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Price Dynamics, the Law of One Price, and Quantile Regressions

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The Law of One Price is a dated but still puzzling economic concept. Studies have found that violations of the law are frequent and numerous, although scholars have pointed that these failures are likely to be due to a lack of informative datasets. In addition, for storable commodities, the possible interactions of spatial and temporal arbitrage may hide the implications of the law, invalidating the conclusions of the studies. Based on a simplified two-market model of spatiotemporal arbitrage, I review the implications of the Law of One Price and test for them with a rich dataset of weekly prices of storable commodities and information on transaction costs, trade, and storage. I conclude that most statements implied by the Law of One Price are not empirically violated.

Key words: arbitrage, storage, trade, transaction cost

Introduction

Arbitrage—which Delbaen and Schachermayer (2006) define as "the possibility to make a profit in a financial market without risk and without net investment of capital"—implies that the prices for a commodity marketed in different areas will converge. There are two types of arbitrage: Spatial arbitrage is the core of the Law of One Price (Fackler and Goodwin, 2001), and temporal arbitrage is key in competitive storage models (Williams and Wright, 2005). The Law of One Price (LOP) defines markets as the spaces within which the price of a good tends toward uniformity, with allowances being made for transaction costs (Stigler, 1966, cited in Fackler and Goodwin, 2001, p. 974). The role of transaction costs is crucial but still puzzling and responsible for numerous violations of the law (Goodwin, 1990; Fackler and Goodwin, 2001; Steinwender, 2018).

Indeed, the LOP has been violated more than any other economic law (e.g., Lamont and Thaler, 2003; Crucini, Shintani, and Tsuruga, 2010; Gopinath et al., 2011). A vast majority of empirical studies rely only on price data, and it plausible to conclude that these violations are due to the inability to make an inference using a single variable (i.e., price) that embeds all information deriving from the market fundamentals. Despite adopting several sophisticated empirical methods to validate the LOP (e.g., Richardson, 1978; Ardeni, 1989; Engel and Rogers, 2001; Goodwin and Piggott, 2001; Taylor, 2001; Gopinath et al., 2011; Novy, 2013; Santeramo, 2015; Goodwin et al., 2018), its empirical validity is still debated.

Ignoring trade flows and transportation costs (also induced by policy interventions) may lead to weak results on market integration (Goodwin, Grennes, and Wohlgenant, 1990; Miljkovic, 1999; Lence, Moschini, and Santeramo, 2018; Antonioli and Santeramo, 2022). Barrett (2001) argues that improved statistical methods of price analysis cannot compensate for the absence of essential information. Fackler and Goodwin (2001, p. 978) argue that, because the LOP relies on

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an equilibrium concept, the violation of the theory could be due to an unstable trading relationship or to a disequilibrium situation. It is therefore important to test for the validity of the LOP using a larger set of information. The existing literature has also underinvestigated another issue: the effects of temporal arbitrage. The two arbitrage forces (temporal and spatial) have different implications for price dynamics (e.g., Goodwin, Grennes, and Craig, 2002); therefore, both should be considered when testing for the validity of the LOP.

The present analysis investigates the empirical validity of the LOP for separated markets when storage and trade occur. The proposed tests are admittedly simple, but they require an informative dataset with data on trade, storage, and transaction costs. The tests are coupled with a quantile regressions approach which allows me to draw conclusions about price dynamics and arbitrage opportunities.

The paper makes (at least) two contributions: First, I use a rich dataset with a relatively higher frequency (i.e., weekly) for price data and information on transaction costs, trade flows, and stock levels. Second, I propose a novel econometric approaches—beyond the state of the art in the price transmission literature—that allows me to draw conclusions about price dynamics and to suggest directions for future research. In addition, the conceptual framework emphasizes the importance of considering two "inactivity bands" (rather than one) in the price transmission analyses.

A Simple Conceptual Framework

Testing for the validity of the LOP is not trivial. Goodwin (1990) and Barrett (2001) point out that it would be wise to enrich the econometric models of price transmission with information other than price. A simple formulation of the LOP is as follows:

$$\text{(1)} \qquad \textit{Absence of Arbitrage Opportunities} \Rightarrow \left| E\left[P^i\right] - E\left[P^j\right] \right| \leq \textit{Transaction costs},$$

where $E[P]$ is expected price, i and j are markets, and the transaction costs include trade, storage, and all other costs incurred by traders.

More precisely, the LOP implies that expected prices are at the boundaries of the (spatial and temporal) arbitrage costs band if trade and storage take place, and at the boundaries of the spatial (i.e., trade) arbitrage costs band if only trade occurs. These conditions define two "inactivity bands" and allow researchers to depict two stylized facts:[1]

(i) Price differences fall outside the larger "inactivity band" if neither spatial not temporal arbitrage are occurring;

(ii) Price differences fall within the smaller "inactivity band" if trade is not profitable (and possibly only storage occurs).

To allow me to draw conclusions about the validity of the LOP in this context, I define regimes based on the activities of spatial and temporal arbitrage. Few (weak) assumptions on expectations, price dynamics, markets, and cost structure are required: Rational arbitrageurs forecast prices based on available information;[2] trade and storage are costly, and trade to distant markets is more expensive than storage in the domestic market.[3] I also assume that trade takes one (or more) period(s) to occur.[4]

[1] The literature on price transmission refers to only one "inactivity band," defined as the maximum price differences that trigger spatial arbitrage activity.

[2] More technically, without loss of generalization, hereafter, I define i to be the export market and j to be the import market. Rational arbitrageurs, based on their information sets (Ω), forecast prices at exporting and importing location: $E_t[P^i_{t+1}|\Omega_t] = P^i_{t+1} + \nu_t$, with $\nu_t \sim \xi(0, \sigma^2)$, and $E[\nu_t, \nu_{t-1}] = 0$, where ν_t represents the one-period-ahead forecast error (compare Cumby and Obstfeld, 1981). More generally, if storage or trade contracts take place over multiple periods, say p, forecast errors serially correlated up to $p-1$ periods are coherent with the LOP (compare Cumby and Obstfeld, 1981).

[3] As in Coleman (2009), trade costs (T) exceed storage costs (k), there is no capacity limitation in trade and storage, and storage costs are constant ($T_t > k_t = \bar{k}$, $\forall\, t > 0$). If storage were more costly than trade, it would never be profitable to trade and store at the same time (Coleman, 2009).

[4] I recognize that if trade takes more time, price dynamics may differ (compare Goodwin, Grennes, and Wohlgenant, 1990) and, in particular, we would observe lagged price responses to large price differentials. In the empirical setting, I use different specifications to allow for lagged adjustments up to four periods. Further exploration in this direction is left as future step.

These assumptions and the spatial and temporal arbitrage conditions allow me to define three regimes: Regime I comprises both spatial and temporal arbitrage; regime II occurs if temporal arbitrage is in place while spatial arbitrage is absent, and regime III is defined by the absence of arbitrage (either temporal and spatial).

In regime I, trade and storage occur and prices are expected to differ by less than trade costs (i.e., price differences fall within the smaller "inactivity band"). Spatial arbitrage (i.e., trade) exists until profitable opportunities are fully exploited. The joint effect of trade and storage results in a low (or null) autocorrelation of the price differences.[5] On the other hand, temporal arbitrage can induce high price serial correlation (Cafiero et al., 2011): Prices of storable goods are expected to be serially correlated when storage is positive, but serial correlation cannot be explained by the competitive storage model during stockouts. I expect to observe nonzero correlation when storage is positive and lower (or zero) correlation during stockouts.[6]

Last, if arbitrage occurs, I expect arbitrage opportunities to be exploited and I therefore expect to find an high speed of price differences reversion to the band in the regime with trade, with a speed that should increase with the magnitude of arbitrage opportunities.

The empirical identification of the price regimes relies on the observed level of trade across markets and on the storage activities in the export market.[7] The regime definitions rule out endogeneity issues that might have arisen if, differently, the regimes had been defined as functions of price levels or price dynamics.[8]

The presence of spatial and temporal arbitrage defines regime I: Expected price differences should equate to the expected transaction costs, net of storage costs. Put differently, the expected price differences minus the expected arbitrage costs (trade costs and storage costs) should be (on average) zero. Also, according to the LOP, price differences should fall within the smaller "inactivity band" (defined by trade costs). As for the price serial correlation, we observe contrasting effects: Spatial arbitrage tends to eliminate price serial correlation, whereas the temporal arbitrage induces serial correlation. Assessing the net effect on price serial correlation is an empirical question that depends on the prevailing force (the high correlation induced by the temporal arbitrage or the zero correlation implied by spatial arbitrage).

Regime II is defined by the presence of temporal arbitrage and the absence of spatial arbitrage. The temporal arbitrage implies that price differences should not exceed the expected storage costs. In addition, if trade is not occurring, price differences are expected to differ by less than the spatial arbitrage costs. Therefore, when storage is positive and trade is absent, I expect to observe price differences to be less than the net arbitrage costs (spatial arbitrage costs minus temporal arbitrage costs). Price differences falling within the "inactivity band" and serial correlation would be consistent with the LOP.

The absence of both temporal and spatial arbitrage defines regime III. When temporal and spatial arbitrage are not occurring, price differences may exceed or not trade costs net of arbitrage costs,

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[5] A few words of caution are needed. In fact, as pointed by a referee, another source of autocorrelation (not dismantled by spatial arbitrage) may be due to the autocorrelation of the trading costs.

[6] Indeed, in the empirical analysis, I define years with no (further) storage activities as those in which the level of storage is lower than that observed in the previous year. For instance, if in 2004, 2005, and 2006 the storage levels are, respectively, 1,000, 1,200, and 1,100 tonnes, the year 2005 will be defined as one with (further) storage activities ($S_{2005} > 0$), whereas the year 2006 will be defined as a year without (further) storage activities ($S_{2006} = 0$). While (as pointed by a reviewer) a lower storage level does not imply stockout, which occurs only when the level of storage is zero, the adopted approach is conservative. If findings are found using a conservative approach, it is legitimate to conclude that including years with zero storage would confirm, and exacerbate, the results.

[7] Trade reversal is allowed and observed in the data. However, the focus is on the normal course of arbitrage activities and I therefore rule out trade reversal by excluding from the analysis the periods in which trade reversals occur. Therefore, analytically, regimes I, II, and III do not include periods with trade reversal. Similarly, I do not consider storage activities in the import market. Coleman (2009) argues that storage in the import market should never be profitable if trade exists. These stringent conditions allow me to tightly connect the empirical analysis to the theoretical implications of the Law of One Price.

[8] In particular, Lence, Moschini, and Santeramo (2018) show that when regimes are defined as functions of price differentials, the inference on arbitrage activities tends to be poor.

due to unexpected demand rises and convenience yield (Brennan, 1976). In fact, price differences may spread less than the full carrying charges, due to the convenience yield (Kaldor, 1976). The convenience yield is low when stocks are abundant but positive when stocks are low. However, because of convenience yield, large differences in prices may be not exploited by arbitrageurs. In fact, the usefulness of holding stocks may be motivated by the convenience of delaying the provision of goods or to answer to unexpected demand rises and ensure the continuity of exploitation. Therefore, the absence of arbitrage (either temporal or spatial) may be due either to the absence of profitable arbitrage opportunities (i.e., the price in the export market is not expected to rise, and the price in the import market differs from the price of the export market by less than trade costs) or to the physical absence of the product (i.e., the price in the export market is expected to rise but there is no product left for storage or the price in the import market differs from the price in the export market by more than trade costs but no product can be traded). Thus, in regime III, two opposite cases would be consistent with the LOP: Price differences are less than trade costs minus storage costs or price differences exceed trade costs. Last, the absence of trade and storage does not allow one to draw conclusions about serial correlation; therefore, either zero or positive serial correlation are consistent with the LOP.

Empirical Strategy

To evaluate the implications of the arbitrage conditions, I construct the *profitable trade* variable, which is equal to the logarithm of the ratio of price differences over (freight rate) trade costs:

$$E\left[\pi_t^T\right] = \ln\left(\frac{P_t^i - P_{t+p}^j}{T_t}\right), \tag{2}$$

where P_j and P_i are the (spot) price in the import and export locations, respectively. Equation (2) is valid when traders have perfect foresight, or (more realistically) when a large amount of trade is contracted before shipping. In fact, when $E[\pi_t^T] > 0$, the expected profit from trade is positive because the price differences are larger than the trade costs. Conversely, if $E[\pi_t^T] < 0$, then trading is not profitable. The variable described above is strictly related to the findings of the literature on price transmission: $E[\pi_t^T] > 0$ indicates that price differences are in the "outer" regime (i.e., prices "deviate" from their long-run relationships), while $E[\pi_t^T] < 0$ indicates that price differences fall in the "inside" regime. The logarithmic transformation implies that positive and negative values are, respectively, indicators of profitable and nonprofitable spatial arbitrage. In addition, the log form allows me to interpret regression coefficients as elasticities.[9] The arbitrage activities may restore the equilibrium after one or more periods (Goodwin, Grennes, and Wohlgenant, 1990); price adjustments therefore require time. I generalize the variable *profitable trade* by allowing up to p periods for arbitrage adjustments to take place. Hereafter, I use the notation *profitable trade* 4 to indicate that the price adjustments require four periods to occur. The variable *profitable trade* is used to evaluate how price differences are distributed with respect to the arbitrage costs, to determine whether and how they are serially correlated, and to draw conclusions about how profitable arbitrage opportunities tend to be eliminated through arbitrage.

The general strategy implemented in this paper is first to evaluate, through nonparametric tests, whether the price differences have similar median values and similar distributions across the three regimes. If spatial and temporal arbitrage act in a similar way, price differences will have similar median values and similar distributions. Indeed, I expect to find that medians differ and that price differences are distributed differently across regimes. This preliminary step allows me to establish whether arbitrage alters levels and distributions of the price differences. I first evaluate whether price differences tend to be equal or smaller than the arbitrage costs and compare the median values

[9] A word of caution is necessary: The proposed measure provides a benchmark to interpret the results but should not be taken as theoretical foundation for the derivation (one-to-one) of the empirical model.

through a semiparametric regression: the median regression (Koenker, 2005). Second, I evaluate the serial correlation in price differences by applying the test for autocorrelation proposed by Cumby and Huizinga (1992). Third, I evaluate whether the arbitrage tends to eliminate profitable opportunities. The analysis is conducted using a quantile autoregressive model (Koenker and Xiao, 2006): When arbitrage is occurring, profitable opportunities (proxied by the positive values of the variable *profitable trade*) should be quickly exploited; moreover, the larger the arbitrage opportunities (i.e., the larger the values of *profitable trade*), the faster the elimination of such opportunities should be. All in all, the analysis allows me to characterize how the price dynamics are altered by the temporal and spatial arbitrage, and how arbitrage eliminates (unexploited) profitable opportunities.

I apply formal nonparametric tests of equality of median values and equal distribution. The Kruskal–Wallis test is a rank-sum statistic that tests for equality of median values across samples. The Kolmogorov–Smirnov test is a nonparametric test of equality of probability distributions that quantifies the distance between the empirical cumulative distribution function (CDF) of two samples, and it may be used to evaluate the distance (and potential statistically significant differences) with respect to the CDF of a reference distribution.

The median regression (a robust techniques with respect to outliers) has been adopted to evaluate whether the price differences tend to exceed arbitrage costs. The median regression, $Q_E[\pi_t^T](0.5) = \theta_0(0.5)$, is solved through a minimization problem (Koenker and Hallock, 2001):

$$\hat{\alpha} = argmin_{\alpha \in \Re} \sum_{t=1}^{T} \left| E\left[\pi_t^T\right] - \alpha \right|, \tag{3}$$

where α is the estimated median value and $E[\pi_t^T]$ is the *profitable trade* variable. Koenker (2005) argues that the median autoregression is a strongly consistent estimator for the median value. In my framework, the median regression indicates whether price differences tend to be larger (positive coefficient) or smaller (negative coefficient) than arbitrage costs. To evaluate the dynamics of price differences, I adopt the test of serial correlation proposed by Cumby and Huizinga (1992). Under the null hypothesis, the time series have a moving average, while the alternative hypotheses is that autocorrelations of the time series are nonzero at lags greater than that specified.

Finally, I estimate a quantile autoregression model (Koenker and Xiao, 2006) able to capture the "local" dynamics of the price series (i.e., local stationary or local unit-root behavior) and therefore to underline the speed at which deviations from the long-run equilibrium revert to the equilibrium. I estimate the model on the whole sample and on two subsamples of positive and negative values. The estimates on the entire sample allow me to draw conclusions about the global behavior of price series, while the estimates on positive values allow me to report on how profitable arbitrage opportunities of different magnitudes are differently exploited. The autoregressive model is as follows:

$$Q_{E\left[\pi_t^T\right]}\left(\tau | Q_{E\left[\pi_t^T\right]_{t-1}}\right) = \theta_0(\tau) + \theta_1(\tau) E\left[\pi_t^T\right]_{t-1}, \tag{4}$$

where τ is the quantile at which the model is evaluated, θ_0 and θ_1 are the estimated coefficients with the inverse of $1 - \theta_1$ representing the "speed of reversion," and $h = \frac{\ln(0.5)}{\ln(\hat{\theta}_1)}$ represents the "half-life" (i.e., the number of periods required to achieve a 50% adjustment toward the equilibrium). I consider three values of τ : 0.25, 0.5, and 0.75. Due to the limited number of observations per regime, I estimate the quantile autoregression specification using a system of three equations. In addition, I compute the interquantile coefficient ("[0.25–0.75]") and test for statistical significance. Intuitively, the larger profitable arbitrage opportunities should be exploited faster than the smaller ones; therefore, the higher the quantile, the faster the reversion of price differentials should be. The quantile autoregression model should reveal lower estimated coefficients (θ_1) at higher quantiles and therefore I expect quantile coefficients to follow a concave function. Put differently, I expect to find $\theta_1(0.75) < \theta_1(0.5) < \theta_1(0.25)$, so that larger profit opportunities are eliminated (via arbitrage) faster (Figure 1).

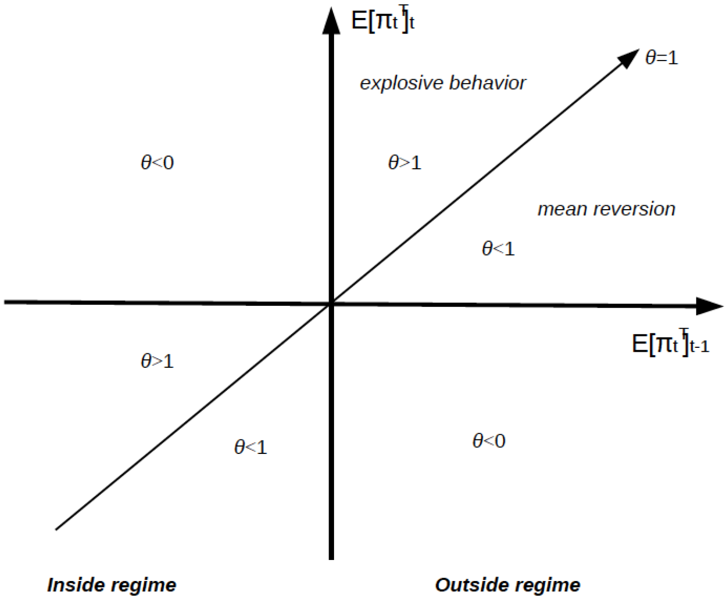

Figure 1. Quantile Autoregression on $E[\pi_t^T]$: Price Dynamics in the Inside and Outside Regimes

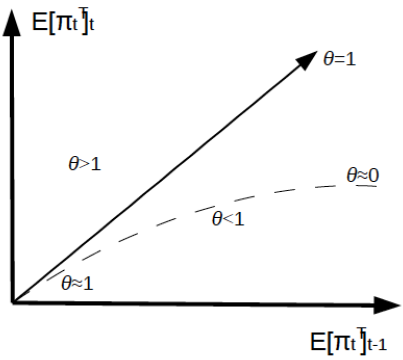

Figure 2. Quantile Autoregression on $E[\pi_t^T]$: Local Price Behavior in the Outside Regime

The specification I adopt shares analogies with the threshold cointegration model proposed by Balke and Fomby (1997). I elaborate more on the intuition by presenting the analogy that my approach shares with the threshold cointegration model of price transmission. The positive values of the *profitable trade* variable ($E[\pi_t^T]^+$) are those allocated in the outside regime of the threshold cointegration model in that the positive values imply that the differences in prices exceed the transaction costs. Conversely, negative values of the *profitable trade* variable ($E[\pi_t^T]^-$) correspond to the observations allocated in the inside regime of the threshold cointegration model (Figure 2). Given this analogy, the coefficients of the threshold quantile autoregression model (θ_1) are inversely related to the "speed of reversion": If θ_1 converges to 0, then the mean reversion is immediate and arbitrage opportunities are exploited immediately. If θ_1 converges to 1, then the local persistence is strong and arbitrage opportunities tend to last longer. If $\theta_1 > 1$, then the time series show a locally explosive tendency that would imply that arbitrage opportunities tend to be increased by further opportunities. Again, the coefficients can be easily interpreted as by considering the "speed of reversion" an the half-lives.

Data

Prices have been extracted from the International Grain Council (IGC), which provides export prices for several grain commodities. Export prices are free on board (FOB) and quoted in US$ per tonne. The export prices are nearest position, so they are indicative and do not constitute actual market prices (International Grain Council, 2014).

Among the price series available from the IGC, I have selected the prices of three commodities (wheat, barley, and rice) for which data related to a similar type of commodity were available at different locations. I have therefore excluded the series that contain large shares of missing values. More specifically, the dataset includes freight rates (priced in US$ per tonne) for the following markets: US Gulf (USA), Rouen (France), and Hamburg (Germany) for wheat; Adelaide (Australia), Rouen, and Hamburg for barley; and Bangkok (Thailand), Chi Minh (Vietnam), and Karachi (Pakistan) for rice. Data span a 10-year period, from April 2005 to May 2014, and are available at a weekly frequency. The dataset contains no or few missing data points for the three price series (0.8% missing for the Australian barley price, 2.5% for the German barley price, and 5.2% for the Vietnamese rice price), which have been opportunely treated through interpolation.

The dataset also includes information on the annual stock levels for the selected countries and commodities, collected from the US Department of Agriculture, and on monthly trade flows, collected from the UN Comtrade database.

Empirical Results

Preliminary analysis shows that the three regimes are not always occurring for the six market pairs (Table 1). In addition, the regimes contain a limited number of observations in that I exclude years in which trade is observed in both directions. As a result, in four out of six cases I identify only two of the three regimes. The share of price differences exceeding the freight costs is generally larger in regime I than in regimes II and III; the maximum number of consecutive deviations (i.e., the number of consecutive periods in which price differences have exceeded freight rate costs) is larger in regime I with respect to regimes II and III: Deviations are more likely to be reported when trade is occurring. The medians and the distributions of price differences are different across regimes (Tables 2 and 3). In particular, the null hypotheses of equal medians (Kruskal–Wallis test) and of equal distribution (Kolmogorov–Smirnov test) are rejected more often when regimes I and II are compared to regime III: Arbitrage alters the distribution of price differences. The results are more evident when I allow for a longer adjustment period (i.e., using the variable *profitable trade* 4). The type of arbitrage (spatial or temporal) does matter: It alters proportional differences and their distributions.

The median regression analysis shows that in most cases the LOP is not violated (Table 4): When spatial or temporal arbitrage is occurring, prices tend to differ by less than arbitrage costs, as implied by the LOP. Interestingly, price differences for rice tend to be much larger than arbitrage costs. A deeper investigation reveals that when direct trade is conspicuous in both directions,[10] price differences are less likely to differ by less than arbitrage cost. Intuitively, this suggests that, in these cases, goods movements through trade "causes" deviations from the equilibrium rather than helping to restore the equilibrium conditions. Conversely, when direct trade is mainly unilateral (as for the barley and wheat pairs), the implications of the LOP are well satisfied in that price differences are smaller than the arbitrage costs. Therefore, in order to draw conclusions about the LOP, the median regression needs to be interpreted jointly with data on direct trade.

The tests of serial correlation also confirm the implications of the LOP. In particular, the null hypothesis of no serial correlation at four lags of the Cumby and Huizinga (1992) test cannot be rejected in regime I for most market pairs (Table 5). The implications of the LOP are more evident when I allow for a longer adjustment period in that in regime I the presence of temporal arbitrage

[10] This is the case for the France–USA pair in wheat and for the Pakistan-Vietnam and Pakistan–Thailand pairs in rice.

Table 1. Number of Deviations per Regime

Market Pair	Regime I $X > 0,\ S > 0$	Regime II $X = 0,\ S > 0$	Regime III $X = 0,\ S = 0$
Wheat: France–United States	52	52	n/a
	[44.2%] [22]	[46.1%] [21]	
Wheat: Germany–United States	n/a	138	n/a
		[14.4%] [17]	
Barley: France–Australia	52	152	307
	[46.2%] [7]	[13.3%] [9]	[51.0%] [15]
Barley: Germany–Australia	n/a	203	305
		[5.2%] [4]	[9.6%] [11]
Rice: Pakistan–Vietnam	52	103	46
	[86.5%] [29]	[49.5%] [16]	[44.2%] [18]
Rice: Pakistan–Thailand	104	n/a	12
	[80.7%] [76]		[19.2%] [5]

Notes: "n/a" indicates "not available." The first row of each market pair reports the number of observations for each regime. Values in brackets are the percentage of price differences exceeding freight rate costs and the maximum number of consecutive deviations (i.e., price differences exceeding freight rate costs.

Table 2. Kruskal–Wallis Equality-of-Populations Rank Test

Market Pair	Adjustment	All Sample	I vs. II	I vs. III	II vs. III
Wheat: France–United States	1 week	0.468	0.339		
	4 weeks	0.425	0.779		
Wheat: Germany–United States	1 week				
	4 weeks				
Barley: France–Australia	1 week	0.001	0.159	0.557	0.000
	4 weeks	0.001	0.002	0.547	0.001
Barley: Germany–Australia	1 week	0.001			0.001
	4 weeks	0.001			0.001
Rice: Pakistan–Vietnam	1 week	0.001	0.115	0.011	0.058
	4 weeks	0.001	0.007	0.135	0.001
Rice: Pakistan–Thailand	1 week	0.000		0.000	
	4 weeks	0.001		0.000	
No. of rejections	1 week	4 out of 5	0 out of 3	1 out of 3	2 out of 3
	4 weeks	4 out of 5	2 out of 3	1 out of 3	3 out of 3
Overall share of rejections	1/4 weeks	66.6%	33.3%	33.3%	62.5%

Notes: The number of rejections refers to a 10% significance level.

Table 3. Two-Sample Kolmogorov–Smirnov Test for Equality of Distribution Functions

Market Pair	Adjustment	I vs. II	I vs. III	II vs. III
Wheat: France–United States	1 week	0.417		
	4 weeks	0.349		
Wheat: Germany–United States	1 week			
	4 weeks			
Barley: France–Australia	1 week	0.103	0.458	0.000
	4 weeks	0.004	0.607	0.000
Barley: Germany–Australia	1 week			0.001
	4 weeks			0.001
Rice: Pakistan–Vietnam	1 week	0.011	0.001	0.021
	4 weeks	0.000	0.252	0.000
Rice: Pakistan–Thailand	1 week		0.000	n/a
	4 weeks		0.000	
No. of rejections	1 week	0 out of 3	2 out of 3	2 out of 3
	4 weeks	2 out of 3	1 out of 3	3 out of 3
Overall share of rejections	1/4 weeks	33.3 %	50 %	62.5 %

Notes: The number of rejections refers to a 10% significance level.

Table 4. Median Regression Analysis

Market Pair	Regime I		Regime II		Regime III	
Wheat: France–United States	−0.095	0.268*	0.039	0.041		
	[0.115]	[0.146]	[0.136]	[0.154]		
Wheat: Germany–United States			−0.816***	−0.693***		
			[0.089]	[0.096]		
Barley: France–Australia	−0.930***	−0.666***	−1.022***	−0.847***	−0.544***	−0.588***
	[0.179]	[0.196]	[0.085]	[0.098]	[0.084]	[0.076]
Barley: Germany–Australia			−1.204***	−1.065***	−0.780***	−0.663***
			[0.085]	[0.075]	[0.071]	[0.069]
Rice: Pakistan–Vietnam	0.405***	0.163***	0.120	0.606***	0.064	0.001
	[0.075]	[0.177]	[0.152]	[0.126]	[0.246]	[0.250]
Rice: Pakistan–Thailand	1.813***	1.875***			0.124**	0.178**
	[0.156]	[0.125]			[0.052]	[0.077]

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. The first and second columns for each regime report, respectively, results for *profitable trade* 1 and *profitable trade* 4.

Table 5. Serial Correlation Tests, *profitable trade* 1

Market Pair	Adjustment	All Sample	Regime I	Regime II	Regime III
Wheat: France–United States	1 week	0.000	0.014	0.019	
	4 weeks	0.000	0.432	0.727	
Wheat: Germany–United States	1 week	0.000		0.606	
	4 weeks	0.228		0.737	
Barley: France–Australia	1 week	0.001	0.073	0.194	0.075
	4 weeks	0.102	0.539	0.615	0.217
Barley: Germany–Australia	1 week	0.000		0.016	0.134
	4 weeks	0.429		0.960	0.324
Rice: Pakistan–Vietnam	1 week	0.000	0.001	0.001	0.002
	4 weeks	0.023	0.333	0.626	0.249
Rice: Pakistan–Thailand	1 week	0.000	0.000		0.047
	4 weeks	0.000	0.005		0.767
No. of rejections	1 week	6 out of 6	2 out of 4	1 out of 5	1 out of 4
	4 weeks	2 out of 6	1 out of 4	0 out of 5	0 out of 4
Overall share of rejections	1/4 weeks	66%	37.5%	10%	10%

Notes: The reported values are the *p*-values of the Cumby and Huizinga (1992) test. The number of rejections refers to a 10% significance level.

Table 6. Serial Correlation Tests, *profitable trade* 4

Market Pair	Adjustment	All Sample	Regime I	Regime II	Regime III
Wheat: France–United States	1 week	0.000	0.011	0.162	
	4 weeks	0.002	0.078	0.699	
Wheat: Germany–United States	1 week	0.000		0.558	
	4 weeks	0.353		0.891	
Barley: France–Australia	1 week	0.000	0.093	0.387	0.000
	4 weeks	0.426	0.573	0.630	0.447
Barley: Germany–Australia	1 week	0.000		0.081	0.005
	4 weeks	0.481		0.528	0.492
Rice: Pakistan–Vietnam	1 week	0.000	0.001	0.000	0.002
	4 weeks	0.000	0.151	0.080	0.298
Rice: Pakistan–Thailand	1 week	0.000	0.000		0.026
	4 weeks	0.000	0.108		0.356
No. of rejections	1 week	6 out of 6	2 out of 4	1 out of 5	3 out of 4
	4 weeks	3 out of 6	0 out of 4	0 out of 5	0 out of 4
Overall share of rejections	1/4 weeks	75%	25%	10%	30%

Notes: The reported values are the *p*-values of the Cumby and Huizinga (1992) test. The number of rejections refers to a 10% significance level.

Table 7. Quantile Autoregression ($\boldsymbol{\theta}_1$ estimates and interquartile estimates)

	Quantiles			Interquartile Estimates [0.25–0.75]		
Market Pair	**0.25**	**0.50**	**0.75**	**Whole Sample**	$E[\pi_t^T] < 0$	$E[\pi_t^T] > 0$
Wheat: France–United States	1.05***	0.79***	0.63***	−0.43***	−0.12	−0.14***
	(0.06)	(0.04)	(0.04)	(0.05)	(0.16)	(0.07)
Wheat: Germany–United States	0.95***	0.80***	0.66***	−0.29***	−0.35***	0.06
	(0.04)	(0.04)	(0.04)	(0.05)	(0.08)	(0.09)
Barley: France–Australia	0.90***	0.74***	0.57***	−0.33***	−0.38***	−0.05
	(0.04)	(0.05)	(0.03)	(0.04)	(0.07)	(0.07)
Barley: Germany–Australia	0.89***	0.75***	0.62***	−0.26***	−0.30***	−0.12
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.02)
Rice: Pakistan–Vietnam	0.93***	0.86***	0.73***	−0.19***	−0.20***	0.07***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.09)	(0.01)
Rice: Pakistan–Thailand	1.02***	0.98***	0.92***	−0.11***	0.02	0.10***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)

Notes: Values in parentheses are (100 bootstrapped) standard errors. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively.

induces serial correlation (Table 6). In regime II, I should reject the null hypothesis in that the absence of trade and the presence of storage suggest that price difference may be serially correlated. Indeed, I find that price differences are serially correlated for only a few periods (i.e., I reject the null of no serial correlation at one lag but fail to reject at four lags). This is not surprising: Storage links prices in the same market over time, but it does not link prices in spatially separated markets. Therefore, again, price differences are serially correlated only in the very short run. Similarly, serial correlation for price differences dies out after a few periods when spatial arbitrage and temporal arbitrage are absent in that prices are linked by no arbitrage forces. The results are not very dissimilar across markets. Further evidence of the role of arbitrage on serial correlation comes from the analysis on the whole sample: The null hypothesis of no serial correlation is frequently rejected. In contrast, the differences on serial correlation are detected when arbitrage is considered. In short, the price differences tend not to be serially correlated when spatial arbitrage is occurring: Spatial arbitrage tends to eliminate serial correlation. The presence of storage induces serial correlation in price differences for very few periods. Again, interpreting the analyses with trade and storage data, as well as with data on transaction costs, is important to draw conclusions about the validity of the LOP.

As for the quantile autoregression model, a statistically significant autoregressive coefficient (lower than 1 in absolute value) would suggest that arbitrage opportunities are gradually eliminated: The smaller the coefficient (in absolute terms), the faster the elimination of arbitrage opportunities will be (Figures 1 and 2). Arbitrage opportunities tend to be exploited. However, trade facilitates the elimination of profitable arbitrage opportunities, while storage makes it less likely to occur. In a few cases, the estimated coefficients exceed 1, indicating that arbitrage opportunities are not exploited (and indeed favor further opportunities of profitable arbitrage). However, these exceptions are related to lower quantiles (0.25), thus they are related to small arbitrage opportunities. In addition, the local unit roots (i.e., the local explosive behavior) are more evident in the three cases in which trade is bilateral:[11] Reasonably, profitable arbitrage is relatively more difficult if it is necessary to forecast incoming and outgoing trade flows rather than forecasting only outgoing trade flows.

As far as the speed at which profitable opportunities are exploited, the coefficients tend to decrease monotonically from the lower (0.25) to the higher (0.75) quantile (i.e., larger deviations

[11] Again, this is the case for the France–United States wheat pair and for the Pakistan–Vietnam and Pakistan–Thailand rice pairs.

Table 8. Half-Lives by Quantiles (in weeks)

	0.25	0.50	0.75
Wheat: France–United States	∞	3.1	1.4
Wheat: Germany–United States	13.5	3.1	1.6
Barley: France–Australia	6.6	2.3	1.2
Barley: Germany–Australia	5.9	2.4	1.2
Rice: Pakistan–Vietnam	6.5	4.3	2.2
Rice: Pakistan–Thailand	∞	22.7	8.3

are eliminated faster than small ones). Intuitively, a large deviation means that the arbitrage opportunities are large; this is likely to attract a large number of arbitrageurs, and profitable opportunities are soon exploited. While these results are evident in Table 7, there is an even stronger evidence when I compute half-lives (Table 8). The differences in estimates across quantiles (0.25–0.75) are statistically significant (see column 5 of Table 7): The price dynamics are different at different levels of price spreads. The negative sign for the interquantiles estimate suggests that large arbitrage opportunities tend to be exploited faster than smaller ones, in that the coefficients estimated at lower quantiles (0.25) are larger than those estimated at higher quantiles (0.75). By limiting the estimates to the outside regime the results are unaltered: When statistically significant, the interquantiles estimate is negative, so the coefficients estimated at lower quantiles (0.25) are larger than the coefficients estimated at higher quantiles (0.75).[12] Again, a richer set of information is important to empirically validate of the LOP.

Concluding Remarks

The empirical validity of the Law of One Price has been doubted and challenged numerous times. Complex statistical analyses may fail to be conclusive due to the lack of informative datasets (Barrett, 2001). A second important issue is that investigations of the validity of the LOP have usually ignored the potential implications of different arbitrage regimes induced by the presence (or absence) of trade and storage. In order to revise the validity of the statements of the LOP, I review the implications of the law and use a rich dataset that includes weekly data on prices and transaction costs as well as data on trade flows and stock levels. I use nonparametric tests and quantile regressions to highlight the price dynamics when arbitrage is occurring and to draw conclusions about the validity of the law. Goodwin, Grennes, and Wohlgenant (1990) point out that including data on transaction costs reduces the ability to detect violations of the Law of One Price. I found similar evidence. Most of the statements of the LOP are confirmed. First, I found that price differences tend to be smaller than arbitrage costs when arbitrage is occurring. Second, serial correlation in price differences, observed throughout the entire sample, is less evident when spatial arbitrage is occurring, and it dies out in a few weeks. Third, arbitrage tends to eliminate unexploited profit opportunities, and larger profit opportunities are exploited more quickly than smaller opportunities, especially when spatial arbitrage is occurring.

Several key points may be derived from the present analysis: First, the empirical validity of the Law of One Price may be better proved when the statistical inference is coupled with trade and storage data. Second, quantile regression is a promising tool for investigating price dynamics and, in particular, to deepen on the persistency of arbitrage opportunities (i.e., usually detected as violations of the LOP) that may arise during stockouts or excess of exports. Third, quantile autoregression is a useful tool to investigate price dynamics in abnormal situations (e.g., when price differences are very low or very high) and should be adopted in future research.

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[12] The same evidence is also found for the inside regime.

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Appendix: On Spatiotemporal Arbitrage Conditions

I describe arbitrage behavior when trade and storage are feasible options. Traders and stores are assumed to be price-takers, and to hold rational expectations based on the available information. Profit-seeking agents exploit arbitrage opportunities arising from spatial or temporal disequilibria.

I describe the behavior of forward-looking agents at time $t+1$. Spatial arbitrage conditions imply that, in expectation, prices of homogeneous goods in two separated markets may differ at most by the transaction costs necessary to reallocate the goods from the relatively good-abundant market to the good-scarce market. I assume that trade takes time: Specifically, if traders commit in period t to ship a good to the other market, the good will be marketed in the destination market at time $t+1$ (compare previous studies such as Goodwin, Grennes, and Wohlgenant, 1990; Coleman, 2009). The arbitrage conditions can be stated as follows:

$$\text{(A1)} \qquad E_t\left[P^i_{t+1}|\Omega_t\right] - E_t\left[P^j_{t+1}|\Omega_t\right] < E_t\left[T^{ij}_t|\Omega_t\right] \text{ for } X^{ij}_t = 0,$$

$$\text{(A2)} \qquad E_t\left[P^i_{t+1}|\Omega_t\right] - E_t\left[P^j_{t+1}|\Omega_t\right] = E_t\left[T^{ij}_t|\Omega_t\right] \text{ for } X^{ij}_t > 0,$$

where $E[\cdot]$ is the expectation operator; P^i_t and P^j_t are the prices in market i and j, respectively; $E_t[T^{ij}_t]$ are expected unit cost to ship from i to j at time t; X^{ij}_t is the quantity traded from i to j; and Ω_t is the information set.[13] Transaction costs (at time t) are known by informed agents. Without loss of generality, I assume that $P^i_t < P^j_t$ and that $T^{ij}_t = T^{ji}_t = T_t$; thus, $E_t[T^{ij}_t|\Omega_t] = T_t$. Therefore agents will face no uncertainty on *expected* prices at the final location, although the expected prices will differ from the *realized* price for a "forecast" error term ($\varepsilon^P_t \overset{i.i.d.}{\sim} (0,\sigma^2)$), assumed to be *i.i.d.* with 0 mean.[14] Notationally, this means that $E_t[P^i_{t+1}|\Omega_t] = P_{t+1} + \varepsilon^P_{t+1}$ (i.e., price expectations differ by realized price for a 0 mean error term). In a more compact notation, we may rewrite the trade arbitrage conditions for the two markets as follows:

$$\text{(A3)} \qquad \left(E_t\left[P^i_{t+1}|\Omega_t\right] - E_t\left[P^j_{t+1}|\Omega_t\right] - T_t\right) \cdot X_t = 0,$$

where X_t represents the traded quantity. Since there is no reason to transfer goods between the two locations if there is no price gap, conditions (A1) and (A2) suggest that trade will not occur if prices differ by less than transaction costs. This implies that prices will tend to move toward the boundaries of the (expected) "transaction costs band" if trade is occurring, while they will have no relationships if trade is not occurring.

Temporal arbitrage conditions implies that the expected (and discounted) future price will differ from current price at most for the costs of storage:

$$\text{(A4)} \qquad \frac{(1-\delta)}{(1+r)} E_t\left[P^i_{t+1}|\Omega_t\right] - E_t\left[P^i_t|\Omega_t\right] < E_t\left[k_t|\Omega_t\right] \text{ for } S_t = 0,$$

$$\text{(A5)} \qquad \frac{(1-\delta)}{(1+r)} E_t\left[P^i_{t+1}|\Omega_t\right] - E_t\left[P^i_t|\Omega_t\right] = E_t\left[k_t|\Omega_t\right] \text{ for } S_t > 0,$$

where k_t represents the cost to store goods for one period, δ is the depreciation rate, r is the interest rate, and S_t is the quantity stored. The net interest rate will be $r-\delta$. I assume that k_t is the same for locations i and j and is constant over time ($k_t = k \ \forall \ t > 0$). Noting that $E_t[P^i_t|\Omega_t] = P^i_t$, and

[13] The model assumes that information is available regardless of the location of traders. Allowing for different information sets is feasible and left as future advance.

[14] The model can easily incorporate uncertainty in transaction costs.

$E_t[k_t|\Omega_t] = k_t = k$, the expressions (A4) and (A5) greatly simplify. In sum, I only assume that storage costs and expected future prices are known, while realized future prices are uncertain.[15]

Since there is no reason to store goods if prices are not expected to rise faster than the net interest rate and by more than the storage costs, conditions (A4) and (A5) suggest that storage will not occur if prices at time $t+1$ and time t are expected to differ by less than storage costs.[16] To have a clearer picture, I rewrite the above conditions as follows:[17]

$$\left(E_t\left[P^i_{t+1}|\Omega_t\right] - P^i_t - k\right) \cdot S_t = 0. \tag{A6}$$

This implies that (virtually) prices at different timing (t and $t+1$) will move within the boundaries of the "storage costs band" if storage is zero, and (in expectation) the first-order difference ($E[\Delta P_{t+1}] \equiv E_t[P_{t+1} - P_t]$) will equal k if storage takes place.

Different from spatial arbitrage that allows transfer of goods in both directions (from market i to market j and vice versa), temporal arbitrage allows to transfer goods only in one direction (from period t to period $t+1$). In both cases, arbitrageurs are profit-seeking agents, so spatial and temporal arbitrage will be substitution strategies.[18]

Assuming that transaction costs are constant over time ($T_t = T \ \forall\, t > 0$), spatial arbitrage implies the following:

$$|E_t\left[P^i_{t+1}|\Omega_t\right] - E_t\left[P^j_{t+1}|\Omega_t\right]| \leq T \text{ for } X_t > 0. \tag{A7}$$

However, as long as $T > k$ (i.e., spatial arbitrage is more costly than temporal arbitrage), it will be not profitable to store the imported good. Therefore, condition (A8) is also valid:[19]

$$\left|E_t\left[P^i_{t+1}|\Omega_t\right] - E_t\left[P^j_{t+1}|\Omega_t\right]\right| \leq T - k \text{ for } X_t > 0 \text{ and } S_t > 0. \tag{A8}$$

Based on these arbitrage conditions, I derive propositions implied by the LOP and evaluate the validity of the LOP under different trade and storage regimes.

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[15] For simplicity, I set r and δ equal to 0. The results are not sensitive to this assumption, which is in line with literature on storage (compare Wright and Williams, 1984). Moreover, I assume there will not be convenience yield.

[16] Recall that $r = \delta = 0$.

[17] For simplicity, I only write them for market i.

[18] In particular, trade is at least a partial substitute for storage (see Miranda and Glauber, 1995), while the opposite is not true. Thus, trade reduces storage, while the opposite is not necessarily true.

[19] Coleman (2009) also report this result.