Global Supply Chain Flexibility:

The Role of Contracts in LNG

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Abstract

This paper studies how relationships governed by long-term contracts enable global supply chains to adjust to unanticipated shocks. We show that, in the LNG industry, contracts respond more than spot markets to weather-related demand fluctuations. Contract shipment surplus is shared with sellers to compensate them for forgoing spot markets at times of high demand and for exerting relationship-specific effort to deliver at these times. A counterfactual analysis that supplies all shipments to spot markets while holding final destinations constant suggests that adaptation within contracts contributed significantly to global LNG industry value between 2009 and 2019.

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1 Introduction

Recent supply chain disruptions have made supply chain risk and uncertainty a top priority for both firms and policymakers (Baldwin and Freeman, 2022). Ongoing challenges—ranging from climate change and geopolitical tensions to emerging technologies from the Fourth Industrial Revolution—are expected to sustain this heightened uncertainty for the foreseeable future (World Economic Forum, 2021). Given the potential for severe disruption across the global economy, firms seek to build resilience by designing value chains that offer flexibility in the face of unpredictable events. This paper shows that the organization of global supply chains plays a crucial role in determining their ability to adapt to unanticipated shocks.

We study liquefied natural gas (LNG), which is transacted within long-term contractual relationships between buyers and sellers and also on spot markets. LNG is a growing source of global energy, supplying around 13% of world demand.[1] Energy is a critical source of supply chain vulnerability across many countries. Its demand is uncertain, and supply is largely invariant in the short run. Supply disruptions in energy pose significant costs on households and businesses, particularly in energy-importing nations and also in energy-exporting nations due to the global nature of the industry. The energy crisis of 2022 in Europe is a stark example of the cost-of-living crisis caused by energy disruptions.

LNG provides a technology whereby natural gas produced in oil-rich locations can be transported to destinations where it is transformed back into gas and used as an input to power generation. Around three quarters of LNG volumes are transacted across country borders within long-term contracts between buyers and sellers. While the share of LNG sold on spot markets had been increasing, this trend reversed in 2019. Recent developments show that buyer and sellers remain keen to negotiate new contracts, suggesting that they find value in contracting amid the intense uncertainty faced in the industry.[2]

The literature on contracts along global supply chains establishes that buyer-supplier relationships governed by contracts can create value by enabling relationship-specific investments (Grossman and Hart, 1986; Hart and Moore, 1990; Antràs, 2003). Moreover, the future value of contractual relationships can serve to discipline opportunistic behavior (Antras and Foley, 2015; Macchiavello and Morjaria, 2015; Araujo, Mion, and Ornelas, 2016). There is, however, relatively little study of how these benefits of contracts can be realized in settings where market fundamentals are uncertain ex ante. Uncertainty can make contracting

[1] Natural gas provides around 23% of the world's energy, nearly 50% of which is supplied in its liquefied form (International Energy Agency, 2021; Statista Research Department, 2024).

[2] This trend is described in https://globallnghub.com/the-share-of-spot-lng-trade-in-the-global-market-fell-to-a-new-low-of-26.html. For example, In 1999, Petronet LNG, India's largest LNG importer, entered into a long-term SPA with QatarEnergy for the annual supply of 7.5 million tonnes of LNG, set to expire in 2028. In February 2024, both parties agreed to extend this contract for an additional 20 years, from 2028 to 2048. In a second example, TotalEnergies had an existing LNG supply agreement with CNOOC, China's largest LNG importer. In October 2024, the agreement was extended by five years, ensuring the annual delivery of 1.25 million tonnes of LNG until 2034.

costly, and the costs associated with specifying all possible contingencies have been shown to prohibit efficient contracting, in favor of spot markets on the one hand or vertical integration on the other. Both these alternative organizational structures enable ex post adaptation to be achieved more easily (Williamson, 1979; Joskow, 1988). Uncertainty can also make contracting less valuable by masking opportunistic behavior(Martin, Mejean, and Parenti, 2023).

We study the tradeoff between costs and flexibility in the face of uncertainty in LNG supply chains. Using shipment-level data between 2009 and 2019, we first show that LNG volumes shipped on global routes respond to unpredictable weather shocks at the destination.[3] We find that the volumes are particularly responsive to local demand conditions when buyers and sellers have long-term contracts on a route. That is, contracts adapt more flexibly to demand shocks than spot markets in this industry. Consistent with this finding, routes ending in destinations with unpredictable weather are also more likely to have contracts in place.

We then ask how contractual relationships adapt to demand shocks. We construct a model of shipment demand and supply where contractual relationships are incentive compatible for both parties. In each period, a buyer requests a contract shipment if its payoff exceeds the payoff the buyer would receive from transacting on the local spot market given weather shocks and spot market prices and thickness. The seller can choose to exert costly relationship-specific effort to increase the value of a contract shipment to the buyer or can sell on global spot markets, subject to transport costs.

We solve the model to derive the probability a buyer will request a contract shipment on a contract route in a given week as well as the share of relationship surplus a seller must receive in order to fulfill the contract shipment request. Intuitively, the effect of weather shocks on the probability of a contract shipment identifies the returns to relationship-specific effort. Weather shocks, together with variation in the storage capacity, also identify the parameters determining the elasticity of contract shipments to demand shocks. Holding the weather shock constant, variation in spot prices and spot market thickness identify the distribution of shocks to spot market value. The average share of contract shipments determines each shipment's fixed costs. The seller's incentive compatibility constraint is used to identify the marginal cost of relationship-specific effort and the seller's share of contract shipment surplus. Parameter identification is therefore made possible by independent variation over time in the relationships between contract shipment timing and spot prices, holding weather constant, and between contract shipment timing and weather shocks, holding spot prices constant.

Because the model focuses on route-week-level buyer decisions, it does not explicitly take into account seller capacity constraints or any trade-offs the seller has to make between demand from multiple contract

[3]The shipment-level data include origin and destination, volumes, and whether the shipment was a contract or spot transaction. These data were made available to us by Kpler, a provider of data and analytic solutions for commodity markets.

partners in any one period. In estimating the model, we focus on route-years where there is a tradeoff between spot and contract shipments. We study route-years that have at least one contract in place and hence have revealed preference for contract shipments being feasible. To determine the relative values of contract and spot shipments, we also focus on route-weeks where either a contract shipment occurs or where no contract shipment takes place but both the buyer and seller are transacting in spot markets. This last criterion ensures sellers could have allocated more shipments to contract partners without being capacity constrained.[4]

Using the model estimates to predict the non-targeted moments of the elasticity of contract shipments with respect to weather shocks and spot prices gives values that are close to those in the data. With the model parameters in hand, we construct distributions of the estimated willingness to pay for LNG in contract and spot shipments on each route-week in the sample. A cubic meter in a contract shipment rather than a spot market is 32% more valuable, on average, given the current size of the spot markets. There are three model mechanisms that explain this difference. Buyers tend to request contract shipments during weeks when they experience positive demand shocks; sellers exert relationship-specific effort to further increase buyer value; and thin spot markets limit the value of spot shipments. The lower bound on the share of contract shipment surplus that sellers must extract via the contract price in order for contractual relationships to be incentive compatible is estimated to be 30%.

There are several features of LNG supply chains that provide opportunities for sellers to deliver valuable relationship-specific effort within contractual relationships. First, the geography of the industry leads to frictions associated with travel time. The average shipment in our sample takes 8 days to travel from the origin to the destination.[5] Second, the industry technology creates large indivisibilities. LNG vessels are large relative to total industry volumes and the data feature many zeros at the route-week level.[6] We argue that bilateral negotiations within contracts allow both parties to work together to deliver shipments at times, and with volumes, that fit buyer demand.[7]

[4]The theoretical moments derived in the model relate only to weeks where the buyer receives some positive quantities, either contract or spot shipments, so we also restrict the estimation sample to route-week observations where this is the case.

[5]As detailed in the Appendix, Qatar has been the largest supplier of LNG for many years, and is now rivaled by the United States. Australia and Russia are the next two largest supplier countries. Japan has been the largest importer of LNG and China now imports similar volumes. South Korea is the next biggest importer.

[6]The global fleet of LNG vessels consisted of around 730 large ships in 2024, around one quarter of the number of crude oil carriers. The median number of ships dispatched per week from origins that are active in a given year is two, and the median number of ships received by destinations active in a given year is one. For those routes that have at least one shipment in a given year, the median number is only three.

[7]Contract shipment prices are typically indexed to oil prices, which tends to mean their prices are less volatile than spot market prices, but buyers' relative value for contract shipment is higher when controlling for spot market price. In addition, buyers' value for spot market shipments increases with spot market thickness, holding price constant, suggesting shipments

Our findings raise the question of whether contracts are valuable only because they make up such a large share of the industry. That is, the network of buyer-seller contracts creates an externality on the size of the spot market (Harris and Nguyen, 2022).[8] We conduct a counterfactual analysis that asks how much long-term contracts contribute to industry value compared to a world where all LNG is traded on local spot markets and show that this externality does not explain all of the industry value that contracts create.

In the counterfactual, we hold fixed total global supply and sellers' allocations of shipments to destinations in each week. We convert all arriving contract shipments to spot and add them to the spot shipments already arriving at the destination in a given week, giving us a counterfactual spot market in each destination. Because we have estimated the relationship between local spot market thickness and expected spot value, we can simulate the expected values buyers would have obtained in these enlarged counterfactual spot markets.[9]

We show that the efficiency of the LNG industry would have been significantly reduced in the absence of contracts between 2009 and 2019. The gains from contracts outweighed the fixed and variable costs of maintaining them, contributing around 30% of the total gains from trade in the industry over this period.

One potentially important issue our analysis does not consider is seller market power. In theory, it could be that sellers choose to fulfill contract shipment requests in order to withhold quantities from spot markets and gain from the resulting higher spot prices. We do not allow sellers' supply decisions to include these strategic considerations. The main reason for this choice is that the routes between sellers and buyers tend to either be contract or spot. That is, if a seller has a contract with a buyer, it is unlikely that they are also selling on the spot market at that destination, and vice versa.[10]

This paper relates to several literatures. First, are industry-specific studies of the pros and cons of long-term quantity contracts. These include Joskow (1988), and Pirrong (1993), and the discussion in Lafontaine and Slade (2012). Zahur (2022) has studied the LNG industry in depth and has focused on the long-term contracts that we investigate here. The study shows that contracts allow greater capital investments at the cost of allocative efficiency but does not examine whether contractual relationships

are differentiated in tangible ways.

[8] Kranton (1996) sets out theoretically how spot market externalities can be large enough or small enough to determine whether relationships are efficient.

[9] This approach allows us to sidestep the challenge of estimating counterfactual spot prices because we focus on the total surplus created by each shipment as a function of weather conditions, rather than how the unobserved counterfactual spot price divides this surplus. Setting up the counterfactual in this way does not take into account any allocative efficiency gains possible in the spot market if sellers were to divert spot shipments to locations where they anticipate higher prices.

[10] While there are several large firms in this industry that have minority ownership stakes in multiple sellers, the majority ownership stake is often a state energy company with no cross-seller links.

create value through week-to-week adaptation to shocks. Our analysis is consistent with its finding that contracts are often signed around the time of the capital investments, which, due to the long life of capital, then raises the issue we explore here of the efficiency implications of contract flexibility in delivery timing.[11]

In our setting, unpredictable weather causes exogenous demand shocks that we exploit to identify how supply chains respond. We establish that long-term contracts are sufficiently flexible to allow the supply side to adapt and add to overall industry value. This finding complements work showing that vertical integration can permit adaptation to unforeseen circumstances. Forbes and Lederman (2009) and Forbes and Lederman (2010) study vertical integration in the airline industry. They show that major airlines tend to own regional airline partners when adverse weather is more likely and where a route is more integrated into the major's network. Integrated routes also respond to weather shocks and perform better than non-integrated routes at the same airport on the same day. Costinot, Oldenski, and Rauch (2011) show that the boundaries of U.S. multinational firms reflect the extent to which sectors involve non-routine tasks. Vertical integration along the supply chain is more likely in sectors with high problem-solving intensity, consistent with ownership facilitating adaptation to changing circumstances. We find that long-term contracts enable adaptation in LNG supply chains in terms of delivery volumes and timing. We highlight that this finding implies contracts increase the resilience of the industry supply chain to demand shocks.[12]

The literature on relational contracts establishes how the prospect of future rents effectively deters short term opportunism in a range of empirical settings (Macchiavello (2022)). Macchiavello and Morjaria (2015) use the dynamic incentive compatibility constraints implied by repeated seller-buyer interactions to estimate lower bounds on the value of relationships in the Kenyan flower industry, a setting of imperfect contract enforcement. We show that the future value of formal, but incomplete, contracts in the global LNG industry governs the short term actions of the sellers in the industry. Buyers, however, compare contemporaneous costs and benefits, interpreting contracts as call options to request shipments at times when they are particularly valuable.

Harris and Nguyen (2022) estimate the incentives that govern both relationship formation and the actions of buyers and sellers in U.S. trucking. Relationships form between trading partners with a high match quality, but the large number of contract relationships leads to thin spot markets, increasing the search costs for trading partners. Tolvanen, Darmouni, and Essig Aberg (2021) also find that frictions in spot markets provide an insurance role for buyers, in their analysis of transactions data from a large producer in the U.S. pulp industry. In our setting, we show that relationship surplus is an endogenous outcome reflecting demand shocks and seller incentives to exert costly relationship-specific effort to increase

[11] Because our counterfactual does not vary each shipment's destination, we do not explore allocative efficiency.

[12] Recent global events, perhaps most notably the Covid-19 pandemic, have prompted much political debate and study of the efficiency implications of potential supply-side disruptions within global value chains (see Grossman, Helpman, and Lhuillier (2023), Grossman, Helpman, and Sabal (2023), and the papers cited therein).

buyer value. Even though these costs are saved in the counterfactual that eliminates contracts, the increased thickness of the spot market is insufficient to compensate for the lost returns of seller effort.

Our interpretation of the relatively low buyer values for spot market shipments is that spot markets do not supply the quantities of LNG that buyers need at the ideal delivery times, even in the counterfactual thicker spot markets, due to frictions related to bulky shipping technology and the long distances between buyers and sellers.[13] Brancaccio, Kalouptsidi, and Papageorgiou (2020) document how frictions arise in global shipping when country-level trade imbalances in dry bulk commodities lead to shipping price differences across markets. We note that LNG vessels are specialized and there is no two-way trade. We infer that LNG contracts were efficient in this industry because the total market size was too small, over the time period studied, for spot markets to overcome these geographical and technological frictions.

This paper proceeds as follows: Section 2 describes the industry and summarizes the data. Section 3 is the reduced-form analysis relating contract volumes to weather conditions. Section 4 presents the structural model, Section 5 discusses estimation, and Section 6 presents the results. Section 7 is the counterfactual analysis. Section 8 concludes.

2 Industry and Data

2.1 Industry overview

Natural gas provides around 23% of the world's energy (International Energy Agency, 2021) and is supplied either via pipelines (49%) or LNG (51%) (Statista Research Department, 2024). Its contribution has grown significantly in recent decades, and it made up only 7% of global natural gas supplies in 2004. LNG is produced in dispersed, oil-rich, locations and liquefied by cooling it to minus 160° centigrade then transported via ships to locations with regasification capacity. Large, long-lived, location-specific capital investments are required at both origins and destinations, which are typically located far apart from each other. Appendix A shows that the largest exporters in 2019, the last year of data used in this study, were Qatar, Australia, the USA, and Russia, together accounting for over 60% of all volumes. In the same year, more than half of all LNG volumes were shipped to regasification plants in Japan, China, or South Korea, and a further 35 countries received positive shipments.[14]

Long-term sales and purchase agreements (SPAs) are contracts between sellers and buyers that govern the bulk of delivered LNG volumes and can be signed either before or after capital investments are made

[13] Bai, Fernández-Villaverde, Li, and Zanetti (2024) establish that congestion at ports create inefficiencies in shipping markets.

[14] Recent disruptions to pipeline gas in the EU due to the Russia-Ukraine war have led to many new LNG regasification investments. The import capacity in the EU and the UK is set to increase by one third by 2024, after expanding only modestly in the 10 years to 2022. https://www.eia.gov/todayinenergy/detail.php?id=54780.

(Zahur, 2022). Residual LNG volumes are traded on spot markets at spot prices that vary by destination. Contracts specify annual volumes and a pricing formula. Much of the detail in the contracts relates to their "take or pay" nature over a specified time period, a feature shared with pipeline gas contracts (Masten and Crocker, 1985).

In the majority of contracts, prices are linked to the oil price index at the destination, which means that the seller bears risk related to the forgone opportunity of selling to the spot market when LNG spot prices are high relative to oil prices. The buyer typically bears the quantity risk, in that there is an obligation to take the total quantity over the course of the year, whether they need it or not, or incur demurrage charges to compensate the seller. Contracts also contain various clauses related to unforeseen contingencies and the length of acceptable delivery windows.

SPAs do not specify the exact timing of contract shipments. Individual shipments are governed by separate Confirmation Notices that prescribe timing, quantity, and other shipment-specific details. Confirmation Notices are agreed bilaterally prior to each shipment. Therefore, the governing contracts require buyers and sellers to negotiate exactly when and how each shipment is delivered (or collected, if the buyer is responsible for shipping).[15] Our goal is to understand how these contractual terms affect sourcing decisions and efficiency in the LNG industry.

2.2 Data

We obtain data from Kpler LNG on contract and spot market LNG shipments from January 2009 to December 2019. Our data covers 42,047 shipments and for each shipment we observe the origin, destination, volume at origin, volume at destination, distance traveled, time taken, vessel capacity and type, and whether the shipment is a contract or spot transaction.[16] LNG evaporates during shipment, so the volume arriving at the destination is always lower than the volume that left the origin—an example of iceberg trade costs in action.

In this shipment sample, we observe shipments that arrive at 130 different destinations, which are regasification terminals spread across 38 countries. Japan has been by far the largest importer historically, receiving a total of 14,521 shipments at 36 different terminals during our sample. South Korea has the second highest number of shipments, at 5,587, to only six terminals. China has steadily increased imports, from around 100 shipments in 2009 to overtaking South Korea in 2019 as the second largest importer, with 864 shipments delivered to 20 terminals. There are 13 countries that imported at least 500 shipments in

[15] Although contractual agreements are proprietary, template SPAs are publicly available. For example, BP publishes its master sales and purchase agreement template on its website: https://www.bp.com/content/dam/bp/business-sites/en/global/bp-trading-and-shipping/documents/bp-master-ex-ship-lng-sale-and-purchase-agreement-2019-edition%20(3)%202.pdf. A template Confirmation Notice can be found on pp. 46-49.

[16] We exclude shipments that arrive in destinations located in LNG-exporting countries, and vice versa.

total over the 11 years in the data.

We observe shipments from 47 origin installations, which are liquefaction plants in 19 countries. For analysis, we aggregate the data to 35 origins. This is because there are 16 countries in the data where all the liquefaction installations are majority-owned by a state-owned company, with integrated oil companies typically owning minority stakes, so we group to the exporting country level.[17] The other 19 origins are separate liquefaction facilities in Australia (10), Russia (3), and the USA (6). We treat these plants as distinct origins because they have different owners and/or geographies. For example, the Russian plant in Sakhalin is in the far east of the country, very near Japan, whereas the other two Russian plants, Yamal and Vysotsk, are in the west of the country.

We define a route as an origin-destination combination. With 130 destinations and 35 origins, we have $4,550$ routes in the dataset and $50,050$ route-year observations. Of these, only $28,069$ are feasible in that the origin plant and destination terminal are both active for at least some weeks during the year, since some facilities came into operation during the sample. Of all feasible route-years, only $5,432$, or 19%, have any positive volumes, illustrating how sparse trade flows are in this industry.

In the empirical analysis, we restrict attention to routes ending in one of the 10 countries with large LNG spot markets, where weekly spot price data is available. These are the 87 regasification terminals in Belgium, China, France, India, Japan, South Korea, Spain, Taiwan, Turkey, and the United Kingdom.[18] These 10 countries receive $35,779$, or 85% of all the shipments in our data. After restricting the sample to destinations in these 10 countries, we have 33,495 route years over the 11 years in the data, but both the origin and destination are operational for 19,947 route-years. Out of these feasible route-years, only $4,415$ route-years have positive trade. Splitting shipments into contract and spot transactions, there are $3,310$ route-years with non-zero contract shipment volumes and $2,214$ with non-zero spot volumes.

We complement the shipment-level data from Kpler with several other data sources. We obtain weekly LNG spot prices for the 10 destination countries we study from EIKON. We convert the mmBtu prices provided by EIKON to prices per cubic meter of LNG, which is the quantity unit that we use throughout the paper.[19] The spot price series are shown in Figure 1.

Temperature data is from the World Bank's climate knowledge portal.[20] Following the climatology

[17] These countries are: Algeria, Angola, Brunei, Egypt, Equatorial Guinea, Indonesia, Malaysia, Nigeria, Norway, Oman, Papua New Guinea, Peru, Qatar, Trinidad and Tobago, United Arab Emirates, and Yemen.

[18] We assume buyers in Taiwan can access the Chinese spot market due to its proximity. There is also spot price data for the US, but we exclude US destinations because the US is predominantly an exporter of LNG. We also exclude the LNG spot markets in Argentina, Brazil, and Mexico, which do have spot price data available, because they are relatively small markets where our data shows demand appears not to vary with weather.

[19] To convert mmBtu into cubic meters: $1 mmBtu = 0.048$ cubic meters of LNG.

[20] See: https://climateknowledgeportal.worldbank.org/download-data.

literature (see, for example, Nicholson (1993)), we measure weather shocks for each country-month using the standardized difference between observed and expected temperatures. That is, we define the weather shock as the mean temperature in a country that month minus the average mean temperature across years in that country-month, divided by the standard deviation of the country-month mean temperatures across years. We use the negative of this standardized variable, so that a positive value of the weather shock implies it is colder than expected in the country that month given the expected monthly temperature and typical temperature variation in that month. Figure 2 shows the distribution of weather shocks at the route-week level for the active routes in our data sample.

We obtain data on journey time and shipping cost for each route in 2020 from Wood Mackenzie, a large energy sector data provider.[21] The shipping cost data are more appropriate than distance measures to capture the trade costs associated with a route between a buyer and a seller because they account for the indirect paths taken by sea, and the delay or cost associated with congested shipping routes, including any Suez and Panama canal crossings. Finally, we use data on the LNG storage capacity in each country in each year, from the GIIGNL annual reports.[22]. We allow storage capacity to affect the responsiveness of demand to weather shocks.

2.3 Descriptive statistics

Table 2 presents descriptive statistics for our baseline empirical sample at the route-week level. We define an active route-year as a route-year combination for which we observe positive shipment volumes. The baseline sample comprises active route-years for which: (i) the destination terminal is in one of the 10 countries with LNG spot price data, and; (ii) we observe the destination LNG spot price that week. There are 192,911 route-week pairs in the sample.

Panels (a) and (b) show summary statistics for the number of shipments and volume of LNG shipped; both in total and divided into contract shipments and spot shipments. Panel (a) reports statistics computed over all of the route-week combinations in the sample, including those with no shipments. The mean number of shipments is 0.15 and the mean volume is 21 thousand cubic meters. The largest number of shipments

[21] While the Kpler data contain the journey time for each shipment in the data, these times are endogenous to realised weather conditions and possibly also some re-routing during the journey. In contrast, the Wood Mackenzie journey time measure is based on daily shipping charter rates, distance traveled, fuel used, and canal fees. Not all origins and destinations in our sample are included in the Wood Mackenzie data. For routes between origins and destinations where nearby alternatives were available, we used the journey times and costs to these closeby alternatives. There remained some destinations where there were no closeby alternatives. These are the Yamal liquefaction plant in Northwest Siberia, Russia, and regasification terminals in Sweden, Finland, and in Okinawa, Japan, the last of which is in the East China Sea, far from other Japanese terminals.

[22] GIIGNL is the industry association of the International Group of Liquefied Natural Gas Importers. The annual reports are available here: https://giignl.org/resources2/.

on any route-week is five, but 98% of route-week observations have either zero or one shipment. The number of contract shipments and volumes is greater than the number of spot shipments and volumes, with contract shipments accounting for 85% of total volumes in the sample.

Panel (b) reports statistics for each variable restricted to the subset of route-week observations for which the variable is non-zero. There are 25,466 route-weeks with positive shipments, meaning that shipments are observed on 13% of route-weeks in the sample. The mean number of shipments conditional on there being any shipment is 1.15 and on 85% of route-weeks with positive shipments there is only one shipment. The mean shipment volume is 159 thousand cubic meters. Although contract shipments are more frequent than spot shipments and account for a larger share of total volumes, individual contract and spot shipments are similar in size. The average contract shipment is 137.5 thousand cubic meters and the average spot shipment is 137.4 thousand cubic meters.

In panels (c) and (d), we report summary statistics on spot prices, temperatures, journey times and journey costs. Panel (c) reports statistics across all route-weeks in the sample, while panel (d) restricts the sample to route-weeks with positive shipments. From panel (c), we see that the mean spot price of LNG across all observations is 187 USD per cubic meter. There is considerable volatility in spot prices, as evidenced by the large standard deviation of 85 USD. Spot price volatility is also shown in Figure 1, which plots the LNG spot price by country over time. Across destination countries in our sample, the lowest mean monthly temperatures are in China and the highest are in India. The mean number number of days taken per journey in panel (c) is 10.24, and the mean journey cost is 16.86 USD per cubic meter, which is around 9% of the spot price. There are five routes in the data with positive flows where shipments take an average of less than a day, four of which are between Algeria and destinations in Spain, and one of which is between Sakhalin 2 in Russia and a destination in Northern Japan. The routes that take the most journey days are between Norway and either China, South Korea, or Japan.

We now present some descriptive statistics about which route-years are active in the data, in that they have positive LNG flows. Because there are significant trade frictions related to the geography of the industry, we expect gravity to play a role, here, as for trade in most other goods and services.

In Table 3, we explore whether traditional gravity-style variables predict which of the 19,556 feasible route-years, with operational facilities at either end, are the 4,415 active routes. Suppose l denotes an origin liquefaction plant and g denotes a destination regasification terminal. Let H_{lgy} be a dummy variable that takes value one when there is at least one shipment on active route lg in year y, and zero otherwise. We estimate regressions of the form:

$$H_{lgy} = days_{lg} + Q_{ly} + Q + gy + \Gamma_y + \epsilon_{lgy}, \tag{1}$$

where $days_{lg}$ is the number of days it takes for an LNG vessel to travel between l and g, Q_{ly} is the total

volume of LNG exported by origin l in year y, and Q_{gy} is the total amount of LNG imported at destination g in year y. Table 3 shows the results of three regressions with journey days as an independent variable and then replacing journey days with τ_{lg}, the route-specific estimate of transport cost per cubic meter. In columns 2 and 4, we include the total volume produced or received at the origin and destination in that year, and in columns 3 and 6, we include origin-year and destination-year fixed effects. Column 1 shows that an increase in journey length of one day decreases the probability of the route-year being active by two percentage points, which is 5% of the mean probability. Column 2 includes the total volume of the origin and destination as controls, and column 3 includes origin and destination fixed effects. The coefficient on journey time remains very similar. Column 2 also shows that routes starting from origins or arriving at destinations with larger total quantities in a year are more likely to be active.

Columns 4 to 6 show the impact on the probability a feasible route-year is active is lower when transport costs are higher. A one dollar increase in the per cubic meter transport cost decreases the probability of having any positive volumes on the route-year by one percentage point, which is 5% of the mean probability a route-year is active. Overall, Table 3 shows that active routes tend to be from larger origins to larger destinations, and to destinations that are close by and have low transport costs, which is consistent with gravity.

For most active route-years, we observe either only contract shipments or only spot shipments. Figure 3 shows the share of volumes on a route-year that is under contract. The distribution is bimodal and bunches around zero and one. For 70% of the active route-years in the sample, contract shipments account for at least half of total shipment volumes. For later use, we define a contract route as an active route-year for which at least 50% of total volumes are contract volumes.

Finally, in this section, we investigate selection into being a contract route-year, conditional on being active. Because we are interested in how well the supply chain adapts to demand shocks, we regress the contract route dummy on gravity-type variables as well as a measure of weather variability. Let CR_{lgy} be an indicator that the route has at least 50% of its volumes in a year being contracted volumes. We estimate regressions of the form:

$$CR_{lgy} = days_{lg} + Q_{ly} + Q_{gy} + V_g + \Gamma_y + \epsilon_{lgy}, \tag{2}$$

where the right hand side variables are as described in equation (1) other than V_g, which is the mean value across months of the standard deviation in mean temperature in that month across years at the destination. That is, it summarizes how variable the mean temperature is in a destination.

The results are reported in Table 4. In column (1), we show that distance, as measured by journey days, is insignificantly related to whether a route is a contract route or not. Columns (2) shows that both origin and destination size, as measured by total volumes supplied and purchased, respectively, are

associated with increased likelihood of being a contract route. Column (3) includes origin-year fixed effects and shows that a given origin is more likely to have contracts with larger destinations.

In columns (4)-(6), we include the measure of weather variability at the destination level. Since weather variability does not vary across years, we cluster standard errors by year and destination. Column (4) shows that destinations with greater weather variability are more likely to have contract routes. Column (5) shows that this result is robust to including gravity-type variables of journey days, total origin volumes, and total destination volumes. Finally, column (6) shows it is robust to including origin-year fixed effects.

Since this measure of weather variability varies only by destination country, and its association with having LNG routes that are contracted could be related to other country-level factors. In the following section, we use the richer month to month temperature variability to investigate LNG volume responsiveness and whether the responsiveness varies for contracted routes.

3 Reduced form Responses to Demand Shocks

LNG demand fluctuates unpredictably in the face of weather and economic shocks. For example, colder than expected temperatures increase demand in countries that rely on LNG for heating. We start our analysis by studying how LNG shipments respond from week to week to demand shocks caused by unexpected variation in temperatures. In particular, we analyze whether LNG shipments respond to temperature shocks through adjustments in contract shipments and/or spot shipments.

It is not obvious which margin of adjustment will operate. One hypothesis is that the spot market provides flexibility for buyers to satisfy excess demand that cannot be met through contract shipments. From this perspective, contracts are rigid and contract shipments operate like buses running along fixed routes on a fixed timetable, which does not adjust when demand shocks hit. By contrast, spot shipments are flexible like taxis, and buyers can use the spot market to absorb changes in demand. If this hypothesis holds, we expect to see that colder than expected temperatures in a destination increase spot shipments, but do not affect contract shipments.

However, an alternative hypothesis is that LNG contracts are designed to enhance the flexibility of LNG supply chains by allowing buyers to adjust to demand shocks using contract shipments. In this worldview, endogenous contract incompleteness allows for flexibility in the timing of contract shipments. Consequently, buyers adjust to demand shocks through changes in the timing of contract shipments rather than by varying their spot market purchases. The analysis below supports this hypothesis rather than the more conventional view that adjustment occurs through spot markets. In Section 4, we develop a model to rationalize this feature of the LNG market.

We start by looking at how volumes respond to temperatures in levels. Let Q_{lgt} be the volume of LNG shipped on the route between liquefaction plant l and regasification terminal g in week t, where volumes

are measured in thousand cubic meters. And let $temp_{gt}$ be the mean temperature at the destination in degrees centigrade, where temperatures are observed at the monthly frequency. We start by estimating:

$$Q_{lgt} = \alpha temp_{gt} + \Gamma_{lgy} + \epsilon_{lgt}, \tag{3}$$

where Γ_{lgy} are route-year fixed effects. We estimate this specification for the sample of all active route-years and cluster standard errors at the destination country-month level, which is the level at which the temperature variable is defined.

Table 5 shows the results from estimating equation (3). In column (1), we see that a one-degree increase in the mean monthly temperature at the destination is associated with a 216 cubic meter reduction in volumes, which is about one percent of the mean weekly volume on active route-years. This estimate confirms that lower temperatures are associated with higher LNG shipments. In column (2), we add an interaction between the mean temperature and a dummy for whether the route-year is a contract route. Recall that a contract route is a route-year where contract shipments account for at least 50% of the total volume shipped. We estimate that a one-degree increase in the mean temperature is associated with a 79 cubic meter fall in volumes on spot routes, but a 279 cubic meter fall on contract routes. In columns (3) and (4), the dependent variable is contract volumes and spot volumes on each route, respectively. We find that contract volumes fall by 0.98% and spot volumes fall by 1.3% relative to their mean levels when the temperature is one-degree higher.

Much of the variation in mean temperature across months at a given destination is predictable and the finding in Table 5 that greater volumes arrive in cold weeks is unsurprising. Our interest lies in how buyers respond to unexpected demand shocks. To examine this, we use the weather shock variable defined in Section 2.2, which is (the negative of) the deviation in the mean temperature in a given month from that month's average across years divided by its standard deviation at that destination. This allows us to explore whether more LNG arrives at destinations when it is unseasonably, or unexpectedly, cold. We denote the weather shock variable w_{gt} and estimate:

$$Q_{lgt} = \alpha w_{gt} + \Gamma_{gm} + \epsilon_{lgt}, \tag{4}$$

This specification includes destination-month fixed effects, Γ_{gm}, which control for the average volumes arriving at a destination in a given month of the year. The coefficient of interest α identifies how volumes shipped deviate from this average when the weather is unexpectedly cold.

The results of estimating equation (4) with standard errors clustered at the destination country-month level are shown in Table 6. Because a positive weather shock means that the weather is unpredictably cold at the destination that month, the positive and significant coefficient in column (1) shows that more LNG arrives at the destination when it is colder than in the same calendar month in other years. The coefficient

of 1.042 implies that an increase of one standard deviation in the weather shock is associated with an increase in LNG volumes on a route week of 1.042 thousand cubic meters, or 5% of mean route-week volumes. Column (2) shows that this result is robust to including controls for the total volume supplied by the origin in a year and for route distance, in terms of journey days.

In column (3), we add the contract route dummy and the interaction of this dummy with the weather shock variable. The coefficient on the contract route dummy is positive and significant, showing that contract routes to a destination tend to have larger weekly volumes than spot routes. The coefficient on the weather shock remains positive but is now smaller and insignificant, showing that there is no significant increase in volumes on spot routes when it is unexpectedly cold. However, the interaction of the contract route indicator and the weather shock is positive and significant, suggesting that it is the volumes on contract routes that adjust to unexpected weather shocks. A one standard deviation increase in the weather shock is associated with 5.9% larger volumes on contract routes. We might expect that origins that produce larger quantities of LNG, or that are closer to the destination, are able to respond more quickly to weather shocks. If these routes are also contract routes, then the increased responsiveness on contract routes could be due to this selection effect. However, column (4) shows that the increase in contract route volumes in response to weather shocks remains when controlling for origin size and route distance.

Next, in Table 7, we replace the destination-month fixed effects Γ_{gm} with route-month fixed effects Γ_{lgm}. The route-month fixed effects control for all route-specific factors—such as distance, volume supplied at the origin, and average demand at the destination—and allow for route-specific seasonality in the timing of shipments. Including these fixed effects allows us to identify the effect of weather shocks using variation across years in volumes shipped on a route in a calendar month.

Column (1) of Table 7 shows that, within route-months, total volumes are greater when the temperature is unexpectedly low. In columns (2) and (3), we divide total weekly volumes on each route into contract volumes and spot volumes, respectively. We estimate that a positive weather shock increases contract volumes, but does not have a significant effect on spot volumes. These estimate are consistent with the results in Table 6 showing that volumes are more responsive to weather shocks on contract routes than on spot routes. In columns (4)-(6) we also include the weather shock squared w_{gt}^2 to assess whether the relationship between weather shocks and volumes is non-linear. However, we find no evidence of a quadratic relationship.

Tables 6 and 7 show that contract volumes are responsive to weather shocks, whereas spot volumes are unresponsive. Considered together, the reduced form estimates provide evidence that LNG buyers respond to demand uncertainty not through spot market purchases, but by adjusting contract shipment volumes. This suggests that contracts provide greater flexibility in responding to demand shocks than the spot market offers. In the standard text of LNG contracts, shipment timing over the course of a year is left

unspecified and must be bilaterally negotiated and agreed on a shipment-by-shipment basis. Our analysis suggests that buyers and sellers are able to take advantage of the incomplete nature of LNG contracts to agree shipments at times when they are most valuable for buyers. This insight, together with the condition that maintaining a contractual agreement must be incentive compatible for sellers given their spot market outside option, motivates the structural model of LNG sourcing that we develop in the following section.

4 LNG sourcing model

This section develops a simple theory of buyers' sourcing decisions in the LNG market. We take the set of seller-buyer contracts as given and model whether buyers choose to purchase LNG on the spot market or through a contractual relationship. Motivated by the reduced form evidence in Section 3, we focus on how demand shocks affect the trade-off between contract and spot purchases. Our goal is to build a structural model that is consistent with the reduced-form evidence above and that we can estimate and use to quantify whether contract responsiveness to demand shocks increases the surplus generated by the LNG industry.

4.1 Model environment

We consider a discrete time environment, where t denotes periods. There are two types of agents: L sellers, $l \in 1, 2, ..., L$, and G buyers, $g \in 1, 2..., G$. All agents are risk neutral. Each seller l produces a fixed quantity of LNG in each period t. Each buyer g has fixed installed regasification capacity, allowing them to create value from LNG shipments.

Buyers and sellers are geographically dispersed and vessels containing LNG may travel from sellers to buyers each period.[23] When mapping the model to the data in Section 5, we assume that a period t is a week.[24]

All possible lg pairs are feasible trading routes, and on an exogenous subset of routes the seller l and buyer g have a long-term contract for LNG supply and purchase. In line with the characterization of LNG contracts in Section 2.1, we assume that contracts include a pricing formula that determines how the surplus from each transaction is shared between the seller and the buyer. We model the division of contract shipment surplus by assuming that the seller receives a fraction β_{lg} of the shipment surplus. In addition, contracts are incomplete since they do not specify the timing, or other characteristics, of individual

[23] We do not model the shipping stage of the value chain. Specialized LNG vessels are usually owned by, or on long-leases to, either the seller or the buyer. We assume total shipping capacity is not constrained, and that each available vessel is of a large fixed size.

[24] As shown in Table 2 panel (d), the mean number of days between origin and destination for the shipments on active routes in weeks where there are positive volumes on the route is 8.5. The median is 7.6 days.

shipments. Instead, timing, quantity and other shipment-specific details (such as vessel specifications) must be agreed bilaterally between seller and buyer prior to each shipment.

In this environment, every buyer g with positive LNG demand in period t must decide whether to request a shipment from a contract partner or purchase LNG from the spot market. And, any seller l that receives a request for a contract shipment must decide whether to fulfill the request or sell their output on the spot market. These decisions depend on the payoffs buyers and sellers receive from contract versus spot market shipments, which we turn to next.

4.2 Shipment values

The value that buyers realize from LNG purchases depends on both demand for natural gas in the buyer's location and how successfully the buyer manages the arrival of LNG shipments to maximize the value of its production given its regasification capacity. Because LNG arrives in large, discrete shipments, capacity management requires that buyers optimize over the exact timing of shipments, as well as ensuring that the vessels used have the right specifications for docking at the regasification terminal.

We use a reduced-form model of shipment value that captures these dependencies. Positive demand shocks increase value regardless of whether a shipment is purchased under contract or on the spot market. We model this channel by assuming that shipment value depends on the weather shock w_{gt} that buyer g faces in period t. Weather conditions are observed at the start of each period before buyers and sellers make decisions. We do not model the buyer's quantity choice, since this is determined by its regasification capacity independently of whether it makes purchases under contract or on the spot market.[25] Likewise, sellers produce a fixed quantity of LNG per period.

A buyer's opportunity to manage regasification capacity by purchasing its ideal shipment (in terms of timing, vessel type, etc.) depends on whether it buys a contract shipment or uses the spot market. For contract shipments, the seller can work with the buyer to meet their needs, but this imposes a cost on the seller. We model this cost as having both a non-contracted component, which we label relationship-specific effort, and a contractible fixed cost component.

By contrast, for spot purchases the buyer must simply choose from the shipments available in its location-specific spot market in period t. If the buyer is lucky, it will find a shipment that meets its needs. But, given that LNG spot markets are relatively thin, luck is not guaranteed.[26] We capture this feature of the spot market by assuming that the value of spot purchases is stochastic and depends on the thickness of the local spot market.

[25] Figure 4 shows the distributions of the volumes of contract and spot shipments. The distributions are similar and the mean contract shipment is 138 thousand cubic meters, whereas the mean spot shipment is 137 cubic meters.

[26] Across the 10 destination countries in our sample, the mean number of spot shipments arriving on all active routes ending in that destination country in a week is 1.3 and the median is 1.

4.2.1 Contract shipments

Formally, we assume that the surplus V^c_{lgt} generated by a contract shipment delivered from seller l to buyer g in period t is given by:

$$V^c_{lgt} = v_{gt}\left(w_{gt}\right)\left(h_{lgt}\right)^{\mu} - \tau_{lg} - F_{lt}, \tag{5}$$

where w_{gt} is the weather shock in the buyer's location, $v_{gt}\left(w_{gt}\right)$ is a function that maps the weather shock to the value of a shipment, h_{lgt} denotes the seller's relationship-specific effort and F_{lt} is the fixed cost of a contract shipment. We allow the value function $v_{gt}\left(w_{gt}\right)$ to vary across buyers g and periods t to capture variation in the extent to which weather shocks affect LNG demand. Because the weather shock is defined such that w_{gt} is higher when the weather is cold, and cold weather increases LNG demand, $v_{gt}\left(w_{gt}\right)$ is strictly increasing in w_{gt}. The parameter $0 \leq \mu < 1$ governs the elasticity of the surplus to the seller's relationship-specific effort.

As discussed above, the contract specifies that the seller receives a fraction β_{lg} of the shipment surplus V^c_{lgt}, while the buyer receives the remaining fraction $1 - \beta_{lg}$. Therefore, the seller chooses its relationship-specific effort to maximize $(\beta_{lg} V^c_{lgt} - z h_{lgt})$ where z is the constant marginal cost of effort. Solving this maximization problem implies that the seller's optimal effort level satisfies:

$$h_{lgt} = \left[\frac{\mu\beta_{lg}}{z} v_{gt}(w_{gt})\right]^{\frac{1}{1-\mu}}. \tag{6}$$

The equation shows that seller effort is increasing in the weather shock w_{gt}. A positive weather shock increases shipment value, all else constant, which increases the returns to relationship-specific effort. This complementarity captures the idea that obtaining the ideal shipment to manage capacity utilization is more valuable during periods of high demand. Seller effort is also increasing in the seller's share of surplus β_{lg}, but decreasing in the marginal cost of effort z.

By substituting optimal effort from equation (6) into the surplus equation (5) we obtain:

$$V^c_{lgt} = v_{gt}\left(w_{gt}\right)^{\frac{1}{1-\mu}} \left(\frac{\mu\beta_{lg}}{z}\right)^{\frac{\mu}{1-\mu}} - \tau_{lg} - F_{lt}, \tag{7}$$

which gives the surplus of a contract shipment as a function of the weather shock and model parameters. Note that the buyer's payoff from a contract shipment is given by $\left(1 - \beta_{lg}\right) V^c_{lgt}$.

4.2.2 Spot shipments

Let V^s_{gt} denote the surplus buyer g obtains from purchasing a spot shipment in period t. As for contract shipments, the surplus depends on the weather shock through $v_{gt}\left(w_{gt}\right)$. But because there is no bilateral negotiation on the spot market, it is unlikely that g will be able to buy a spot market shipment that exactly

matches their ideal shipment characteristics. To model this form of shipment differentiation, we introduce a gt-specific shock to spot market value ϕ^s_{gt} and let:

$$V^s_{gt} = \frac{v_{gt}\left(w_{gt}\right)}{\phi^s_{gt}}. \tag{8}$$

We assume $\phi^s_{gt} \geq \Phi_{gt}$ is drawn from a Pareto distribution $F\left(\phi\right) = 1 - \left(\frac{\phi}{\Phi_{gt}}\right)^{-\lambda}$ where $\Phi_{gt} > 0$ is decreasing in the thickness of the local spot market for buyer g in period t. Equation (8) shows that the surplus is decreasing in ϕ^s_{gt}, implying that the expected surplus is increasing in spot market thickness (since $\mathbb{E}\left(\frac{1}{\phi}\right) = \frac{\lambda}{(1+\lambda)\Phi_{gt}}$, which is strictly decreasing in Φ_{gt}). This relationship captures the idea that buyer g is likely to find a better fit for its needs when there are relatively more spot shipments available.

The buyer pays the local spot market price p^s_{gt} for the shipment and the buyer's payoff from using the spot market is $V^s_{gt} - p^s_{gt}$. Any seller l that chooses to supply the spot market in location g receives the spot market price p^s_{gt} less the route-specific transport cost τ_{lg}, implying the seller's payoff is $p^s_{gt} - \tau_{lg}$.

4.3 Shipment choices

In each period t, a buyer g that has a long-term contract with seller l has three options: request a shipment from seller l; purchase a shipment from the location g spot market, or; not purchase LNG this period. Following the evidence in Section 3 showing that contract volumes increase at times when there is an adverse weather shock, we assume that buyers' decisions are consistent with per-period incentive compatibility.

A seller l that receives a shipment request from buyer g has two options: fulfil the request and supply LNG to buyer g, or; sell its output on the spot market. Consistent with the evidence presented in Section 3 showing that sellers choose to fulfil contract shipment requests even in times when their spot market outside alternative is particularly valuable, we assume that sellers' decisions satisfy a dynamic incentive compatibility constraint that accounts for the future value of maintaining a contractual relationship.

We assume that before making decisions, all parties observe the weather shock w_{gt} and the spot price p^s_{gt} in each location, as well as the spot market value shock ϕ^s_{gt} for each buyer. Thus, there is no uncertainty about period-specific payoffs at the point when decisions are made.

4.3.1 Buyer's incentive compatibility constraint

Requesting a contract shipment is incentive compatible for buyer g if and only if the shipment generates positive surplus (i.e. $V^c_{lgt} > 0$) and the buyer's payoff from the contract shipment is greater than its payoff from using the spot market. This condition holds when:

$$(1 - \beta_{lg})V^c_{lgt} \geq V^s_{gt} - p^s_{gt},$$

and using equations (7) and (8) to substitute for the contract surplus V^c_{lgt} and the spot market surplus V^s_{gt}, this inequality is satisfied when:

$$(1-\beta_{lg})\left[v_{gt}\left(w_{gt}\right)^{\frac{1}{1-\mu}}\left(\frac{\mu\beta_{lg}}{z}\right)^{\frac{\mu}{1-\mu}}-\tau_{lg}-F_{lt}\right]\geq\frac{v_{gt}\left(w_{gt}\right)}{\phi^s_{gt}}-p^s_{gt}. \tag{9}$$

4.3.2 Seller's incentive compatibility constraint

To obtain the seller's incentive compatibility constraint, we assume that buyer g plays a trigger strategy, whereby if the seller does not send a contract shipment on request, the buyer ends the contractual relationship. Once the contract is broken, the seller's only option is to supply the spot market. Therefore, sellers choose to fulfil contract shipment requests if and only if the payoff from providing a contract shipment this period plus the expected future value of the contractual relationship exceeds the expected value of selling to the spot market in all periods.

Seller l's payoff from fulfilling a contract request from buyer g in period t equals its share of the surplus generated by a contract shipment less the variable effort costs it incurs: $\beta_{lg}V^c_{lgt}-zh_{lgt}$. By contrast, when selling to the spot market the seller supplies the location where the spot price net of transport costs is highest and receives payoff: $\max_{g'\in G}\left(p_{g't}-\tau_{lg'}\right)$. Hence, the seller's incentive compatibility constraint can be written as follows:

$$\beta_{lg}V^c_{lgt}-zh_{lgt}+\delta_{lt,t+1}U^c_{lgt+1}\geq\sum_{t'\geq t}\delta_{lt,t'}\mathbb{E}\left[\max_{g'\in G}\left(p^s_{g't'}-\tau_{lg'}\right)\right], \tag{10}$$

where U^c_{lgt+1} denotes the expected value for seller l of being in a contractual relationship with buyer g at the start of period $t+1$ and $\delta_{lt,t'}$ denotes the seller's discount factor between t and t'. The summation on the right hand side of equation (10) is taken over all future periods in the lifetime of the contract.

4.3.3 Equilibrium

Conditional on purchasing a shipment in period t, buyer g requests a contract shipment from seller l when $(1-\beta_{lg})V^c_{lgt}\geq V^s_{gt}-p^s_{gt}$. From equation (9) this occurs when the buyer's spot market value shock ϕ^s_{gt} exceeds a threshold ϕ^{s*}_{lgt} given by:

$$\phi^{s*}_{lgt}=\frac{v_{gt}(w_{gt})}{(1-\beta_{lg})\left[v_{gt}(w_{gt})^{\frac{1}{1-\mu}}\left(\frac{\mu\beta_{lg}}{z}\right)^{\frac{\mu}{1-\mu}}-\tau_{lg}-F_{lt}\right]+p^s_{gt}}. \tag{11}$$

Recalling that ϕ^s_{gt} is distributed Pareto with scale parameter Φ_{gt} and shape parameter λ, it follows that the probability that the buyer chooses a contract shipment rather than a spot shipment is:

$$P\left(\phi^s_{gt}\geq\phi^{s*}_{lgt}\right)=\left(\frac{\phi^{s*}_{lgt}}{\Phi_{gt}}\right)^{-\lambda}. \tag{12}$$

We assume contracts are designed to ensure that sellers prefer remaining in a contractual relationship to selling on the spot market. This means that the seller's share of shipment surplus β_{lg} is such that the seller's incentive compatibility constraint in equation (10) is always satisfied, implying that sellers fulfill all requests for contract shipments. Given this assumption, equations (11) and (12) yield the probability that a shipment purchased by buyer g is supplied under contract.

Differentiating these equations implies that the probability of a contract shipment is increasing in in the spot market price p^s_{gt} and decreasing in spot market thickness, the marginal cost of relationship-specific effort z and the fixed cost of providing a contract shipment F_{lt}. Intuitively, a lower spot price or a thicker spot market makes using the spot market more attractive, while lower contract-related costs increase the surplus generated by contract shipments.

Interestingly, conditional on the spot price, the effect of the weather shock w_{gt} on the probability of contract shipments is ambiguous. An increase in w_{gt} raises the value of both contract and spot shipments by increasing $v_{gt}(w_{gt})$. On the one hand, this increase creates an incentive for the buyer to use the spot market to avoid sharing the shipment surplus with the seller. On the other hand, the returns to relationship-specific effort are greater when $v_{gt}(w_{gt})$ is higher, which creates an incentive to request a contract shipment. Provided the parameter μ, which determines the elasticity of contract shipment surplus to relationship-specific effort, is sufficiently large, the later effect dominates, implying that a cold weather shock raises the probability of a contract shipment conditional on the spot price. When estimating the model we use the observed relationship between weather shocks and shipment types to infer the value of μ.

5 Model estimation

In this section, we structurally estimate the model developed above. We start by using the model to derive theoretical moments that relate the probability a buyer purchases a contract shipment to model parameters and observable variables. We then discuss the data that is used to estimate the model. Finally, we describe the empirical moments that we use and how we implement the estimation.

5.1 Theoretical moments

We estimate the model using variation across routes and over time in whether buyers purchase contract shipments or spot shipments. The equilibrium conditions in equations (11) and (12) give the probability that a shipment purchased by buyer g from seller l in period t is a contract shipment. To map these conditions to moments that we can use for estimation, we start by making some functional form assumptions.

We assume that the function $v_{gt}(w_{gt})$, which maps the weather shock to the value of a shipment, differs across destinations and over time depending on the extent to which destinations can satisfy LNG demand using their storage capacity. In some countries, LNG is a core energy source, while in others it serves as a

"peak shaver" at times of high demand. Consequently, investment in storage capacity varies greatly across destinations. Let R_{gt} denote the ratio of total annual LNG demand to storage capacity. Our hypothesis is that a higher value of this ratio implies that destinations are less able to use inventories to smooth out demand shocks, meaning that the value function $v_{gt}(w_{gt})$ will be more responsive to weather shocks. Specifically, we assume:

$$v_{gt}\left(w_{gt}\right) = k_0 + k_1 w_{gt}^{\alpha_0 R_{gt}^{\alpha_1}},$$

where k_0, k_1, α_0 and α_1 are model parameters. If shipment values are more responsive to weather shocks in destinations with more demand relative to storage capacity, then $\alpha_1 > 0$.

Next, we assume that Φ_{gt}, which governs the position of the distribution of shocks to spot market value, depends on the thickness of the local spot market. Specifically, we assume $\Phi_{gt} = (TH_{gt})^{-\phi}$, where TH_{gt} measures spot market thickness in destination g at time t, while $\phi > 0$ is a parameter to be estimated. When $\phi > 0$, the expected surplus from purchasing a spot shipment is increasing in the thickness of the market. Finally, we assume that the fixed cost of fulfilling a contract shipment F_{lt} is higher in periods were the seller provides more contract shipments than usual. We let $F_{lt} = F_0 N_{lt}^{F_1}$, where F_0 and F_1 are parameters, and N_{lt} is defined as the ratio of the number of contract shipments in t to the mean number of contract shipments a seller fulfills in each period.

Let $\mathbb{P}^c_{lgt}$ denote the probability that a shipment from seller l to buyer g in period t is a contract shipment. Substituting the functional form assumptions into equations (11) and (12), and recalling that the surplus generated by a contract shipment V^c_{lgt} satisfies equation (7), gives the key equation that we use to estimate the model:

$$\mathbb{P}^c_{lgt} = \left[\frac{k_0 + k_1 w_{gt}^{\alpha_0 R_{gt}^{\alpha_1}}}{\left(\left(1 - \beta_{lg}\right) V^c_{lgt} + p^s_{gt} \right) \Phi_{gt}} \right]^{-\lambda}, \tag{13}$$

where the shipment surplus satisfies:

$$V^c_{lgt} = \left(k_0 + k_1 w_{gt}^{\alpha_0 R_{gt}^{\alpha_1}} \right)^{\frac{1}{1-\mu}} \left(\frac{\mu \beta_{lg}}{z} \right)^{\frac{\mu}{1-\mu}} - \tau_{lg} - F_0 N_{lt}^{F_1}. \tag{14}$$

Equations (13) and (14) express the probability a shipment is purchased under contract as non-linear functions of model parameters and the observable variables w_{gt}, R_{gt}, TH_{gt}, p^s_{gt}, τ_{lg}, and N_{lt}. There are ten parameters to estimate k_0, k_1 α_0, α_1, ϕ, λ, F_0, F_1, z, and μ, as well as the seller's share of surplus on each route β_{lg}.

Appendix D establishes that each parameter except z and β_{lg} can be separately identified from the theoretical moments in equations (13) and (14). Intuitively, the effect of variation in the weather shock w_{gt} on the probability of a contract shipment identifies the returns to relationship-specific effort μ as discussed in Section 4.3.3. Together with variation in the inverse storage capacity R_{gt}, we also use the weather shock

to identify k, α_0, and α_1. Holding the weather shock constant, variation in spot prices p_{gt} and spot market thickness TH_{gt} identifies ϕ and λ. Likewise, the response of $\mathbb{P}^c_{lgt}$ to N_{lt} gives F_0 and F_1.

The marginal cost of relationship-specific effort z and the seller's share of contract shipment surplus β_{lg} cannot be separately identified from these moments, as they enter equation (13) similarly. Both these parameters affect the seller's incentives to fulfill a contract shipment request. Therefore, to separate them, we combine the theoretical moments in equations (13) and (14) with the seller's incentive compatibility constraint given in equation (10). Specifically, we assume that β_{lg} is such that the incentive compatibility constraint holds with equality, meaning that the seller's expected present discounted payoff from fulfilling contract shipment requests equals the payoff from rejecting the request, breaking the contract and selling on the spot market. This restriction allows us to infer a lower bound for β_{lg} on each route and, consequently, to estimate z.

5.2 Estimation data

Section 4 models decisions about contract shipments at the lgt level given the existence of a contract on route lg at time t, and the ability of supplier l to fulfil buyer g's contract shipment request if one is made. It hence abstracts from several key aspects of the buyer and seller's broader problems. For the purposes of model estimation, we select a subset of the available lgt data to limit the impact of these simplifications.

First, we restrict attention to lgt observations on lg routes where there is a contract in place. To do this we consider those active route-years where at least 50% of the observed shipments are contracted. As shown in Figure 3 and described in Section 2.3, the distribution of contracted shipments is concentrated at zero or one. Second, we focus only on weeks where one of two conditions holds: either we observe at least one contracted shipment on that route-week, or both the seller and buyer are present in the spot market. The second condition ensures that the seller either decided to fulfil all contract shipment requests from the buyer or chose to not fulfil a request and sold on the spot market instead. It also ensures that the buyer had some positive demand in that week. This ensures that the contract shipment surplus defined in equation (7) is positive, which is a necessary condition for the probability a contract shipment is requested by g to be expressed as equation (12). When contract shipment surplus is positive, the buyer's decision is only whether or not to request a contract shipment from a contract seller origin rather than a spot shipment, conditional on having positive demand.[27]

One comment relevant to estimation sample selection is that we use the full set of observations described in Table 2 and in Section 2.3 to construct the gt-specific measure of spot market thickness, Th_{gt}. This variable allows us to estimate how the idiosyncratic shock to spot shipment value varies with the nature of

[27] Our model suggests weeks where buyers receive both contract and spot shipments are times when the buyer would have preferred to receive more contract shipments, but their additional requests were unfulfilled by the seller(s). We implicitly assume that, when they are asked, sellers $l \in L$ send sufficient contract shipments on a route to avoid relationship breakdown.

the local spot market. Our preferred measure is the inverse of the extent to which spot market shipment are concentrated within weeks across the month in each spot market. We find the HHI, summing the squared shares of the spot shipments arriving in each week that month, then divide one by this value. In many spot markets, there are very few shipments in total and the mean of the HHI-type measure is 0.43.[28]

We also use the full set of observations described in Table 2 and in Section 2.3 to construct N_{lt}, which is the number of contracts seller l fulfils in t relative to the typical number. This variable is included in the estimation in the specification that includes the F_1 parameter to allow the fixed costs of contracts to reflect any seller congestion in contract supply in t.

Finally, the discount factor used is $\delta_{lt'} = \frac{1}{1+r_{lt'}}$, where $r_{lt'}$ is the seller-time-specific real interest rate in period t'. This is relevant for estimating the seller's incentive compatibility constraint given in equation (10).[29] Because buyer g makes decisions that are incentive compatible in each time period, estimating the model parameters does not require making any assumptions about buyers' discount factors.

5.3 Empirical moments

There are $30,050$ lgt observations that satisfy the sample restrictions in subsection 5.2. That is, they are on a contract route, where there is either at least one contract shipment on the route, or both the buyer and seller are in the spot market that period.

The empirical moments are the share of all observed shipments that are contract rather than spot. We aggregate the selected route-week observations to the origin-destination country level and find the share of all shipments in a given week to destinations in a given country that are contract shipments. This aggregation gives us $16,818$ empirical moments that we can relate to data on weather and spot price shocks, which are are the destination country-month and destination country-week level, respectively. We call this variable C_{lgt}, with the slight abuse of notation that buyer g now denotes the destination country rather than the destination plant.

In this sample of $16,818$ empirical moments, the share of contract shipments C_{lgt} is positively correlated with the weather shocks, w_{gt}, and with the local spot price, p^s_{gt}, in regressions that include country destination month fixed effects. Although local spot price variation is correlated with weather shocks, there is sufficient independent variation that including both in a regression on C_{lgt} gives positive and significant coefficients for both variables.[30] We will use the coefficients in these three regressions as non-targeted moments in our estimation as a robustness check for the parameter estimates. The regression

[28] Appendix C gives a detailed description of how Th_{gt} is constructed.

[29] These country-year interest rates are taken from the World Development Indicators.

[30] The observations in this regression are weighted by the number of shipments on a route-week observation, lgt.

is:

$$C_{lgt} = \gamma_0 + \gamma_1 w_{gt} + \gamma_2 p^s_{gt} + \varepsilon_{lgt}. \tag{15}$$

We use the weather shock as defined in Section 2.2 and also normalize the distribution of local spot prices, so that the magnitudes of the coefficient estimates are comparable. The regression results are shown in Table 8. The estimated coefficients in the specification with both weather shocks and spot prices on the left hand side, as in equation (15), are $\hat{\alpha}_1 = 0.0167$ and $\hat{\alpha}_2 = 0.0021$, and both are significant at the 1% level.

With both the theoretical moments given in equation (13) and the empirical moments C_{lgt} in hand, we employ non-linear least squares to estimate the model parameters $\boldsymbol{\theta} = \{k_0, k_1, \alpha_0, \alpha_1, \mu, \lambda, \phi, F_0, F_1, \beta, z\}$. We find the parameter values that solve the following minimization problem under the seller's incentive compatibility constraint:

$$\min_{\boldsymbol{\theta}} \sum_{t=1}^{T} \sum_{g=1}^{G} \sum_{l=1}^{L} \left(\left(\frac{\phi^{s*}_{lgt}}{\Phi_{gt}} \right)^{-\lambda} - C_{lgt} \right)^2, \tag{16}$$

where $t = (1, ..., T)$ are the weeks in the data, $g = (1, ...G)$ are destination country buyers, and $l = (1, ..., L)$ are sellers.

6 Results

6.1 Parameter estimates

Estimating equation (16) by non-linear least squares gives model parameter estimates. In this section, we present the model specification that best fits the non-targeted moments. In this version, k_1 is set equal to 1, and both α_1 and F_1 are set equal to zero.

Table 1: Parameter Estimates

Parameter	Description	Estimate	Confidence Interval
k_0	Value function intercept	456	[454, 458]
α_0	Value function elasticity	7.68	[7.56, 7.79]
μ	Effort intensity	0.06	[0.05, 0.06]
z	Marginal effort cost	4.19	[4.08, 4.30]
F	Contract fixed cost	8.97	[8.80, 9.14]
ϕ_0	Spot market thickness position	0.13	[0.12, 0.13]
λ	Spot market thickness elasticity	1.51	[1.48, 1.53]
β	Seller share of contract surplus	0.30	[0.30, 0.30]

All estimates are significantly different from zero. The positive value function elasticity parameter α_0 shows that the value g receives from a shipment is higher when there is a positive weather shock, that is,

when it is unexpectedly cold. The positive estimates of λ shows that the value g receives from spot market shipments is positively associated with Th_{gt}, our measure of local spot market thickness at time t. The coefficient μ of 0.06 shows that relationship-specific seller effort contributes positively to contract shipment value. The positive coefficient F suggests there are fixed costs associated with each contract shipment.

We note that the seller exerts efforts for all contract shipments (since $h > 0$), which incurs variable costs. The seller's share of the contractual relationship surplus is sufficient to compensate them for foregoing spot markets and also exerting effort.[31] In the model, h is an increasing function of the weather shock, and there is a strong positive correlation between estimated h_{lgt} values and w_{gt}. That is, sellers exert effort within contractual relationships when their contract partners face unexpectedly cold weather.

The parameter predictions allow us to predict the responsiveness of C_{lgt}, the share of contract shipments, to observed variation in weather and spot prices using equation (15). Table 9 gives the estimated moments using model parameters. These non-targeted moments are close to the actual data, with the model predicting more variation with each variable than we see in the data.

6.2 Shipment value estimates

The estimated values of the observed contract shipments are shown in Figure 5. The far right histogram in the figure presents calculated shipment values from equation (5) given the functional form assummption for $v(w_{gt})$ made in Subsection 5.1:

$$V^c_{gt}(w_{gt}, h_{lgt}) = (k_0 + k_1 w^{\alpha_0}_{gt})(h_{lgt})^{\mu}$$

The middle histogram subtracts estimated fixed costs, F. The left (purple) histogram is the surplus of contract shipments net of estimated variable seller effort costs, $c(h_{lgt})$. The mean of the left (purple) distribution, weighted by the number of shipments, is 481 and the standard deviation is 76.

The expected spot market shipment value can be calculated from local weather and the estimate of $\Phi_{gt} = Th^{-\phi}_{gt}$, where Th_{gt} is the observed thickness of the local spot market.[32]

It is:

$$E(V^s_{gt}) = E\left(\frac{k_0 + k_1 w^{\alpha_0}_{gt}}{\phi^s_{gt}}\right) = (k_0 + k_1 w^{\alpha_0}_{gt})\frac{\lambda}{(1+\lambda)\Phi_{gt}} \tag{17}$$

Figure 6 shows the calculated expected spot values together with the net contract surplus net of variable effort costs (purple histogram) from Figure 5.

In Figure 6, the blue histogram gives the expected values of spot shipments when at least one spot shipment is observed in lgt, weighted by the actual number of spot shipments observed in the data. The

[31] We note that the seller receives only a β share of the additional surplus generated through its effort, and so effort is suboptimal.

[32] The derivation is: $E(V^s_{gt}) = E\left(\frac{v_{gt}(w_{gt})}{\phi^s_{gt}}\right) = v_{gt}(w_{gt})\int_{\Phi_{gt}}^{\infty}\frac{1}{\phi^s_{gt}}\cdot\lambda\frac{\Phi^{\lambda}_{gt}}{(\phi^s_{gt})^{\lambda+1}}\,d\phi^s_{gt} = v_{gt}(w_{gt})\frac{\lambda}{\lambda+1}\frac{1}{\Phi_{gt}} = \frac{\lambda}{\lambda+1}\frac{1}{\Phi_{gt}}(k_0 + k_1 w^{\alpha_0}_{gt})$.

mean of the distribution is 313 and the standard deviation is 62. The estimated mean value of a spot shipment is hence only 65% of the mean value of a contract shipment. Around 71% of the gains from trade in the current spot market goes to the buyer and around 29% goes to buyers. Note that we estimate $\beta = 0.29$, which is the share of surplus going to sellers in the contract relationships, suggesting that the sellers extract a very similar share of the gains from trade in spot shipments compared to their of the surplus in contract shipments. However, because the magnitude of the surplus is larger for contract shipments, the sellers have around 50% larger gains from trade in contract shipments.

7 Counterfactual Analysis

We now ask how much long-term contractual relationships contribute to industry value relative to a situation where the same vessels arrived in each destination in each period and were transacted in the spot market. That is, the counterfactual is larger spot markets in each lgt where contract shipments are currently observed. The trade-off is that all shipments become "anonymous" arm's length transaction, and sellers exert no relationship-specific effort and incur zero contract fixed and variable costs.

We are able to estimate this counterfactual because the ϕ and λ parameter estimates from Section 6 allows us to calculate the expected spot shipment value as a function of the observed weather shock and the counterfactual spot market thickness, Th_{gt}, using equation (17).

One appeal of this approach is that we do not need to simulate counterfactual spot prices. We also avoid needing to address the seller's allocation problem, that is, where they would send vessels in the absence of contracts. A related benefit is that our counterfactual estimates are invariant to transport costs, which are currently excluded from the analysis, but which remain constant in the counterfactual.

For this analysis, we estimate the counterfactual values of all contract and spot shipments, including those that did not satisfy the estimation sample restrictions in Subsection 5.2. This gives us $31,201$ contract shipments and $6,198$ spot shipments, so $37,399$ shipments in total.

The predicted values of these $37,399$ shipments sold in the enlarged spot markets is given in the red histogram in Figure 7. For comparison, the blue histogram is the distribution of actual spot shipment values given the observed much smaller number of spot shipments, as shown in Figure 6. Figure 7 also includes the observed shipment surplus for contracts net of variable costs (the purple histogram). The red histogram reflects higher counterfactual spot values than in the blue histogram because buyers expect to receive a spot shipment that is a closer fit to their needs in larger spot markets.

Because the counterfactual holds all transport costs fixed, and varies only the value created for buyers, it is possible to compare total welfare in the observed and counterfactual cases.

The total change in welfare can be decomposed into three parts, where the variables with asterisks denote the number of counterfactual shipments, Q_s^*, and the expected value of the distribution of the

expected value of those counterfactual shipments, $E(V_s^*)$:

$$\begin{aligned}\Delta W &= \Delta W_s + \Delta W_c \\ &= Q_s^* E(V_s^*) - (Q_s E(V_s) + Q_c(V(h) - F - c(h)) \\ &= (Q_s + Q_c)E(V_s^*) - (Q_s E(V_s) + Q_c(V(h) - F - c(h))) \\ &= Q_s(E(V_s^*) - E(V_s)) + Q_c(E(V_s^*) - V(h)) + Q_c(F + c(h)) \end{aligned} \tag{18}$$

The first term in equation (18) is the percentage increase in the value of current spot shipments in the counterfactual larger spot market. This change is small, at 0.4%. The second term is the percentage reduction in the value of the shipments that are currently transacted via contracts, and is estimated to be 28.3%. This loss can be attributed to the loss in shipment value from the fact that sellers no longer match these shipments to buyers' exact needs and exert no relationship-specific costly effort to ensure the quality of the match. The third term in equation (18) is the welfare gain coming from the savings in the seller's variable effort costs and fixed costs associated with contract shipments. This saving is equivalent to 1.5% for variable cost savings and 1.5% for fixed cost savings of industry value over the time period studied.

The net impact of the removal of contracts is a reduction in industry value of 24.70%. We infer that total industry size remains too small for spot markets to deliver shipments to buyers that fit their demand even if all industry supply were transacted on global spot markets rather than via contracts.

8 Conclusion

Long-term contracts dominate the LNG industry and the nature of these relationships shapes industry value. This paper brings insights from recent advances in the theory of incomplete contracts to bear on detailed transaction-level data. Our main contribution is the finding that these contracts allow transactions to flexibly adjust to unexpected demand circumstances. We also quantify the significant role played by relationship-specific seller effort in creating value for the buyer. Adaptation, enabled by non-contractible effort, increases industry efficiency relative to a counterfactual of LNG spot markets characterized by frictions from technology and geography. The analysis reveals that the value of the global LNG industry would have been three quarters of its actual size between 2009 and 2019 in the absence of adaptation within long-term contracts.

Figures

Figure 1: LNG spot prices by destination country over time, USD

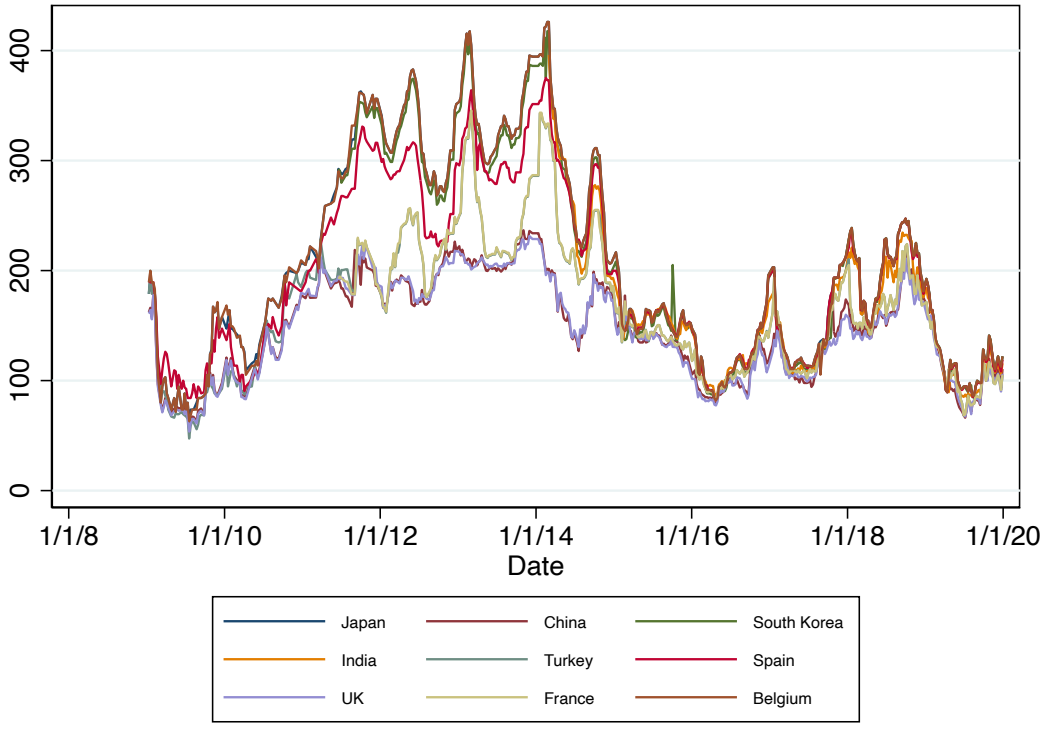
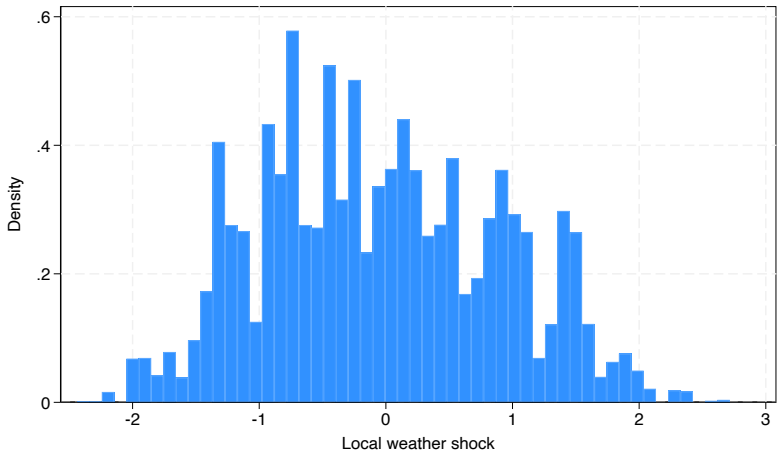


Figure 2: Destination-month temperature shocks, standardized



B.5.

Figure 3: Share of route-year volumes under contract

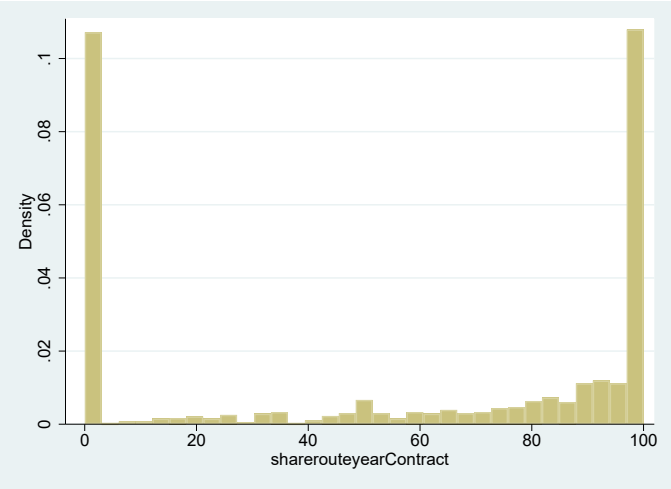


Figure 4: Volume distribution for Contract and Spot shipments

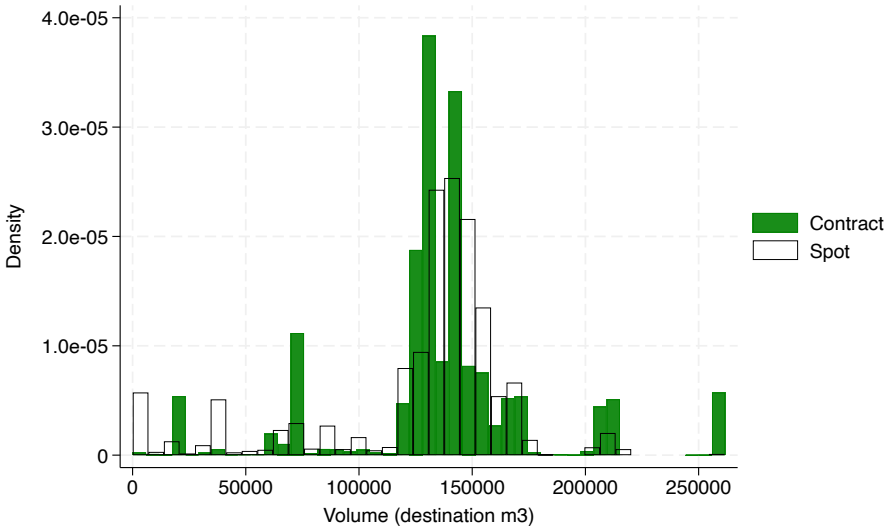


Figure 5: Estimated value of contract shipments

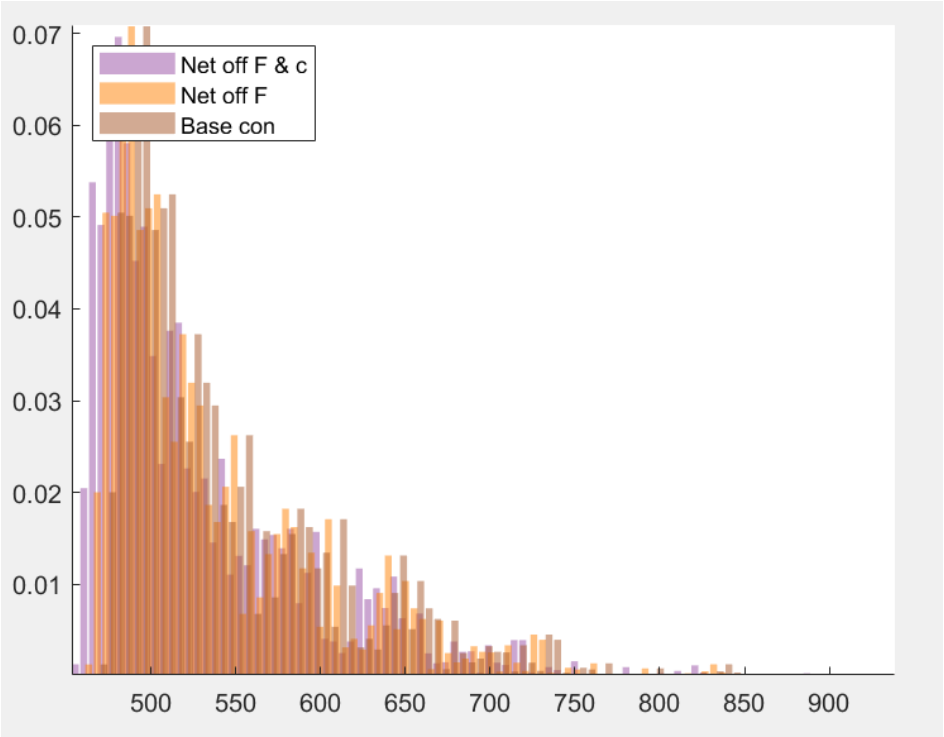


Figure 6: Expected value of spot and contract shipments

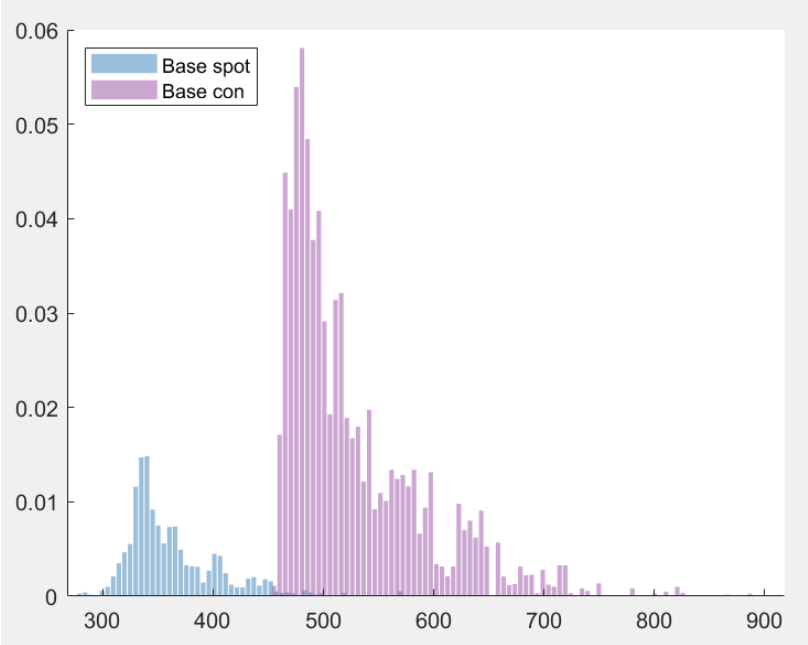
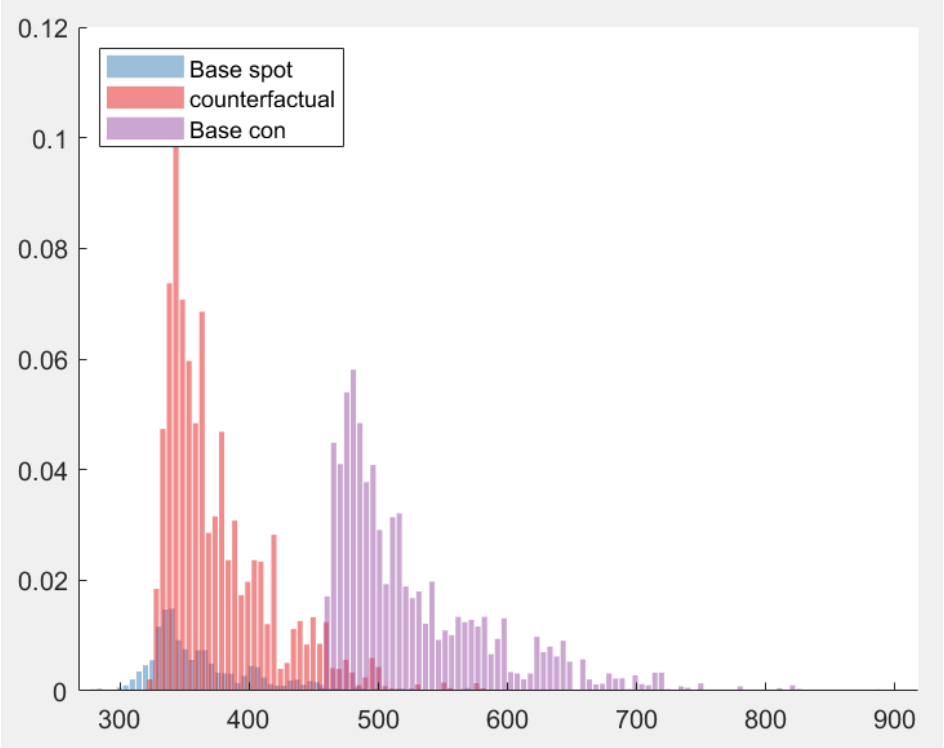


Figure 7: Observed and Counterfactual Shipment Values



Tables

Table 2: Summary statistics for active route-weeks, 2009 to 2019

	Obs	Mean	Std.dev	Min	Max
(a) All weeks					
Total shipments	192,911	0.15	0.42	0	5
Total volumes, $'000m^3$	192,911	20.95	60.77	0.00	999.98
Contract shipments	192,911	0.13	0.39	0	5
Contract volumes, $'000m^3$	192,911	17.72	56.84	0.00	999.98
Spot shipments	192,911	0.02	0.16	0	3
Spot volumes, $'000m^3$	192,911	3.23	21.83	0.00	437.62
(b) Weeks with positive flows of relevant variable					
Total shipments	25,466	1.15	0.42	1	5
Total volumes, $'000m^3$	25,466	158.71	78.15	0.15	999.98
Contract shipments	21,474	1.15	0.43	1	5
Contract volumes, $'000m^3$	21,474	159.21	80.62	0.15	999.98
Spot shipments	4,424	1.03	0.17	1	3
Spot volumes, $'000m^3$	4,424	140.79	37.61	0.87	437.62
(c) All weeks					
Local spot price, USD per m^3	192,911	187.34	84.80	47.34	426.06
Local mean temp, °c	192,911	12.34	8.94	-8.99	31.25
Local temp shock, °c	192,911	-0.04	0.93	-2.44	2.61
Journey days	189,982	10.24	6.49	0.24	28.79
Journey cost, USD per m^3	189,982	16.86	9.39	3.37	45.66
(d) All weeks with positive total volumes					
Local spot price, USD per m^3	25,466	195.90	88.42	47.34	426.06
Local mean temp, °c	25,466	11.63	8.99	-8.99	31.25
Local temp shock, °c	25,466	0.01	0.93	-2.44	2.61
Journey days	25,247	8.47	5.31	0.24	28.79
Journey cost, USD per m^3	25,247	14.30	7.54	3.37	45.66

Table 3: Probability route active in a year.

	(1)	(2)	(3)	(4)	(5)	(6)
Journey days	-0.02***	-0.01***	-0.02***			
	(0.00)	(0.00)	(0.00)			
Volume at origin		0.04***			0.04***	
		(0.00)			(0.00)	
Volume at dest		0.18***			0.18***	
		(0.00)			(0.00)	
Cost per m^3				-0.01***	-0.01***	-0.01***
				(0.00)	(0.00)	(0.00)
Constant	0.44***	0.22***	0.47***	0.46***	0.24***	0.49***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	19556	19556	19556	19556	19556	19556
R^2	0.079	0.235	0.374	0.082	0.238	0.374
Fixed effects	year	year	year, l, g	year	year	year, l, g

Observations are at the route-year level.

Standard errors in parentheses, clustered by year in columns 1,2, 4, and 5

and by year, origin, and destination in columns 3 and 6.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Probability active route mostly contract in a year.

	(1)	(2)	(3)	(4)	(5)	(6)
Journey days	-0.004	-0.004	-0.012		-0.004	-0.014**
	(0.003)	(0.003)	(0.009)		(0.006)	(0.005)
l-year volume		0.014***			0.018***	
		(0.002)			(0.003)	
g-year volume		0.025***	0.055***		0.007	0.028**
		(0.006)	(0.013)		(0.014)	(0.009)
Weather variability				0.338***	0.338***	0.259**
				(0.098)	(0.100)	(0.094)
Constant	0.719***	0.650***	0.756***	0.403***	0.375**	0.594***
	(0.026)	(0.025)	(0.093)	(0.096)	(0.146)	(0.127)
Observations	5059	5059	5059	4264	4205	4196
R^2	0.015	0.033	0.201	0.032	0.062	0.294
Fixed effects	y	y	l-y	y	y	l-y

The dependent variable is the probability an active route is a contract route.

Weather variability is the mean standard deviation in month level temperatures across years.

Standard errors in parentheses, clustered at the year level in all columns, also at the origin level in column 3 also at the destination country level in columns 4 and 5 and also at the origin-year level in column 6.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Route-week volumes

	(1)	(2)	(3)	(4)
	Total	Total	Contract	Spot
Mean temp	-0.216***	-0.079***	-0.173***	-0.043***
	(0.016)	(0.020)	(0.013)	(0.007)
Mean temp * contract route		-0.200***		
		(0.025)		
Constant	23.610***	23.650***	19.855***	3.755***
	(0.237)	(0.238)	(0.192)	(0.119)
Observations	192910	192910	192910	192910
R^2	0.361	0.361	0.389	0.087
Fixed effects	route-year	route-year	route-year	route-year

Observations are route-week volumes on active route-years.

Volumes are in ′000 cubic meters.

Standard errors in parentheses, clustered at destination country-month level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Route-week volumes

	(1)	(2)	(3)	(4)
	Total	Total	Total	Total
Weather shock	1.042***	0.946***	0.113	0.379
	(0.184)	(0.184)	(0.243)	(0.272)
Total vol origin		3.066***		2.811***
		(0.273)		(0.270)
Journey days		-0.908***		-0.878***
		(0.047)		(0.060)
Contract route			19.714***	14.243***
			(0.847)	(0.662)
Weather shock * contract route			1.125***	0.681**
			(0.297)	(0.321)
Constant	21.001***	18.751***	7.240***	9.423***
	(0.009)	(0.970)	(0.588)	(1.093)
Observations	192909	189980	192909	189980
R^2	0.067	0.123	0.086	0.132
Fixed effects	dest-month	dest-month	dest-month	dest-month

Observations are route-week volumes on active route-years.

Volumes are in ′000 cubic meters.

Standard errors in parentheses, clustered at destination country-month level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Route-week volumes

	(1) Total	(2) Contract	(3) Spot	(4) Total	(5) Contract	(6) Spot
Weather shock	0.745***	0.648***	0.097	0.754***	0.662***	0.092
	(0.175)	(0.156)	(0.075)	(0.175)	(0.154)	(0.076)
Weather shock sq				-0.099	-0.166	0.067
				(0.184)	(0.164)	(0.079)
Constant	20.988***	17.757***	3.232***	21.074***	17.900***	3.174***
	(0.008)	(0.007)	(0.004)	(0.159)	(0.140)	(0.068)
Observations	192859	192859	192859	192859	192859	192859
R^2	0.350	0.369	0.110	0.350	0.369	0.110
Fixed effects	route-month	route-month	route-month	route-month	route-month	route-month

Observations are route-week volumes on active route-years.

Volumes are in ′000 cubic meters.

Standard errors in parentheses, clustered at destination country-month level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Non-targeted moments share of contract shipments.

	(1) prob	(2) prob	(3) prob
Weather shock	0.062***		0.043***
	(0.012)		(0.013)
Local spot price (normalized)		0.063***	0.056***
		(0.011)	(0.011)
Constant	0.366***	0.376***	0.351***
	(0.009)	(0.006)	(0.010)
Observations	19588	16818	16818
R^2	0.002	0.002	0.003

Observations are the share of shipments that are via contract on origin-destination country routes in weeks that satisfy sample selection criteria.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Non-targeted moments

Coefficient	Data	Model predictions
Weather shock	0.0167***	0.0164***
	(0.0055)	(0.0013)
Local spot price	0.0021***	0.0020***
	(0.0002)	(0.0005)

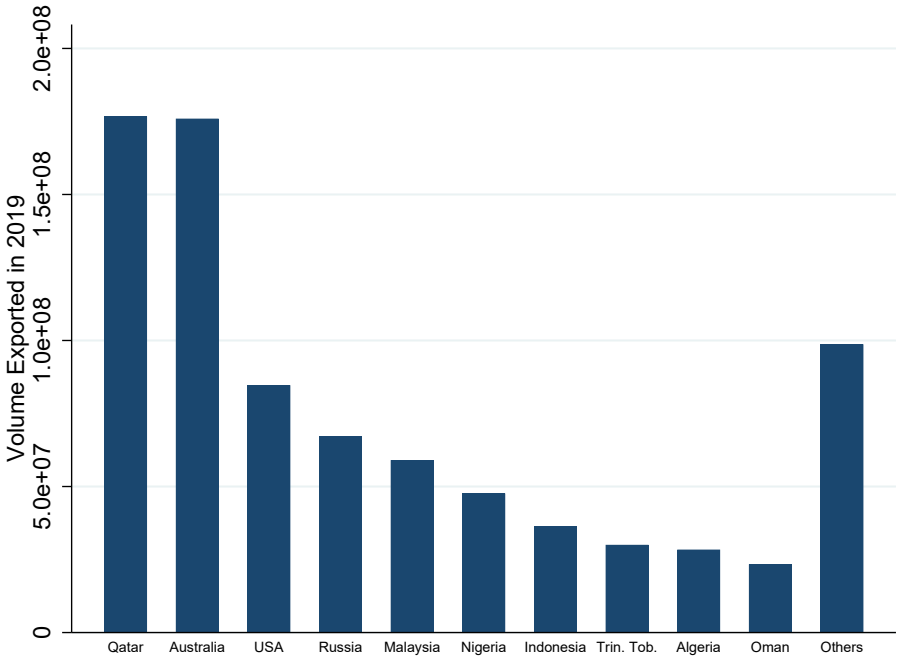
Appendix

A Global supply and demand in 2019

A.1 Supply

The shipment-level data we use, which runs from the start of 2009 to the end of 2019, contains shipments from 19 countries. Qatar has been the largest exporter historically, with over 500 shipments in each of the 11 years. Australia has increased exports over the time period, and exported more than 500 shipments in the last four years in the data. After Qatar and Australia, the largest exporter countries are Malaysia, Indonesia, Algeria, and Nigeria. Figure A.1 focuses on 2019, and shows total volumes exported by source country in cubic metres. The USA, Russia, and Trinidad and Tobago are more prominent in 2019 than in the period as a whole.

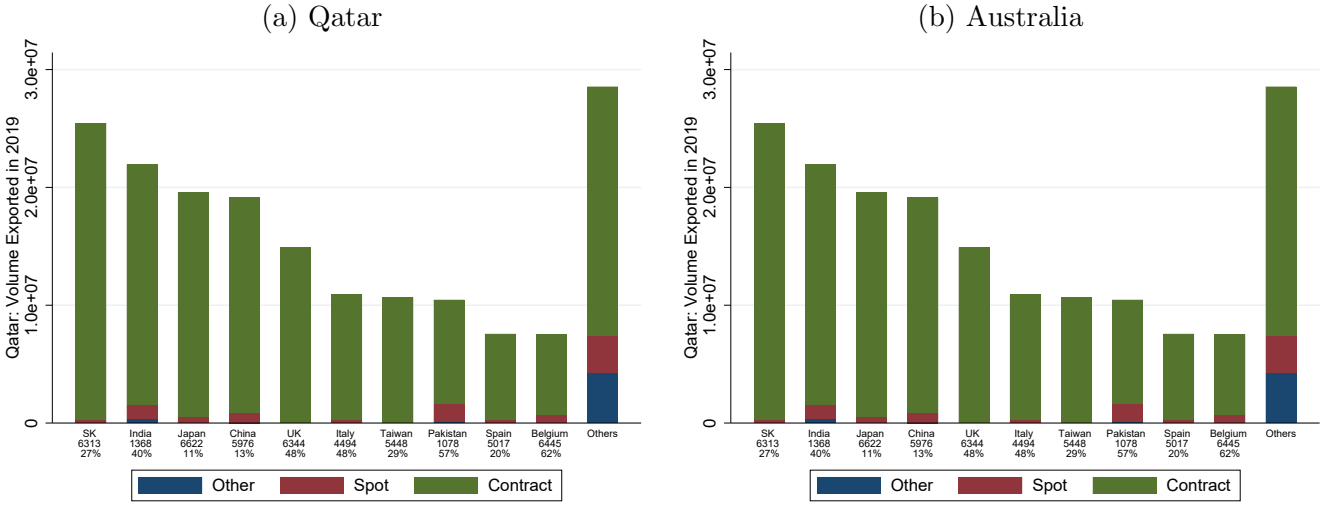
Figure A.1: Largest exporter countries in 2019



Because the LNG industry is a costly shipping technology for a commodity product, we might think that

both sellers and buyers have incentives to minimize the distance travelled. The overall flows confirm this, in general. For example, Figure A.2 shows that the two largest destinations for Australia are the relatively close Japan and China, where Australia supplies 39% and 47% of these countries' LNG, respectively. Qatar supplies less of these countries' demand, at 11% and 13%. The figures below the country name show the average mileage travelled on routes between the source and destination countries. The LNG travelling to Japan and China from Australia travels much shorter distance than the LNG from Qatar.

Figure A.2: Volume by Destination, 2019



However, there are exceptions. For example, Qatar supplies 27% of South Korea's LNG and 29% of Taiwan's despite LNG having to travel over 5,000 miles to get there. Australia is much closer to both destinations and supplies only 19% and 27%, respectively.[33] We suspect deviations from gravity relate to the staggered timing at which liquefaction and regasification capacity was installed in different countries and the agreed long term contracts between buyers and sellers.

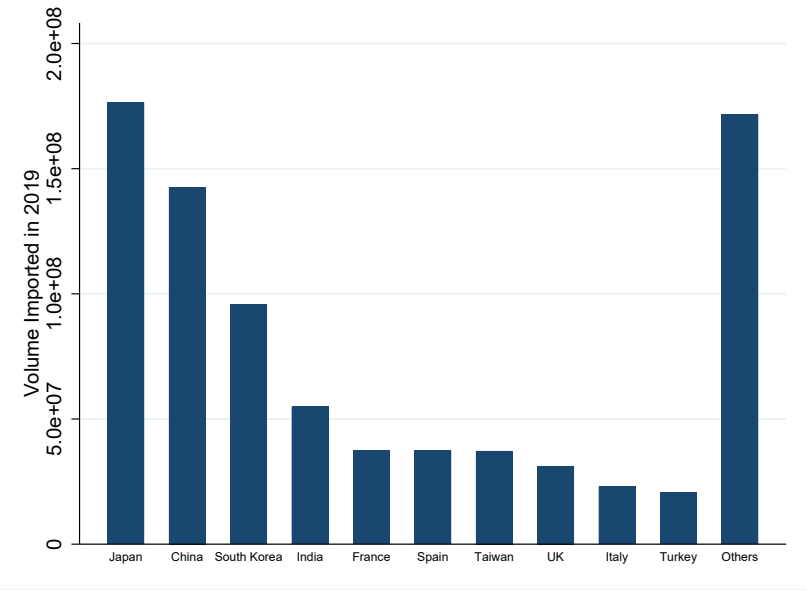
Figure A.2 also offers some insight about how shipments are organized. The bulk of LNG exports from Qatar in 2019 were contracted quantities, meaning very little LNG from Qatar ended up in the spot market. For Australia, spot volumes were relatively more common.

Figure A.3 focuses on 2019, and shows total volumes imported by destination country.

Figure A.4 shows the volumes arriving in Japan in 2019 by source country. The figures below the country names are the average distance travelled and the share of that country's LNG exports arriving in Japan. There are some interesting comparisons. Australia sends Japan 39% of its output but is much

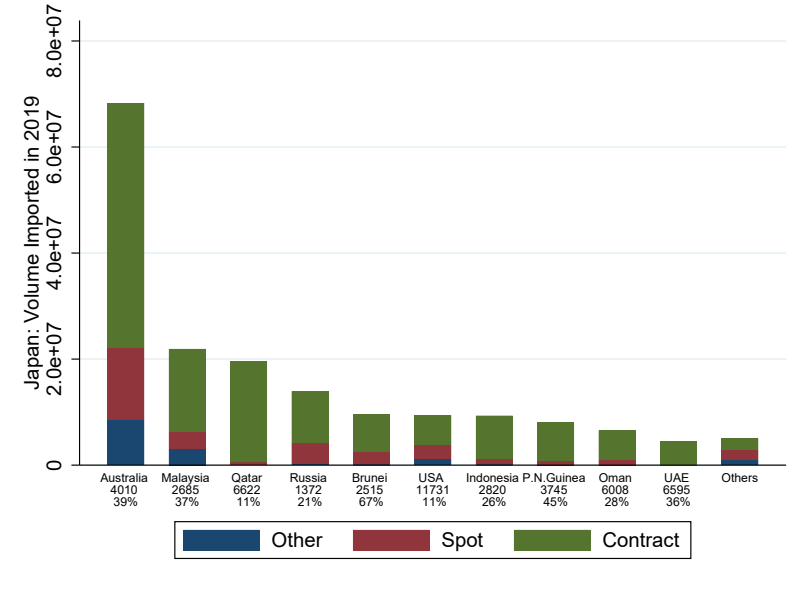
[33] We have some data on production costs. Qatar has a much lower operating production cost than the installations in Australia (see supply functions in earlier update), so the delivered cost from Qatar may still be much lower than from Australia.

Figure A.3: Largest importer countries in 2019



further away than Malaysia, which sends a similar share of its total output to Japan.

Figure A.4: Japan imported volumes by Origin, 2019



B Lower bounds on buyer values for contract shipments

This appendix estimates lower bounds on the value of receiving LNG in a contract shipment rather than a spot shipment. It takes as given the thickness of the spot market and status quo spot prices. Our starting point is the analysis in Section 3, showing that buyers request contract shipments in periods when they have positive demand, which is also when spot prices tend to be high. We ask how much more valuable contract shipments must be to buyers in order to be consistent with contract prices that are sufficiently

high to ensure both buyers and sellers find it incentive compatible to maintain the contract .

We introduce the notation that will also be used in the model in Section 4. When there is a contract in place on a given seller-buyer route, the downstream buyer, g, has a value V_{lgt} for one cubic metre of LNG arriving from seller l in a contract shipment at time t. The value g has for a spot shipment in t is V^s_{gt}, which is not l-specific.

The per cubic metre prices for LNG arriving via contract and spot are denoted p^c_{lgt} and p^s_{gt}, respectively. A seller can deliver shipments at time t to any of their contract partners or sell on any spot market, so the relevant spot price for the seller is the highest available spot price in t, net of the destination-specific transport costs. The object of interest in this section is $V^c_{lgt} - V^s_{gt}$ and the challenge is that only p^s_{gt} and bilateral transport costs, τ_{ij} are observed in the data (using Wood Mackenzie data on bilateral transport costs.)

We start by considering the buyer's surplus from a contract shipment, $V^c_{lgt} - p^c_{lgt}$, and appeal to revealed preference: whenever the buyer receives a contract shipment, it must create more value for them than would a spot shipment at the local prevailing spot price. That is, buyer incentive compatibility requires:

$$V^c_{lgt} - p^c_{lgt} \geq V^s_{gt} - p^s_{gt},$$

or, equivalently,

$$V^c_{lgt} - V^s_{gt} \geq p^c_{lgt} - p^s_{gt}. \tag{19}$$

Turning next to the seller's incentive compatibility constraint, we argue that sellers must, on average, receive at least as much as what they could earn selling the same quantities on spot markets over the contract relationship. For simplicity, in this section, we let the seller be forward-looking only over the month of a relevant contract shipment. The seller's dynamic incentive compatibility constraint implies that the contract prices they receive in expectation, net of transport costs to g, must exceed the expected highest net spot price in t in the periods t when contract shipments are delivered:

$$E(p^c_{lgt} - \tau_{ij}) \geq E(max_G(p^s_{gt} - \tau_{lg})), \tag{20}$$

where expectations are taken over all spot markets, G, over the contracted time period. We note that this is clearly a lower bound on the surplus required to align sellers' incentives in the relationship since it does not account for any variable or differential fixed costs incurred on contract shipments (other than the transport costs).

If both parties' expectations are consistent, we can combine the incentive compatibility constraints (19) and (20) to give:

$$E\left(V^c_{lgt} - V^s_{gt}\right) \geq E(p^c_{lgt}) - p^s_{gt} \geq E(max_G(p^s_{gt} - \tau_{lg})) + \tau_{lg} - p^s_{gt}. \tag{21}$$

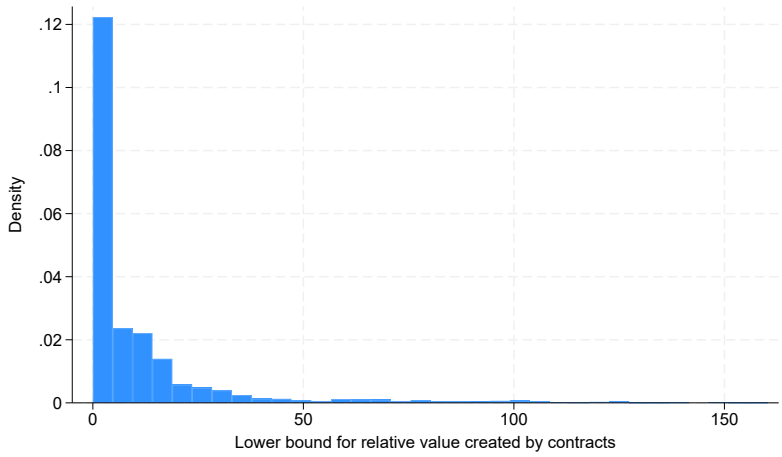
The right had side of inequality (21) can be calculated using data on spot prices in all g and bilateral transport costs τ_{lg} at all destination at times when contracts are received by buyer g.

The data yield an estimate of a lower bound on $E\left(V^c_{lgt} - V^s_{gt}\right)$ per cubic metre of LNG received under contract by destination g in month t, which is the contract period under consideration in this section. We find estimates at the contract shipment level and then find the mean for each route-year. $3,070$ route-years. Mean contract shipment value per shipment is \$10.97 per cubic meter, which is 5.9% of the mean spot price net of transport costs for the lgt observations where we have contract shipments and all the required data.

While we have made some strong assumptions to derive these lower bounds on the value contract shipments create for buyers under prevailing spot prices, the logic follows the simple intuition that the relative expected value from a contract is sufficient to compensate the seller for not switching to the spot market when the spot price is high together with the amount required to compensate the buyer for not switching to the spot market when the price is low at times of similar demand.

Figure B.5 is a histogram of the estimated lower bounds of the relative value per cubic metre of LNG arriving at the destination in contract shipments compared to available spot shipments for the $1,158$ buyer-months in this analysis.

Figure B.5: Relative value of contract shipments



A regression of route-year mean contract shipment value on 11 year fixed effects has an adjusted R-squared of 0.06. Including only fixed effects for the 82 buyers that appear in this data sample gives an adjusted R-squared of 0.36. A regression with 556 fixed effects for the interaction of buyer and year fixed effects gives an adjusted R-squared of 0.75.[34]

The estimated lower bounds can be interpreted as the value of a contract shipment over a unilateral

[34] A similar exercise grouping time periods by destination-specific demand shock and assuming the difference between contract shipment value and contract price is at least as large as the difference between the highest and lowest prices paid for spot shipments under similar demand conditions yields similar estimates of relative contract value lower bounds.

deviation to a spot shipment in the same week, conditional on the vector of global spot prices at that time and the matrix of bilateral transport cost. In order to derive estimates of the relative value, rather than lower bounds, we need a structural model that delivers estimates of LNG demand and the relationship between spot market size and buyer spot value, as well as the nature of seller effort in contractual relationships and the division of contract surplus. This is the purpose of the Section 4 where we exploit exogenous weather shocks as well as local spot price variation.

C Measuring spot market thickness, Th_{gt}

Our preferred measure of spot market thickness relates to the extent to which spot shipments arriving at a destination country are bunched within weeks over a month.[35] The intuition is that if spot shipments are more evenly spaced during the month then sellers have, collectively, made spot shipments available to buyers in that market throughout that month. In contrast, if spot shipments are all bunched in a week then perhaps buyers would not have been able to easily find a spot shipment to fit their needs at any point during the month.

The degree of spot market concentration within a month is the sum of the squares of the shares of monthly spot shipments arriving in each week during that month. We calculate this from the shipment-level data used in the reduced form estimates in Section 3. Because of the relative sparseness of spot markets, we aggregate the five European countries (Belgium, France, Spain, Turkey, and the UK) to one spot region while keeping the Asian countries as separate spot regions. This HHI-type variable can be constructed for all spot region-months with at least one spot shipment, which is $1,254$ observations. The mean of the distribution is 0.43, the standard deviation is 0.23, with the minimum value at 0.20 and the maximum at 1.

Spot market thickness, Th_{gt}, is the inverse of the concentration measure. That is, the less concentrated the arrival times, the thicker the spot market in that region that month.

This definition of spot market thickness lends itself well to constructing a measure for the counterfactual analysis. In the counterfactual, all contract shipments arriving in a destination are added to those already on the spot market, to produce an enlarged spot market. To calculate the degree of concentration of all shipment arrival times per week within a month, we find the sum of squares of the share of shipments arriving in each week. This measure can be constructed for $1,138$ spot market-month observations, for all those with at least one shipment in total.

The distribution of HHI-type measures produced in this counterfactual is shifted to the left, that is, shipments are far less concentrated by week. The mean is 0.25 and the standard deviation is 0.03. The

[35] We also have data on the share of spot shipments in a market and the relative vessel size distribution of spot shipments in a market, but these measures are less easily adapted for the counterfactual analysis.

range is 0.2 to 0.56. The spot market thickness in a spot market-month in the counterfactual is the inverse of this measure.

D TO BE UPDATED. CURRENT VERSION IS FOR PRIOR MODEL. Model identification proof.

We employ Nonlinear Least Squares estimation to identify the model parameters, denoted $\boldsymbol{\theta} = \{k, \alpha_0, \alpha_1, \lambda_0, \lambda_1, F_0, F_1,$ Specifically, we find the parameter values that solve the following minimization problem:

$$\min_{\boldsymbol{\theta}} \sum_{t=1}^{T} \sum_{g=1}^{G} \sum_{l=1}^{L} \left((\phi_{lgt}^{s*})^{-\lambda_{gt}} - C_{lgt} \right)^2 .$$

This appendix shows that this highly nonlinear model with numerous parameters is identified. Silvey (1970) state that a model is identifiable if no two different sets of parameter values result in the same model. One obvious cause of non-identifiability, therefore, is parameter redundancy, when a model can be respecified in terms of a smaller set of parameters (Catchpole and Morgan (1997)).

Cole, Morgan, and Titterington (2010) provided a comprehensive framework for detecting parameter redundancy. Applied to our model, it starts with defining the vector $\boldsymbol{\kappa} = [\kappa_{111}, \kappa_{121}, ...\kappa_{lgt}.., \kappa_{LGT}]^T$ with $\kappa_{lgt} = (\phi_{lgt}^{s*})^{-\lambda_{gt}}$. If the rank of $\boldsymbol{C} \equiv \frac{\partial \boldsymbol{\kappa}}{\partial \boldsymbol{\theta}}$, denoted r, is smaller than the number of parameters q in $\boldsymbol{\theta}$, then the model is parameter redundant and will be non-identifiable. This scenario aligns with the concept of rank-deficient nonlinear least squares, which typically does not yield a unique solution (Eriksson and Gulliksson, 2004). Conversely, if $r = q$, the model is of full rank, not parameter redundant, and will be at least locally identifiable.[36].

Given our two functional forms of interest, $v(w_{gt}) = k w_{gt}^{\alpha_0 R_{gt}^{\alpha_1}}$ and $\lambda_{gt} = \lambda_0 T H_{gt}^{\lambda_1}$, with $k > 0, \alpha_0 > 0, F_0 > 0, \lambda_0 > 0, \mu > 0$, where R_{gt} is the ratio of annual demand to storage capacity, w_{gt} is the normalized weather shock, and Th_{gt} is spot market thickness, we can express κ_{lgt} as follows:

$$\begin{aligned}
\kappa_{lgt} &= \left(\frac{v(w_{gt})}{(1-\beta) v(w_{gt})^{\frac{1}{1-\mu}} (\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} - (1-\beta)F + E(P_{gt})} \right)^{-\lambda_{gt}} \\
&= \left(\frac{(1-\beta) v(w_{gt})^{\frac{1}{1-\mu}} (\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} - (1-\beta)F + E(P_{gt})}{v(w_{gt})} \right)^{\lambda_{gt}} \\
&= \left((1-\beta)(\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} (k w_{gt}^{\alpha_0 R_{gt}^{\alpha_1}})^{\frac{\mu}{1-\mu}} - (1-\beta)F \frac{1}{k} w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} + E(P_{gt}) \frac{1}{k} w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} \right)^{\lambda_0 T h_{gt}^{\lambda_1}},
\end{aligned}$$

which can be rewritten as:

$$\kappa_{lgt} = \left(G (k w_{gt}^{\alpha_0 R_{gt}^{\alpha_1}})^{\frac{\mu}{1-\mu}} - \tilde{F} \tilde{k} w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} + E(P_{gt}) \tilde{k} w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} \right)^{\lambda_0 T h_{gt}^{\lambda_1}},$$

[36] See Cole, Morgan, and Titterington (2010), Theorem 2a

where

$$\tilde{k} = \frac{1}{k},$$
$$\tilde{F} = (1-\beta)F,$$
$$G \equiv (1-\beta)\left(\frac{\beta\mu}{c}\right)^{\frac{\mu}{1-\mu}}.$$

Because an increase in the marginal seller effort cost c can be offset by a decrease in the seller share of surplus β, c cannot be separately identified. Therefore, the parameters that need to be checked for identifiability are $\theta = [\tilde{k}, \alpha_0, \alpha_1, \tilde{F}, G, \mu, \lambda_0, \lambda_1]$.

The first derivative matrix for κ_{lgt}, $\boldsymbol{C} \equiv \frac{\partial \boldsymbol{\kappa}}{\partial \boldsymbol{\theta}}$, is given by

$$\boldsymbol{C} = \frac{\partial \boldsymbol{\kappa}}{\partial \boldsymbol{\theta}} = \begin{bmatrix} \frac{\partial \kappa_{111}}{\partial \theta_1} & \frac{\partial \kappa_{121}}{\partial \theta_1} & \dots & \frac{\partial \kappa_{LGT}}{\partial \theta_1} \\ \frac{\partial \kappa_{111}}{\partial \theta_2} & \frac{\partial \kappa_{121}}{\partial \theta_2} & \dots & \frac{\partial \kappa_{LGT}}{\partial \theta_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \kappa_{111}}{\partial \theta_9} & \frac{\partial \kappa_2}{\partial \theta_9} & \dots & \frac{\partial \kappa_{LGT}}{\partial \theta_9} \end{bmatrix}$$

If the model is not parameter redundant, then the rank of the matrix $\boldsymbol{D}$ should be equal to the number of parameters, in which case the matrix has full row rank. To demonstrate this, we derive the first derivatives contained within the matrix:

$$\frac{\partial \kappa_{lgt}}{\partial \tilde{k}} = \lambda_{gt}\kappa_{lgt}^{\frac{\lambda_{gt}-1}{\lambda_{gt}}}\left(-G\frac{\mu}{\mu-1}(kw_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}})^{\frac{1}{\mu-1}} - \tilde{F} + E(P_{gt})\right) w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}}$$

$$\frac{\partial \kappa_{lgt}}{\partial \alpha_0} = -\lambda_{gt}\kappa_{lgt}^{\frac{\lambda_{gt}-1}{\lambda_{gt}}}(E(P_{gt}) - \tilde{F}_0 G S_{lt}^{F_1}\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} + G\frac{\mu}{\mu-1}(\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}}))\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} R_{gt}^{\alpha_1}\ln w_{gt}$$

$$\frac{\partial \kappa_{lgt}}{\partial \alpha_1} = -\lambda_{gt}\kappa_{lgt}^{\frac{\lambda_{gt}-1}{\lambda_{gt}}}(E(P_{gt}) - \tilde{F}_0 G S_{lt}^{F_1}\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} + G\frac{\mu}{\mu-1}(\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}}))\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} \alpha_0 R_{gt}^{\alpha_1}\ln w_{gt}\ln R_{gt}$$

$$\frac{\partial \kappa_{lgt}}{\partial F_0} = \lambda_{gt}\kappa_{lgt}^{\frac{\lambda_{gt}-1}{\lambda_{gt}}} G S_{lt}^{F_1}\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}}$$

$$\frac{\partial \kappa_{lgt}}{\partial F_1} = \lambda_{gt}\kappa_{lgt}^{\frac{\lambda_{gt}-1}{\lambda_{gt}}} \tilde{F}_0 G S_{lt}^{F_1}\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}}\ln GS_{lt}$$

$$\frac{\partial \kappa_{lgt}}{\partial G} = \lambda_{gt}\kappa_{lgt}^{\frac{\lambda_{gt}-1}{\lambda_{gt}}}(\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}})^{\frac{\mu}{\mu-1}}$$

$$\frac{\partial \kappa_{lgt}}{\partial \mu} = -\lambda_{gt}\kappa_{lgt}^{\frac{\lambda_{gt}-1}{\lambda_{gt}}}(G(\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}})^{\frac{\mu}{\mu-1}}\frac{\ln(\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}})}{(\mu-1)^2})$$

$$\frac{\partial \kappa_{lgt}}{\partial \lambda_0} = \kappa_{lgt} \ln \kappa_{lgt}^{\frac{1}{\lambda_{gt}}} T h_{gt}^{\lambda_1}$$

$$\frac{\partial \kappa_{lgt}}{\partial \lambda_1} = \kappa_{lgt} \ln \kappa_{lgt}^{\frac{1}{\lambda_{gt}}} \lambda_0 T h_{gt}^{\lambda_1} \ln T h_{gt}$$

The matrix $\boldsymbol{C}$ is of full row rank if the only solution to the following equation, satisfied simultaneously for all lgt-level data, is $\beta^i = 0, \forall i \in \boldsymbol{\theta}$.

$$\beta^{\tilde{k}} \frac{\partial \kappa_{lgt}}{\partial \tilde{k}} + \beta^{\alpha_0} \frac{\partial \kappa_{lgt}}{\partial \alpha_0} + \beta^{\alpha_1} \frac{\partial \kappa_{lgt}}{\partial \alpha_1} + \beta^{F} \frac{\partial \kappa_{lgt}}{\partial F} + \beta^{G} \frac{\partial \kappa_{lgt}}{\partial G} + \beta^{\mu} \frac{\partial \kappa_{lgt}}{\partial \mu} + \beta^{\lambda_0} \frac{\partial \kappa_{lgt}}{\partial \lambda_0} + \beta^{\lambda_1} \frac{\partial \kappa_{lgt}}{\partial \lambda_1} = 0 \tag{22}$$

where β^i represents the coefficients associated with each parameter i in the parameter set $\boldsymbol{\theta}$. This condition requires that each parameter i in $\boldsymbol{\theta}$ does not contribute linearly to the model outcomes, which ensures that $\boldsymbol{C}$ is of full row rank by demonstrating the linear independence of its rows.

Upon substituting the first derivatives into the matrix $\boldsymbol{D}$ and collecting terms, we obtain the following expression:

$$\begin{aligned}
0 =& (\beta^{\tilde{k}} - \beta^{\alpha_0} \tilde{k} R_{gt}^{\alpha_1} \ln w_{gt} - \beta^{\alpha_1} \tilde{k} \alpha_0 R_{gt}^{\alpha_1} \ln w_{gt} \ln R_{gt}) H_{lgt}^{v} \\
&+ (\beta^{F_0} + \beta^{F_1} \tilde{F}_0 \ln G S_{lt}) H_{lgt}^{F} \\
&+ (\beta^{C} - \beta^{\mu} (G \frac{\ln(\tilde{k} w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}})}{(\mu - 1)^2})) H_{lgt}^{G} \\
&+ (\beta^{\lambda_0} \frac{1}{\lambda_0} + \beta^{\lambda_1} \ln T h_{gt}) H_{lgt}^{\lambda}
\end{aligned} \tag{23}$$

where $H_{lgt}^{v} \equiv (E(P_{gt}) - \tilde{F}_0 G S_{lt}^{F_1} \tilde{k} w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}} + G \frac{\mu}{\mu - 1} (\tilde{k} w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}})^{\frac{1}{\mu - 1}}) w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}}$, $H_{lgt}^{F} \equiv G S_{lt}^{F_1} \tilde{k} w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}}$, $H_{lgt}^{G} \equiv (\tilde{k} w_{gt}^{\alpha_0 R_{gt}^{\alpha_1}})^{\frac{\mu}{\mu - 1}}$, and $H_{lgt}^{\lambda} \equiv \kappa_{lgt}^{\frac{1}{\lambda_{gt}}} \ln \kappa_{lgt}^{\frac{1}{\lambda_{gt}}}$.

Parameter redundancy in a model can be categorized into two types: intrinsic parameter redundancy, which is inherent to the model structure regardless of the data, and extrinsic parameter redundancy, which arises due to the characteristics of the dataset used. For instance, consider a scenario where $w_{gt} = 1 \, \forall gt$. In such a case, the parameters β^{α_0} and β^{α_1} can assume any values, while all other parameters $\beta^i = 0 \, \forall i \neq \alpha_0, \alpha_1$, thus satisfying equation (22) and leading to parameter redundancy induced by this specific dataset. This prevents the identification of β^{α_0} and β^{α_1}.

Given a sufficiently large and varied dataset, our analysis is concentrated on intrinsic parameter redundancy, under the assumption of an ideal dataset. This entails that the functions $H_{lgt}^{v}, H_{lgt}^{F}, H_{lgt}^{G}, H_{lgt}^{\lambda}$ are linearly independent, given our parameter assumptions that $k > 0, \alpha_0 > 0, F_0 > 0, \lambda_0 > 0, \mu > 0$.

Consequently, it must follow that each coefficient in front of $H^i, i \in \{v, F, G, \lambda\}$, is equal to 0:

$$\begin{aligned}
\beta^{\tilde{k}} - \beta^{\alpha_0}\tilde{k}R_{gt}^{\alpha_1}\ln w_{gt} - \beta^{\alpha_1}\tilde{k}\alpha_0 R_{gt}^{\alpha_1}\ln w_{gt}\ln R_{gt} &= 0 \\
\beta^{F_0} + \beta^{F_1}\tilde{F}_0 \ln GS_{lt} &= 0 \\
\beta^{G} - \beta^{\mu}(G\frac{\ln(\tilde{k}w_{gt}^{-\alpha_0 R_{gt}^{\alpha_1}})}{(\mu-1)^2}) &= 0 \\
\beta^{\lambda_0}\frac{1}{\lambda_0} + \beta^{\lambda_1}\ln Th_{gt} &= 0
\end{aligned} \tag{24}$$

These four conditions must hold for any lgt, within a perfect dataset. Consequently, the solution to these equations is $\beta^i = 0 \, \forall i \in \boldsymbol{\theta}$. This establishes the proof for the identifiability of our nonlinear least squares model.

Equations (23) and (24) also explain the variations utilized to separately identify each parameter. From equation (23), variations in $H_{lgt}^v, H_{lgt}^F, H_{lgt}^G$, and H_{lgt}^λ enable the separate identification of parameters associated with the value function, fixed costs, returns to scale, and market thickness, respectively. Similarly, equation (24) indicates that variation in $R_{gt}^{\alpha_1}\ln w_{gt}$ allows for the separate identification of α_0 from $\tilde{k}$, and variation in $\ln R_{gt}$ allow for the identification of α_1 from α_0.

The same intuition also applies to the other parameters.

E TO BE UPDATED. CURRENT VERSION IS FOR PRIOR MODEL.

Estimating simple versions of model to demonstrate identification

The full model is that in each period t, g calls in a contract shipment i iff $(1-\beta_u)S_{lgt} \geq E(U_{lt}^s)$, that is, if $(1-\beta_u)S_{lgt} - E(U_{gt}^s) \geq 0$. S_{udtc} is the surplus from a contract shipment:

$$S_{lgt} = v(w_{gt})^{\frac{1}{1-\mu}}(\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} - F_{lt}$$

$$E(U_{gt}^s) = \frac{v(w_{gt})}{\phi_{gt}^s} - E(P_{gt})$$

Therefore, $(1-\beta_u)S_{lgt} \geq E(U_{lt}^s)$ yields

$$(1-\beta_u)S_{lgt} - \frac{v(w_{gt})}{\phi_{gt}^s} + E(P_{gt}) \geq 0$$

$$\phi_{lgt}^s \geq \frac{v(w_{gt})}{(1\beta_u)S_{lgt} + E(P_{gt})} \equiv \phi_{lgt}^{s*}$$

$$\phi_{lgt}^s \geq \frac{v(w_{gt})}{(1-\beta_u)S_{lgt} + E(P_{gt})} \equiv \phi_{lgt}^{s*}$$

The probability that g requests a contract shipment from l is the probability give in expression (12):

$$\Pr(\phi_{lgt}^s \geq \phi_{lgt}^{s*}) = (\phi_{lgt}^{s*})^{-\lambda}$$

We estimate equation (15) in the main text to give the two non-targeted moments relating to this probability. The two moments are the weather shock and spot price elasticities in the data. Equation (15) is:

$$C_{ldt} = \alpha + \theta_w w_{dt} + \theta_p p_{dt} + \epsilon_{ldt}$$

The estimated coefficients are (see Table 8):

$$\theta_w = 0.043$$

$$\theta_p = 0.056$$

$$\alpha = 0.351$$

We estimate different model specifications, successively adding parameters and evaluate how well each model specification fits the non-targeted moments.[37]

E.1 Model 1, with only k and λ_0

This gives the on-targeted moments of $\theta_p = 0.015, \alpha = 0.494$. Equation (15) simplifies to:

$$\begin{aligned} C &= (\frac{E(P_{gt})}{v(w_{gt})})^{\lambda} \\ &= (\frac{E(P_{gt})}{k})^{\lambda} \end{aligned}$$

The estimated model parameters are:

$$\lambda = 0.0141$$

$$k = 8.19e + 20$$

Note that this model specification gives an unreasonably large estimate of k. The λ estimate shows that the spot value responds positively to spot market thickness.

E.2 Model 2, adding α_0 to k and λ_0

This gives the non-targeted moments $\theta_w = 8.457$, $\theta_p = 0.435, \alpha = -8.203$. Equation (15) simplifies to:

$$\begin{aligned} C &= (\frac{E(P_{gt})}{v(w_{gt})})^{\lambda} \\ &= (\frac{E(P_{gt})}{k w_{gt}^{\alpha_0}})^{\lambda} \end{aligned}$$

The estimated model parameters are:

$$\lambda = 9798.877$$

[37] Throughout this Appendix, $Th_g t = D10m^3. * spot_{ctm}/(contract_{ctm} + spot_{ctm})$. The estimates will be redone to ensure consistency with the model specifications estimated in the main text and in Appendix **??**

$$k = 7330.472$$

$$\alpha_0 = -9999$$

These parameter value are all large in (absolute) value.

E.3 Model 3, setting $\beta = 0.3$, with k, λ_0, α_0, and also adding μ and c, and then also F_0.

Adding μ and c gives the non-targeted moments of $\theta_w = 0.049$, $\theta_p = 0.001, \alpha = 0.467$. Equation (15) simplifies to:

$$\begin{aligned} C &= (\frac{(1-\beta_u)S_{lgt} + E(P_{gt})}{v(w_{gt})})^{\lambda} \\ &= ((1-\beta_u)(kw_{gt}^{\alpha_0})^{\frac{\mu}{1-\mu}}(\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} + \frac{E(P_{gt})}{kw_{gt}^{\alpha_0}})^{\lambda} \end{aligned}$$

The estimated model parameters are:

$$\lambda = 2.009$$

$$k = 7355.060$$

$$\alpha_0 = 1.152$$

$$\mu = 0.032$$

$$c = 31.410$$

Now also including F_0 gives the non-targeted moments of $\theta_w = 0.049$, $\theta_p = 0.000, \alpha = 0.467$ Equation (15) simplifies to:

$$\begin{aligned} C &= (\frac{(1-\beta_u)S_{lgt} + E(P_{gt})}{v(w_{gt})})^{\lambda} \\ &= ((1-\beta_u)(kw_{gt}^{\alpha_0})^{\frac{\mu}{1-\mu}}(\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} - \frac{(1-\beta_u)F_0}{kw_{gt}^{\alpha_0}} + \frac{E(P_{gt})}{kw_{gt}^{\alpha_0}})^{\lambda} \end{aligned}$$

The estimated model parameters are:

$$\lambda = 1.992$$

$$k = 881878.753$$

$$\alpha_0 = 4.737$$

$$\mu = 0.008$$

$$c = 93.175$$

$$F_0 = 29.739$$

E.4 Model 4, with $\beta = 0.3$, $k, \lambda_0, \alpha_0, \mu, c, F_0$, and D

This gives the non-targeted moments $\theta_w = 0.044$, $\theta_p = 0.000, \alpha = 0.47033$. That is, it still gives a spot price elasticity that is almost zero. Equation (15) simplifies to:

$$\begin{aligned} C &= (D\frac{(1-\beta_u)v(w_{gt})^{\frac{1}{1-\mu}}(\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} - (1-\beta_u)F_0 + E(P_{gt})}{v(w_{gt})})^{\lambda} \\ &= D^{\lambda}((1-\beta_u)v(w_{gt})^{\frac{\mu}{1-\mu}}(\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} - \frac{(1-\beta_u)F_0}{v(w_{gt})} + \frac{E(P_{gt})}{kw_{gt}^{\alpha_0}})^{\lambda} \end{aligned}$$

The estimated model parameters are:

$$\lambda = 0.380$$

$$k = 263.555$$

$$\alpha_0 = 0.158$$

$$\mu = 0.487$$

$$c = 0.207$$

$$F_0 = 67.030$$

$$D = 0.002$$

Note that including the constant term D, which can be interpreted as the share of contract shipments when w_{lgt} and p_{gt} are both equal to zero, gives a much more reasonable estimate of k.

E.5 Model 5, as in Model 4, and further adding α_1 and F_1.

This is the full model, with the exception of setting $\beta = 0.3$. It gives the non-targeted moments $\theta_w = 0.044$ $\theta_p = 0.223, \alpha = 0.343$. Note that this specification gives a predicted price elasticity that is far higher than in the data. Equation (15) is:

$$\begin{aligned} C &= (D\frac{(1-\beta_u)v(w_{gt})^{\frac{1}{1-\mu}}(\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} - (1-\beta_u)F_0 CS_{lt}^{F_1} + E(P_{gt})}{v(w_{gt})})^{\lambda_0 Th_{gt}^{\lambda_1}} \\ &= D^{\lambda}((1-\beta_u)v(w_{gt})^{\frac{\mu}{1-\mu}}(\frac{\beta\mu}{c})^{\frac{\mu}{1-\mu}} - \frac{(1-\beta_u)F_0 CS_{lt}^{F_1}}{v(w_{gt})} + \frac{E(P_{gt})}{kw_{gt}^{\alpha_0 R_{gt}^{\alpha_1}}})^{\lambda_0 Th_{gt}^{\lambda_1}} \end{aligned}$$

The estimated model parameters are:

$$\lambda = 8.440$$

$$k = 15.558$$

$$D = 0.212$$

$$\alpha_0 = 0.007$$

$$\mu = 0.294$$

$$c = 0.016$$

$$F_0 = 96.14$$

$$\alpha_1 = 0.094$$

$$\lambda_1 = 0.929$$

$$F_1 = 0.301$$

Note that the main results in Section 6 flexibly estimated β, but leave out F_1 and α_1.

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