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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 heterogeneous oil and refined products, we show that the shale boom boosted U.S. real GDP by a little more than 1 percent and improved the oil trade balance as a share of GDP by about 1 percentage point 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, a policy in effect until the end of 2015, was a binding constraint, and would likely have remained a binding constraint thereafter had the policy not been removed.

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. Several recent papers have focused on the local or regional implications of the U.S. shale boom, suggesting positive economic effects (see, for example, Feyrer

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et al., 2017; Allcott and Keniston, 2018). 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. We do so using 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 has shown that shocks to economically small sectors, such as oil and gas, that feature complementarities with other inputs of production can have disproportionate aggregate effects (Baqaee and Farhi, 2019) and that trade in primary commodities is important with notably large gains from trade compared to gains from trade in standard models (Farrokhi, 2020; Fally and Sayre, 2018).

The relatively few general equilibrium models that do feature oil generally assume that it is a homogeneous 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 of one type: 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. The importance of this mismatch was potentially magnified by the U.S. export ban on crude oil, a policy in effect until the end of 2015.

In assessing the implications of the U.S. light oil boom quantitatively, we make two contributions to the literature. First, we introduce two previously unexamined 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 stems from the difference between refineries in the U.S. and the rest of the world (ROW). Our model also features an occasionally binding export ban on U.S. crude oil.

Our second contribution is to 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 two ways. First, we use simulated method of moments (SMM) to estimate a number of model parameters to match moments from oil-related and macro data. Of particular note, we estimate three key parameters related to the refining sector: the elasticities of substitution across different oil types and the elasticity of substitution between oil and other factors of production. Second, we carefully calibrate other model parameters targeting a set of first 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. We also show these heterogeneities are key to properly understand the impacts of the crude export ban.

An essential initial step for our analysis is to document how some important oil market variables have changed during the U.S. shale oil boom. 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. These facts help motivate the features of our model.

Our two-country (U.S. and ROW) general equilibrium model with heterogeneities and an export ban also has the following features. In addition to oil and refined products (fuel), both countries produce a non-oil good.[1] The non-oil good is used for consumption and investment, which is costly to adjust, and as an input in the production of oil. 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. An internationally traded bond allows for the possibility of trade imbalances. To simplify, we abstract from distinguishing between traded and non-traded goods, a common feature in many commodity and resource papers that discuss the Dutch disease effect. The reasons are that, contrary to even other advanced (small) open economies that are net commodity exporters, where the commodity sector can be relatively large, the share of oil and gas in U.S. GDP is relatively small, having not exceeded 3 percent since the early 1980s. The U.S. also remains a net importer of crude oil.

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 are three. First, we find that the shale oil boom had important impacts on several U.S. macroeconomic variables, notably on real GDP and trade balances. According to our model, the boom boosted U.S. real GDP by a little over 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

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

recovery from the Great Recession. There is also major improvement in the U.S. oil trade balance, by about one percentage point (as a share of GDP), in line with the data.

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. This includes the sharp drop in U.S. imports of light crude oil, the increased use of light oil by U.S. refiners, and the drop in both the use and imports of medium crude oil by U.S. refiners. On the other hand, we find a counterfactual decline in U.S. refiner use and imports of heavy crude oil. However, we show that the model can explain the changes in the heavy crude data successfully if we add a second shock, a ROW heavy oil supply shock, into the model.

Third, we find that the U.S. crude export ban was a binding constraint, particularly in 2014 and 2015, and that it primarily distorted the upstream and downstream oil sectors and petroleum trade, with negligible impacts on macroeconomic aggregates. We find the ban artificially depressed U.S. light crude oil prices, inflated light crude oil prices outside the U.S., and distorted the relative price of light crude to other types of crude oil. Oil producers, with the exception of light crude producers outside the U.S., were negatively impacted by these price distortions. We find U.S. refiners benefited from those price distortions, as they provided a cost-advantage, leading them to over-process light crude oil and take market share from refiners elsewhere. However, the ban had little impact on the global fuel supply or fuel prices as there was no ban on trade in refined products. Impacts on households, both in the U.S. and ROW, were negligible. Finally, we show that taking into account the heterogeneity in crude quality, and properly modeling and calibrating the refinery sector are key to examine the effects of the ban.[2]

1.1. Related literature

Our paper analyzes 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. The model and calibration approach we use are similar to a number of other papers that focus on oil and international real business cycles. More generally, our work draws on and has connections with several literatures that focus on commodities and the macroeconomy.

First and foremost, our paper relates to a large literature that uses real business cycle models to analyze the effects of oil price fluctuations and other oil shocks on the economy.[3] One distinguishing aspect of our work from much of this prior literature is that we analyze the impact of an oil boom brought about by a technology shock in the domestic oil sector. The DSGE literature has tended to focus on how the domestic economy is affected by exogenous oil price shocks or oil supply shocks that originate outside the economy. The model developed in this paper is closely related to Bodenstein et al. (2011) with some key differences regarding the distinction between different types of oil, oil production and the inclusion of a refining sector. Careful modeling of oil production and refining are theoretical contributions of our paper, allowing a granular analysis of the oil market. Our paper also relates to Manescu and Nuno (2015) who analyze the international effects of the U.S. shale oil boom using the three-country model of Nakov and Nuno (2013). In addition to differences in modeling, such as different types of oil, a refinery sector and explicit components of the U.S. economy, our discussion focuses heavily on U.S. macroeconomic aggregates and disaggregated oil market variables.

Our paper complements two recent studies, Farrokhi (2020) and Fally and Sayre (2018), 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. Farrokhi (2020) develops a static, multi-country, general equilibrium framework that incorporates a detailed model of global sourcing of oil inputs by refineries, and downstream demand for refined petroleum products. He then conducts several policy experiments, including the U.S. oil boom from 2010 to 2013 and the implications of lifting the U.S. crude oil export ban.[4] Some key differences between our work and Farrokhi (2020) are that we study the dynamic effects of the shale oil boom on macroeconomic aggregates, upstream and downstream oil sectors, and trade, through the lens of a two-country DSGE model. Our model also allows for capital accumulation and trade deficits.

More broadly, our work relates to an extensive literature on resource booms. Earlier studies in this literature have focused on small countries with a large dependence on resource production, and many suggest an adverse impact on economic growth (see van der Ploeg, 2011 for an overview). More recent papers, however, find that a resource boom can have a positive effect on the overall economy if it is driven by increasing resource activity (see, for example, Bjornland and Thorsrud, 2016; Bjornland et al., 2019; Allcott and Keniston, 2018).[5]

[2] In Section 6 we consider a model where oil is a homogeneous good; a model where light, medium and heavy crude oil are highly substitutable; and a counterfactual where U.S. refiners process more light and less heavy crude oil. We find that the export ban is not binding in the first two cases and only slightly binding in the latter case.

[3] Examples of this type of work include Kim and Loungani (1992), Backus and Crucini (2000), Leduc and Sill (2004), Nakov and Nuno (2013) and Olovsson (2019).

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

[5] Charnavoki and Dolado (2014) show that the source of a shock is important for finding evidence of a Dutch disease effect. They don't find a Dutch disease effect if commodity prices rise due to a positive aggregate demand shock, but a Dutch disease is manifested if the price increase is driven by a global commodity-specific shock.

The non-traded sector has been a key component of the analysis done in this line of research.[6] Our work, while linked with this literature given our focus on U.S. oil boom, does not consider the non-traded sector and is, therefore, silent on any issues related to it. There are two other important differences between our paper and this literature. The first is the relative importance of the commodity sector for the domestic economy. Even in the developed small open economies studied in the resource boom literature, the GDP share of the commodity under study can be as high as 12 percent, with the share in exports up to 30 percent. The share of the oil and gas sector in U.S. GDP, on the other hand, is relatively small, having a recent peak of 2.2 percent in 2008, while the share of crude oil in U.S. exports was 3.7 percent in 2019. A second difference is the net importer status of the U.S.: the U.S. was a major net importer of crude oil at the beginning of the resource boom and remains a net importer now.[7]

Several recent papers analyzing the regional effects of shale oil and gas booms in the U.S., provide useful insights on the impact of natural resources on economic performance. Using detailed micro data, these studies show that oil and gas booms increased overall income and wages and non-mining jobs in the producing regions (see for example, Weber, 2014; Feyrer et al., 2017).[8]

In addition, a line of empirical research has discussed the impact of the U.S. oil boom on crude oil price differentials between U.S. and international crude oil prices (see for example, Bornstein et al., 2018; Agerton and Upton, 2019; Plante and Strickler, 2020). Kilian (2016) also examines how the oil boom has affected the evolution of crude oil and gasoline prices.

Our work complements these papers by analyzing the implications of the shale oil boom, a resource boom stemming from a resource (technology) shock, for the global oil market and the U.S. using a DSGE model. 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. Our main results are discussed in Section 5 while Section 6 discusses sensitivity analysis with respect to a number of model features. We conclude in Section 7. An online appendix presents additional results (including extensive figures related to the sensitivity analysis), a variety of analytical results derived from simpler stylized models, and details on our data, calibration, and estimation procedures.

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.[9]

2.1. Introduction to crude oil quality

Although crude oil is generally viewed as a homogeneous 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.

Fig. 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

[6] In related work, Bodenstein et al. (2018) examine the effects of commodity shocks in small, advanced economies with a resource sector, in a model with and without a non-traded sector.

[7] Analytical results in Appendix C show that both the relative size of the oil and gas sector and the net importer status of the country in question play an important role in how some of the variables respond to a domestic production boom.

[8] Baumeister and Kilian (2016) discuss the potential impact of the rise of the shale oil sector on the transmission of oil price shocks to the U.S. economy. There are also studies looking at the global implications of the U.S. oil boom. For example, Mohaddes and Raissi (2018) investigate the global macroeconomic consequences of declining oil prices due to the U.S. oil revolution.

[9] 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. However, we note that in a related paper Arezki et al. (2017) focus on the U.S. shale gas boom and find that the shale gas boom has led to an expansion in energy intensive manufacturing sector relative to less energy intensive sectors and an increase in U.S. manufacturing exports.

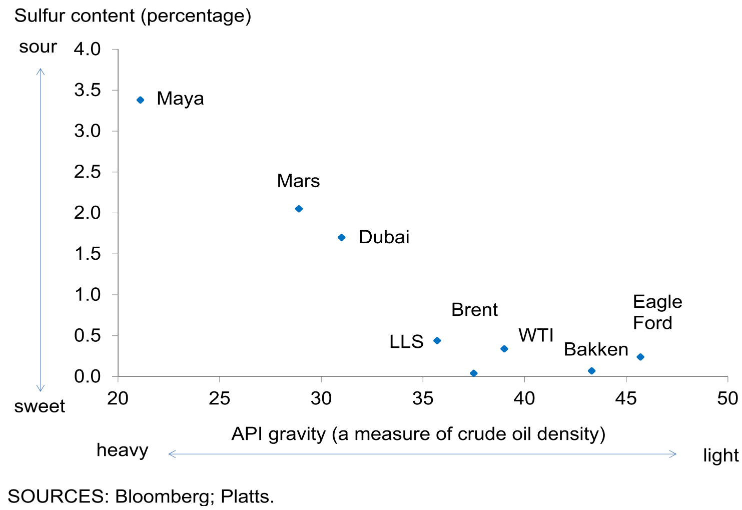

Fig. 2.1. Characteristics of various crude oils.

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). 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. Fig. 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.[10] 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.[11] 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 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.[12]

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. Fig. 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 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

[10] 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.

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

[12] 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.

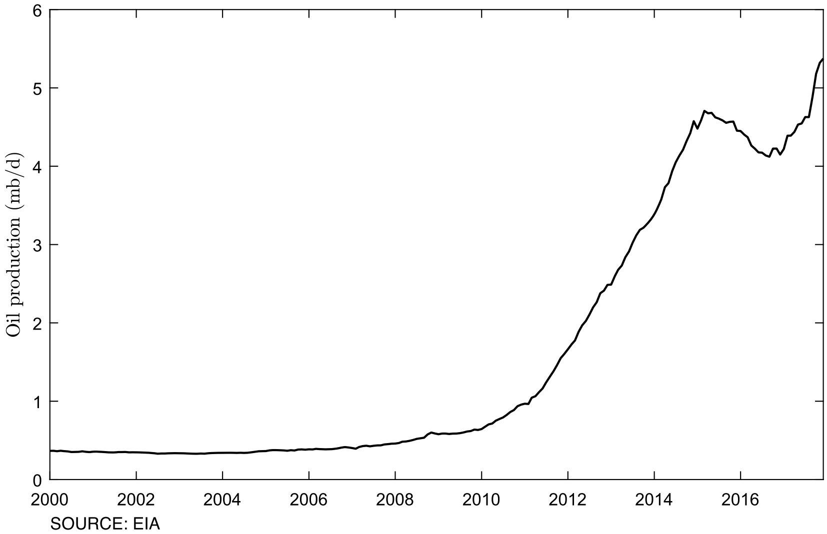

Fig. 2.2. U.S. shale oil production.

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

the rest of the world from the 2017 version of Eni's World Oil and Gas Review Eni (2017). 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.[13] 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.[14] Following Eni, we define heavy crude oil as oil with an API less than 26, medium from 26 up to 35, and light crude oil with an API of 35 and above.[15] 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.[16]

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.

[13] 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) only provides annual data from 2010 to 2013. Moreover, a significant portion of U.S. crude production is unclassified in *DrillingInfo* data.

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

[15] 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.

[16] 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.

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

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. 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.[17] 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.

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.[18] 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.

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.[19] 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

[17] 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.

[18] 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).

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

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

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.

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.[20] 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 refinery has an NCI of 1 while the largest and most complex refineries can have scores of over 15.[21] 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

[20] See Çakır Melek and Ojeda (2017) for more details.
[21] See Johnston (1996) for more details.

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

Finally, U.S. refiners have continued increasing their usage of heavy crude oil over these years. Based on the Eni data, world production of heavy crude was about 1.3 mb/d higher in 2015 than in 2010. U.S. refiners processed about 31 percent of the increase, with the crude being imported from other countries.

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) and similar to Bodenstein et al. (2011). The key differences are that we introduce heterogeneous 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 an occasionally 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 ω_i^c and $(1-\omega_i^c)$ as follows

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

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 terms connected with the variable $\Phi_{b,t}$, 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 when discussing variables and equations.

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 $K_{i,t+1}^j$, according to the following law of motion

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

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). Similar to Heathcote and Perri (2002), bond holdings are non-stationary in our linearized model. To ensure stationarity of the debt-level, we follow Bodenstein et al. (2011) 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.[22] We also follow the literature in assuming that the profits associated with the intermediation fee accrue to country 2 and appear in their budget constraint (Benigno, 2002, for example).[23]

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 et al. (2015). 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:

$$\Pi^{ok}_{i,t} = P^{ok}_{i,t} Y^{ok}_{i,t} - \Gamma^k_{i,t},$$

where

$$\Gamma^k_{i,t} = \frac{\left(\frac{Y^{ok}_{i,t}}{Z^{ok}_{i,t}}\right)^{1+\frac{1}{\eta^k_i}}}{1+\frac{1}{\eta^k_i}}$$

denotes the production costs, representing the quantity of the non-oil good needed to produce a given amount of oil. These costs can be considered as (non-energy) inputs needed to produce oil, such as rigs. $Y^{ok}_{i,t}$ is production of oil type k and $Z^{ok}_{i,t}$ 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 $P^{ok}_{i,t}$. Profit maximization implies

$$P^{ok}_{i,t} = (Z^{ok}_{i,t})^{-1}\left(\frac{Y^{ok}_{i,t}}{Z^{ok}_{i,t}}\right)^{\frac{1}{\eta^k_i}},$$

[22] We are unaware of any formal proof in the literature that shows the bond holdings are non-stationary, but we have confirmed it for our model by simulating the model with and without the intermediation fee. Bond holdings are not stationary in the latter case.

[23] This implies no resources are used in connection with the intermediation fee. We also considered a version of the model where the costs required the use of the non-oil good. We found this had no impact on our results, as these costs were generally very small in size.

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 combining crude oil and non-oil 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.

Crude oil is an essential input for producing fuel with the highest cost share. This cost share varies over time and is highly correlated with the price of oil, motivating the use of a CES structure for the production function.[24] Another important feature of the production process in the refining sector is that substitution between oil and other inputs is very limited. Hence, we consider a constant returns to scale CES of an oil composite and a non-oil composite to allow for the possibility that the elasticity between oil and other inputs is less than one.

For the choice of the capital and labor aggregate, we favor a structure where capital and labor form a Cobb-Douglas composite. One reason is that the labor share in the refining sector does not seem to vary much in response to significant oil price changes.[25] Moreover, in most macroeconomic quantitative applications, a Cobb-Douglas function is used when inputs are capital and labor, which also facilitates the calibration of the parameters using the available refining sector data.

Consequently, we assume the following production function for fuel, which 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,

$$Y_{i,t}^f = \left[\omega_i^f \left(Z_i^f (N_{i,t}^f)^{\chi_i^f} (K_{i,t}^f)^{1-\chi_i^f}\right)^{-\rho_i^f} + (1-\omega_i^f) G(O_{i,t}^{fl}, O_{i,t}^{fm}, O_{i,t}^{fh})^{-\rho_i^f}\right]^{\frac{1}{-\rho_i^f}} \tag{3.5}$$

where Z_i^f represents technology in the sector, and $N_{i,t}^f, K_{i,t}^f$ denote labor and capital inputs. The parameter ω_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 $0 < \omega_i^f, \chi_i^f < 1$. 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.

Motivated by the discussion on relative prices and processing of different crude types in section 2, suggesting varying substitutability across different crude types, we assume that oil composite is a nested-CES of the three types of oil, $O_{i,t}^{fl}, O_{i,t}^{fm}, O_{i,t}^{fh}$. Using a CES aggregator allows us to introduce the idea that the oils are imperfect substitutes for each other in a relatively parsimonious way, and 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:

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

where light and medium crudes form their own composite. The ω_i^{oh} and ω_i^{ol} 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 $\frac{1}{1+\eta_i^{oil}}$. 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, motivated by the relative price of light crude to medium being much less volatile over time than the relative price of light to heavy.[26] As we show later, allowing the elasticity to be different between light and medium vs. heavy allows us to model this feature of the data.[27]

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

$$\Pi_{i,t}^f = P_{i,t}^f Y_{i,t}^f - W_{i,t}^f N_{i,t}^f - R_{i,t}^f K_{i,t}^f - P_{i,t}^{ol} O_{i,t}^{fl} - P_{i,t}^{om} O_{i,t}^{fm} - P_{i,t}^{oh} O_{i,t}^{fh},$$

24 The correlation between Brent crude price and cost share of crude in producing gasoline is around 92% over 2000-2010.

25 For example, from 2000 to 2010, oil prices almost tripled and the cost share of oil in producing gasoline in the U.S. increased from around 0.4 to 0.7, while the share of labor in the U.S. refining sector stayed relatively stable.

26 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.

27 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.

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

$$Y^a_{i,t} = \left[\omega^a_i \left(Z^a_{i,t}(N^a_{i,t})^{\chi^a_i}(K^a_{i,t})^{1-\chi^a_i}\right)^{-\rho} + (1-\omega^a_i)(M^f_{i,t})^{-\rho}\right]^{\frac{1}{-\rho}}, \tag{3.7}$$

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, ω^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, $\forall k = h, l, m$, we have

$$Y^{ok}_{1,t} + Y^{ok}_{2,t} = O^{fk}_{1,t} + O^{fk}_{2,t}.$$

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

$$Y^f_{1,t} + Y^f_{2,t} = C^f_{1,t} + C^f_{2,t} + M^f_{1,t} + M^f_{2,t},$$

$$\sum_i^{i=1,2} Y^a_{i,t} = \sum_i^{i=1,2} C^a_{i,t} + \sum_i^{i=1,2}\sum_j^{j=a,f} I^j_{i,t} + \sum_i^{i=1,2}\sum_k^{k=h,l,m} \Gamma^k_{i,t} + \sum_i^{i=1,2} G_i.$$

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, $P^{ok}_{1,t} = P^{ok}_{2,t}$, $\forall k = h, l, m$, and $P^f_{1,t} = P^f_{2,t}$.[28]

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

$$\frac{p^b_t}{\Phi_{b,t}}\Delta B_{1,t+1} = Y^a_{1,t} - P^f_{1,t}M^f_{1,t} + P^f_{1,t}Y^f_{1,t} - \sum_k^{k=h,l,m} P^{ok}_{i,t}O^{fk}_{1,t} + \sum_k^{k=h,l,m}\left(P^{ok}_{i,t}Y^{ok}_{1,t} - \Gamma^k_{1,t}\right)$$
$$- C^a_{1,t} - P^f_{1,t}C^f_{1,t} - \sum_j^{j=a,f} I^j_{1,t} - G_1 + \left(1 - \frac{P^b_t}{\Phi_{b,t}}\right)B_{1,t}.$$

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

3.4.1. Export ban on U.S. crude oil

A crude oil export ban was in place until the end of 2015. 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

$$O_{1,t}^{fk} - Y_{1,t}^{ok} \geq 0, \tag{3.8}$$

for $k = h, m, l$.[29]

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.[30] 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) 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.[31] 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 E 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 F provides the full description of the starting values, moments and parameter settings in the calibration. A discussion of the moment-matching exercise is deferred until later.

Several parameters related to preferences, capital accumulation and production functions are calibrated to be equal across countries. The discount factor 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). 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.[32] This produces a low price elasticity of demand for refined products, in line with previous empirical estimates.[33] Following Bodenstein et al. (2011), 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).[34] This ensures that oil supply is fairly inelastic in response to price changes, a key feature of the data.

Without loss of generality, we normalize U.S. GDP to 1, which allows us to calibrate several variables in terms of GDP ratios. The total time available in the U.S., $\bar{L}_1$ is normalized to 1. The share of world GDP due to the U.S. was 17% in 2010 and the U.S. population share was 4.5%, based on UN data. We use these facts to calibrate ROW GDP and the total time available in ROW, $\bar{L}_2$. For both the U.S. and ROW, we assume an average time allocation of $\frac{2}{3}$ 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).

29 Further mathematical details about how we set up the export ban can be found in the Appendix G.

30 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 Bornstein et al. (2018).

31 We use the Dynare software package developed by Adjemian et al. (2011) to solve our model.

32 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.

33 See for example Coglianese et al. (2017) and Levin et al. (2017).

34 Bornstein et al. (2018) 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) report an elasticity close to 0.

Table 4.1
Calibration.

	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
$\frac{Y_2^{GDP}}{Y_1^{GDP}+Y_2^{GDP}} = .83$	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	$\eta^k = 0.12$	Elas. of oil supply for $k = l, m, h$
$\rho = 4$	Elas. of sub. for fuel (0.2)		
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

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.[35]

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.[36] The EIA provides data on world consumption of petroleum and other liquids by region and end-use sector. Finally, Exxon, 2016 Energy Outlook 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.[37] To determine the shares of each type of oil processed in the U.S. refineries, we use the estimates presented in subsection 2.4. These shares determine the starting values for $O_{k_1}^f$ for $k = l, m, h$. Data on refinery gains for the ROW that come from the EIA and IEA are used to pin down total ROW fuel production, Y_2^f.

We set total U.S. oil production to match the fact that U.S. production in 2010, in mb/d, was 35% of U.S. refinery output of fuel. The U.S. share in global oil production in 2010 was 0.073, which determines total ROW oil production. The steady state values of light, medium, 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.[38] 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 ω_1^f. For the labor share of value-added in the refining sector, χ_1^f and χ_2^f, we rely on data from the World Input

[35] 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.

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

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

[38] 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.

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 choose values for 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}. We estimate the value of these parameters using simulated method of moments (SMM), following the procedure documented in Ruge-Murcia (2007) and Ruge-Murcia (2012). Before discussing the estimation results, we introduce the data used to generate the target moments and provide an outline of our estimation approach. Appendix I contains additional details on the procedure.

To guide the estimation of the parameters for the shocks, we use data on U.S. and ROW real GDP as well as U.S. and ROW crude oil production. Data on U.S. real private fixed investment is used to inform the estimation of the capital adjustment cost parameter. For the refining parameters, we make use of data on total crude oil inputs to U.S. refiners (refiner runs) and prices of light, medium and heavy crude oil. The ROW GDP series is an index based on an average real GDP growth rate taken across a large number of countries. The series comes from the Database of Global Economic Indicators.[39] Data on U.S. GDP and investment comes from 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 is not available, even for the U.S. The U.S. total crude oil input series comes from the EIA. We use data on the prices of LLS, Dubai and Maya for light, medium and heavy crude oil prices, respectively.

We construct annual averages for the series and then take logs of the annual data. 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. The oil price series goes from 1984 to 2016. The sample of detrended data runs from 1986 to 2010. We remove data after 2010 to remove the influence of the shale boom, as we want to treat that as the "shock" in our DSGE model.

We constrain the autocorrelations and volatilities of the technology shocks for different oil types to be equal, although they can differ across countries. This is done because, as noted earlier, we do not have a long time series available for crude production by type. We also constrain the investment adjustment cost parameter and the refining elasticities to be equal across countries. This gives a total of 12 parameters that need to be estimated.

The first stage of our estimation procedure uses Generalized Method of Moments (GMM) to estimate the moments in the data, denoted as Ψ_d, and the diagonal of the long-run variance-covariance matrix of the moments, Σ_d. The long-run variance of the moments is estimated with a Newey-West estimator using the Bartlett Kernel. We choose 12 moments from the de-trended data to estimate: the first-order autocorrelations and the volatilities of U.S. GDP, ROW GDP, U.S. oil production and ROW oil production; the volatility of U.S. investment; the volatility of total crude oil inputs to U.S. refiners; the correlation between (real) light and medium oil prices; and the correlation between (real) light and heavy oil prices.

The second stage uses SMM to estimate the model parameters. The parameter values are chosen to minimize the loss function

$$J = (\Psi_d - \Psi_m)' \, \Sigma_d^{-1} \, (\Psi_d - \Psi_m)\,, \tag{4.1}$$

where Ψ_m are the moments from simulated model data. To derive the standard errors of the parameter estimates, we estimate the model 2000 times using different sequences of shocks, which allows us to construct the empirical distribution of the parameter estimates.

We report the mean and standard deviation of the estimated parameter values in Table 4.2. The σ_z and ρ_z parameters are the volatilities and persistence of the technology variables. We find that the technology processes are moderately persistent, while the oil technology processes are significantly more volatile than the non-oil ones. The mean value of ρ^{f} implies an elasticity of substitution between value-added and oil of 0.119, 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. The standard deviation of this elasticity, from its empirical distribution, is 0.026. The mean value of η^{oil} implies an elasticity of substitution between light

[39] The DGEI collects real GDP data for 40 of the largest advanced and emerging economies representing more than 90% of world output, calculates growth rates for each country and then averages across the individual growth rates weighting them by their PPP weights. See Grossman et al. (2014) for more details.

Table 4.2
Estimated parameter values.

	Mean	SD		Mean	SD
σ_{za1}	0.0063	0.0002	ρ_{zo1}	0.5800	0.0478
σ_{za2}	0.0062	0.0002	ρ_{zo2}	0.7669	0.0310
σ_{zo1}	0.0286	0.0011	κ	0.0337	0.0083
σ_{zo2}	0.0313	0.0011	ρ^f	7.3743	1.7817
ρ_{za1}	0.5451	0.0404	η^{oil}	−0.6887	0.0287
ρ_{za2}	0.4110	0.0492	ρ^{oil}	−0.3037	0.0760

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

Variable	Data		Model	
	AC(1)/Correlation	Volatility	AC(1)/Correlation	Volatility
U.S. oil production (total)	0.609	0.027	0.609	0.027
ROW oil production (total)	0.760	0.023	0.761	0.023
U.S. GDP	0.618	0.016	0.618	0.016
ROW GDP	0.520	0.011	0.520	0.011
U.S. investment		0.065		0.065
U.S. refiner inputs/runs (total)		0.022		0.022
Light and medium oil prices	0.980		0.980	
Light and heavy oil prices	0.930		0.930	
Medium and heavy oil prices	0.949		0.933	
Log of light oil price		0.145		0.102
Log of medium oil price		0.138		0.106
Log of heavy oil price		0.156		0.098

and medium crude oil of 3.21, while the elasticity between heavy and the composite of light-medium crude is 1.44. This suggests light and medium oil are more substitutable with each other than with heavy oil, in line with our intuition.

The properties of the model-based moments are compared to the data in Table 4.3. The model does a good job in matching the targeted moments. Its ability to match several untargeted moments varies. The model comes close to matching the observed correlation between medium and heavy crude prices, while the model can only account for 60 to 70 percent of the oil price volatilities.[40]

5. Results

5.1. 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 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 during the boom, our baseline model incorporates the ban.

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. A full set of results are available upon request. The impulse responses for those variables are shown in Fig. 5.1 and Fig. 5.2. U.S. 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.

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.[41]

The top left panel of Fig. 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.

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

[41] 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 H and in Çakır Melek and Ojeda (2017).

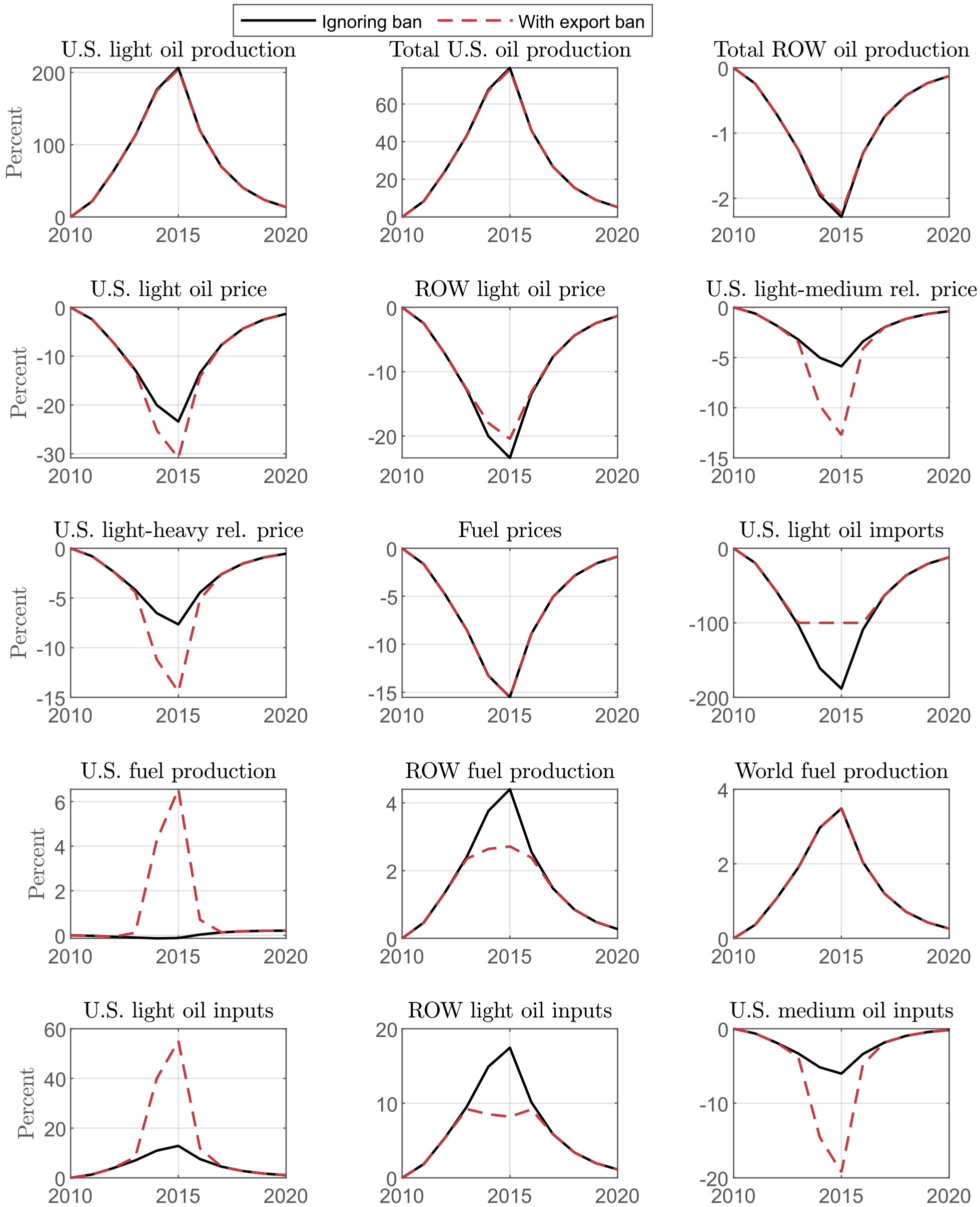

Fig. 5.1. A light oil technology shock (oil market response).

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. U.S. light oil imports decline, as the increase in light oil use by U.S. refiners is not enough to absorb all the new light oil production. The supply increase is eventually 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.

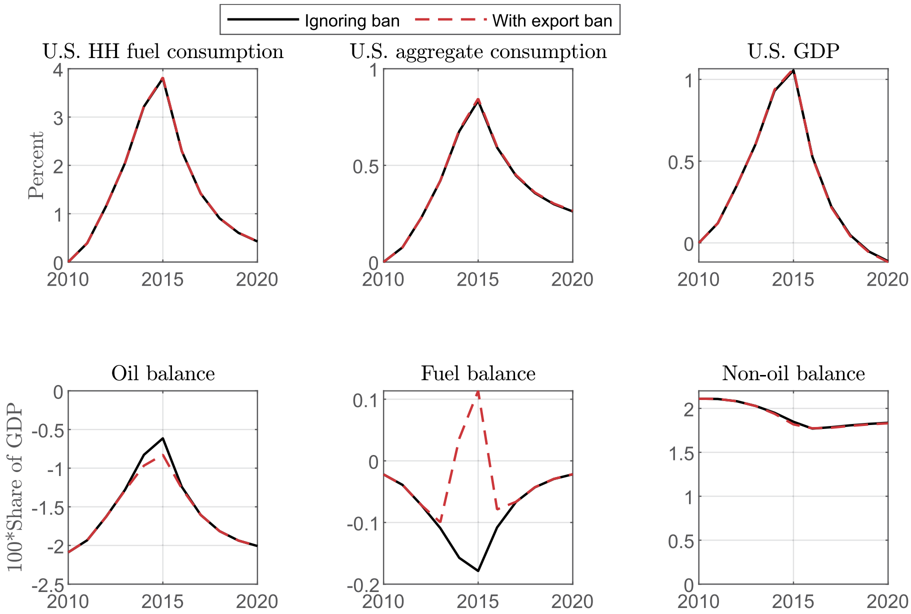

Fig. 5.2. A light oil technology shock (U.S. response).

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

Variable	Data	Baseline model	Baseline model w/heavy shock
U.S. light oil production	204	204	204
U.S. total oil production	75	78	78
U.S. light oil prices	−42	−31	−35
U.S. - ROW light oil price differential	−4	−10	−10
U.S. light oil imports (net)	−95	−100	−100
U.S. light refiner inputs	57	56	56
U.S. medium oil imports	−23	−33	−31
U.S. medium refiner inputs	−17	−19	−18
U.S. heavy oil imports	12	−5	11
U.S. heavy refiner inputs	11	−4	9

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.

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 15.5 percent both in the US and the ROW as fuel is traded freely.[42] 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.

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. Looking at the second and the third columns, U.S. light oil production in the model grows by exactly the same amount as the data, by default. 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. The model's prediction for the decline in medium oil inputs is also quite close to the data. On the other hand, the model cannot generate an increase in U.S. heavy oil input use and heavy oil imports, which will be explored later. 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.

Fig. 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 3.8 percent and aggregate consumption by about 0.85 percent. We find that the level of U.S. real GDP is 1.07 percent higher

[42] 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 Bornstein et al. (2018).

in 2015 than in 2010, accounting for about one tenth of actual economic growth over the same period.[43] We discuss the GDP result in more detail in section 5.3.

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 a little under 1 percent in 2015, very close to what we observe in the data. With higher fuel production from the U.S. crowding out ROW fuel production, the U.S. becomes a net exporter of fuel by 2014. We find the non-oil balance deteriorates slightly by about 0.3 percentage points, as a share of GDP.

5.2. *Counterfactual: no ban on U.S. crude oil exports*

We now use our model to study the oil boom in a model without the export ban – i.e. with free trade in crude oil. This counterfactual exercise will give us insights into the implications of the export ban, which our baseline results show was a binding constraint for several years. The solid lines in Figs. 5.1 and 5.2 present the results under free trade.

Broadly speaking, we find that the ban primarily distorted the upstream and downstream oil market and petroleum trade. We show that had there been no ban during the shale oil boom from 2010 to 2015, U.S. 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. In addition, the relative prices of light to medium, and light to heavy crudes would not have declined as much with free trade. Although the export ban distorts oil prices, we find this had little impact on U.S. or ROW crude oil production. Supply elasticities are low and the size of the price distortions is not overly large, limiting the distortionary impact of the ban.

As ROW refiners are specialized in processing light crude relative to the U.S., the ROW would have processed the increased light oil supply rather than the U.S. Essentially, to the extent the ban was binding, it only influenced who processed the new supply of crude oil. This is due, in part, to the fact that the U.S. never had an export ban on refined petroleum products. As a result, the total increase in world fuel supply is very similar to the baseline, and so is the decline in fuel prices.

The responses of most macro aggregates, such as aggregate consumption or real GDP, are also similar to the baseline model with the ban. These findings imply that for our case of interest, the distortionary effects of the ban are primarily concentrated in oil prices, the refining sectors and oil trade flows.

We next consider who wins and who loses from the export ban policy. To help with this analysis, we plot how the responses differ between the baseline (export ban) and the free trade case for a handful of particularly relevant variables in Fig. 5.3.[44] The first row plots the differences for oil prices and oil production, while the second row shows the differences for refiner market share (as a share of world fuel production), GDP, aggregate consumption and leisure. Solid and dashed lines are for the U.S. and ROW variables, respectively.

In terms of oil producers, we find only one clear winner: light oil producers in the ROW. They see higher oil prices under the baseline than the free trade case. By 2015, light oil prices outside the U.S. are about 3 percentage points higher under the export ban. On the other hand, the biggest losers are light oil producers in the U.S. By 2015, U.S. light oil prices are more than 5 percentage points lower in the export ban case than the free trade case. Both U.S. and ROW producers of medium and heavy crude also face modestly lower prices, because the export ban induces the U.S. refining sector to substitute away from those crude types towards U.S.-produced light crude oil.

However, these price distortions do not result in any major changes in crude production, as previously mentioned. U.S. oil production in 2015 is a little under 1 percentage point lower with the export ban, while ROW supply is up very slightly. On net, world oil production (not shown) is about 1 basis point lower with the export ban.

In regards to refiners, we find that U.S. refiners benefit from the ban at the expense of oil producers and ROW refiners. U.S. refiners are able to access artificially cheap light crude oil that ROW refiners cannot access. As a result, U.S. refiner market share is higher under the baseline than free trade.

Finally, we consider how the policy may have impacted households. Overall, these impacts seem to be very small. While U.S. aggregate consumption is higher by about a basis point with the ban, leisure is lower.[45] U.S. GDP is also about a basis point higher. We find opposite, but even smaller, impacts on ROW GDP, consumption and leisure.

5.3. *Understanding the impact on GDP*

A major finding of our paper is that the increase in light oil production from 2010 to 2015 boosts the level of U.S. GDP by a little over 1 percent. We now discuss the mechanisms behind this result in more detail. This discussion builds off of additional analysis contained in sections A and B of the Appendix.

[43] 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) present a 0.2 percent increase in the GDP of oil importers from 2010 to 2018.

[44] Specifically, Fig. 5.3 plots $x_t^{\text{ban}} - x_t^{\text{noban}}$, where x_t^{ban} and x_t^{noban} are the percent-deviation of variable x_t from its starting value for the baseline and free trade case, respectively. This is equivalent to taking the difference between the dashed and solid lines found in Figs. 5.1 and 5.2.

[45] Ideally we would compare welfare across the two models but we work with a first-order approximation of the true model and the results in Kim and Kim (2003) suggest that welfare comparisons across models could be incorrect with a first-order approximation. Addressing this potential issue would require solving the non-linear version of the model or a second-order approximation, both non-trivial to do because of the inequality constraint and the large number of endogenous state variables in our model.

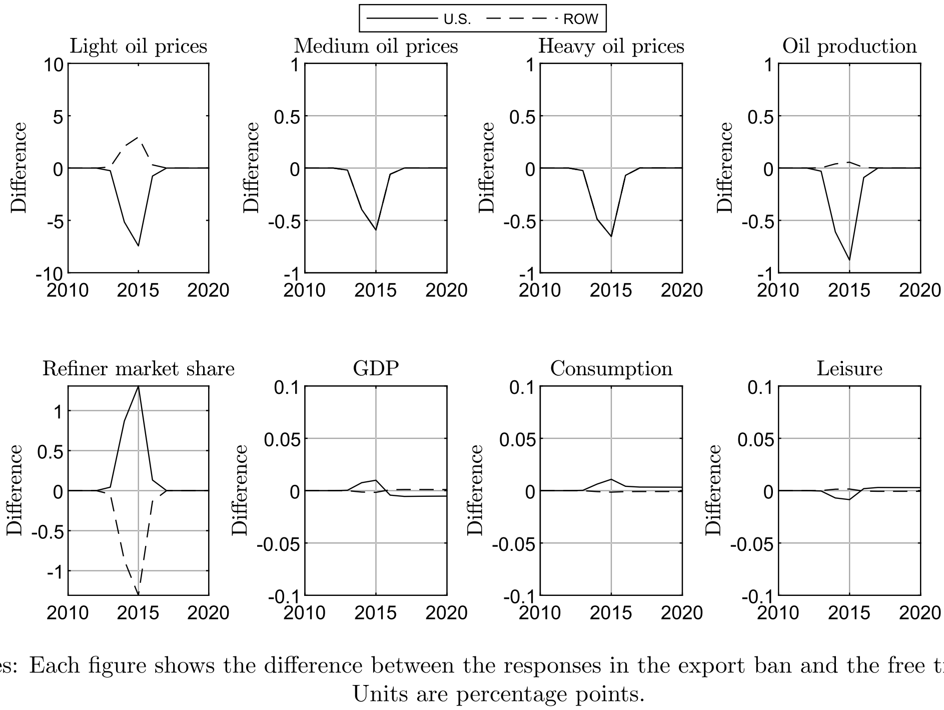

Fig. 5.3. Comparing differences between the export ban and free trade case. Notes: Each figure shows the difference between the responses in the export ban and the free trade case. Units are percentage points.

Gross Domestic Product (GDP) is given by a fixed-price measure that sums the value-added of the non-oil, refining and oil sectors:

$$Y_{1,t}^{GDP} = \left(Y_{1,t}^{a} - P_1^f M_{1,t}^f\right) + \left(P_1^f Y_{1,t}^f - \sum_{k}^{k=h,l,m} P_1^{ok} O_{1,t}^{fk}\right) + \sum_{k}^{k=h,l,m} \left(P_1^{ok} Y_t^{ok} - \Gamma_t^{ok}\right), \tag{5.1}$$

where prices are held fixed at their steady-state values and we drop the time subscript t. A first-order approximation of this equation tells us that the total change in national income will be a function of the changes in value-added in the three sectors, each weighted by their (initial) share of overall GDP.

The "direct" impact of the oil boom on GDP is due to the increase in value-added in the oil sector. The quantitative importance of this direct impact is determined by how large the production increase is, the share of GDP due to the oil sector, and the share of oil sector value-added due to light oil production. While the size of the production change we consider is very large, it is tempered by the fact that the U.S. oil sector is a relatively small part of the overall economy. Despite this, we find that the direct effect is the most important contributor to the total change in GDP, making up 0.99 percentage points of the roughly 1.07 percentage point increase.

There are also several "indirect" channels through which greater oil production can affect GDP. These operate through changes in value-added related to goods besides light crude oil. We find that the indirect mechanisms are all significantly less important than the direct effect, for reasons explained below. On net, the non-oil sector and refining sector contribute 0.05 and 0.03 percentage points to the overall change, respectively.

One negative, indirect impact works through lower production of other types of crude oil. The low price elasticity of supply, however, limits how much medium and heavy oil production adjust in the U.S., and their shares of GDP are very small. Therefore, this channel has almost no impact.

There are also positive, indirect impacts through higher value-added in the non-oil and the refining sectors due to lower costs of fuel and crude oil. In the non-oil sector, the cost-share of fuel plays an important role in the quantitative importance of this channel. In the U.S., though, this cost-share is small, limiting its importance. The cost-share of crude oil is much larger in the refining sector, but the share of the refining sector in U.S. GDP is relatively small.

Negative spillovers may also affect value-added in the refining and non-oil sector. One of these, explored at length in Appendices C and D, is the possibility that labor is re-allocated across sectors, potentially lowering output in the non-oil sector. We show that these spillovers, if they occur, will be very small when it comes to the U.S. This is true even if we explicitly model labor in the oil production function. The reason is that the shares of hours worked and employment in the refining and oil sectors are trivial compared to the non-oil sector, limiting their ability to impact the non-oil sector.

5.4. Additional results

5.4.1. Taking into account domestic oil price differentials

One important feature of the U.S. oil boom was the emergence of unusually large price differentials between West Texas Intermediate (WTI) light crude oil, sold in Cushing, OK, and light crude oil sold elsewhere, especially on the U.S. Gulf Coast, such as Louisiana Light Sweet (LLS). These differentials were especially prevalent from 2011 to 2013 and were due to a temporary lack of pipeline capacity to move crude oil. This led to the use of costlier forms of transportation, including barge, rail and truck. Here, we extend our baseline model to take into account this feature of the data.

To do this, we assume that there is an exogenous cost, $\tau_{1l,t}$, of moving U.S. produced light crude oil from the oil producer to a refiner. If the price the refiner pays for light crude oil is given by P^{ol}_{1t}, then the wellhead price of oil, i.e. the price received by the oil producer, is given by

$$P^{ol}_{1t}/(1+\tau_{1l,t}). \tag{5.2}$$

Essentially, we treat the wellhead price as WTI in Cushing while the refiner price is LLS.[46]

We assume the transportation costs entail the use of the non-oil good, as opposed to being iceberg costs. As pointed out in Farrokhi (2020), the use of iceberg costs would imply that some crude oil is produced, but not refined, which is at odds with actual oil market data. While our setup is simplistic and somewhat reduced form, it allows us to capture two key features of the U.S. experience. First, U.S. oil producers receive a price for light crude oil that is lower than the waterborne price of light crude oil. Second, unusually high spreads mean greater resources are being allocated to moving the oil, which is consistent with the higher marginal cost associated with using barges, rail and trucks to transport crude oil.

To solve the model, it is necessary to specify a stochastic process for the transportation costs and re-calibrate the model. As in Caldara et al. (2018), we assume the trade costs follow an AR(1) process,

$$\tau_{1l,t}=(1-\rho_\tau)\mu_\tau+\rho_\tau\tau_{1l,t-1}+\exp(\sigma_\tau)\epsilon_{\tau,t}, \tag{5.3}$$

where $\epsilon_{\tau,t}$ has standard Normal distribution. The innovation captures unexpected changes in the level of trade costs.

The model is calibrated using the procedure outlined in Section 4. To get values for the parameters in Table 4.2, we re-estimated the model using SMM by including data on the WTI-LLS differential from 1986 to 2010. We find the parameter estimates are essentially the same as in the Table 4.2. Prior to 2010, the differential between WTI and LLS was generally very small and not very volatile, so it had little impact on the estimation. The parameter ρ_τ is estimated to be 0.497 while $\exp(\sigma_\tau)$ is found to be 0.007.

For the experiment, we jointly solve for the transportation cost shocks and light oil supply shocks so that 1) the WTI-LLS differential in the model matches the data from 2011 to 2015; and 2) the path of U.S. light oil production growth matches that in the data, as in our baseline results. We assume the WTI-LLS differential returns to a value of roughly 4 percent thereafter, consistent with its 2010 value. We first compare responses with and without the export ban. We find that the responses are very similar to those presented in Figs. 5.1 and 5.2. Specifically, we find that the export ban was binding in 2014 and 2015, that U.S. GDP increased by a little over 1 percent comparing 2015 to 2010 levels, and fuel prices fall by roughly 15 percent.

Next, we ask what would have happened had the WTI-LLS differential not widened out? For this experiment, we feed in the light oil supply shocks, but set the transportation shocks to zero. We find that the results are not too different. The main reason is that, when looking at annual averages, the WTI-LLS differential was never very large. For example, at its largest in 2012, the differential was about 12 percentage points higher than it was in 2010. This may seem large but the impacts on light oil production are modest because supply elasticities are relatively low. The model predicts U.S. light crude production would have been about 1.4 percent higher in 2012, if the differential had not widened out. This is not large enough to significantly impact other variables in the model.

5.4.2. Taking into account ROW heavy oil production increase

Our baseline results consider only one shock, a U.S. light oil technology shock, replicating the annual percent change in U.S. light oil production data from 2010 to 2015. Despite relying on a single shock, the baseline model does a good job in explaining some of the key changes in the data, but it is not successful in explaining changes in U.S. heavy oil imports and refiners' heavy oil use.

During 2010-2015, while U.S. heavy oil production was stable, ROW heavy oil production increased (see Table 2.1). One possible explanation for higher U.S. heavy oil inputs and imports, given the higher complexity of U.S. refiners relative to the rest of the world, could be higher ROW heavy oil production. Motivated by these facts, we introduced an ROW heavy oil technology shock into the baseline model to see whether it could help account for changes in U.S. heavy oil imports and input use.

[46] For simplicity, we continue to assume there are no international transportation costs. We also do not model these costs for U.S. medium or heavy crude production, as there is no evidence that their prices were affected by a lack of pipeline capacity during this period of time.

Similar to our baseline experiment, we numerically solve for the series of the ROW heavy oil technology shock so that the model generates the same annual percentage changes in ROW heavy oil production as in the data. Keeping all model features and calibration the same, we then feed this shock into the model along with the light oil technology shock. A subset of responses presenting how various variables respond to the increased ROW heavy oil production along with the increased U.S. light oil production can be found in Appendix A.1.

Comparing these results with the baseline model results, we observe that higher ROW heavy oil production results in a smaller decline in total ROW oil production and a smaller decline in the light-heavy price differential. As U.S. refiners are geared towards processing heavier crude, U.S. heavy oil imports and heavy oil inputs increase. Indeed, the extended model can account for 92 and 82 percent of the changes in heavy imports and inputs data, respectively (see the second and fourth columns in Table 5.1). The declines in medium oil imports and input use are slightly smaller, closer to the data.

6. Sensitivity analysis

6.1. The role of heterogeneous oil

In order to highlight the importance of heterogeneous crude oil in examining the impact 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 but leaves the rest of the model unchanged. We re-calibrate and re-estimate the one oil model and repeat our earlier exercise. For this case, we feed in a sequence of shocks so that the one oil model replicates the change in U.S. aggregate oil production predicted by the heterogeneous oil model. To conserve space, figures are relegated to Appendix B.1.

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. In the one oil model, the ban only binds if total U.S. production exceeds total use of oil by U.S. refiners, something which never happened in the data. We also find that 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 the different oil types are aggregated, we find that the macroeconomic effects of the oil boom would also be somewhat smaller.

6.2. Greater substitutability across oil types

We next considered a case where there is greater substitutability between different crude oil types in the U.S. refining sector. Specifically, we consider an extreme case where the three oil types are almost perfect substitutes by setting the elasticities of substitution to 50 (η^{oil} and ρ^{oil} to -0.98). While not a realistic calibration, this exercise provides insights into the role these elasticities play in our baseline results. A subset of responses can be found in Appendix B.2. We find that in this case the export ban is not a binding constraint, as U.S. refiners substitute away from other crude types towards greater use of light oil. Because of this, the response of U.S. and ROW fuel production mimics that of the homogeneous oil model. The changes in U.S. consumption and GDP are similar to the baseline model. Relative prices of the different crude types change significantly less in this case relative to the baseline.

6.3. Complete vs. incomplete financial markets

Our baseline model assumes the existence of an internationally traded bond, which we believe is the most realistic assumption for our questions of interest. Here we discuss results using two other common assumptions about market completeness: financial autarky and complete markets. Under financial autarky, trade balances each period and capital accumulation is the sole mechanism for smoothing consumption. Complete markets allow the two countries to perfectly insure themselves against country-specific risk.

We present a set of impulse responses in Fig. 6.1. Additional responses are in Appendix B.3. For our shock of interest, we find little impact on oil market variables, such as the change in the crude oil balance and the response of oil prices (not shown here), but more notable differences in the non-oil balance and non-oil consumption.

Under financial autarky (FA), the improvement in the crude oil balance must be offset by shifts in the non-oil balance. As a consequence, consumption of the non-oil good is significantly higher under financial autarky. The non-oil good does most of the adjustment, because fuel is a small portion of overall consumption. We also find higher levels of investment (not shown here), as the capital good is the only method for smoothing consumption across time in the FA case.

In the bond model, the U.S. saves income by accumulating the international bond, which reduces the change needed in the non-oil balance, non-oil consumption and investment. In the complete markets (CM) case, these impacts are lessened even further, as the U.S. gives up additional consumption of the non-oil good to the ROW as insurance. The impact on leisure, not shown here, is also amplified under complete markets: the U.S. works more than it would otherwise, as this is another margin on which to pay for the insurance provided to the ROW.

6.4. Counterfactual U.S. refinery calibration

We also investigated the importance of U.S. refineries being geared towards processing heavy crude relative to the rest of the world. In our baseline calibration, the distribution parameters controlling the relative use of different types of oil in the

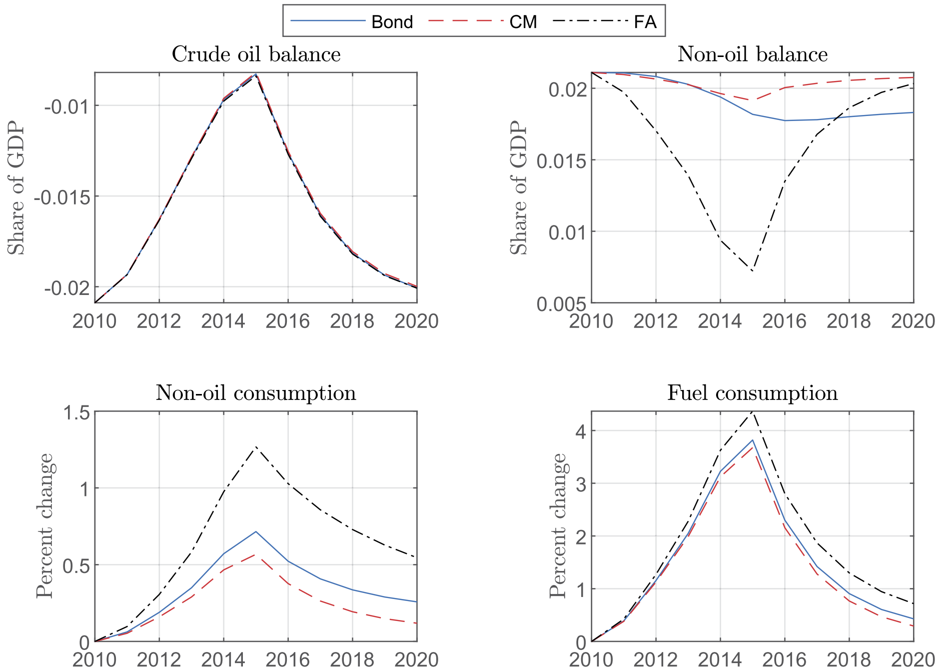

Fig. 6.1. Comparing incomplete vs complete markets.

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. A subset of results are presented in Appendix B.4. 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.

6.5. 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.

We present a subset of results in Appendix B.5. Overall, the higher light oil supply elasticity amplifies the responses. A higher elasticity of supply means lower production costs for light oil producers in the U.S., leading to higher output than the baseline. We find that total U.S. oil production increases by about 90 percent compared to a 78 percent increase in the baseline. This in turn brings a sharper decline in light oil prices, much higher use of light oil inputs by U.S. refineries and much higher U.S. fuel production. For example, U.S. light oil prices decline by about 37 percent compared to a 31 percent decline in the baseline. 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.

6.6. 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. Appendix B.6 shows a subset of results for this experiment. Under this scenario, our model predicts that the export ban would have remained a binding constraint through 2020 and its distortionary effects oil prices, refining sectors, and trade balances would have been amplified.

6.7. Oil production function

Our baseline model uses a cost function where oil is produced using the non-oil good. This function allows us to easily set a low price elasticity of supply for the oil sector, a key feature of the sector. In Appendix C, we derive analytical results for a number of stylized one and two-country models that allow us to get greater insight into the role of the production function. We do this by comparing the solutions from models where oil is produced using labor with a decreasing returns to scale Cobb-Douglas technology versus cases using our cost function.

These results provide the following key insights regarding the oil production function. First, the impact of an oil production increase on U.S. GDP is modestly higher for cases with the cost function. We find the elasticity of U.S. GDP with respect to a change in U.S. oil production is slightly above 0.012 for the Cobb-Douglas case with labor and about 0.014 with the cost function. Second, when labor is an input into the oil production function there are potential negative spillovers to non-oil output, as labor can flow out of the non-oil sector into the oil sector. We find that these spillovers are relatively small for our case, though. This is because that the quantitative importance of those spillovers is heavily influenced by the fraction of total hours worked in the oil sector, which is quite small for the U.S. On a slightly different note, we also show that, to a first-order approximation, our cost function is analogous to a decreasing returns to scale Cobb-Douglas technology where the non-oil good is used as an input to produce oil. Appendix C contains additional details.

6.8. Other sensitivity analysis

We undertook additional sensitivity analysis. First, we considered a model with no capital adjustment costs. We found this had little impact on our main results. The reason is that the response of investment spending in the non-oil sector to our shock of interest is not particularly large, whether the model has adjustment costs or not. The international bond is the primary mechanism used to smooth consumption and the impact of the supply increase on the marginal product of capital is not very large. This limits the impact on other variables in the model. However, we note that without the adjustment costs the model would, in general, produce too much volatility in investment spending relative to the data, because other shocks play a much bigger role in affecting investment spending.

Second, we examined the role of the bond holding intermediation costs. We found that as the costs become increasingly large, the results of the model become closer to the financial autarky case, discussed in Section 6.3. Essentially, if intermediation costs are very high, the international bond is not attractive as a vehicle for smoothing consumption. In the extreme case, the only practical method of saving is the capital good, as in the financial autarky case. We also considered a model where the intermediation costs result in the use of the non-oil good and found that it had no impact on the results, as the costs are generally small.

Finally, Appendices C and D provide a large number of analytical results using stylized one- and two-country models. We investigate models with and without household demand for oil, firm demand for oil, and the refining sector. These sections also provide a discussion on the various channels through which increased domestic oil production can influence GDP in our model. We also show the importance of using a two-country model in examining the impacts of increased domestic oil production on the U.S. economy. The two-country setup allows us to take account of the fact that the U.S. was a net oil importer at the start of the shale boom, which qualitatively affects some of the model solutions. The two-country setup also allows one to properly calibrate the relatively small size of the oil sector vis-a-vis the non-oil sector in the U.S., which plays an important role in some of the results. Finally, the analytical solutions also provide some intuition about how other parts of the calibration affect the model results, such as the elasticities of substitution in utility and production functions. The interested reader is referred to the appendix for the solutions and more discussion about the 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 an occasionally 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 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 about 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 U.S. crude export ban was a binding constraint, particularly in 2014 and 2015, and that it primarily distorted the upstream and downstream oil sectors and petroleum trade, with negligible impacts on macroeconomic aggregates.

We believe a number of avenues exist for future research. Our framework can be used to examine experiences of other countries or different time frames. For example, the model could be used to analyze the macroeconomic implications of shale resources in China or Argentina, if their resources are ultimately developed further. With trade policies receiving considerable attention over the past few years, one extension would be analyzing the effects of tariffs or quotas on crude oil or refined products, as our model allows for trade in both. Finally, another interesting question would be a long-run analysis of the U.S. refining sector, which can shed light on how refineries adopt to changing availability of crude inputs over time.

Appendix. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.red.2020.11.006.

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