/d.

Second, 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 other sources, suggest that most, if not all, of the oil exported to Canada was of the light variety.[25] 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.

Table 2.3 presents 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

[24] Outside of the U.S, data are limited even for overall crude oil inventory changes.

[25] See Çakır Melek and Ojeda (2017) [16] for more details.

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	17.9	30.4	5.4
2005	4.1	7.0	4.2	17.6	36.0	6.0
2010	4.2	6.1	4.4	18.8	35.5	6.1
2011	4.2	5.8	4.5	18.1	37.0	6.0
2012	4.9	5.6	4.5	18.7	37.9	5.9
2013	5.3	5.3	4.5	18.9	37.5	6.2
2014	6.1	5.1	4.7	18.7	38.7	6.2
2015	6.6	5.1	4.8	19.0	39.4	6.9
2016	6.3	5.1	5.0	19.0	40.0	6.4

refinery has an NCI of 1 while the largest and most complex refineries can have scores of over 15.[26] 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 of the changes since 2010

There have been dramatic changes in the oil market since the U.S. shale oil boom. We take stock of these changes in Table 2.4 by comparing how select data for the U.S. have changed from 2010 to 2015.

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

[26] See Johnston 1996 [29] for more details.

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

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

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

Motivated by the facts documented in this section, we present our theoretical framework used to evaluate the implications of the U.S. shale oil boom in the next section.

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), building on Backus and Crucini (2000) [5] and similar to Bodenstein et al. (2011) [12]. The key differences are that we introduce heterogenous oil, oil production and refining, and adapt the model to account for key features of the global oil market described previously. Our model also features a potentially binding export ban on U.S. crude oil. We refer to the U.S. as country 1 and ROW as country 2. Both countries produce 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 and heavy crude. Production of refined products requires capital, labor, and a composite of the three types of crude oil with different elasticities of substitution across inputs. The non-oil good is produced using capital, labor, and refined products. The household consumption bundle is a composite of refined products and the non-oil good. 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

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

where $c_{i,t}$ and $L_{i,t}$ are aggregate consumption and leisure, respectively. The parameter $0 < \beta < 1$ denotes the discount factor, μ_i governs the time spent in the workplace, and γ 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 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

$$c_{1,t}^a + p_{1,t}^f c_{1,t}^f + \sum_j^{j=a,f} I_{1,t}^j + \frac{p_t^b}{\Phi_{b,t}} B_{1,t+1} = \sum_j^{j=a,f} W_{1,t}^j n_{1,t}^j + \sum_j^{j=a,f} R_{1,t}^j K_{1,t}^j + \sum_j^{j=a,f,o} \Pi_{1,t}^j + B_{1,t} + T_{1,t}, \tag{3.2}$$

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 $p_{i,t}^f$ 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_i^j and R_i^j, respectively. Households own the firms operating in the economy and hence receive profits from all sectors: $\Pi_{i,t}^a$, $\Pi_{i,t}^f$, and $\Pi_{i,t}^o$. Profits from the oil sector are given by $\Pi_{i,t}^o = \sum_k \Pi_{i,t}^{ok}$ 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 δ is the depreciation rate. Physical capital formation is subject to adjustment costs. 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) [12] and assume that households in country 1 pay a small intermediation fee, $\Phi_{b,t}$, given by

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

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

Finally, household activities exhaust total hours available:

$$\bar{L}_i - L_{i,t} - n^a_{i,t} - n^f_{i,t} = 0, \tag{3.4}$$

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) [6]. 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:

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

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, 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. $y_{i,t}^{ok}$ is production of oil type k and $z_{i,t}^{ok}$ represents a stochastic process for the evolution of technology. Marginal costs increase with production increases, reflecting the difficulty of producing an additional unit of oil as oil production increases, and decrease with better technology. 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 η_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 output-elasticity of the marginal cost of producing oil.

3.2.2 Refined products production

For the refining sector, we choose to 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 for fuel 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,

$$y_{i,t}^f = \left[w_i^f \left(z_i^f (n_{i,t}^f)^{\chi_i^f} (K_{i,t}^f)^{1-\chi_i^f} \right)^{-\rho_i^f} + (1 - w_i^f) G(o_{i,t}^{fl}, o_{i,t}^{fm}, o_{i,t}^{fh})^{-\rho_i^f} \right]^{\frac{1}{-\rho_i^f}} \tag{3.5}$$

where z_i^f represents technology in the sector, and $n_{i,t}^f, K_{i,t}^f$ denote labor and capital inputs.[27] The parameter w_i^f governs the share of value-added in gross output in country i, and χ_i^f governs the labor share in value-added in country i, with $0 < w_i^f, \chi_i^f < 1$. The elasticity of substitution between the capital-labor composite and the oil composite is $\frac{1}{1+\rho_i^f}$. Hence, we allow for the possibility that the cost-shares and technology levels vary across countries, and 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, $o_{i,t}^{fl}, o_{i,t}^{fm}, o_{i,t}^{fh}$. 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:

$$G(o_{i,t}^{fl}, o_{i,t}^{fm}, o_{i,t}^{fh}) = \left[w_i^o (o_{i,t}^{fh})^{-\rho_i^{oil}} + (1 - w_i^o) \left(\omega_i^o (o_{i,t}^{fl})^{-\eta_i^{oil}} + (1 - \omega_i^o)(o_{i,t}^{fm})^{-\eta_i^{oil}} \right)^{\frac{\rho_i^{oil}}{\eta_i^{oil}}} \right]^{\frac{1}{-\rho_i^{oil}}}, \tag{3.6}$$

where light and medium crudes form their own composite. The w_i^o and ω_i^o 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 $\frac{1}{1+\rho_i^{oil}}$, and the elasticity of substitution between light oil and medium oil is $\frac{1}{1+\eta_i^{oil}}$.

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.[28] As we

[27] In reality, refiners face a joint production problem as they produce different products rather than a homogenous "fuel" product. Such distinction is of particular interest if one wants to examine subjects like the behavior of different fuel prices over time. We are not primarily interested in the differential impacts of the shale boom on various fuel prices. Moreover, explicitly incorporating a joint production problem would require an even more complex production function than the one we consider, so we leave this for future research. Some early works on the subject include Manne (1951) [36] and Griffin (1977) [25].

[28] 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.

show later, allowing the elasticity to be different between light and medium vs. heavy allows us to model this feature of the data.[29]

The representative producer of refined products in each country chooses $n^f_{i,t}$, $K^f_{i,t}$, $o^{fl}_{i,t}$, $o^{fm}_{i,t}$, and $o^{fh}_{i,t}$ to maximize profits

$$\Pi^f_{i,t} = p^f_{i,t} y^f_{i,t} - W^f_{i,t} n^f_{i,t} - R^f_{i,t} K^f_{i,t} - p^{ol}_{i,t} o^{fl}_{i,t} - p^{om}_{i,t} o^{fm}_{i,t} - p^{oh}_{i,t} o^{fh}_{i,t},$$

subject to equations 3.5 and 3.6. 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 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

$$y^a_{i,t} = \left[w^a_i \left(z^a_{i,t} (n^a_{i,t})^{\chi^a_i} (K^a_{i,t})^{1-\chi^a_i} \right)^{-\rho} + (1 - w^a_i)(m^f_{i,t})^{-\rho} \right]^{\frac{1}{-\rho}}, \tag{3.7}$$

where $z^a_{i,t}$ represents a stochastic process for the evolution of technology, $n^a_{i,t}$, $K^a_{i,t}$ denote labor and capital inputs, and $m^f_{i,t}$ is the input of refined products. The parameter χ^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 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 $n^a_{i,t}$, $K^a_{i,t}$, 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 3.7. 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. production of each good must equal the total use of that good. In the oil market,

[29] Another indication 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.

$\forall k = h, l, m$, we have

$$y_{1,t}^{ok} + y_{2,t}^{ok} = o_{1,t}^{fk} + o_{2,t}^{fk}.$$

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

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

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

Finally, the bond market clears when

$$B_{1,t} = -B_{2,t}.$$

3.4 Trade in goods and financial assets

The model assumes that all goods can be traded freely except for crude oil in the U.S., which will be discussed next. We abstract from transportation costs; as a result both purchasing power parity (PPP) and the law of one price hold for oil and fuel prices. That is, $p_{1,t}^{ok} = p_{2,t}^{ok}$, $\forall k = h, l, m$, and $p_{1,t}^{f} = p_{2,t}^{f}$.[30]

The evolution of bond holdings is determined by the U.S. budget constraint, equation (3.2). Through substitution, it can be re-written as

$$\begin{aligned} \frac{p_t^b}{\Phi_{b,t}} \Delta B_{1,t+1} = {} & y_{1,t}^{a} - p_{1,t}^{f} m_{1,t}^{f} + p_{1,t}^{f} y_{1,t}^{f} - \sum_{k}^{k=h,l,m} p_{i,t}^{ok} o_{1,t}^{fk} + \sum_{k}^{k=h,l,m} \left(p_{i,t}^{ok} y_{1,t}^{ok} - C_{1,t}^{k} \right) \\ & - c_{1,t}^{a} - p_{1,t}^{f} c_{1,t}^{f} - \sum_{j}^{j=a,f} I_{1,t}^{j} - G_1 + \left(1 - \frac{p_t^b}{\Phi_{b,t}} \right) B_{1,t}. \end{aligned}$$

3.4.1 Export ban on U.S. crude oil

During most of the U.S. shale boom, a crude oil export ban was in place. We incorporate the U.S. crude oil export ban into our baseline model as follows. 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

$$o_{1,t}^{fk} - y_{1,t}^{ok} \geq 0, \tag{3.8}$$

[30] Assuming iceberg trade costs would generate a constant differential between prices.

for $k = h, m, l$.[31]

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 U.S. and ROW light oil prices. Second, while the oil market becomes segmented, the fuel market does not because there is no prohibition on exporting refined products.[32] Finally, 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) [27] 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.[33] 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 and 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

[31]Further mathematical details about how we set up the export ban can be found in the Appendix C.

[32]This means that if light crude oil prices are distorted by the ban, it will provide a cost-advantage to U.S. refiners who will be able to buy oil at a discounted price but sell fuel at the market price. Similar intuition holds for example for cases where oil prices are distorted by pipeline bottlenecks, see for example Borenstein and Kellogg (2014) [14].

[33]We use the Dynare software package developed by Adjemian et al. (2011) [1] to solve our model.

	Description		Description
Targets			
$c_1^f = 0.022$	U.S. household fuel use	$m_1^f = 0.022$	U.S. firm fuel use
$y_1^f = 0.995\left(c_1^f + m_1^f\right)$	U.S. fuel production	$o_1^f = 2.675\ y_1^o$	Total oil input to U.S. refiners
$y_1^o = 0.35\ y_1^f$	U.S. total oil production	$\frac{y_2^o}{y_1^o+y_2^o} = .927$	Determines ROW total oil production
$p^{ol}/p^{om} = 1.06$	Rel. price of light to medium crude	$p^{ol}/p^{oh} = 1.18$	Rel. price of light to heavy crude
$\frac{y_2^g}{y_1^g+y_2^g} = .83$	Size of ROW economy	$\frac{\bar{L}_2}{\bar{L}_1+\bar{L}_2} = .955$	Size of ROW population
$L_1 = 2/3$	U.S. time allocated to leisure	$L_2 = 2/3\ \bar{L}_2$	ROW time allocated to leisure
Shared parameters			
$\beta = 0.96$	Discount factor	$\gamma = -1$	Inter. elas. of sub.
$\delta = 0.10$	Depreciation rate of capital	$\frac{1}{\delta\phi} = 0.032$	Capital adjustment costs
$\rho = 4$	Elas. of sub. for fuel (0.2)	$\rho^f = 4$	Elas. of sub. in refining (0.2)
$\eta^{oil} = -0.71$	Elas. of sub. for o^{fl}, o^{fm} (3.5)	$\rho^{oil} = -0.49$	Elas. of sub. for o^{fh},comp. (1.95)
$\eta^k = 0.12$	Elas. of oil supply for $k = l, m, h$		
Other parameters			
$\chi_1^f = 0.164$	Labor share in U.S. refining	$\chi_2^f = 0.297$	Labor share in ROW refining
$\chi_1^a = 0.60$	Labor share in U.S. non-oil sector	$\chi_2^a = 0.55$	Labor share in ROW non-oil sector

Table 4.1: Calibration

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 β is set to 0.96. The depreciation rate of capital, δ, is set to 0.10. The curvature parameter determining the household's coefficient of relative risk aversion, γ, is set at -1, as in Backus and Crucini (2000) [5]. The elasticity of substitution between refined petroleum products and the non-oil good consumption, given by $\frac{1}{1+\rho}$, is set at 0.20.[34] This produces a low price elasticity of demand for refined products, in line with previous empirical estimates.[35] Following Bodenstein et al. (2011) [12], we constrain this elasticity to be equal for households and firms in both countries. The (annual) elasticity of supply of oil is set to 0.12 consistent with the estimate in Bornstein et al. (2018) [15].[36] 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

[34] For a differential change in fuel prices, the (partial-equilibrium) price elasticity of demand is given by $\frac{dc^f p^f}{c^f dp^f} = -\sigma$. The actual response in our model will vary a small amount from this due to general equilibrium affects.

[35] See for example Coglianese et al. (2017) [18] and Levin et al. (2017) [33].

[36] Bornstein et al. (2018) [15] report an extraction elasticity of 0.12 and state "A one standard deviation (27) percent increase in the price of oil raises the extraction rate from 2.8 percent to 2.9 percent, resulting only in a 3.3 percent increase in production." This leads to a price-elasticity of supply of $0.1\bar{2}$, which we round to 0.12. Using monthly data, Anderson et al. (2018) [4] report an elasticity close to 0.

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 $\frac{2}{3}$ 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 ϕ_b is set to 0.001 as in Bodenstein et al. (2017) [13].

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 calculations using BEA and EIA data.[37]

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.[38] The EIA provides data on world consumption of petroleum and other liquids by region and end-use sector. Finally, Exxon 2016 Energy Outlook [20] 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 χ_1^a and χ_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.[39] To determine the

[37] Non-household petroleum spending is obtained as the difference between total spending (excluding NGLs) from Table ET1 of the EIA State Energy Data 2015 report and our calibration for household spending. For 2010, we find that it is 2.2% of GDP. While our calibration is for 2010, the average shares over 2000-2009 are not too different: 2.01% for households and 1.83% for firms.

[38] See Timmer et al. (2015) [39] for details on the database.

[39] This is due to a volumetric expansion that occurs when crude oil is processed into refined petroleum products.

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 $o^f_{k_1}$ 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^f_2 .

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, 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.[40] 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, χ^f_1 and χ^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.

4.2 Moment-matching exercise

The parameters governing the autoregressive processes for the technology shocks are not determined by the deterministic steady state. We also need to calibrate the capital adjustment cost parameter, ϕ, the elasticities of substitution across different oil inputs, η^{oil} and ρ^{oil}, as well as the elasticity of substitution between value-added and oil in the refining production function, ρ^f. To calibrate these parameters, we use simulated method of moments to have

[40]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.

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 of Global Economic Indicators.[41] 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 a sufficiently long time series data is not 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. We 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 technology shocks for different oil types to be equal.[42] 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 4 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,

[41] See Grossman et al. (2014) [26] for more details.

[42] They can differ between the U.S. and ROW, but as noted earlier, we do not have long time series data on oil production by type to do otherwise.

Shock type	AR(1) coefficient	Volatility
Technology (U.S.)	.645	.0055
Technology (ROW)	.379	.0061
Oil supply (U.S.)	.693	.0278
Oil supply (ROW)	.736	.0327

Table 4.2: Calibration of shock parameters

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 the statistics of interest from the filtered data.

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, while its ability to match oil price volatilities is weaker. Still, the model can account for 60 to 70 percent of the volatilities.[43]

Our exercise leads to an elasticity between light and medium ($\frac{1}{1+\eta^{oil}}$) of 3.5. The elasticity between heavy and the composite of light-medium crude ($\frac{1}{1+\rho^{oil}}$) is 1.95. 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 Baseline Results

Our goal is to investigate the effects of the U.S. shale oil boom on the U.S. economy, trade, and the global oil market. We model the shale oil boom as a series of exogenous technology shocks that lower the cost of producing light oil in the U.S., i.e. a set of positive shocks to $z^{ol}_{1,t}$. In order to generate the path for the shocks, we conduct the following exercise. We

[43] We note that other works that use a similar modeling framework, such as Bodenstein et al. (2011) [12], also have difficulty matching oil price volatility at business cycle frequencies.

Variable	Data AC(1)/ Correlation	Data Volatility	Model AC(1)/ Correlation	Model Volatility
U.S. oil production (total)	0.698	0.03	0.698	0.03
ROW oil production (total)	0.737	0.024	0.737	0.024
U.S. GDP	0.714	0.016	0.717	0.016
ROW GDP	0.495	0.011	0.497	0.011
U.S. investment		0.066		0.065
U.S. refiner inputs/runs (total)		0.024		0.024
Light and medium oil prices	0.981		0.981	
Light and heavy oil prices	0.954		0.954	
Medium and heavy oil prices	0.953		0.958	
Log of light oil price		0.159		0.097
Log of medium oil price		0.150		0.102
Log of heavy oil price		0.162		0.095

Table 4.3: Properties of the key variables, Data vs Model

have data on the annual percent change in U.S. light oil production from 2010 to 2015 (see Table 2.1). We numerically solve for the values of the technology 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 light oil production. Given that the export ban was in place, our baseline model incorporates the ban.

We find that the shale boom had significant effects on the U.S. economy, trade flows and the global oil market. In addition, 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.[44]

Given the large number of 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 and Figure 5.2.[45] 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 baseline results, i.e. the responses with the ban.

The top left panel of Figure 5.1 shows the path of U.S. light oil production, which by 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.

[44] 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 D.4 and in Çakır Melek and Ojeda (2017) [16].

[45] A full set of results are available upon request.

Figure 5.1: A light oil technology shock (oil market response)

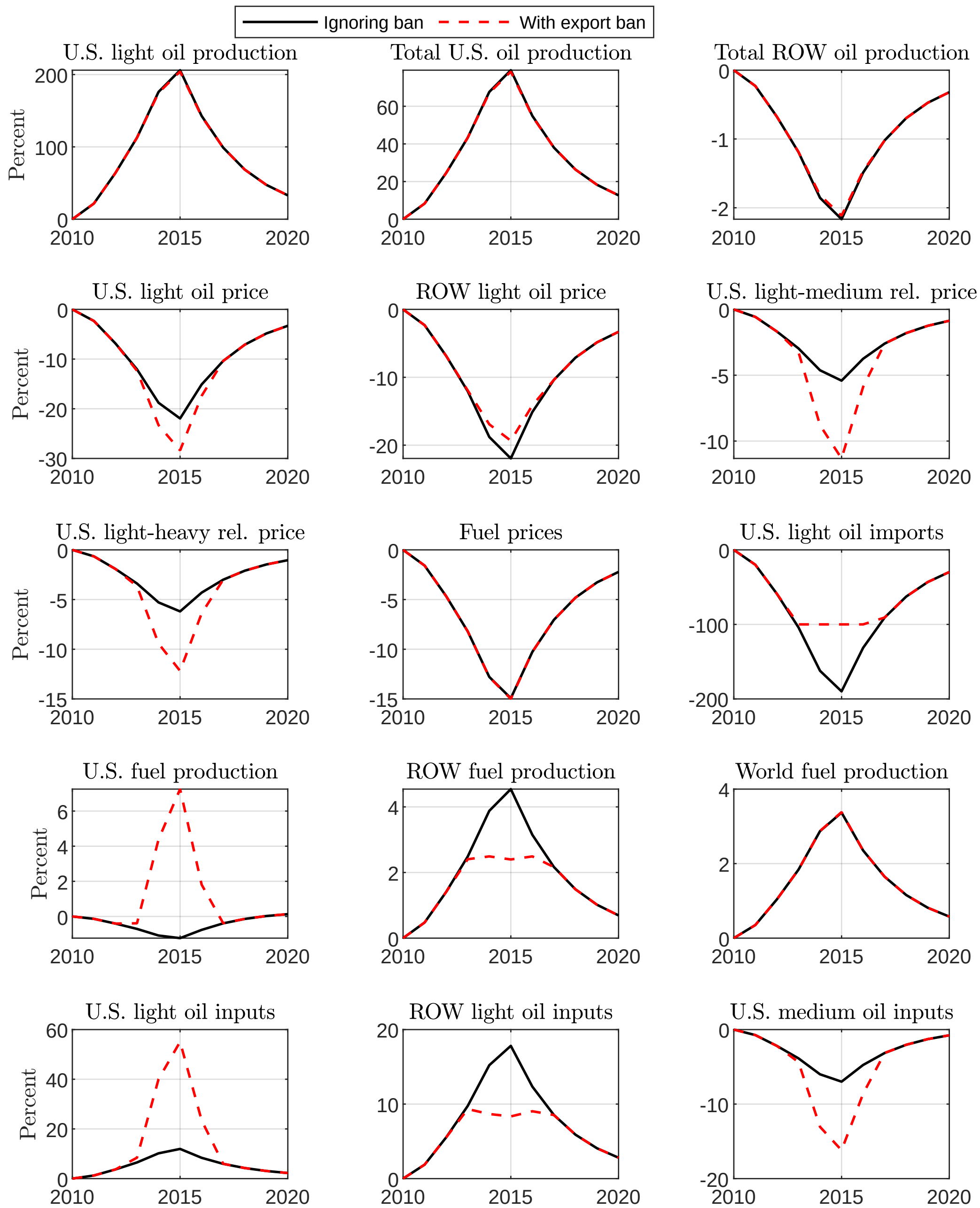


Table 5.1: Percent changes from 2010 to 2015: Model vs. Data

Variable	Data	Model
U.S. light oil production	204	204
U.S. total oil production	75	78
U.S. light oil prices	-42	-28
U.S. - ROW light oil price differential	-4	-8
U.S. light oil imports (net)	-95	-100
U.S. light refiner inputs	57	55

Note: Annual data for real LLS and Brent oil prices are considered for the U.S. and the ROW light oil prices, respectively. Data and model results rounded to whole numbers.

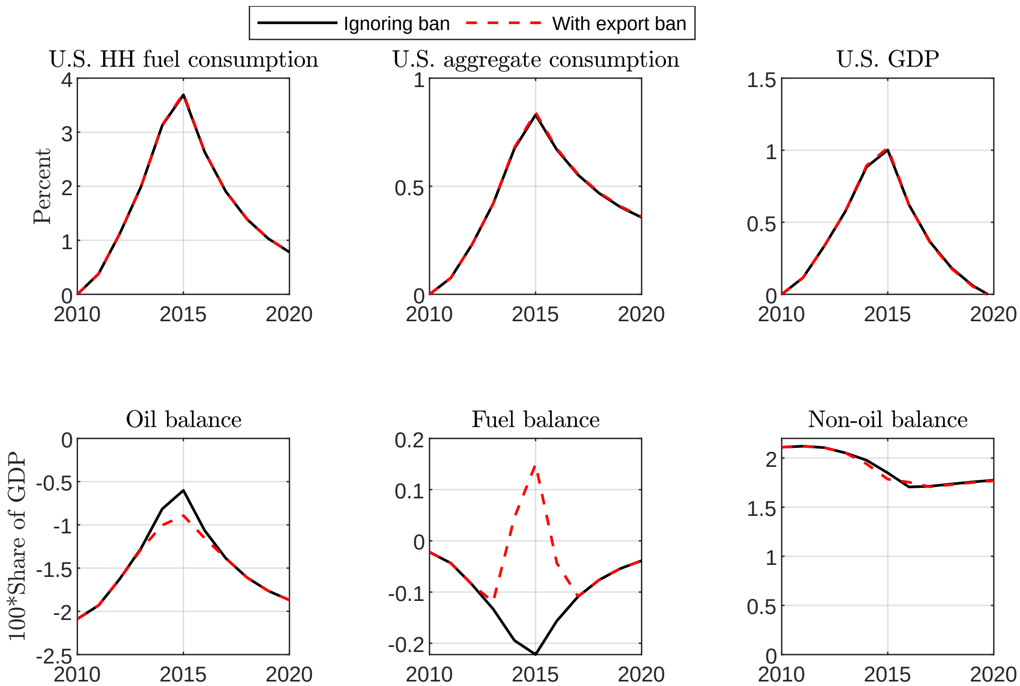
The increased light oil production lowers the price of light oil in the U.S. and the ROW. As the supply increase is solely in light oil, the price of light oil falls by more than the prices of medium and heavy crudes. The lower relative price of light oil leads to more processing of light crude by both U.S. and ROW refiners. As light oil is a substitute for medium oil, the use of medium crude by U.S. refiners declines. The increase in light oil use by U.S. refiners is not enough to absorb all the new light oil production, as a result, U.S. light oil imports decline. Indeed, the supply increase is large enough to make the export ban a binding constraint, particularly in 2014 and 2015.

During the periods when the band binds, the price of light 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. For example, the model predicts a decline of about 30 percent in U.S. light oil prices, compared to a 20 percent decline in ROW light oil prices by 2015. The discounts that emerge between light oil in the U.S. and the rest of world as well as against other grades of crude incentivize U.S. refiners to absorb the excess supply when the export ban binds. This cost advantage leads U.S. refiners to over-process light crude oil and take market share from refiners elsewhere. In addition, the use and imports of medium and heavy crudes by U.S. refiners decline due to 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 and the ROW as fuel is traded freely.[46] Fuel prices declining less than light oil prices incentivizes higher world fuel production. In particular, U.S. refiners produce significantly more refined petroleum product than the ROW when the ban binds.

[46] The finding that fuel prices fall by the same amount in the U.S. and ROW implies that the differential between U.S. and foreign oil prices does not pass through to U.S. fuel prices, similar to Borenstein and Kellogg (2014) [14].

Figure 5.2: A light oil technology shock (U.S. response)



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 that the fall in net oil imports and increase in U.S. light refiner inputs in the model are very close to the changes in the data. Overall, the model does a good job in explaining some of the key changes seen in the data despite the fact that we only relied on a single shock to generate these changes.

Figure 5.2 plots the responses of a select number of U.S. macroeconomic aggregates and trade balances. We find that the shale boom had significant effects on the macroeconomy. Cheaper fuel prices increase household fuel consumption by about 3.6 percent and aggregate consumption by about 0.7 percent. Although not presented in the figure, lower fuel prices also boost firm fuel use leading to higher non-oil output. Driven by a higher marginal product of capital, U.S. aggregate investment increases as well. As a result, U.S. real GDP increases. We find that the level of U.S. real GDP is 1 percent higher in 2015 than in 2010, accounting for about one tenth of actual economic growth over the same period.[47] Although the share of oil sector in the aggregate economy is small (1.2 percent of U.S. GDP in 2010), our results suggest positive spillovers from the sector to the rest of the economy.

The increase in oil production and the resulting decline in oil imports lead to a substantial improvement in the oil trade 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 about 0.5 percentage points, as a share of GDP. The non-oil balance response is largely driven by our assumption that there is an internationally traded bond. 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. With higher fuel production from the U.S. crowding out ROW fuel production, the U.S. becomes a net exporter of fuel by 2014.

5.1 Counterfactual: No ban on U.S. crude oil exports

We use our model to investigate the potential implications of the U.S. crude oil export ban. In a counterfactual exercise, we consider the U.S. shale boom in an alternative model that ignores the ban, i.e. a free trade model. The solid lines in Figure 5.1 and Figure 5.2 present results under free trade.

We find that had there been no ban during the shale oil boom from 2010 to 2015, domestic light oil prices would have been higher and the U.S. would have become a net exporter of light crude oil, consistent with the recent data.[48] In addition, the relative price of light to both medium and heavy crudes would have been more than 5 percentage points lower than the case with the ban. However, the improvements in price differentials under free trade would have had only minor implications for crude production levels due to low oil supply elasticity.

As ROW refiners are specialized in processing light crude relative to the U.S., the ROW would have processed the increased light oil supply and gained market share. The U.S., thereby, would have become a net importer of fuel. The increase in world fuel supply and the decline in fuel prices would have been similar to the baseline though, as there was no ban on refined products. With the decline in fuel prices essentially unchanged relative to the baseline model that takes the ban into account, the responses of most macro aggregates,

[47] 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 global implications of the U.S. shale oil boom. For example, using a general equilibrium model, under a hypothetical scenario based on EIA 2014 projections for U.S. shale oil, Manescu and Nuno (2015) [35] present a 0.2 percent increase in the GDP of oil importers from 2010 to 2018.

[48] For example, the U.S. exported about 1.2 million barrels per day of crude oil on average in 2017.

such as aggregate consumption or real GDP, would have been similar to the baseline model with the ban. These findings imply that the distortionary effects of the ban are primarily concentrated in oil prices, the refining sectors and oil trade flows.

6 Additional Results

6.1 The role of heterogenous oil

In order to highlight the importance of examining detailed oil data and introducing heterogeneity in crude oil types and refining technology in examining the quantitative implications of the shale oil boom, we consider a simplified version of the model with only one type of oil. This requires modifications to the oil and refining sectors in the baseline model with the household and non-oil sectors staying the same. We use aggregate data and pool different types of crude oil into one oil, and re-calibrate the full model. The shale oil boom is again modeled as an exogenous technology shock that lowers the cost of producing crude oil in the U.S. But this time we feed a sequence of shocks into the model that replicates the changes in U.S. aggregate crude oil production from 2010 to 2015.[49]

We find that modeling heterogeneous oil types is necessary to discuss the implications of the shale boom for trade in different types of oil, relative oil prices, and refinery specialization. It is also crucial for discussing the distortionary effects of the crude export ban properly. The model's ability to explain some key changes in the data, such as aggregate oil imports or total oil inputs, would be worse than the baseline model. When different oil types are aggregated, we find that macroeconomic effects of the oil boom would also be smaller.[50]

6.2 Higher supply elasticity for U.S. light oil

In our baseline calibration, we restricted the supply elasticity of different types of oil to be equal to each other across the two countries. In reality, though, the supply of shale oil appears to be more responsive to price changes than other types of oil production. Shale producers are smaller and more nimble than many conventional oil producers, and shale wells can come online significantly faster than many other types of oil wells. In order to investigate the implications of higher supply elasticity for U.S. light oil, we consider an alternative calibration where we set the price-elasticity of supply for U.S. light oil production to 0.36, three times its baseline value.

[49] In the data, total oil production increased 75 percent from 2010 to 2015 (Table 2.4).
[50] Appendix D.1 presents a subset of results.

Overall, the higher light oil supply elasticity amplifies the responses.[51] A higher elasticity of supply means lower production costs for light oil producers in the U.S., leading to higher output than the baseline. This in turn brings a sharper decline in light oil imports, lower light oil prices, increased use of light oil inputs by U.S. refineries and more U.S. fuel production. The increase in light oil production improves the oil balance, and the higher fuel production leads to an improved fuel balance. Fuel prices decline more than the baseline model resulting in higher U.S. aggregate consumption and slightly higher U.S. real GDP.

6.3 Alternative U.S. refinery calibration

We also investigate the importance of U.S. refineries being geared towards processing heavy crude relative to the rest of the world for 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 accounting for the distortions the export ban created in the oil and refining sectors.

6.4 Longer-term increase in U.S. 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 technology 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 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 that the boom would have continued to boost U.S. real GDP at a similar rate and the export ban would have remained a binding constraint through 2020. The distortionary effects of the ban on oil prices, refining sectors, and trade balances would have been amplified.[52]

[51] For a subset of results, see Appendix D.2.

[52] See Appendix D.3 for a subset of results.

7 Conclusion

In this paper, we study the implications of the U.S. shale oil boom for the U.S. economy, trade balances, and the global oil market through the lens of a two country DSGE model. Our model incorporates heterogeneous oil and refining sectors, and a potentially binding export ban on U.S. crude oil. These novel features allow us to take into account the fact that shale oil is primarily light crude while the U.S. refining sector has a comparative advantage in processing heavier crude oils relative to the ROW and that there was a crude export ban during a large part of the boom.

We model the shale boom as a series of technology shocks that boosts U.S. light oil production as in the data from 2010 to 2015. We find that the shale boom boosted U.S. economic activity significantly with the level of U.S. real GDP increasing by 1 percent from 2010 to 2015. Despite relying on a single technology shock, 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. oil trade balance as in the data.

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 ban primarily affected oil prices, the refining sector and trade balances.

We believe a number of avenues exist for future research. One potentially interesting extension would be to estimate the DSGE model to identify the impacts of various shocks over time.

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:

Rest-of-world real GDP: Quarterly series based on 39 countries. Individual data is aggregated with U.S. trade weights. Source: Database of Global Economic Indicators, Federal Reserve Bank of Dallas.

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.

U.S. and world population: Annual series, total population. Data source: United Nations.

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

Description	**Symbol**	**Value**
	U.S.	
GDP	y_1^g	1
Government spending	G_1	0.193 y_1^g
Fuel prices	p_1^f	1
Total time	$\bar{L}_1$	1
Time allocated to leisure	L_1	2/3
Household fuel use	c_1^f	0.022
Firm fuel use	m_1^f	0.022
Fuel production	y_1^f	$0.995\left(c_1^f + m_1^f\right)$
Total oil production	$y_1^o = y_1^{ol} + y_1^{om} + y_1^{oh}$	0.35 y_1^f
Light oil production	y_1^{ol}	0.390 y_1^o
Medium oil production	y_1^{om}	0.504 y_1^o
Heavy oil production	y_1^{oh}	0.106 y_1^o
Total oil input to refiners	$o_1^f = o_1^{fl} + o_1^{fm} + o_1^{fh}$	2.675 y_1^o
Light oil used by refiners	o_1^{fl}	0.286 o_1^f
Medium oil used by refiners	o_1^{fm}	0.415 o_1^f
Heavy oil used by refiners	o_1^{fh}	0.299 o_1^f
Relative price of light oil to medium	p^{ol}/p^{om}	1.06
Relative price of light oil to heavy	p^{ol}/p^{oh}	1.18
Cost-share of oil in refining	$\sum_k^{k=l,m,h}\left(p^{ok}o_1^{fk}\right)/\left(p_1^f y_1^f\right)$	0.774
	ROW	
GDP	y_2^g	83% of world GDP
Government spending	G_2	0.193 y_2^g
Total time	$\bar{L}_2$	95.5% of world population
Time allocated to leisure	L_2	2/3 $\bar{L}_2$
Total oil production	$y_2^o = y_2^{ol} + y_2^{om} + y_2^{oh}$	92.7% of world total
Light oil production	y_2^{ol}	0.300 y_2^o
Medium oil production	y_2^{om}	0.559 y_2^o
Heavy oil production	y_2^{oh}	0.141 y_2^o
Total fuel production	y_2^f	1.017 o_2^f
Household fuel use	c_2^f	1/2 of firm use

Table B.1: Baseline Calibration: Targets

Shared parameters

Description	Symbol	Parameter value
Discount factor	β	0.96
Curvature parameter in utility function	γ	-1
Depreciation rate of capital	δ	0.10
Capital adjustment cost	$\frac{1}{\delta\phi}$	0.032
Elasticity of substitution (fuel, non-oil good)	$1/(1+\rho)$	0.20
Elasticity of substitution in refining (light, medium crude)	$1/(1+\eta^{oil})$	3.5
Elasticity of substitution in refining (heavy, composite)	$1/(1+\rho^{oil})$	1.95
Elasticity of substitution in refining (value-added, oil)	$1/(1+\rho^{f})$	0.20
Elasticity of oil supply, for $k=l,m,h$	η^k	0.12
U.S.		
Weight on value-added in refining production	w_1^f	0.993
Labor's share in refining value-added	χ_1^f	0.164
Weight on o_1^{fl} in refining production	ω_1^o	0.488
Weight on o_1^{fh} in refining production	w_1^o	0.288
Labor's share in non-oil production	χ_1^a	0.60
Weight on fuel in non-oil production	$(1-w_1^a)$	$5.141e-09$
Weight on fuel in utility function	$(1-w_1)$	$1.603e-07$
Weight on leisure in utility function	μ_1	0.308
ROW		
Weight on value-added in refining production	w_2^f	0.985
Labor's share in refining value-added	χ_2^f	0.297
Weight on o_2^{fl} in refining production	ω_2^o	0.469
Weight on o_2^{fh} in refining production	w_2^o	0.169
Labor's share in non-oil production	χ_2^a	0.55
Weight on fuel in non-oil production	$(1-w_2^a)$	$7.4558e-09$
Weight on fuel in utility function	$(1-w_2)$	$8.0657e-09$
Weight on leisure in utility function	μ_2	0.319

Table B.2: Baseline Calibration: Parameter values

C Modeling the export ban

We model the U.S. oil export ban 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 $p^{ok}_{11,t}$ 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

$$E_0 \sum_{t=0}^{\infty} \beta^t \lambda_{1,t} \left\{ p_{1,t}^{ok} o_{1,t}^{fk} - p_{11,t}^{ok} y_{1,t}^{ok} - p_2^{ok} o_{1,t}^{mk} \right\}$$

subject to

$$o_{1,t}^{fk} = y_{1,t}^{ok} + o_{1,t}^{mk}$$

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

where $o_{1,t}^{mk}$ is the import of type k crude oil, $o_{1,t}^{fk}$ is type k crude oil demand by the refineries.[53]

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 ψ_t^k 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

$$p_{1,t}^{ok} = p_{11,t}^{ok}$$

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

$$p_{2,t}^{ok} = p_{1,t}^{ok} + \frac{\psi_t^k}{\lambda_{1,t}},$$

and

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

In the case where the ban does not bind, ψ_t^k equals zero and the price of type k oil in the U.S., $p_{1,t}^{ok}$, will be equal to the cost of importing the marginal barrel of type k oil from

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

country 2. The market clearing condition for type k oil will be given by

$$y_{1,t}^{ok} + y_{2,t}^{ok} = o_{1,t}^{fk} + o_{2,t}^{fk}.$$

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 $o_{1,t}^{fk} = y_{1,t}^{ok}$ and $o_{2,t}^{fk} = y_{2,t}^{ok}$.

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

$$E_0 \sum_{t=0}^{\infty} \beta^t \lambda_{2,t} \left\{ p_{2,t}^{ok} o_{2,t}^{fk} - p_{22,t}^{ok} \left(y_{2,t}^{ok} - o_{1,t}^{mk} \right) \right\}$$

subject to

$$o_{2,t}^{fk} = y_{2,t}^{ok} - o_{1,t}^{mk}.$$

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

$$p_{2,t}^{ok} = p_{22,t}^{ok}.$$

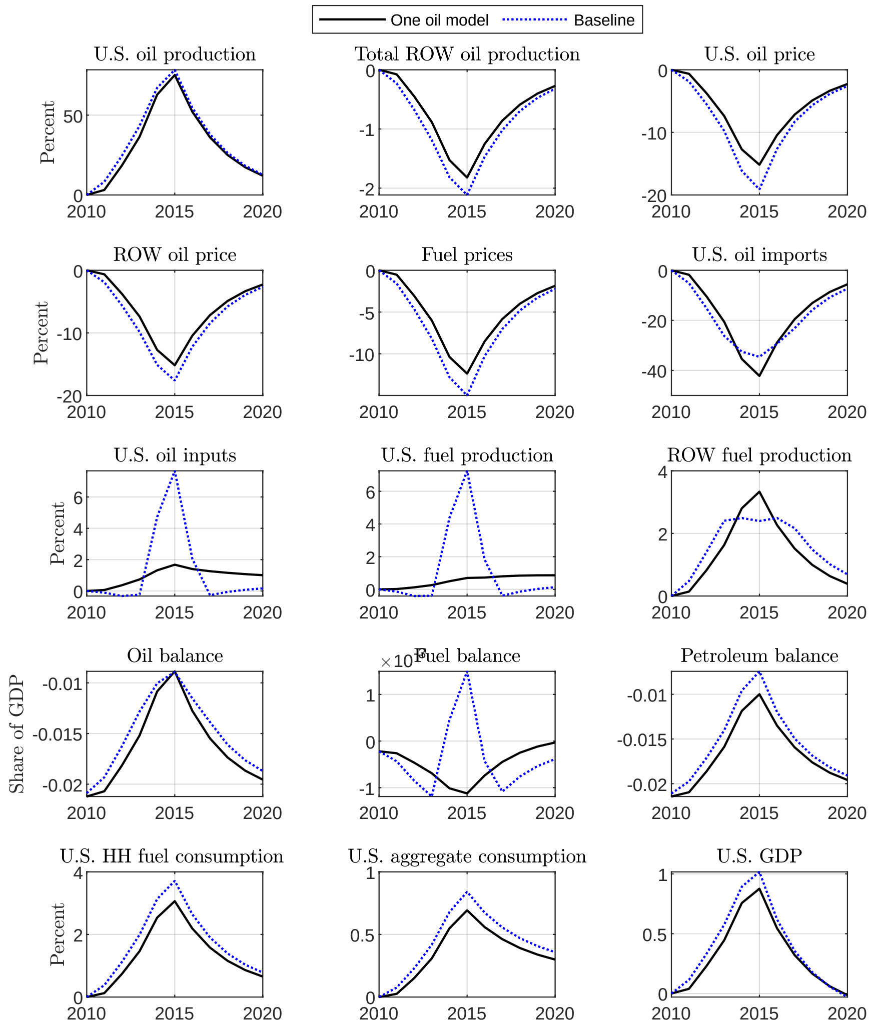
C.2 Solution method

It is useful to briefly map our model conditions into the notation used in Guerrieri and Iacoviello (2015) [27]. In our model, country 1's crude oil imports are subject to an occasionally binding constraint, $o_{1,t}^{mk} \geq 0$ for $k = l, m, h$. The complementary slackness condition implies that $\psi_t^k = 0$ when the constraint is slack. When the constraint binds, $o_{1,t}^{mk} = 0$. The conditions in the reference regime, $M1$, encompass $\psi_t^k = 0$, and the function g captures $o_{1,t}^{mk} \geq 0$. The conditions in alternative regime, $M2$, encompass the case when $o_{1,t}^{mk} = 0$ and the function h captures $\psi_t^k > 0$.

D Additional Results

D.1 The role of heterogenous oil

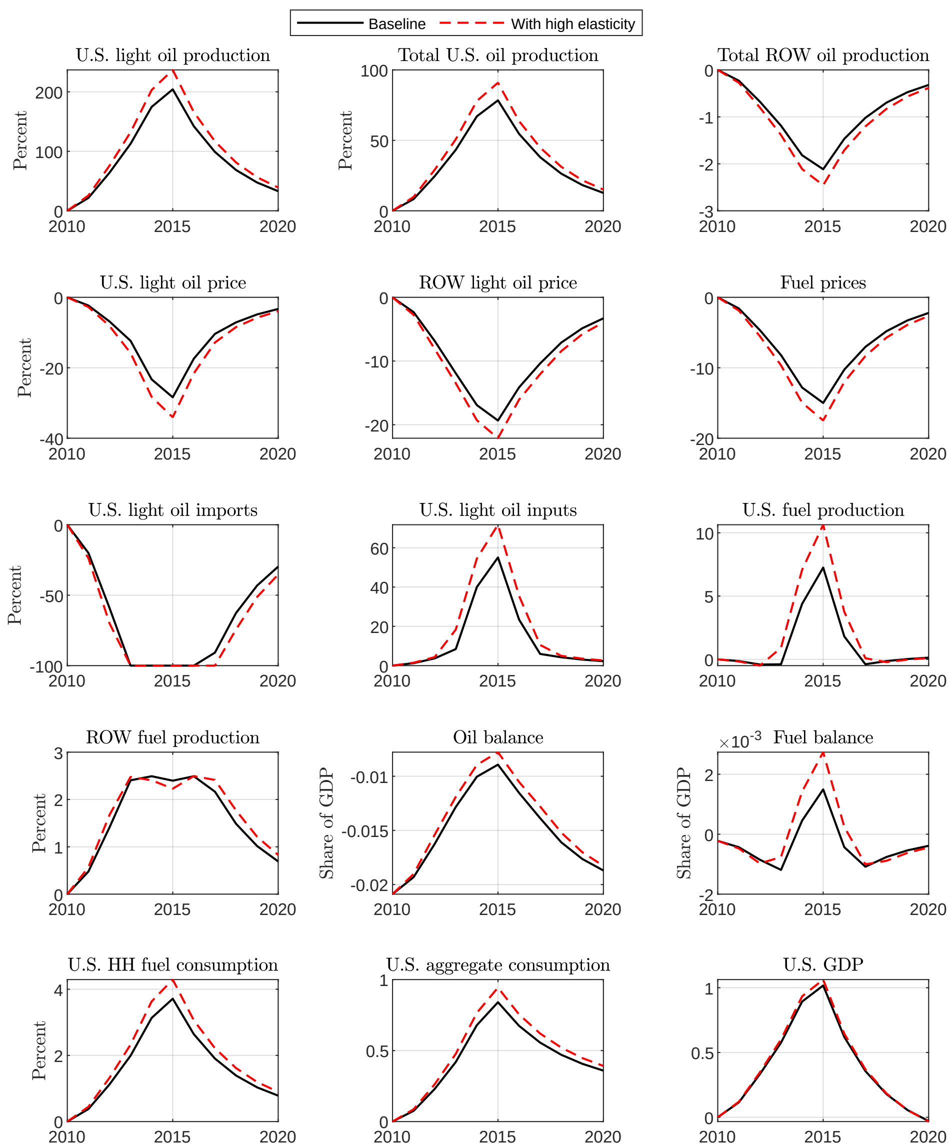
Figure D.1: Impulse responses for one oil model vs. baseline model



Note: Units are percent deviations from the steady state.

D.2 Higher supply elasticity for U.S. light oil

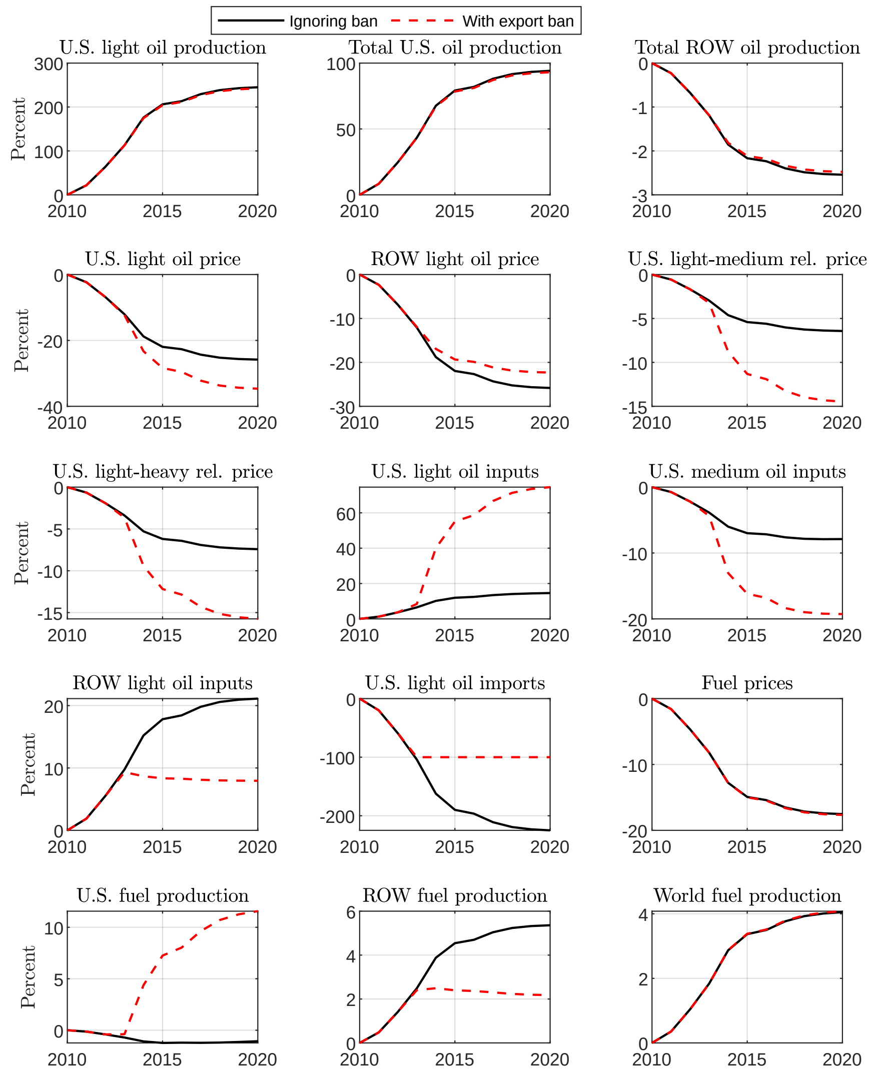
Figure D.2: Impulse responses with higher U.S. light oil supply elasticity (0.36 vs. 0.12)



Note: Units are percent deviations from the steady state.

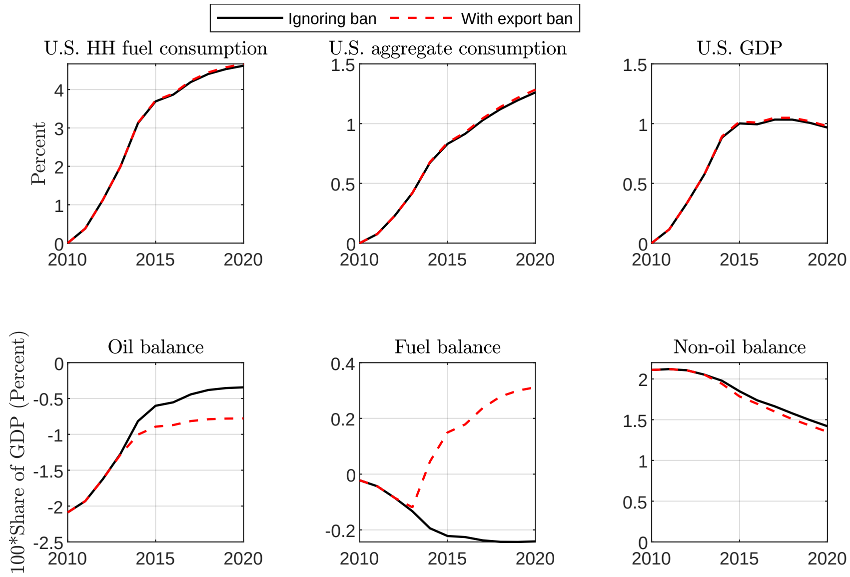
D.3 Longer-term increase in U.S. light oil supply

Figure D.3: Impulse responses when production follows the EIA forecasts through 2020



Note: Units are percent deviations from the steady state.

Figure D.4: Impulse responses when production follows the EIA forecasts through 2020



Note: Units are percent deviations from the steady state.

D.4 Was the ban binding in reality?

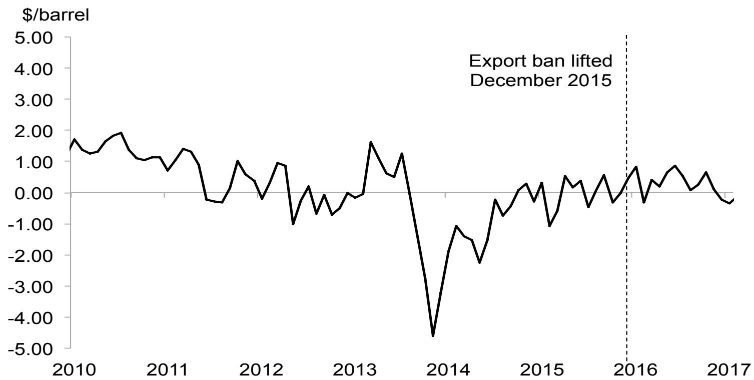
According to our model, the export ban on crude oil was a binding constraint primarily from 2014 to 2015. We review some evidence to see whether the model prediction is consistent with the data. First, we consider several predictions from the model that can be checked in the data by focusing primarily 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 when 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.[54] Using West Texas Intermediate crude prices may be problematic as the interior of the U.S. faced some logistical constraints that affected

[54]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 focus on light crude oil.

Figure D.5: Price spread between Louisiana Light Sweet and Brent crude oil



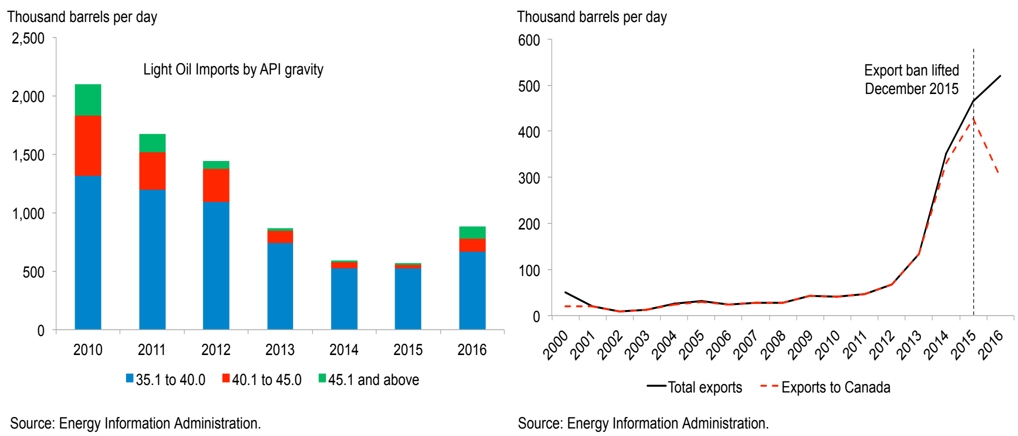
Source: Bloomberg.
Note: Price spread is real, May 1983 dollars.

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 D.5 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 D.6. 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 again that our modeling decision to define "light" oil as API gravity 35 and above is driven by data limitations for the production data. 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 D.6. 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.

Figure D.6: U.S. light oil imports by API gravity and U.S. total oil exports



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.

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