On the Price Spread of Benchmark Crude Oils: A Spatial Price Equilibrium Model*

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Abstract

Benchmark crude oils that are almost identical in physical composition exhibited dramatic divergence in prices in the recent decade, a phenomenon that rarely occurred in earlier decades. This paper develops a rational expectations two-period model of spatial price equilibrium, and departs from standard models by assuming an increasing marginal cost curve of transportation. We econometrically validate our model using a dataset that covers an extended time period. We demonstrate that this simple two-period model is sufficient to characterize key observed behaviors of the crude oil markets. The model allows us to determine the underlying causes of the unique phenomenon of the widening and subsequent narrowing of crude oil price spreads over the past decade. We find that the widening of the Brent-WTI spread from 2011 to 2013 was due to a positive supply shock in the Midwest that was constrained by insufficient transportation infrastructure, and that its subsequent narrowing from 2013 was primarily due to a structural decrease in the marginal cost of transportation out of Midwest to the rest of the U.S.

Keywords: Crude oil, price spread, marginal cost of transportation, storage
JEL Classification: N50, N70, Q31, R32

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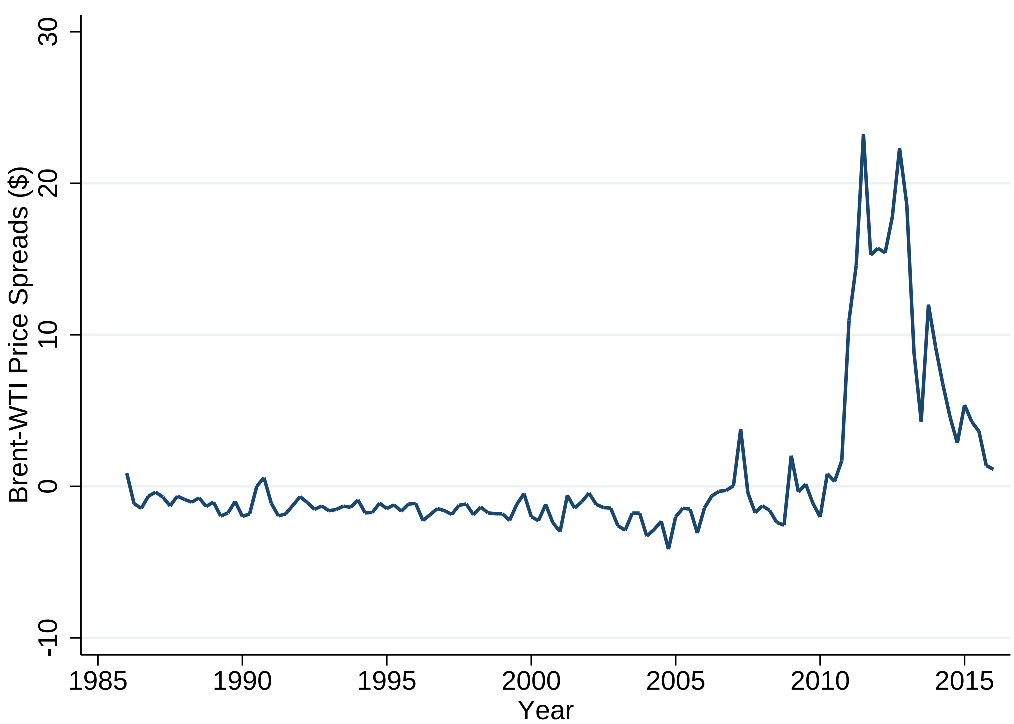
1 Introduction

Crude oil is critically important for the world economy. To the average consumer of oil, however, it's often easy to get the impression that there is a single global market for crude oil. In reality, there are many different types of crude oil, and there are benchmark oils that serve as references for buyers and sellers of crude oil around the world. Two primary global benchmark oils are West Texas Intermediate (WTI) and Brent Blend. WTI is priced in Cushing, Oklahoma and used primarily in the U.S., whereas Brent is priced in the United Kingdom and used primarily in Europe but also all around the world.

The most easily refined crude oil, and thus the most valuable, is light sweet crude. WTI and Brent are both light sweet crude oils, and are almost identical in physical composition. As such, any substantial deviation in price between these crude oils can only be a consequence of spatial price equilibrium and not differences in intrinsic value.

Historically, Brent and WTI have traded with very small price differentials (see Figure 1). Prior to 2011, the price differential between WTI and Brent had generally been smaller than $5 dollars-per-barrel. Arbitrage between the two markets seemed to ensure that localized supply and demand shocks affected each price relatively equally: "world" oil prices moved in tandem.

Figure 1: *Quarterly Brent-WTI spot price spreads from 1986Q1 to 2016Q1.*



However, in the beginning of 2011, Brent and WTI prices started to diverge dramatically[1], and in the months that followed the Brent-WTI spread widened to as much as $25 per barrel. The Brent-WTI spread subsequently narrowed starting from 2013.

The decoupling of Brent and WTI is of practical concern for two reasons. First, market participants in the petroleum industry peg crude oil prices to benchmarks, and if one benchmark is an inaccurate or unrepresentative gauge of the oil prices then it ceases to be useful. Second, WTI and Brent are the underlying crude oils for the New York Mercantile Exchange (NYMEX) and Intercontinental Exchange (ICE) crude oil futures contracts, which are by far the largest crude oil futures markets and are used by economic agents around the world to hedge their exposure to the price fluctuations of oil. If either WTI or Brent ceases to be a good indicator of oil prices, then economic agents will be hindered in their ability to effectively hedge themselves.

Unfortunately, dramatic changes in spatial price spreads of tradable commodities (e.g. oil) cannot be readily explained with standard models in the economic literature. The literature on spatial price equilibrium, whereby no-arbitrage conditions are applied to geographic price differentials of a homogenous commodity, has generally used the existence of transportation costs to rationalize price spreads. Standard models in this literature assume that the marginal cost of transportation is constant. We will show in Section 4.2 that if the marginal cost of transportation is truly constant as in standard models, then the only explanation of a widening spread is an exogenous upward shift in the marginal cost curve of transportation.[2] However, as we will demonstrate in this paper, an exogenous upward shift in the marginal cost curve would cause the observed quantity of transportation between pricing points to decrease, but in regards to the Brent-WTI spread, the quantity of transportation between the regions actually increased along with increases in Brent-WTI spread, contradicting the predictions derived from a model that assumes constant marginal cost of transportation. Furthermore, we will go on to include the possibility of storage that doesn't appear in standard spatial price equilibrium models. In sum, there is a theoretical gap in the literature that we seek to fill: we will build and validate a model of spatial price equilibrium with increasing marginal costs of transportation and with storage.

The theoretical model that we build is useful in at least two respects. First, the model is built with simple assumptions that are in line with salient features of the crude oil

[1] To be clear, this paper is concerned about the *level* of price spreads, not volatility. The key puzzle we are trying to rationalize is the dramatic widening and narrowing of the price spreads of benchmark crude oils that apparently have little difference in their intrinsic values.

[2] This could occur for many reasons, such as the transportation market becoming less competitive, energy becoming more expensive, or transportation infrastructure depreciating and becoming unusable.

market, and generates clear and testable theoretical predictions. Because our empirical analysis is closely tied to model, the empirical analysis has strong theoretical grounds and straightforward interpretations. We avoid concerns about data mining that could arise if we work directly with data. Second, the features of the crude oil market that we build into our model are observed in many other commodities markets. In this sense our theoretical model can readily be adapted to inform price spread patterns in other commodities markets.

In the end, we would like to apply our theory to identify causes of the dramatic changes of the Brent-WTI spread seen in Figure 1. With regard to the 2011-2013 widening of the Brent-WTI spread, two hypotheses have been widely discussed: (1) A negative supply shock in the Middle East. In particular, Arab Spring and loss of Libyan oil put upward pressure on Brent prices while transportation constraints between Cushing and Europe isolated WTI from this effect. (2) A positive supply shock in the Midwest of the United States, specifically Cushing, Oklahoma. In early 2011, new pipelines were built bringing more Canadian oil into Cushing, and transportation constraints between the Cushing and Europe isolated Brent from this effect.

Our model will demonstrate that both of the above hypotheses are plausible causes of a widening spread, among others. The model provides a direct way to test the efficacy of each of these hypotheses as well as other potential causes of the widening spread. The model is also informative about the cause of subsequent narrowing of the Brent-WTI spread. The empirical strategy involves exploiting the observed relationships among inventories, transportation, and the Brent-WTI spread.

Our results indicate that the increase in Brent-WTI price spread from 2011 to 2013 should be attributed to positive supply shocks in the Midwest, particularly in Cushing, Oklahoma. This is consistent with the findings of Büyükşahin et al. (2013), who provide empirical evidence that this initial bout of Brent-WTI price divergence is directly tied to a North American positive supply shock that was constrained in Cushing, Oklahoma due to limited transportation and storage infrastructure capacities. With regard to the subsequent narrowing of the Brent-WTI spread from 2013, our results suggest that the dominating cause is a structural decrease in the marginal cost of transportation, possibly due to such factors as new pipeline capacities. This is consistent with specific developments during the period such as the reversal of the Seaway Pipeline.

The rest of the paper is organized as follows: Section 2 reviews related literature. Section 3 provides background information on the U.S. crude oil market, with a particular focus on the oil markets at Cushing, Oklahoma, the price settlement point for WTI. Section 4 builds a model of spatial price equilibrium that incorporates increasing marginal costs of transportation and storage, starting from a simple model generalized from the standard literature. We then come up with a testable prediction, as well as identify potential causes of a changing price spread and their respective impacts on transportation and storage. In Section 5, we describe our dataset, and test the model prediction in order to validate our theory. In Section 6, we apply our theory to identify the causes of the changing Brent-WTI spread over time. Section 7 contains some final remarks.

2 Related Literature

Our paper is closely related to several recent papers that study oil price differentials. See, for example, Bacon and Tordo (2004), Borenstein and Kellogg (2014), Büyükşahin et al. (2013), and Lanza, Manera and Giovannini (2005). In particular, Büyükşahin et al. (2013) study specifically the unprecedentedly wide Brent-WTI spread after 2008, by drawing on extant models linking oil inventory conditions to the futures term structure. Our empirical analysis confirms many of the findings of Büyükşahin et al. (2013). Our key contribution to this strand of literature is that we construct a tractable theoretical model that allows us to exactly identify causes of the changes in Brent-WTI price spread over time, and the model is flexible enough to be readily adapted to other commodities markets' price spread patterns.

Our paper is guided by the literature on the applicability of the no-arbitrage condition. The no-arbitrage condition, or the law of one price, should not be taken for granted in the commodities markets. After all, the commodities market has its own idiosyncratic characteristics that may cause the no-arbitrage conditions to fail. Ardeni (1989) uses tests of nonstationarity and co-integration for a group of commodities and show that the law of one price fails as a long-run relationship. He argues that the failure of the law of one price can be rationalized with two factors, namely high costs of arbitrage and institutional barriers. Other papers have shown results consistent with the arguments of Ardeni (1989), such as Fattouh (2010), Richardson (1978), Olsen, Mjelde and Bessler (2015), and Goldberg and Verboven (2005). A common theme in the literature is that markets geographically adjacent to each other tend to be more highly integrated than markets separated by distance, but institutional barriers such as exchange rates still cause the no-arbitrage condition to fail in closeby commodity markets.

As a result, we would like to focus on geographically adjacent regions within the United States in order to ensure the applicability of the no-arbitrage condition. Importantly, Werner (1987) proves that the existence of a price system that admits no arbitrage opportunity for all consumers is sufficient for the existence of an equilibrium, which serves as an additional assurance for our careful selection of geography as we develop a spatial price equilibrium model.

Our theoretical model is related to the literature on transportation costs. There are two distinct kinds of transportation "costs" that are described in the literature: traditional costs of transport and time costs of transport. Models with instantaneous transportation can rationally exhibit spatial price differentials without violating no-arbitrage assumptions because of transportation costs; an uncontroversial result of such a model is that locational price spreads are bounded by transportation costs (see Williams and Wright, 1991). A second type of cost, as described by Coleman (2009), arises from the time that transportation takes. Coleman (2009) explains how unbounded price differentials can exist in the short-run without violating no-arbitrage assumptions if transportation is non-instantaneous. However, in the context of the our benchmark crude oils spread, the applicability of a non-instantaneous transportation model is limited: our chosen regions of focus, St. James and Cushing, are merely 650 miles apart, and thus the delay in transportation is minimal. We will therefore describe the price spread in the context of an instantaneous transportation model. As such, in our model we are constrained by the no-arbitrage condition that the price spread is bounded by the cost of transportation (see Williams and Wright, 1991).

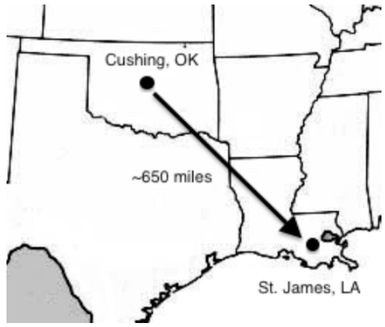
Last but not least, we contribute to the crude oil spatial price equilibrium literature by tying together transportation and storage. Classic models of spatial price equilibrium, as exemplified by Samuelson (1952), directly solve for spatial price relations based on localized supply and demand in the presence of transportation. In addition, seminal work by Deaton and Laroque (1992, 1996) lays out the foundation for analyzing commodity price dynamics with competitive storage motives. More recently, Kilian and Murphy (2014) and Knittel and Pindyck (2016) study the speculative trading behaviors in crude oil markets through the lens of storage and inventories. These papers, though, do not incorporate both transportation and storage into their models at the same time. For our purposes, it is important to tie together both transportation and storage in order to fully characterize the behavior of the price spread of benchmark crude oils.

3 U.S. Crude Oil Market Facts

Cushing, Oklahoma is the delivery point for the NYMEX oil futures contract and therefore refineries, storage facilities, and pipelines have all developed substantial infrastructure in the periphery of the city. As of 2011, it is estimated that storage capacity at Cushing is around 48 million barrels of crude oil, and as much as 600 thousand barrels flow into

Cushing daily.

Figure 2: *Geography of Cushing, OK and St. James, LA*

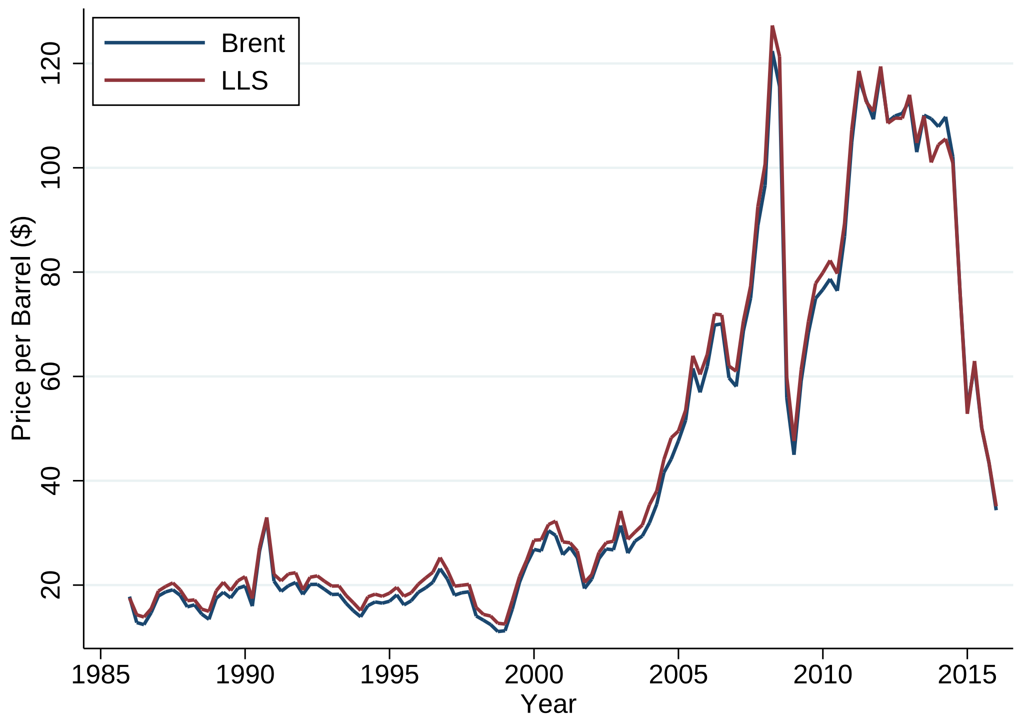


We will use the model developed in this paper to examine the spatial price spread of Brent and WTI. Crude oil at Cushing, Oklahoma is WTI. We proxy crude oil at St. James, Louisiana as Brent. A careful reader will notice that Brent is not priced at St. James, and in fact the crude oil at St. James is known as Light Louisiana Sweet or LLS. We focus on the geography between Cushing, OK and St. James, LA because we want to focus on geographically adjacent regions within the U.S. to ensure applicability of the no-arbitrage condition, as discussed in Section 2. We would like to argue, though, that crude oil at St. James is an appropriate proxy for Brent in the U.S. oil market. The crude oil priced at St. James, which is LLS, is also light sweet crude, so it has little difference from Brent or WTI in terms of intrinsic value. Figure 3 clearly shows that Brent and LLS spot prices trade with very small differentials. To further address the concern that Brent is not priced in the US, we conduct robustness checks by applying our empirical analysis to the LLS-WTI spread in Appendix D.2, and all our results and conclusions hold.

As seen in Figure 2, Cushing, OK and St. James, LA are approximately 650 miles apart. The transportation infrastructure between Cushing and St. James primarily consists of pipelines. Most pipelines transport liquid at a speed of approximately 3 to 13 miles-per-hour; therefore it should only take between two and nine days to transport crude oil from Cushing to St. James. There are, however, additional modes of transportation between Cushing and St. James: notably, rail and trucking. Transportation from Cushing to St. James is estimated to cost between $7 to $10 per barrel by rail and between $11 and $15 per barrel by trucking, which is much more expensive than the estimated $2 per barrel by pipeline.[3] As noted above, a constant marginal cost curve of transportation has been the standard assumption in the literature, which is clearly at odds with transportation costs of oil from Cushing to the Gulf Coast if pipeline capacity is insufficient and therefore some oil must be shipped by other, more expensive, modes of transportation.

[3]CommodityOnline, quoting analysis by Bank of American Merrill Lynch.

Figure 3: *Quarterly Brent and LLS spot prices from 1986Q1 to 2016Q1.*



In late 2010 and early 2011, two large new pipelines that directed oil from Canada to Cushing went online, substantially increasing the availability of crude in Cushing. This occurred over the backdrop of steadily increasing production of crude oil in the Midwest over the past decade. These two forces dramatically increased the quantity of crude flowing into Cushing. Models of spatial price equilibrium with a constant marginal cost of transportation would suggest that this would have no effect on the Brent-WTI spread, as the additional oil would be immediately directed towards the coast via transportation infrastructure (see Section 4.1). However, we will argue in the model that because of rising marginal costs, a positive supply shock at Cushing is a theoretically sound explanation for the widening of the Brent-WTI spread (see Section 4.4).

For the narrowing of the Brent-WTI spread starting from 2013, we note the following event. In May 2012, the 150,000 barrels-per-day (bbl/d) Seaway Pipeline, which had historically been used to transport crude oil north from the Gulf Coast to Cushing, was reversed in order to move crude oil to the higher priced Gulf Coast market. Seaway capacity was expanded by an additional 250,000 bbl/d in early 2013. This development represents a structural decrease in the marginal cost of transportation out of the Midwest, which is a theoretically plausible explanation for the narrowing of the Brent-WTI spread (see Section 4.2).

In addition, in recent years, because of the advances of the hydraulic fracturing technology, the U.S. experienced a wave of shale oil boom, particularly in the state of Texas, which is close to St. James. We will argue in the model that because the marginal cost curve of transportation is assumed to be increasing, a positive supply shock at the Gulf Coast is also a theoretically possible explanation for the narrowing of the Brent-WTI spread after 2013 (see Section 4.4).

4 A Model of Spatial Price Equilibrium

We start by setting up and examining a standard model that assumes constant marginal cost of transportation and no storage. We show that in such a standard model, the only way for the price spread to increase is an exogenous upward shift in the marginal cost curve of transportation; supply shocks have no impact on the price spread.

Then we twist the model by adding in increasing marginal costs of transportation, and storage one at a time – two desirable features that build up our new model of spatial price equilibrium. The increasing marginal costs of transportation will allow supply shocks to influence the price spread. Adding in storage helps us disentangle different possible causes of a widening price spread.

4.1 The standard model

The standard model assumes that the marginal cost of transportation between locations is constant and that there is no option to store commodity. Such standard spatial price equilibrium models are pioneered by Samuelson (1952) and Takayama and Judge (1964).

Consider a non-perishable and non-depreciating commodity, called "x", that trades in two locations, point A and point B. Production of x at both A and B during a given period t, denoted Q_t^A and Q_t^B respectively, is assumed to be given as exogenous to arbitrageurs.[4] This is consistent with a commodity whose production occurs in earlier periods, such as oil, or commodities that have perfectly inelastic supply curves. The corresponding price of x at each point is denoted p_t^A, p_t^B. In this model, arbitrageurs are risk-neutral and have the opportunity to transport commodity x from point A to point B at marginal cost $k_{t,AB}^T$, or from point B to point A at marginal cost $k_{t,BA}^T$.

[4] The variables Q_t^A and Q_t^B, although defined as "production", can be more generally thought of as supply in a region derived by means other than drawing down storage and transporting to or from the other considered region, and could thus include net imports into the region.

Assumption 1. *Assume, in the standard model, that the marginal cost of transportation is constant, such that* $k^T_{t,AB} = \bar{k}^T_{t,AB}$ *and* $k^T_{t,BA} = \bar{k}^T_{t,BA}$*.*

It is clear that in order to maintain no-arbitrage, the spatial price spread, given by $\sigma_t \equiv p^B_t - p^A_t$ must be bounded by the marginal costs of transportation. Explicitly the no-arbitrage condition specifies that

$$-\bar{k}^T_{t,BA} \leq \sigma_t \leq \bar{k}^T_{t,AB}. \tag{1}$$

Within these bounds, transportation will only occur from A to B if $\sigma_t = \bar{k}^T_{t,AB}$ and transportation will only occur from B to A if $\sigma_t = -\bar{k}^T_{t,BA}$. If the spread lies within these bounds then transportation between A and B will yield negative profits, and therefore transportation in either direction will not occur.

No-arbitrage condition (1) is well understood in the literature and is the baseline description of the relationship between the spatial price spread and the marginal cost of transportation. However, it says nothing about the quantity of transportation that will occur. In order to understand this we must tease out the direct effect that transportation has on the spatial price spread.

We begin by describing the determinants of the absolute price of x at each point. The price of x at point A is given by economic agents' demand for consumption of x at point A. The demand curve for x at A will be denoted by $D^A(N^A_t)$, where N^A_t is the quantity of x available at A for consumption during period t. Likewise, the demand curve for x at B is $D^B(N^B_t)$. We maintain the standard assumption for normal goods that the demand curve is downward sloping.

Assumption 2 (Downward sloping demand curves)**.** *Assume that the demand curves have the following property:*

$$\frac{\partial D^A(N^A_t)}{\partial N^A_t} < 0, \textit{ and } \frac{\partial D^B(N^B_t)}{\partial N^B_t} < 0.$$

Although the production of x at A during period t is exogenous, the quantity available for consumption is not; arbitrageurs have the option to pull x out of the market at A to transport it to B.[5] This gives a relationship described by $N^A_t = Q^A_t - T_t$, where T_t is the quantity of x transported from point A to point B. Arbitrageurs at point A will optimally transport commodity x while reacting to their activities' effect on the price of x at A. It

[5]For clarity of exposition, we only consider the case in which arbitrageurs make transportation from A to B, thus $T_t \geq 0$ is assumed to always hold. The reverse case in which arbitrageurs make transportation from B to A is symmetric.

follows that the equilibrium price of x at A would endogenously satisfy[6]:

$$p_t^A = D^A(N_t^A) \equiv D^A(Q_t^A - T_t). \tag{2}$$

The market for x at B is different from the market at A only in that transportation increases the quantity of x available at B, whereas transportation decreases the quantity available at A. Specifically, the quantity of x available at B, denoted N_t^B, is given by the relation $N_t^B = Q_t^B + T_t$. It then follows that the equilibrium price of x at B would satisfy:

$$p_t^B = D^B(N_t^B) \equiv D^B(Q_t^B + T_t). \tag{3}$$

Therefore the equilibrium spatial price spread is determined by what we will refer to as the "spread function," denoted $\sigma_t(T_t, Q_t^A, Q_t^B)$:

$$\sigma_t(T_t, Q_t^A, Q_t^B) = D^B(Q_t^B + T_t) - D^A(Q_t^A - T_t). \tag{4}$$

The spread function is simply the difference in the equilibrium prices of x in the two regions, given supply levels and transportation between the regions. This representation of the spread function illuminates that increases in transportation directly decreases the spatial price spread, holding production exogenous.

We can now explicitly describe the equilibrium level of transportation between A and B. If the spatial price spread without transportation would exceed the constant marginal cost of transportation, then arbitrageurs will increase transportation until the spread decreases to $\sigma_t = \bar{k}_{t,AB}^T$. Additionally, if the spatial price spread without transportation is within the band of marginal costs of transportation between points A and B, then there will be no transportation because it would provide arbitrageurs with negative profits. We formalize this characterization through the following theorem:

Theorem 1. *Under Assumption 1 and the no storage assumption, and taking production Q_t^A and Q_t^B as exogenously given, the spatial price equilibrium is characterized by the following conditions:*

(i) If $\sigma_t(T_t)|_{T_t=0} > \bar{k}_{t,AB}^T$, then $T_t^* \in \mathbb{R}_{>0}$ is such that $\sigma_t^* = D^B(Q_t^B + T_t^*) - D^A(Q_t^A - T_t^*) = \bar{k}_{t,AB}^T$;

(ii) If $\sigma_t(T_t)|_{T_t=0} \leq \bar{k}_{t,AB}^T$, then $T_t^* = 0$.

For an illustration of the equilibrium as described by Theorem 1, see Figure 6 in Appendix B.

[6]Note for the sake of notational cleanness, we don't add $*$ on p_t^A and T_t to indicate equilibrium. This will be the case many times in this paper, and readers should be aware of this notational choice.

A key implication of Theorem 1 is that supply shocks in either point A or B fail to sufficiently explain the widening of the price spread in the context of the model described here: given that $\sigma_t(T_t)|_{T_t=0} \geq \bar{k}^T_{t,AB}$, changes in production levels can only shift the spread function in or out, after which the quantity of transportation will simply adjust to ensure that the spatial price spread stays at $\bar{k}^T_{t,AB}$ (for an example, see Figure 7a in Appendix B). We formalize this implication in Corollary 1.

Corollary 1. *In the standard model, the equilibrium price spread σ^*_t does not change because of shocks in the exogenous supply Q^A_t or Q^B_t.*

In the standard model the only way the spatial price spread can increase beyond the initial $\bar{k}^T_{t,AB}$ is if there is an exogenous upward shift in the marginal cost curve of transportation (see Figure 7b in Appendix B for illustration). If the marginal cost curve of transportation doesn't shift, the equilibrium spread will never exceed $\bar{k}^T_{t,AB}$.

4.2 Incorporating increasing marginal costs of transportation

Introducing increasing marginal costs of transportation makes it possible for supply shocks in either point A or point B to influence the equilibrium spatial price spread beyond the initial marginal cost of transportation. We adapt Assumption 1 and instead assume increasing marginal cost of transportation as follows:

Assumption 3. *Assume now that the marginal cost of transportation is endogenous to and increasing in the level of transportation. Specifically, $k^T_{t,AB} = k^T_{t,AB}(T_t)$ such that $\partial k^T_{t,AB}(T_t)/\partial T_t > 0$.*

In the real world it is likely that the marginal cost curve of transportation is piecewise. There would likely be an initial flat region until the cheapest mode of transportation has reached capacity, and then a jump and another flat region at the second cheapest mode of transportation, and so on, until capacity is reached for all modes of transportation, at which point the marginal cost curve should be perfectly inelastic. However, in order to approximate the effect of multiple modes of transportation we will simply assume that the curve is increasing. This simplifying approximation makes the mathematics easier to deal with, and does not affect the implications of the model.

The no-arbitrage condition (1), briefly restated, becomes

$$-k^T_{t,BA}(T_{t,BA}) \leq \sigma_t(T_t, Q^A_t, Q^B_t) \leq k^T_{t,AB}(T_{t,AB}), \tag{5}$$

where we will just refer to $T_{t,AB}$, the quantity of transportation from A to B, as T_t. The equilibrium conditions in Theorem 1 are no longer based on constant marginal costs of transportation, and instead are described by the following conditional statements

Theorem 2. *Under Assumption 3 and the no storage assumption, and taking production Q_t^A and Q_t^B as exogenously given, the spatial price equilibrium is characterized by the following conditions:*

(i) If $\sigma_t(T_t)|_{T_t=0} > k^T_{t,AB}(0)$, then $T_t^* \in \mathbb{R}_{>0}$ is such that $\sigma_t^* = D^B(Q_t^B + T_t^*) - D^A(Q_t^A - T_t^*) = k^T_{t,AB}(T_t^*)$;

(ii) If $\sigma_t(T_t)|_{T_t=0} \leq k^T_{t,AB}(0)$, then $T_t^* = 0$.

Theorem 2 says that no transportation occurs if and only if the spatial price spread is less than the cost of transporting the first unit of x. The key difference in the results of a model with increasing marginal costs of transportation is that supply shocks at both A and B can now directly influence the equilibrium price spread. We formalize this implication in Corollary 2.

Corollary 2. *Under Assumption 3, supply shocks at A or B influence the equilibrium price spread σ_t^*. Specifically,*

$$\frac{\partial \sigma_t^*}{\partial Q_t^A} > 0, \text{ and } \frac{\partial \sigma_t^*}{\partial Q_t^B} < 0.$$

Figure 8b in Appendix B illustrates Corollary 2, where supply shocks at both A and B directly push the equilibrium spatial price spread above the original marginal cost of transportation.

In addition, an exogenous shift in the marginal cost curve of transportation also has an impact on the equilibrium price spread, just as in the standard model. The impact is characterizes as follows:

Corollary 3. *If there is an exogenous upward shift of the marginal cost curve of transportation, i.e., $k^{T'}_{t,AB}(T_{t,AB}) > k^T_{t,AB}(T_{t,AB}), \forall T_{t,AB}$, then $\sigma_t^{*'} > \sigma_t^*$, and $T_t^{*'} < T_t^*$. Note that notations with prime denote new equilibrium outcomes.*

4.3 Allowing storage

A storage market allows a speculator to purchase a unit of x during period t and store it until period $t+1$ at the marginal cost of storage k_t^S.[7] The storage market enters our model by changing the spread function. As speculators increase storage at A, they directly take units of x out of the market at A, holding all else equal. Let S_t denote the storage

[7] Büyükşahin et al. (2013) show that storage capacity, not just levels, is a key variable for the price spread. The storage capacity can be incorporated into our model by specifying a particular functional form of the marginal cost curve of storage k_t^S.

level at time t at location A.[8] It follows that the availability of x at A, denoted N_t^A, now equals $Q_t^A - \Delta S_t - T_t$, where the change in storage from period $t-1$ to t is denoted as $\Delta S_t = S_t - S_{t-1}$. Our new and final spread function is characterized in Proposition 1.

Proposition 1 (Spread function)**.** *The spread function is* $\sigma_t = D^B(Q_t^B + T_t) - D^A(Q_t^A + S_{t-1} - S_t - T_t)$*. Let* $N_t^A = Q_t^A + S_{t-1} - S_t - T_t$ *and* $N_t^B = Q_t^B + T_t$ *be the total available commodity at A and B, respectively, at time t, then* $\partial\sigma_t/\partial N_t^A > 0$ *and* $\partial\sigma_t/\partial N_t^B < 0$*.*

The statement of Proposition 1 follows directly from the standard assumption that demand curves are downward sloping. It is more important to point out that the statement is consistent with economic intuition: when there is increasing amount of commodity available at A, the price at A becomes depressed due to the abundance of the commodity there, thus enlarging the price spread; likewise for location B. Note that the variables N_t^A and N_t^B each represent the availability of a commodity at each point, and in some contexts should be exactly equal to consumption at each point.

We can now describe an equilibrium condition in this model with increasing marginal costs of transportation, and storage.

Theorem 3. *Under Assumption 3, and given sufficient differentials in* Q_t *and* Q_t^B *such that both transportation and storage are positive, the equilibrium quantities of storage and transportation must satisfy the following no-arbitrage condition:*

$$\sigma_t^* = D^B(Q_t^B + T_t^*) - D^A(Q_t^A + S_{t-1} - S_t^* - T_t^*) = k_t^T(T_t^*).$$

4.4 Implications of changes in spread

So far, we've identified three key causes for the change in the commodity price spread: (i) a positive supply shock at A, namely an increase in Q_t^A; (ii) a negative supply shock at B, namely a decrease in Q_t^B; and (iii) an upward shift in the price spread function $k_{t,AB}^T(T_t)$. Corollary 2 suggests that both a positive supply shock at A and a negative supply shock at B will similarly increase the equilibrium price spread and transportation, but we'd like to look further into how the two supply shocks affect the equilibrium quantities of storage at A. We first state a regularity condition, which requires that the supply shock at B should have limited impacts on storage at A. This regularity condition is innocuous as it conforms to intuition. Formally,

[8] Again, for clarity of exposition, we only consider the case in which storage is allowed at A. Our empirical analysis in Section 5.2 will allow storage at both A and B.

Assumption 4. *Assume that Q_t^B has limited impact on S_t^*, such that*

$$\left|\frac{\partial S_t^*}{\partial Q_t^B}\right| < \left|\frac{\partial T_t^* / \partial Q_t^B}{\partial T_t^* / \partial Q_t^A}\right|$$

We now state the following theorem that characterizes the impacts of supply shocks at A and B on the equilibrium storage.

Theorem 4. *Under the regularity condition, Assumption 4, positive supply shocks at A or B will both weakly increase the equilibrium quantities of storage at the exporting region A. In other words, $\partial S_t^* / \partial Q_t^A > 0$ and $\partial S_t^* / \partial Q_t^B > 0$.*

It follows from Theorem 4 that although a positive supply shock at A or a negative supply shock at B will both similarly increase the price spread, they will have opposite effects on equilibrium quantities of storage: a positive supply shock at A should increase the equilibrium quantity of storage, and a negative supply shock at B should decrease the equilibrium quantity of storage.

As a result, the model allows us to identify different causes of a widening spread by examining distinct relationships among spread, storage, and transportation. The results are summarized in Proposition 2. We will apply this proposition in Section 6 to identify causes of the changing Brent-WTI spread.

Proposition 2 (Causes of a widening spread)**.** *This model predicts generally distinct combinations of effects on equilibrium transportation and storage, given three possible causes of the widening commodity price spread, as follows:*

(i) The first possible cause is an increase in Q_t^A, which will increase both T_t^* and S_t^*;

(ii) The second possible cause is a decrease in Q_t^B, which will increase T_t^* and decrease S_t^*;

(iii) The third possible cause is an upward shift of the $k_{t,AB}^T(T_t)$ curve, which will decrease T_t^* and have an ambiguous effect on S_t^*.

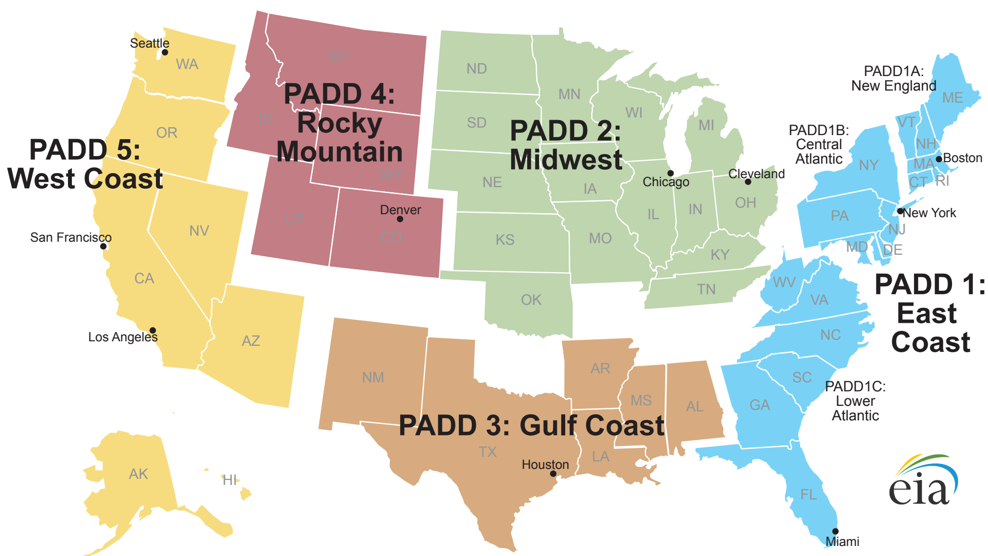
5 Testing the Theory

5.1 Data

As discussed in the introduction, we focus on the geography within the US in order to isolate an individual transportation market.

If we are to apply our model, we must first specify what we mean by "point A" and "point B" in the context of our crude oil spread. Crude oil data from the U.S. Energy Information Administration (EIA) are arguably the most comprehensive and detailed. The EIA reports production, import and export, storage, and transportation data for PADDs, which are five subregions of the United States. PADDs, or Petroleum Administration for Defense Districts, were delineated during World War II to facilitate oil allocation. Since then, they have been used to describe intra-country information on the US crude oil industry. Figure 4 shows the borders of each of the five PADD districts. PADD2 encompasses Cushing, Oklahoma, and therefore is the best proxy for point A, which in the model was the exporting region. Brent is likely a proxy for oil prices in the rest of the United States, and therefore we will use the summations of data for the other four PADDs (or the rest of the US excluding PADD2) as point B, which in the model was the importing region. For brevity, we will henceforth call the regions encompassed by all the PADDs other than PADD2 simply the "US".

Figure 4: *Petroleum Administration for Defense Districts (PADD) Map*



Our dataset spans from 1986Q1 to 2016Q1. We compile spot prices of Brent and WTI from Bloomberg. 1986 is the first year all three spot prices are reported through Bloomberg, so our dataset covers the most extended time period. We compile the rest of our data from the U.S. Energy Information Administration. Pro_t^{PADD2} and Pro_t^{US} denote crude oil productions in PADD2 and the rest of the U.S. at time t, respectively. Sto_t^{PADD2} and Sto_t^{US} denote total commercial crude oil stocks in PADD2 and and the rest of the U.S. at time t, respectively. We should note that Sto_t^{US} only measures commercial crude oil stock and thus excludes the U.S. Strategic Petroleum Reserve (SPR) maintained in PADD3.

Instead, SPR_t denotes the stock of Strategic Petroleum Reserve at time t. Imp_t^{PADD2} and Exp_t^{PADD2} denote imports and exports in and out of PADD2 at time t; likewise, Imp_t^{US} and Exp_t^{US} represent the same variables for the rest of the U.S. Lastly, we also compile detailed crude oil movement data among PADDs. All raw data compiled from the EIA are monthly. We convert them into quarterly data by computing, within the quarter, the averages for the stock variables Sto_t^{PADD2}, Sto_t^{US} and SPR_t, and the sums for all the other flow variables.

For our empirical analysis, we need to construct a number of variables based on the raw data. The $Spread_t$ variable is calculated as the difference between Brent and WTI spot prices. Changes in the stock of commercial crude oil in PADD2 and the rest of the U.S. are defined as:

$$\Delta Sto_t^{PADD2} = Sto_t^{PADD2} - Sto_{t-1}^{PADD2}, \tag{6}$$

$$\Delta Sto_t^{US} = Sto_t^{US} - Sto_{t-1}^{US}. \tag{7}$$

In addition, the variable $Trans_t$, which in the model represents transportation from point A (PADD2) to point B (rest of the U.S.), is computed as transportation via all modes from PADD2 to the rest of the U.S. at time t. In addition, we define net imports for PADD2 and the rest of the U.S. as

$$NetImp_t^{PADD2} = Imp_t^{PADD2} - Exp_t^{PADD2}, \tag{8}$$

$$NetImp_t^{US} = Imp_t^{US} - Exp_t^{US} - \Delta SPR_t. \tag{9}$$

In essence, net imports are simply defined as the difference between imports and exports, but for $NetImp_t^{US}$ we also subtract out increases (or add back decreases) in the stock of Strategic Petroleum Reserve maintained in the region, since changes in the stock of SPR should not be accounted for in the commercial crude oil activities.

Table 1 lists summary statistics for key variables of the data set we compile. The table provides means of variables from 1986Q1 to 2016Q1, separated by four time periods based on observations of the Brent-WTI spread time series showed in Figure 1. The following trends are immediately apparent from Table 1. The Brent-WTI has historically been very low from 1998 to 2005, but started to increase from 2006 to 2010; it saw a huge spike from 2011 to 2013, and tapered off from 2014 but remained quite large by historical standards. Transportation, and storage in both PADD2 and the rest of the U.S. increased consistently over time. It should be noted that net imports to PADDs other than PADD2 dropped off sharply starting from 2011, which potentially supports the hypothesis that there was a negative supply shock abroad. Contrastingly however, field productions, particularly that in PADD2, increased substantially from 2011. This leaves room for the possibility that a positive domestic supply shock contributed to the widening Brent-WTI spread. We will econometrically determine the significance of the relationships among these variables in the context of the model developed in this paper, as a two-step process: we shall first validate our theory in Section 5.2, and then apply our theory to identify the causes of the changing Brent-WTI spread in Section 6.

5.2 Testing the spread function

We will first test the relationship described by the spread function as in Proposition 1, which in our context states that the Brent-WTI spread should be increasing in the amount of available oil in Midwest (PADD2) and decreasing in the amount of available oil in the rest of the US. For testing purposes, we define the two variables denoting the availability of crude oil in PADD2 and the rest of the U.S. at time t as

$$N_t^{PADD2} = Pro_t^{PADD2} + NetImp_t^{PADD2} - Trans_t - \Delta Sto_t^{PADD2}, \tag{10}$$

$$N_t^{US} = Pro_t^{US} + NetImp_t^{US} + Trans_t - \Delta Sto_t^{US}. \tag{11}$$

We include ΔSto_t^{US} because although we assumed away storage at point B for simplicity in the theoretical section of this paper, the assumption departs from the empirics of the US oil market. The inclusion of storage at B simply changes the spread function as seen in the specification above. $NetImp_t^{PADD2}$ and $NetImp_t^{US}$ are included because the US is such a large importer of oil that field production and imports together make up what should be considered exogenous supply of crude oil available for consumption.

The econometric model for the spread function can be written as

$$Spread_t = \beta_0 + \beta_1 N_t^{PADD2} + \beta_2 N_t^{US} + \sum_q \delta_q I_t^q + \varepsilon_t, \tag{12}$$

where N_t^{PADD2} and N_t^{US} are defined by equations (10) and (11), and I_t^q is an indicator variable for quarter q. By including a set of quarter indicator variables we are controlling for the potential seasonal effects of the Brent-WTI spread.

In estimation, we are concerned about the endogeneity of the regressors N_t^{PADD2} and N_t^{US}, which if exists would render parameter estimates inconsistent. Endogeneity typically arises as a result of measurement errors, omitted variables, or simultaneity. Although simultaneity might be less of a concern if we trust the structural model built in

Table 1: *Summary Statistics of Time-Series Data*

This table presents summary statistics for our quarterly crude oil data set. A number of variables are constructed from the raw data, as discussed in Section 5.1. The $Spread_t$ is constructed based on the raw Brent and WTI spot prices data from Bloomberg; all other variables come from the the U.S. Energy Information Administration (EIA) or are constructed based on the raw data from the agency. Variable superscripts, when applicable, represents the corresponding geographic region. "US" is short for all PADDs other than PADD2. All units are in millions of barrels unless otherwise noted. Data reported in this table are the means of the variables in the time period given in the column titles.

Variable	Description	1986-2005	2006-2010	2011-2013	2014-2016Q1
$Spread_t$	Brent-WTI spread (in dollars)	-1.5	-0.4	14.9	4.3
$Trans_t$	Transport from PADD2 to the rest of the U.S.	7.2	13.2	65.1	147.1
Sto_t^{PADD2}	Storage in PADD2	68.5	76.1	106.1	122.7
Sto_t^{US}	Storage in the rest of the U.S., excluding SPR	253.5	257.6	259.6	311.8
SPR_t	Storage of Strategic Petroleum Reserve	579.0	705.5	701.6	693.2
Pro_t^{PADD2}	Field production in PADD2	55.4	50.5	101.2	162.4
Pro_t^{US}	Field production in the rest of the U.S.	554.0	424.2	494.4	665.9
$NetImp_t^{PADD2}$	Net imports to PADD2	66.0	104.8	150.8	195.7
$NetImp_t^{US}$	Net imports to the rest of the U.S.	604.7	769.5	611.1	442.9

Section 4, measurement errors and omitted variables do pose challenges to the consistency of our estimates. For example, we should note that our data on crude oil movements only includes movements reported to the EIA, and therefore may underestimate the actual crude oil movement activities across PADDs, which would cause N_t^{PADD2} and N_t^{US} to be mismeasured; furthermore, N_t^{PADD2} and N_t^{US} are likely not sufficient to fully characterize factors that determine the Brent-WTI spread, so the model as specified in (12) may have the issue of omitted variables. To overcome these potential contaminations, we employ IV to estimate the causal relationships.

To illustrate how we shall implement our IV strategy, we consider the model (12) with the omitted variables problem. The problem of the measurement error, if present, can be tackled in a similar fashion. Because of omitted variables, we interpret the error term ε_t in equation (12) as including the omitted variables. The lagged regressors are often used as potentially valid instruments, since by construction they are not correlated with the contemporaneous error term, but are correlated with the endogenous regressors if the regressors are autocorrelated. However, with time series data, the no serial correlation assumption can often be violated, and the validity of lagged regressors as instruments should be assessed with scrutiny in the presence of serial correlation. Suppose that the error term in our model follows a conventional AR(1) process. In other words, $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$. We should note that the serial correlation could be induced or exacerbated by the autocorrelations of the omitted variables.

One conventional strategy is to transform the model in order to correct for serial correlation. However, it is important to point out that a transformation of the model may be able to remove the serial correlation in the error term, but will not remove the contamination. It is therefore still necessary to find proper instruments for endogenous regressors in the transformed models, which can be challenging. Appendix C discusses why transforming the model is not an appropriate approach to address concerns about serial correlation for our purposes.

As a result, we resort to IV estimation technique that is robust to serial correlation and that does not require transforming the model. Building upon the works of heteroskedasticity and autocorrelation (HAC) consistent estimation, such as Newey and West (1987), Andrews (1991) and Smith (2005), we can correct for serial correlation by generating an estimate for the covariance matrix using the Bartlett kernel function and an appropriate selection of bandwidth. Baum, Schaffer and Stillman (2003, 2007) have detailed discussions on how an HAC consistent IV estimation should be implemented.

Our final model for testing the spread function remains in its original form, as in equation (12):

$$Spread_t = \beta_0 + \beta_1 N_t^{PADD2} + \beta_2 N_t^{US} + \sum_q \delta_q I_t^q + \varepsilon_t,$$

but in light of the concerns of the endogeneity of N_t^{PADD2} and N_t^{US}, we use the method of instrumental variables. Potentially valid instruments include N_{t-j}^{PADD2} and N_{t-j}^{US}, where $j = 1, 2, 3, ...$ In practice, we conduct a series of tests to select an optimal set of valid instruments. Specifically, we start with a set of eight potentially valid instruments, namely N_{t-j}^{PADD2} and N_{t-j}^{US}, where $j = 1, 2, 3, 4$. We test these instruments one at a time for redundancy. After dropping all the redundant instruments, we also test the set of remaining instruments to avoid possibility of weak identification or underidentification. In the end, we conclude that N_t^{PADD2} and N_t^{US} should be optimally instrumented by N_{t-1}^{PADD2}, N_{t-3}^{PADD2}, N_{t-1}^{US}, and N_{t-2}^{US}.

After we come up with the optimal set of instruments, we also conduct endogeneity tests of regressors N_t^{PADD2} and N_t^{US}. The endogeneity tests suggest that, statistically, N_t^{PADD2} and N_t^{US} can be treated as exogenous. As a result, in addition to running regressions where N_t^{PADD2} and N_t^{US} are instrumented, we also run additional regressions where one or neither of N_t^{PADD2} and N_t^{US} is instrumented.

To address concerns of heteroskedasticity and serial correlation, we run all the aforementioned tests in two versions, one with heteroskedasticity and serial correlation robust standard errors and one without. In all regressions that are not HAC robust, homoskedasticity and serial independence are checked to be violated. As a result, all our reported results are HAC robust. In doing the HAC robust estimations, we use the Bartlett kernel function with a bandwidth of 5 that is optimally chosen based on the number of observations in our data set.

The regression results of key specifications are presented in Table 2.

The table reports three types of regressions: OLS, 2S GMM, and LIML. OLS regressions are run when neither N_t^{PADD2} nor N_t^{US} is instrumented. When any of the regressor is instrumented, we use two-step feasible and efficient GMM (2S GMM) estimator instead of 2SLS because GMM is more efficient when heteroskedasticity is present (Baum, Schaffer and Stillman, 2003). We also use the limited information maximum likelihood (LIML) estimator, first derived by Anderson and Rubin (1949), to replicate all regression specifications under the 2S GMM estimator. This is because even though LIML provides no asymptotic efficiency gains over 2S GMM, recent research suggests that their finite-sample performance may be superior, for example in the presence of weak instruments (Hahn, Hausman and Kuersteiner, 2004).

Table 2: *Testing the Brent-WTI Spread Function, Full Sample*

This table presents IV regression results for the testing the spread function on the full sample from 1986Q1 to 2016Q1. The dataset consists of 121 quarterly observations. All regressions reported in this table are heteroskedasticity and serial correlation robust, using Bartlett kernel function with a bandwidth of 5. Depending on the specification, N_t^{PADD2} and N_t^{US} are only instrumented in certain cases. When they are instrumented, the corresponding instrumental variables for N_t^{PADD2} are N_{t-1}^{PADD2} and N_{t-3}^{PADD2}; the corresponding instrumental variables for N_t^{US} are N_{t-1}^{US} and N_{t-2}^{US}. Section 5.2 has full discussions on the test procedures. Asterisks indicate statistical significance at 1%***, 5%**, and 10%* levels.

	Dependent Variable: Brent-WTI Spread, $Spread_t$										
	OLS		2S GMM						LIML		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Coefficient estimates for regressor N_t^{PADD2}:											
Non-instrumented	0.1280***	0.1269***		0.1282***			0.1264***			0.1286***	
	(0.0344)	(0.0346)		(0.0344)			(0.0342)			(0.0345)	
Instrumented			0.1328***		0.1367***	0.1340***		0.1355***	0.1362***		0.1367***
			(0.0356)		(0.0356)	(0.0355)		(0.0363)	(0.0358)		(0.0357)
Coefficient estimates for regressor N_t^{US}:											
Non-instrumented	−0.0182***	−0.0171***			−0.0208***			−0.0191***			−0.0208***
	(0.0059)	(0.0051)			(0.0067)			(0.0058)			(0.0067)
Instrumented			−0.0213***	−0.0202***		−0.0206***	−0.0196***		−0.0209***	−0.0195***	
			(0.0070)	(0.0066)		(0.0071)	(0.0071)		(0.0070)	(0.0066)	
Quarter dummies?	yes	no	yes	yes	yes	no	no	no	yes	yes	yes
R^2	0.53	0.53	0.53	0.54	0.53	0.53	0.53	0.53	0.53	0.54	0.53
Adj R^2	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.55	0.54
Test statistics for instruments validity (p-values for underidentification and overidentification tests, F-statistic for weak identification test)											
Underidentification	–	–	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.02
Weak identification	–	–	276	766	440	162	233	404	276	766	440
Overidentification	–	–	0.60	0.39	0.99	0.77	0.56	0.72	0.60	0.39	0.99

The regression results indicate that the estimates on N_t^{PADD2} and N_t^{US} are largely consistent across specifications, regardless of whether regressors are instrumented or quarter dummies are included, and across estimators used. In all the regressions where instrumental variables are used, our selected set of instruments are shown to be valid with no concerns of underidentification, weak identification, or overidentification, as can be seen from the test statistics for instrument validity reported in the last three lines of the table. In particular, the null hypothesis test for the underidentification test is that the model is underidentified; the weak identification test reports an F statistic that can be compared to critical values compiled by Stock and Yogo (2005), but the rule of thumb is that the F statistic needs to be greater than 10 not to have concerns about weak identification; the null hypothesis for the overidentification test is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation.

Column (3) reports results obtained from our preferred specification estimated using 2S GMM. In this specification, both N_t^{PADD2} and N_t^{US} are instrumented with the selected set of instruments, and quarter dummies are included to control for seasonal effects. Based on the results of this regression, a ten-million barrel per quarter increase in total available crude oil in PADD2 is estimated to cause a \$1.328 increase in Brent-WTI spread, and the estimate is statistically significant at the 1% level; a ten-million barrel per quarter increase in total available crude oil in the rest of the U.S. is estimated to cause a \$0.213 decrease in Brent-WTI spread, and the estimate is statistically significant at the 1% level.

For comparison purposes, we take the means of the estimates across all columns (1) to (11). The means of the estimates suggest the following: a ten-million barrel per quarter increase in total available crude oil in PADD2 is estimated to cause a \$1.318 increase in Brent-WTI spread, and a ten-million barrel per quarter increase in total available crude oil in the rest of the U.S. is estimated to cause a \$0.198 decrease in Brent-WTI spread. These results are very close to those from our preferred regression in column (3).

Because the Brent and WTI spot prices only started to show noticeable divergence from 2006, one concern is that the above empirical results may not hold in the subsample. To address this concern, we conduct robustness check in Appendix D.1 on the subsample from 2006Q1 to 2016Q1.

To sum up, in this section we test the spread function as in Proposition 1, and the results are consistent with the predictions of our theoretical model: an increase in the amount of available oil in the Midwest (PADD2) and in the rest of the U.S. enlarges and narrows, respectively, the Brent-WTI spread. This holds true regardless of whether we use the full sample that covers three decades, or the subsample that covers the past decade when the Brent-WTI spread became elevated.

6 Identifying Causes of the Changing Brent-WTI Spread

Now that we've validated our model in Section 5, we would like to apply our model to identify causes of the changing Brent-WTI over time, particularly over the past decade. Proposition 2 states three possible causes of a changing commodity price spread. In our context, each of the three causes represents the following: a change in Q_t^A represents a supply shock in the Midwest; a change in Q_t^B represents a supply shock abroad; a shift of the $k_{t,AB}^T(T_t)$ represents a structural change in the marginal cost of transportation. These three causes imply different relationships among equilibrium spread, transportation, and storage. Therefore, if spread and transportation are negatively correlated, i.e. $\rho_{\sigma_t,T_t} \leq 0$, then the changing price spread should be attributed to a structural change in the marginal cost of transportation. On the other hand, if spread and transportation are positively correlated, i.e. $\rho_{\sigma_t,T_t} \geq 0$, then there are two further possibilities: if spread and storage are positively correlated, i.e. $\rho_{\sigma_t,S_t} \geq 0$, then the changing spread should be attributed to a supply shock in the Midwest; if spread and storage are negatively correlated, i.e. $\rho_{\sigma_t,S_t} \leq 0$, then the changing spread should be attributed to a supply shock abroad. I summarize these results in Table 3, assuming a widening price spread. The results for a narrowing price spread are similar.

Given these model implications, we can use correlations to determine if the changing spread was due to a supply shock abroad, a supply shock in the Midwest, or a structural change in the the marginal cost of transportation. We compute rolling correlations, bounded by confidence intervals, between transportation and the Brent-WTI spread as well as between storage and the Brent-WTI spread. The rolling correlations are computed using a 28-quarter rolling window. The rolling window is chosen in a balanced way, so that it is long enough to uncover patterns in the data and make correlations valid, but also short enough to capture any instability in the rolling correlation trends. We should note that making reasonable changes to the width of the rolling window does not have an impact on our conclusions.

Figure 5 shows the rolling correlations between Brent-WTI spread and transport, and between Brent-WTI spread and storage in the Midwest (PADD2), with 95% confidence intervals, starting from 2010. As we can see, before 2013 the rolling correlations between Brent-WTI spread and transport, and between Brent-WTI spread and storage in the Midwest (PADD2), are both positive, suggesting that the increase in price spread during the period should be attributed to positive supply shocks in the Midwest. From 2013 and

Table 3: *Implied relationships among spread, transportation, and storage*

This table relates model predictions to the context of the Brent-WTI price spread. Proposition 2 discusses three causes of the changing price spread. Each of the three causes represents different shocks in the U.S. crude oil market. The last two columns summarize the implied correlations among spread, transportation, and storage based from different causes. Section 6 has a full discussion on these implied correlations.

Cause of widening spread	Model interpretation	Implied correlation between...	
		Spread and transportation	Spread and storage
Positive supply shock in Midwest	Increase in Q_t^A	$\rho_{\sigma_t,T_t} \geq 0$	$\rho_{\sigma_t,S_t} \geq 0$
Negative supply shock abroad	Decrease in Q_t^B	$\rho_{\sigma_t,T_t} \geq 0$	$\rho_{\sigma_t,S_t} \leq 0$
Structural increase in MC of transportation	Upward shift of $k_{t,AB}^T(T_t)$ curve	$\rho_{\sigma_t,T_t} \leq 0$	ambiguous

onward, we can see from Figure 5 that both correlations start to turn negative. This is evidence that the dominating cause of the narrowing of the price spread is a structural decrease in the marginal cost of transportation, although a positive supply shock abroad could also possibly be a secondary cause that contributes to the negative correlations between spread and storage.

In sum, we have been able to depict a complete story for the dramatic changes in Brent-WTI price spread over the past decade. From 2011 to 2013, Brent-WTI spread increased from being almost zero to as high as $25 per barrel, due to a positive supply shock in the Midwest. Starting from 2013, the Brent-WTI spread started to narrow, fluctuating around $3.5 per barrel, which was much lower than the peak but remained quite high by historical standards. The primary cause for the narrowing of the spread during the period was a structural decrease in the marginal cost of transportation out of Midwest to the rest of the U.S., possibly due to such factors as new pipeline capacities. This is consistent with the reversal of the Seaway Pipeline, as discussed in Section 3.[9] A positive supply shock abroad, such as the Middle East, was likely a secondary cause for the narrowing of the price spread in recent years, too.

7 Conclusion

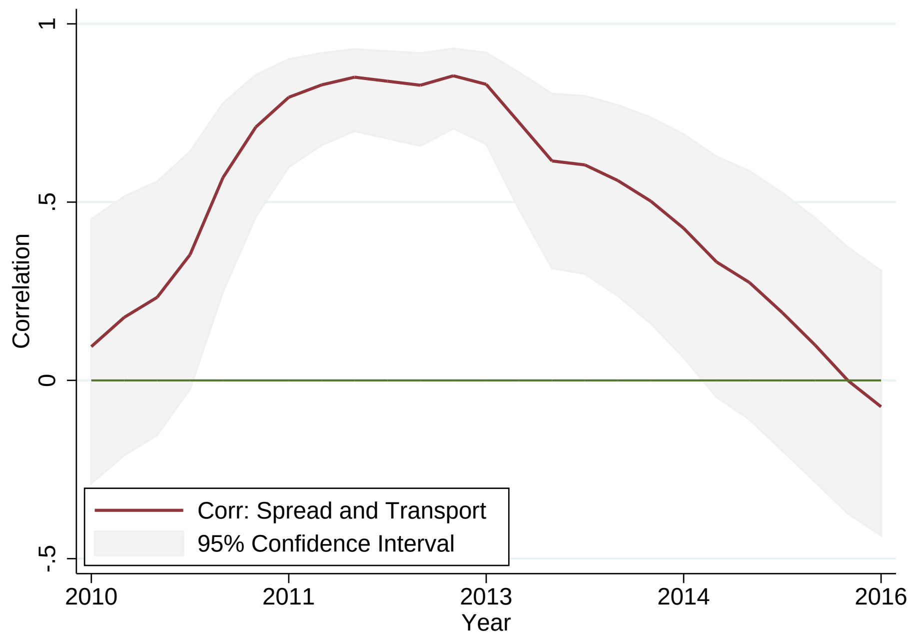
Dramatic price spreads among benchmark crude oils is a phenomenon that emerged in the commodities market in the past decade. This paper serves to enhance our understanding of this unprecedented phenomenon. The addition that this paper provides to the economic literature is both theoretical and empirical. On the theoretical side, the framework of analysis presented here is a generalized and much clearer version of the standard spatial price equilibrium model first pioneered by Samuelson (1952). We explicitly define a spread function and consider the equilibrium level of transportation as the intersection between the spread function and the marginal cost curve of transportation. This perspective makes clear the key differences between a model with constant marginal costs of transportation versus one with increasing marginal costs of transportation. The addition of storage further allows us to draw predictions from the model that help identify unique causes of the changing price spread.

A theory as such is much needed. The theoretical model we build rely on simple assumptions that are in line with salient features of the crude oil market, and generates

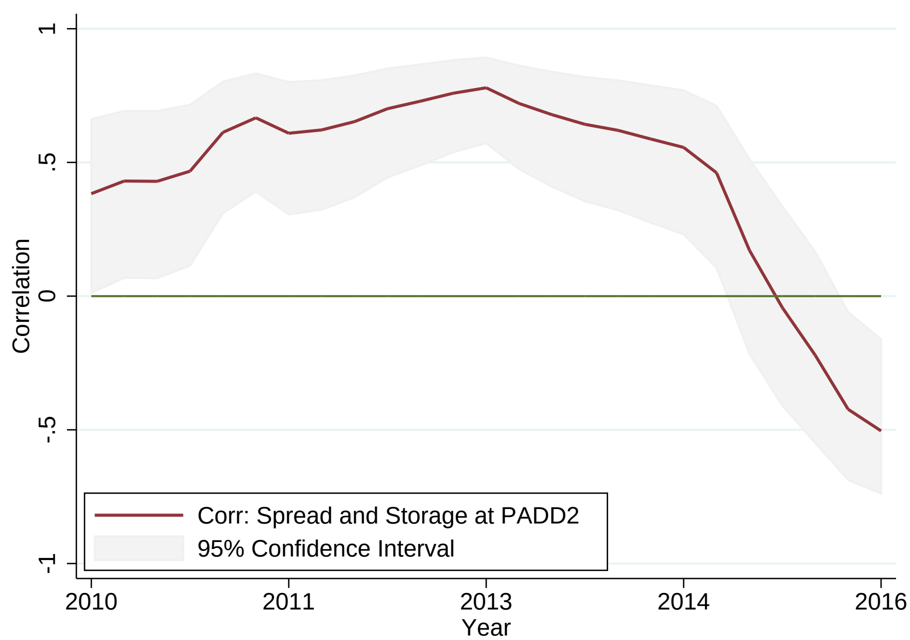
[9]One concern is that the Seaway Pipeline started was reversed in May 2012, but such a structural decrease in the marginal cost of transportation out of Midwest is not reflected in our rolling correlations until later in time. This is due to the nature of rolling correlations that tend to exhibit a lag in uncovering patterns, especially considering we have a seven-year rolling window.

Figure 5: *Rolling correlations among spread, transportation, and storage*

These figures present rolling correlations between the Brent-WTI price spread and transportation from PADD2 to the rest of the U.S., and between the Brent-WTI price spread and storage in PADD2, from 2010. The rolling regression window is chosen to be 28 quarters. The shaded areas indicate 95% confidence intervals.



(a) *Rolling correlations between spread and transportation*



(b) *Rolling correlations between spread and storage* clear and testable theoretical predictions. Our empirical analysis relies on our theory, and thus avoids concerns about data mining that could arise if we work directly with data. In addition, the features of the crude oil market that we build into our model are observed in many other commodities markets. As a result, our theory can readily be adapted to inform price spread patterns in other commodities markets.

On the empirical side, we construct a dataset that covers an extended time period of three decades. This comprehensive dataset allows us to uncover patterns of the crude oil market over a long time horizon, which in a way ensures the robustness of our results. We econometrically validate our model using several testable model predictions, and identify the causes of the changing price spread over the past decade by exploiting the relationships among crude oil price spreads, transportation across regions, and crude oil storage levels.

We find that the widening of the Brent-WTI spread from 2011 to 2013 was due to a positive supply shock in the Midwest, particularly Cushing, that was constrained by insufficient transportation infrastructure. The narrowing of the Brent-WTI spread started from 2013 was primarily due to a structural decrease in the marginal cost of transportation out of Midwest to the rest of the U.S. This is consistent with the reversal of the Seaway Pipeline. Our findings confirm the results in some earlier empirical papers such as Büyükşahin et al. (2013).

In sum, this paper provides a necessary generalization of the literature that addresses the interconnectedness of spatially separated commodity markets. In fact, the applicability of the generalized model presented here is likely not limited to the LLS-WTI spread, and further research should be performed on the applicability of this model to other spatial price spreads that exhibited similarly abrupt changes.

References

Anderson, T. W., and Herman Rubin. 1949. "Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations." *Annals of Mathematical Statistics*, 20(1): 46–63.

Andrews, Donald W. K. 1991. "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation." *Econometrica*, 59(3): 817–858.

Ardeni, Pier Giorgio. 1989. "Does the Law of One Price Really Hold for Commodity Prices?" *American Journal of Agricultural Economics*, 71(3): 661–669.

Bacon, Robert, and Silvana Tordo. 2004. "Crude Oil Prices: Predicting Price Differentials Based on Quality." The World Bank: Oil & Gas Policy Division Viewpoint 275.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman. 2003. "Instrumental Variables and GMM: Estimation and Testing." *Stata Journal*, 3(1): 1–31.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman. 2007. "Enhanced Routines for Instrumental Variables/Generalized Method of Moments Estimation and Testing." *Stata Journal*, 7(4): 465–506.

Borenstein, Severin, and Ryan Kellogg. 2014. "The Incidence of an Oil Glut: Who Benefits from Cheap Crude Oil in the Midwest?" *Energy Journal*, 35(1): 15–33.

Coleman, Andrew. 2009. "Storage, Slow Transport, and the Law of One Price: Theory with Evidence from Nineteenth-Century U.S. Corn Markets." *Review of Economics and Statistics*, 92(2): 332–350.

Deaton, Angus, and Guy Laroque. 1992. "On the Behaviour of Commodity Prices." *Review of Economic Studies*, 59(1): 1–23.

Deaton, Angus, and Guy Laroque. 1996. "Competitve Storage and Commodity Price Dynamics." *Journal of Political Economy*, 104(5): 896–923.

Fattouh, Bassam. 2010. "The Dynamics of Crude Oil Price Differentials." *Energy Economics*, 32(2): 334–342.

Büyükşahin, Bahattin, Thomas K. Lee, James T. Moser, and Michel A. Robe. 2013. "Physical Markets, Paper Markets and the WTI-Brent Spread." *Energy Journal*, 34(3): 129–151.

Goldberg, Pinelopi K., and Frank Verboven. 2005. "Market Integration and Convergence to the Law of One Price: Evidence from the European Car Market." *Journal of International Economics*, 65(1): 283–303.

Hahn, Jinyong, Jerry Hausman, and Guido Kuersteiner. 2004. "Estimation with Weak Instruments: Accuracy of Higher-Order Bias and MSE Approximations." *Econometrics Journal*, 7(1): 46–63.

Kilian, Lutz, and Dan Murphy. 2014. "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil." *Journal of Applied Econometrics*, 29(3): 454âĂŞ478.

Knittel, Christopher R., and Robert S. Pindyck. 2016. "The Simple Economics of Commodity Price Speculation." *American Economic Journal: Macroeconomics*, 8(2): 85–110.

Lanza, Alessandro, Matteo Manera, and Massimo Giovannini. 2005. "Modeling and Forecasting Cointegrated Relationships Among Heavy Oil and Product Prices." *Energy Economics*, 27(6): 831–848.

Newey, Whitney K., and Kenneth D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55(3): 703–708.

Olsen, Kyle K., James W. Mjelde, and David A. Bessler. 2015. "Price Formulation and the Law of One Price in Internationally Linked Markets: An Examination of the Natural Gas Markets in the USA and Canada." *Annals of Regional Science*, 54(1): 117–142.

Richardson, J. David. 1978. "Some Empirical Evidence on Commodity Arbitrage and the Law of One Price." *Journal of International Economics*, 8(2): 341–351.

Roodman, David. 2009. "A Note on the Theme of Too Many Instruments." *Oxford Bulletin of Economics and Statistics*, 71(1): 135–158.

Samuelson, Paul A. 1952. "Spatial Price Equilibrium and Linear Programming." *American Economic Review*, 42(3): 283–303.

Smith, Richard J. 2005. "Automatic Positive Semidefinite HAC Covariance Matrix and GMM Estimation." *Econometric Theory*, 21(1): 158–170.

Stock, James H., and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." In *Identification and Inference for Econometric Models: Essays in Honor of Thomas J. Rothenberg*. , ed. Donald W. K. Andrews and James H. Stock, Chapter 5. Cambridge University Press.

Takayama, Takashi, and George G. Judge. 1964. "Equilibrium among Spatially Separated Markets: A Reformulation." *Econometrica*, 32(4): 283–303.

Werner, Jan. 1987. "Arbitrage and the Existence of Competitive Equilibrium." *Econometrica*, 55(6): 1403–1418.

Williams, Jeffrey C., and Brian Wright. 1991. *Storage and Commodity Markets.* Cambridge University Press.

Appendices

A Appendix: Proofs

Proof of Theorem 1:

Proof. Condition (ii) holds because of the no-arbitrage condition (1). For condition (i), the key is the show that the spread function is downward sloping in T_t. If we differentiate equation (4) with respect to T_t, we get

$$\frac{\partial \sigma_t(T_t)}{\partial T_t} = \frac{\partial D^B(N_t^B)}{\partial N_t^B} + \frac{\partial D^A(N_t^A)}{\partial N_t^A} < 0, \tag{13}$$

where the inequality is the direct result of Assumption 2. Note that the other two arguments Q_t^A and Q_t^B in the spread function $\sigma_t(\cdot)$ are suppressed because they are exogenously given. Because $\sigma_t(T_t)|_{T_t=0} > \bar{k}_{t,AB}^T$, the no-arbitrate condition is violated, suggesting that there is arbitrage opportunity by transporting positive amount of x from A to B. Because $\partial \sigma_t(T_t)/\partial T_t < 0$, there would exist a $T_t^* \in \mathbb{R}_{>0}$ such that $\sigma(T_t^*) = \bar{k}_{t,AB}^T$. Denote $\sigma(T_t^*)$ as σ^*. Hence the proof. □

Proof of Corollary 1:

Proof. Theorem 1 states that the equilibrium price spread σ^* is always equal to $\bar{k}_{t,AB}^T$, where $\bar{k}_{t,AB}^T$ is fixed. As a result of changes in Q_t^A or Q_t^B, T_t^* would change, but σ^* stays the same. □

Proof of Theorem 2:

Proof. We first consider condition (ii). Notice that when $\sigma_t(T_t)|_{T_t=0} \leq k_{t,AB}^T(0)$, the following inequalities hold:

$$\sigma_t(T_t)|_{T_t>0} < \sigma_t(T_t)|_{T_t=0} \leq k_{t,AB}^T(0) < k_{t,AB}^T(T_t)|_{T_t>0}, \tag{14}$$

where the first inequality follows from equation (13) in our proof of Theorem 1, and the last inequality follows from Assumption 3. Therefore, condition (ii) holds.

For condition (i), because $\sigma_t(T_t)|_{T_t=0} > k_{t,AB}^T(0)$, the no-arbitrage condition is violated, suggesting that there is arbitrage opportunity by transporting positive amount of x from A to B. Given equation (13), we have $\sigma_t(T_t') < \sigma_t(T_t)$ when $T_t' > T_t$. Under Assumption 3, we have $k_{t,AB}^T(T_t') > k_{t,AB}^T(T_t)$ when $T_t' > T_t$. As a result, there exists a $T_t^* \in \mathbb{R}_{>0}$ such that $\sigma(T_t^*) = k_{t,AB}^T(T_t^*)$. Denote $\sigma(T_t^*)$ as σ^*. Hence the proof. □

Proof of Corollary 2:

Proof. According to Theorem 2, in equilibrium

$$\sigma(T_t^*) \equiv D^B(Q_t^B + T_t^*) - D^A(Q_t^A - T_t^*) = k_{t,AB}^T(T_t^*). \tag{15}$$

If there is a positive supply shock at A, i.e., $Q_t^{A'} > Q_t^A$, the left-hand side of equation (16) becomes bigger with T^*, i.e., $\sigma(T_t^*|Q_t^{A'}) > \sigma(T_t^*|Q_t^A) = k_{t,AB}^T(T_t^*)$. Because $\sigma(T_t)$ is decreasing in T_t as shown in equation (13), and $k_{t,AB}^T(T_t)$ is increasing in T_t, the new equilibrium must be such that $T_t^{*\prime} > T_t^*$. Hence $\frac{\partial \sigma_t^*}{\partial Q_t^A} > 0$. The analysis for a shock in Q_t^B is similar. □

Proof of Corollary 3:

Proof. Again, according to Theorem 2, in equilibrium

$$\sigma(T_t^*) \equiv D^B(Q_t^B + T_t^*) - D^A(Q_t^A - T_t^*) = k_{t,AB}^T(T_t^*). \tag{16}$$

If there is an exogenous shock that shifts $k_{t,AB}^T(T_t)$ upward, then the right-hand side of equation (16) becomes bigger with T^*, i.e., $\sigma(T_t^*) = k_{t,AB}^T(T_t^*) < k_{t,AB}^{T'}(T_t^*)$. With an analysis similar to the proof for Corollary 2, it's clear that the new equilibrium requires $\sigma_t^{*'} > \sigma_t^*$, and $T_t^{*'} < T_t^*$. □

Proof of Proposition 1:

Proof. This proposition is a direct result of Assumption 2. □

Proof of Theorem 3:

Proof. This theorem is a restatement of condition (i) in Theorem 2. □

Proof of Theorem 4:

Proof. The sensitivity of storage to the exogenous productions at both points can be seen by examining equilibrium condition (i) of Theorem 3:

$$D^B(Q_t^B + T_t^*) - D^A(Q_t^A + S_{t-1} - S_t^* - T_t^*) = k_t^T(T_t^*). \tag{17}$$

For notational convenience, recall $N_t^A = Q_t^A + S_{t-1} - S_t^* - T_t^*$ and $N_t^B = Q_t^B + T_t^*$. If we totally differentiate equation (17) with respect to Q_t^B, we have

$$\frac{\partial D^B(N_t^B)}{\partial N_t^B}\left(1 + \frac{\partial T_t^*}{\partial Q_t^B}\right) - \frac{\partial D^A(N_t^A)}{\partial N_t^A}\left(-\frac{\partial S_t^*}{\partial Q_t^B} - \frac{\partial T_t^*}{\partial Q_t^B}\right) = \frac{\partial k_t^T(T_t^*)}{\partial T_t^*}\frac{\partial T_t^*}{\partial Q_t^B}. \tag{18}$$

Note that $\partial S_{t-1}/\partial Q_t^B = 0$ since S_{t-1} is realized before time t; $\partial Q_t^A/\partial Q_t^B = 0$ since production at A is exogenously given and thus there is no contemporaneous effect of a change in Q_t^B on Q_t^A. After re-arranging equation (18) we get

$$\frac{\partial S_t^*}{\partial Q_t^B} = \frac{\frac{\partial k_t^T(T_t^*)}{\partial T_t^*} - \frac{\partial D^B(N_t^B)}{\partial N_t^B} - \frac{\partial D^A(N_t^A)}{\partial N_t^A}}{\frac{\partial D^A(N_t^A)}{\partial N_t^A}} \frac{\partial T_t^*}{\partial Q_t^B} \tag{19}$$

$$< 0 \tag{20}$$

The inequality in (20) follows because $\frac{\partial D^B(N_t^B)}{\partial N_t^B} < 0$ and $\frac{\partial D^A(N_t^A)}{\partial N_t^A} < 0$ demand curve sloping downward, $\frac{\partial k_t^T(T_t^*)}{\partial T_t^*} > 0$ based on Assumption 3, and we already know that $\frac{\partial T_t^*}{\partial Q_t^B} < 0$.

On the other hand, if we totally differentiate equation (17) with respect to Q_t^A, we have

$$\frac{\partial D^B(N_t^B)}{\partial N_t^B} \frac{\partial T_t^*}{\partial Q_t^A} - \frac{\partial D^A(N_t^A)}{\partial N_t^A} \left(1 - \frac{\partial S_t^*}{\partial Q_t^A} - \frac{\partial T_t^*}{\partial Q_t^A}\right) = \frac{\partial k_t^T(T_t^*)}{\partial T_t^*} \frac{\partial T_t^*}{\partial Q_t^A}. \tag{21}$$

After re-arranging equation (21) we get

$$1 - \frac{\partial S_t^*}{\partial Q_t^A} = \frac{\frac{\partial D^B(N_t^B)}{\partial N_t^B} + \frac{\partial D^A(N_t^A)}{\partial N_t^A} - \frac{\partial k_t^T(T_t^*)}{\partial T_t^*}}{\frac{\partial D^A(N_t^A)}{\partial N_t^A}} \frac{\partial T_t^*}{\partial Q_t^A} \tag{22}$$

If we combine (19) and (22), we get

$$\left(1 - \frac{\partial S_t^*}{\partial Q_t^A}\right) \Big/ \frac{\partial T_t^*}{\partial Q_t^A} + \frac{\partial S_t^*}{\partial Q_t^B} \Big/ \frac{\partial T_t^*}{\partial Q_t^B} = 0 \tag{23}$$

Re-arranging equation (23) gives us

$$\frac{\partial S_t^*}{\partial Q_t^A} = 1 + \frac{\partial S_t^*}{\partial Q_t^B} \frac{\partial T_t^*/\partial Q_t^A}{\partial T_t^*/\partial Q_t^B} \tag{24}$$

Assumption 4 together with inequality (20) and the fact that $\partial T_t^*/\partial Q_t^B < 0$ and $\partial T_t^*/\partial Q_t^A > 0$ gives us the following relation:

$$0 \le \frac{\partial S_t^*}{\partial Q_t^B} < -\frac{\partial T_t^*/\partial Q_t^B}{\partial T_t^*/\partial Q_t^A}. \tag{25}$$

Re-arranging the second inequality of (25) gives

$$\frac{\partial S_t^*}{\partial Q_t^B}\frac{\partial T_t^*/\partial Q_t^A}{\partial T_t^*/\partial Q_t^B} > -1 \tag{26}$$

If we plug (26) into (24), we get

$$\frac{\partial S_t^*}{\partial Q_t^A} = 1 + \frac{\partial S_t^*}{\partial Q_t^B}\frac{\partial T_t^*/\partial Q_t^A}{\partial T_t^*/\partial Q_t^B} > 0. \tag{27}$$

Hence the proof, given (20) and (27). □

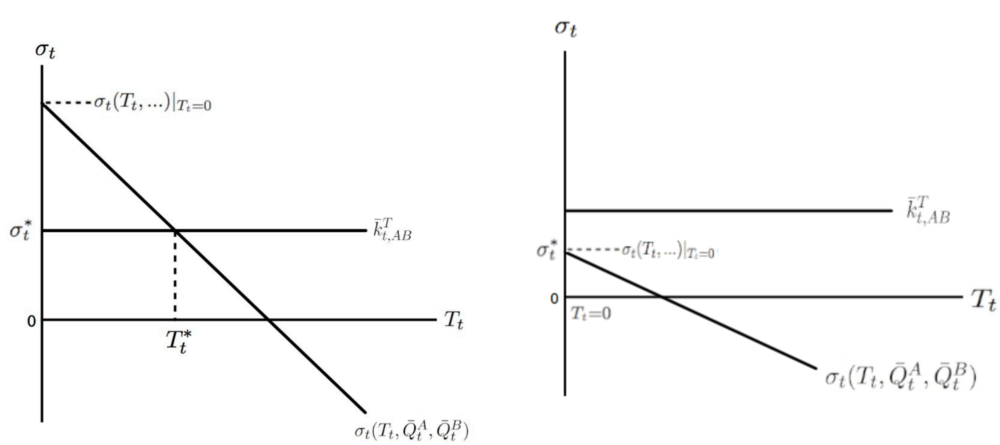
Proof of Proposition 2:

Proof. Conditions (i) and (ii) follow from Corollary 2 and Theorem 4. Condition (iii) follows from Corollary 3. □

B Appendix: Illustrative examples for the model

The following figures provide illustrative examples for the model. Note that the spread curves and the increasing marginal cost curves are linear for illustrative purposes only, whereas we put no linearity restrictions in the model. In fact, any functional forms suffice as long as the monotonicity conditions are satisfied.

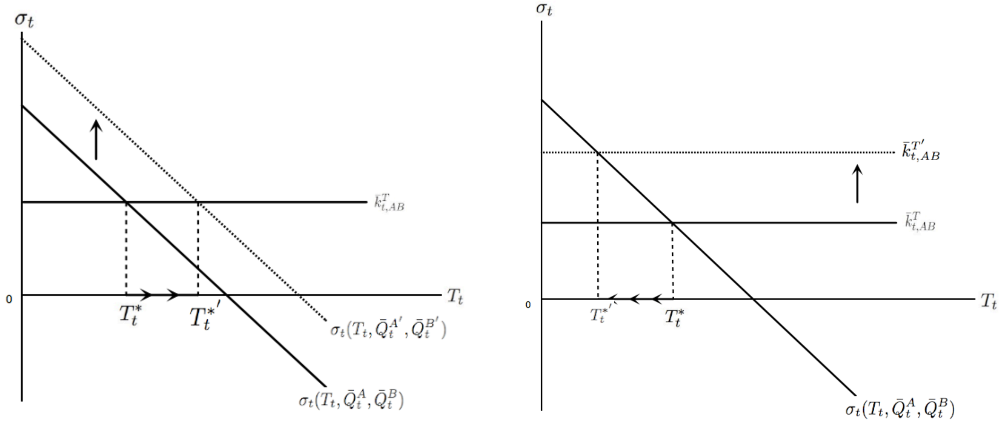
Figure 6: *Equilibrium with constant marginal cost of transportation*



(a) *Graph of condition (i) of Theorem 1. Equilibrium quantity of transportation when $\sigma_t(T_t,...)|_{T_t=0} > \bar{k}^T_{t,AB}$.*

(b) *Graph of condition (ii) of Theorem 1. Equilibrium quantity of transportation when $-\bar{k}^T_{t,BA} < \sigma_t(T_t,...)|_{T_t=0} < \bar{k}^T_{t,AB}$.*

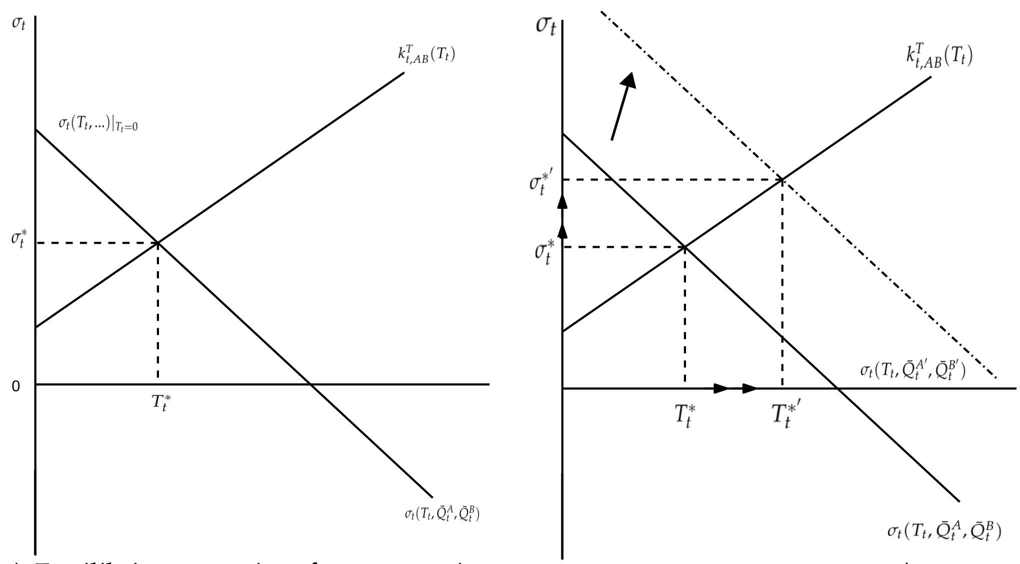
Figure 7: *Illustrations of what can and cannot change the equilibrium price spread in the standard model*



(a) *The spread function can shift out due to a change in production, but equilibrium price spread doesn't change.*

(b) *An exogenous increase in the marginal cost of transportation can increase the equilibrium price spread.*

Figure 8: *Equilibrium With Increasing Marginal Costs of Transportation*



(a) *Equilibrium quantity of transportation and spatial price spread*

(b) *Effects of an increase in Q^A_t or a decrease in Q^B_t*

C Appendix: Empirical strategy

We discuss why transforming our econometric model (12) does not help us resolve concerns about serial correlation. There are two typical ways of transforming a model like (12). The first is

$$Spread_t = \beta_0(1-\rho) + \rho Spread_{t-1} + \beta_1 N_t^{PADD2} - \beta_1 \rho N_{t-1}^{PADD2} + \beta_2 N_t^{US} - \beta_1 \rho N_{t-1}^{US} + \sum_q \delta_q I_t^q - \sum_q \delta_q \rho I_{t-1}^q + u_t. \quad (28)$$

For this transformed model to be estimated consistently, the variables $Spread_{t-1}$, N_t^{PADD2}, N_{t-1}^{PADD2}, N_t^{US}, N_{t-1}^{US} all need to be instrumented. Such a model with many endogenous variables are difficult to identify, and having correspondingly too many instruments can even be dangerous for inference (Roodman, 2009). In addition, given the transformed model, we need to impose constraints on the relationships among coefficients. For instance, the product of the parameter estimates on $Spread_{t-1}$ and N_t^{PADD2} plus the parameter estimates on N_{t-1}^{PADD2} needs to be zero by construction. These constraints on parameters will further undermine the identification of the model.

Another approach is to write out the transformed model in quasi-differenced form:

$$\tilde{Spread}_t = \beta_0(1-\rho) + \beta_1 \tilde{N}_t^{PADD2} + \beta_2 \tilde{N}_t^{US} + \sum_q \delta_q \tilde{I}_t^q + u_t, \quad (29)$$

where $\tilde{x}_t = x_t - \rho x_{t-1}$, with x_t representing any variable in general. In this transformed model, an instrument that itself is in a quasi-differenced form would only work if the original error ε_t is uncorrelated with the instrument at times t, $t-1$, and $t+1$. This rules out first lagged regressors at IVs. The second lagged regressors may work as instruments, only if the quasi-differenced regressors and the second lagged quasi-differenced regressors still have correlations strong enough, because otherwise we would run into weak instrument problems. However, quasi-differencing the regressors typically take out most of the autocorrelation in the transformed regressors by construction, and it would be quite rare to see the quasi-differenced regressors having strong autocorrelations at the second order. In sum, it would be very difficult to justify lagged regressors as proper instruments in this type transformed models.

D Appendix: Robustness checks

We organize our robustness checks into two parts. First, we test the Brent-WTI spread function using subperiod 2006Q1-2016Q1, to address the concern that their prices only started to show divergence from 2006. Second, we run our empirical analysis on the LLS-WTI price spread, to address the concern that Brent is not priced in the US.

D.1 Testing the Brent-WTI spread function using subsample

Because the Brent and WTI spot prices only started to show noticeable divergence from 2006, one concern is that the above empirical results may not hold in the subsample. To address this concern, we repeat our regressions on the subset that covers 2006Q1-2016Q1. All the regression specifications are kept the same as in the full sample regressions, in order to make sure that the results are comparable. In other words, the set of instruments is not re-optimized for the subsample. Table 4 presents the regression results based on the subsample. Because we do not re-optimize the set of instruments, the first point worth discussing is the tests on instrument validity, reported in the last three lines in the table. As we can see, the test statistics indicate that the instruments are valid in various dimensions, therefore we put away concerns about instruments validity even though they are not re-optimized specifically for the subsample.

Our preferred specification in column (3) reports that for the time period from 2006Q1 to 2016Q1, when Brent-WTI spread departed from historical levels, a ten-million barrel per quarter increase in total available crude oil in PADD2 is estimated to cause a \$1.409 increase in Brent-WTI spread, and a ten-million barrel per quarter increase in total available crude oil in the rest of the U.S. is estimated to cause a \$1.070 decrease in Brent-WTI spread. These two estimates are both statistically significant at the 1% level.

In comparison, the means for all estimates suggest the following: a ten-million barrel per quarter increase in total available crude oil in PADD2 is estimated to cause a \$1.417 increase in Brent-WTI spread, and a ten-million barrel per quarter increase in total available crude oil in the rest of the U.S. is estimated to cause a \$0.826 decrease in Brent-WTI spread. Again, just like the full sample, these results are not far away from those of our preferred specification.

D.2 LLS-WTI spread

Because Brent is not priced in the US, one concern is that it cannot be reasonably proxied as crude oil for the rest of the US excluding the Midwest. We showed in Section 3 that Brent trades very closely to LLS, the crude oil priced in St. James, Louisiana, so we do not expect any of our results to change significantly if we conduct analysis on the LLS-WTI spread. We formally test whether this is true in this section.

Despite the fact that LLS is priced within the United States, we choose to focus on Brent because of its economic importance and widespread use. The majority of economists and financial market participants care about the Brent-WTI spread, but not so much about the LLS-WTI spread. One evidence is that there is no outright futures contract that references

LLS.

Our results from using the LLS-WTI spread are reported in Table 5, Table 6, and Figure 9. Because our conclusions do not change in any way, we only briefly discuss the results from using the LLS-WTI spread.

Table 5 tests the spread function using the entire sample from 1986 to 2016. Column (3) reports results obtained from our preferred specification estimated using 2S GMM. In this specification, both N_t^{PADD2} and N_t^{US} are instrumented with the selected set of instruments, and quarter dummies are included to control for seasonal effects. Based on the results of this regression, a ten-million barrel per quarter increase in total available crude oil in PADD2 is estimated to cause a \$1.082 increase in LLS-WTI spread, and the estimate is statistically significant at the 1% level; a ten-million barrel per quarter increase in total available crude oil in the rest of the U.S. is estimated to cause a \$0.114 decrease in LLS-WTI spread, and the estimate is statistically significant at the 5% level.

Table 6 tests the spread function using the subsample from 2006 to 2016. Our preferred specification in column (3) reports when LLS-WTI spread departed from historical levels, a ten-million barrel per quarter increase in total available crude oil in PADD2 is estimated to cause a \$0.704 increase in Brent-WTI spread, and a ten-million barrel per quarter increase in total available crude oil in the rest of the U.S. is estimated to cause a \$0.996 decrease in Brent-WTI spread. These two estimates are statistically significant at 5% and 1% levels, respectively.

Figure 9 helps us identify causes for the changing LLS-WTI spread. The interpretations remain the same as in Section 6.

Table 4: *Testing the Brent-WTI Spread Function, Subsample*

This table presents IV regression results for the testing the spread function on the subsample from 2006Q1 to 2016Q1. The dataset consists of 41 quarterly observations. The specifications are exactly the same as corresponding specifications in Table 2. All regressions reported in this table are heteroskedasticity and serial correlation robust, using Bartlett kernel function with a bandwidth of 4. Depending on the specification, N_t^{PADD2} and N_t^{US} are only instrumented in certain cases. When they are instrumented, the corresponding instrumental variables for N_t^{PADD2} are N_{t-1}^{PADD2} and N_{t-3}^{PADD2}; the corresponding instrumental variables for N_t^{US} are N_{t-1}^{US} and N_{t-2}^{US}. Asterisks indicate statistical significance at 1%***, 5%**, and 10%* levels.

	Dependent Variable: Brent-WTI Spread, $Spread_t$										
	OLS		2S GMM						LIML		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Coefficient estimates for regressor N_t^{PADD2}:											
Non-instrumented	0.1339***	0.1319***		0.1199***			0.1440***			0.1366***	
	(0.0388)	(0.0419)		(0.0375)			(0.0417)			(0.0393)	
Instrumented			0.1409***		0.1546***	0.1556***		0.1404***	0.1510***		0.1497***
			(0.0378)		(0.0404)	(0.0438)		(0.0464)	(0.0428)		(0.0426)
Coefficient estimates for regressor N_t^{US}:											
Non-instrumented	−0.0807**	−0.0667***			−0.0850***			−0.0624***			−0.0818**
	(0.0331)	(0.0240)			(0.0326)			(0.0220)			(0.0336)
Instrumented			−0.1070***	−0.1009***		−0.0620***	−0.0636**		−0.0995**	−0.0992**	
			(0.0376)	(0.0392)		(0.0220)	(0.0251)		(0.0397)	(0.0399)	
Quarter dummies?	yes	no	yes	yes	yes	no	no	no	yes	yes	yes
R^2	0.48	0.44	0.44	0.45	0.47	0.42	0.42	0.43	0.46	0.46	0.47
Adj R^2	0.65	0.62	0.63	0.63	0.64	0.61	0.61	0.62	0.64	0.64	0.65
Test statistics for instruments validity (p-values for underidentification and overidentification tests, F-statistic for weak identification test)											
Underidentification	–	–	0.07	0.03	0.02	0.08	0.04	0.03	0.07	0.03	0.02
Weak identification	–	–	38	65	183	59	40	157	38	65	183
Overidentification	–	–	0.34	0.16	0.71	0.38	0.15	0.62	0.34	0.16	0.71

Table 5: *Testing the LLS-WTI Spread Function, Full Sample*

This table presents IV regression results for the testing the spread function on the full sample from 1986Q1 to 2016Q1. The dataset consists of 121 quarterly observations. All regressions reported in this table are heteroskedasticity and serial correlation robust, using Bartlett kernel function with a bandwidth of 5. Depending on the specification, N_t^{PADD2} and N_t^{US} are only instrumented in certain cases. When they are instrumented, the corresponding instrumental variables for N_t^{PADD2} are N_{t-1}^{PADD2} and N_{t-3}^{PADD2}; the corresponding instrumental variables for N_t^{US} are N_{t-1}^{US} and N_{t-2}^{US}. Section 5.2 has full discussions on the test procedures. Asterisks indicate statistical significance at 1%***, 5%**, and 10%* levels.

	Dependent Variable: LLS-WTI Spread, $Spread_t$										
	OLS		2S GMM						LIML		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Coefficient estimates for regressor N_t^{PADD2}:											
Non-instrumented	0.1041***	0.1033***		0.1041***			0.1077***			0.1040***	
	(0.0365)	(0.0365)		(0.0362)			(0.0359)			(0.0367)	
Instrumented			0.1099***		0.1112***	0.1138***		0.1099***	0.1107***		0.1113***
			(0.0365)		(0.0377)	(0.0374)		(0.0380)	(0.0380)		(0.0377)
Coefficient estimates for regressor N_t^{US}:											
Non-instrumented	−0.0128**	−0.0123**			−0.0155**			−0.0144**			−0.0155**
	(0.0059)	(0.0052)			(0.0066)			(0.0058)			(0.0066)
Instrumented			−0.0147**	−0.0134**		−0.0166**	−0.0155**		−0.0147**	−0.0134**	
			(0.0067)	(0.0063)		(0.0071)	(0.0071)		(0.0067)	(0.0065)	
Quarter dummies?	yes	no	yes	yes	yes	no	no	no	yes	yes	yes
R^2	0.44	0.44	0.44	0.45	0.44	0.44	0.44	0.44	0.44	0.45	0.44
Adj R^2	0.54	0.54	0.55	0.55	0.55	0.54	0.54	0.54	0.55	0.55	0.55
Test statistics for instruments validity (p-values for underidentification and overidentification tests, F-statistic for weak identification test)											
Underidentification	–	–	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.02
Weak identification	–	–	276	766	440	162	233	404	276	766	440
Overidentification	–	–	1.00	1.00	0.94	0.85	0.61	0.70	1.00	1.00	0.94

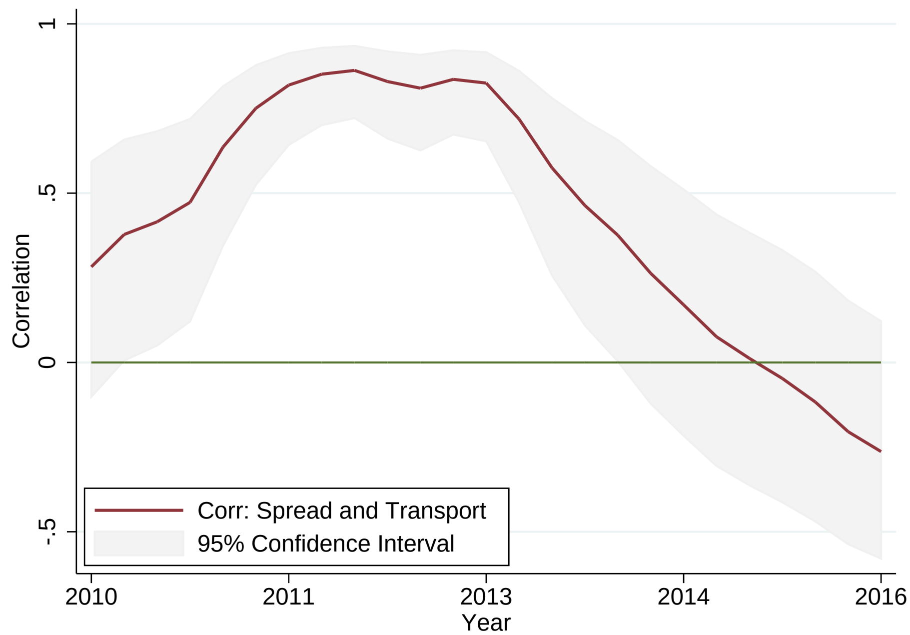
Table 6: *Testing the LLS-WTI Spread Function, Subsample*

This table presents IV regression results for the testing the spread function on the subsample from 2006Q1 to 2016Q1. The dataset consists of 41 quarterly observations. The specifications are exactly the same as corresponding specifications in Table 2. All regressions reported in this table are heteroskedasticity and serial correlation robust, using Bartlett kernel function with a bandwidth of 4. Depending on the specification, N_t^{PADD2} and N_t^{US} are only instrumented in certain cases. When they are instrumented, the corresponding instrumental variables for N_t^{PADD2} are N_{t-1}^{PADD2} and N_{t-3}^{PADD2}; the corresponding instrumental variables for N_t^{US} are N_{t-1}^{US} and N_{t-2}^{US}. Asterisks indicate statistical significance at 1%***, 5%**, and 10%* levels.

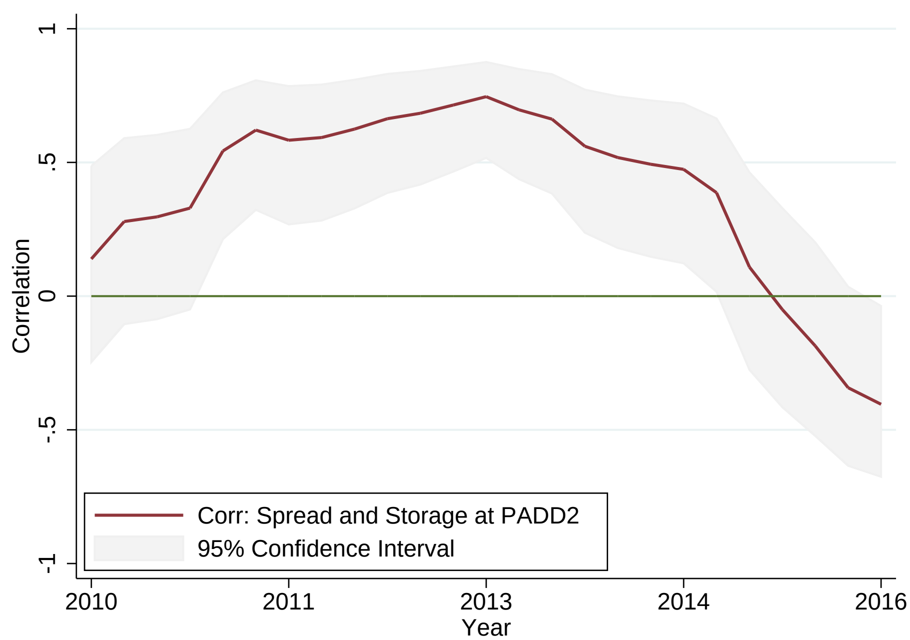
	Dependent Variable: LLS-WTI Spread, $Spread_t$										
	OLS		2S GMM						LIML		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Coefficient estimates for regressor N_t^{PADD2}:											
Non-instrumented	0.0782**	0.0772**		0.0587**			0.0772**			0.0804**	
	(0.0353)	(0.0379)		(0.0300)			(0.0374)			(0.0358)	
Instrumented			0.0704**		0.0914**	0.0775*		0.0756*	0.0896**		0.0885**
			(0.0296)		(0.0367)	(0.0398)		(0.0410)	(0.0384)		(0.0385)
Coefficient estimates for regressor N_t^{US}:											
Non-instrumented	−0.0805***	−0.0651***			−0.0820***			−0.0606***			−0.0812***
	(0.0309)	(0.0227)			(0.0307)			(0.0215)			(0.0309)
Instrumented			−0.0996***	−0.0978***		−0.0582***	−0.0652***		−0.0953***	−0.0951***	
			(0.0359)	(0.0365)		(0.0195)	(0.0234)		(0.0364)	(0.0368)	
Quarter dummies?	yes	no	yes	yes	yes	no	no	no	yes	yes	yes
R^2	0.40	0.34	0.38	0.37	0.39	0.31	0.31	0.34	0.38	0.39	0.39
Adj R^2	0.70	0.67	0.69	0.69	0.70	0.66	0.65	0.67	0.69	0.69	0.70
Test statistics for instruments validity (p-values for underidentification and overidentification tests, F-statistic for weak identification test)											
Underidentification	–	–	0.07	0.03	0.02	0.08	0.04	0.03	0.07	0.03	0.02
Weak identification	–	–	38	65	183	59	40	157	38	65	183
Overidentification	–	–	0.53	0.27	0.81	0.31	0.15	0.52	0.53	0.27	0.81

Figure 9: *Rolling correlations among spread, transportation, and storage*

These figures present rolling correlations between the LLS-WTI price spread and transportation from PADD2 to the rest of the U.S., and between the LLS-WTI price spread and storage in PADD2, from 2010. The rolling regression window is chosen to be 28 quarters. The shaded areas indicate 95% confidence intervals.



(a) *Rolling correlations between spread and transportation*



(b) *Rolling correlations between spread and storage*