# Price dynamics, LOP and quantile regressions

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## Abstract

The Law of One Price is a dated but still a puzzling economic concept. Studies that found violations of the Law are frequent and numerous, although scholars have pointed that failures of the Law are likely to be due to 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 spatio-temporal 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 of the statements implied by the Law of One Price are indeed not empirically violated.

**Keywords**: Arbitrage, Quantile, Storage, Trade, Transaction Cost.

**JEL**: Q11, Q13, Q17, C32, P42

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## Introduction

Arbitrage has been intuitively defined as the possibility to make a profit in a financial market without risk and without net investment of capital (Delbaen and Schachermayer, 2006). It implies that the prices for a commodity marketed in different areas will converge.

There are two types of arbitrage: the spatial arbitrage is the core of the Law of One Price (Fackler and Goodwin, 2001); the 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, allowance 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 et al., 2010; Gopinath et al., 2011). A vast majority of empirical studies rely only on price data, and it plausible to conclude that the violations are due to the inability of making inference using a single variable (the price) that embed all information deriving from the market fundamentals. Despite several empirical, sophisticated, methods have been adopted to validate the LOP (e.g. Richardson, 1978; Ardeni, 1989; Goodwin and Piggot, 2001; Engel and Rogers, 2001; Taylor, 2001; Gopinath et al., 2011; Novy, 2013; Sanetramo, 2015; Goodwin et al., 2018), the empirical validity of the LOP is still debated.

Ignoring trade flows and transportation costs (also induced by policy interventions) may lead to weak results on market integration (Goodwin et al., 1990; Miljkovic, 1999; Lence et al., 2018; Antonioli and Santeramo, 2022). As well argued by Barrett (2001), the 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 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 tests for the validity of the LOP with larger set of information. The existing literature has left underinvestigated another issue: the effects of temporal arbitrage. The two arbitrage forces (temporal and spatial) have different implications for price dynamics (e.g. Goodwin et al., 2002), and therefore should be both taken into account when testing for the validity of the LOP.

Starting from the above mentioned debate, the present analysis investigate the empirical validity of the LOP, for separated markets, when storage and trade occur.

The proposed tests are admittedly simple, but indeed 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 conclude on price dynamics and arbitrage opportunities.

The contribution of the present paper is (at least) twofold: first, I use a rich dataset that has 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-art in the price transmission literature, that allows me to conclude on price dynamics and to suggest directions for future research. In addition, the conceptual framework emphazies the importance of considereing 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. As pointed by Goodwin et al. (1990) and Barrett (2001), it would be wise to enrich the econometric models of price transmission with more information, other than price. A simple formulation fo the LOP is as follows:

$$Absence\ of\ Arbitrage\ Opportunities \Rightarrow |E[P^i] - E[P^j]| \leq$$
$$Transaction\ costs$$

where the $E[P]$ stands for expected price, the markets are labelled as $i$ and $j$, 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"[i] and allows depict two stylized facts: a) price differences fall outside the larger "inactivity band" if neither spatial not temporal arbitrage are occurring; b) price differences fall within the smaller "inactivity band" if trade is not profitable (and possibly only storage occurs).

In order to conclude on the validity of the LOP in this context, I define

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

different regimes according to the activities of spatial and temporal arbitrage. Few (weak) assumptions on expectations, price dynamics, markets and costs structure are required: rational arbitrageurs forecast prices based on available information[ii]; trade and storage are costly, and trade to distant markets is more expensive than storing in the domestic market[iii] I also assume that trade takes one (or more) period(s) to occur[iv].

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

In the first regime 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

[ii] 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 ($\Omega$), 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 $\nu_t$ represents the one-period ahead forecast error (cfr. 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 (cfr. Cumby and Obstfeld, 1981)

[iii] 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 ($T_t > k_t = \bar{k}, \forall t > 0$). It should be noted that if storage was more costly than trade it would never be profitable to trade and store at the same time (Coleman, 2009).

[iv] I recognize that if trade takes more time, price dynamics may differ (cfr. Goodwin e al., 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.

a low (or null) autocorrelation of the price differences[v]. On the other hand, temporal arbitrage is able to 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 non-zero correlation when storage is positive, and lower (or zero) correlation during stockouts[vi].

Lastly, if arbitrage occurs, I expect arbitrage opportunities to be exploited and therefore, I 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 market and on the storage activities in the export market[vii]. The definitions of regimes rule out endogeneity issues that may arise

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

[vi]Indeed, in the empirical analysis I define the years with no (further) storage activities as those in which the level of storage is lower than the one observed in the previous year. For instance, if in 2004, 2005 and 2006 the storage levels are, respectively, 1000, 1200, and 1100 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 with a conservative approach is legitimate to conclude that including years with a level of storage equal to zero would confirm, and exacerbate, the results.

[vii]Trade reversal is allowed and observed in the data. However, the focus is on the normal course of arbitrage activities and therefore I rule out trade reversal by excluding from the analysis the periods in which trade reversals occur. Therefore, analytically, regimes one, two and three, do not include periods with trade reversal. Similarly, I do not consider storage activities in the import market. As argued by Coleman (2009), storage in the

if, differently, regimes would have been defined as function of price levels or price dynamics[viii].

The presence of spatial and temporal arbitrage defines the first regime: expected price differences should equate 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 have contrasting effects: the 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 which depends on the prevailing force (the high correlation induced by the temporal arbitrage or the zero correlation implied by the spatial arbitrage).

The presence of temporal arbitrage, and the absence of spatial arbitrage defines the second regime. 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

import market should never be profitable is trade exist. These stringent conditions allow me to make the empirical analysis tightly connected to the theoretical implications of the Law of One Price.

[viii]In particular, Lence et al. (2018) show that when regimes are defined as function of price differentials the inference on arbitrage activities tends to be poor.

(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 temporal and spatial arbitrage defines the third regime. When temporal and spatial arbitrage are not occurring, price differences may exceed or not trade costs net of arbitrage costs, 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 it is positive when stocks are low. However, exactly 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 to insure the continuity of exploitation. Therefore the absence of arbitrage (either temporal and 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 differ 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 differ from the price of the export market by more than trade costs but no product can be traded). Thus, in the third regime, two opposite cases would be consistent with the LOP: price differences are less than trade costs minus storage costs; price differences exceed trade costs. Lastly, the absence of trade and storage does not allow one to conclude on serial correlation, therefore either zero or positive serial correlation are consistent with the LOP.

## Empirical strategy

In order to evaluate the implications of the arbitrage conditions, I construct the variable profitable trade which equals the logarithm of the ratio of price differences over (freight rate) trade costs:

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

where $P_j$ and $P_i$ are, respectively, the (spot) price in the import and export locations. The above expression is valid when traders have perfect foresights, or (more realistically) when a large amount of trade is contracted before shipping. In fact, when $E[\pi_t^T]$ is greater than zero the expected profit from trade is positive exactly because the price differences are larger than the trade costs. Conversely, if the variable $E[\pi_t^T]$ is less than zero, 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 logarithimic transformation implies that positive and negative values are, respectively, indicators of profitable and non profitable spatial arbitrage. In addition, the log-form allows to interpret regression coefficients as elasticities[ix]. The arbitrage activities may restore the equilibrium after one or more periods (Goodwin et al., 1990), and therefore prices

[ix] 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.

adjustments require time. I generalize the variable profitable trade by allowing up to $p$ periods for arbitrage adjustments to take place. Hereafter, I will use the notation profitable trade 4 to indicate that the price adjustments require four periods to occur. The variable profitable trade will be used to evaluate how price differences are distributed with respect to the arbitrage costs, if and how they are serially correlated, and to conclude on how profitable arbitrage opportunities tend to be eliminated through arbitrage.

Let me elaborate on the general strategy implemented in this paper. Preliminarily, I evaluate, through non-parametric tests, if 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 distribution. Indeed, I expect to find that medians differ and that price differences are distributed differently across regimes. This preliminary step allows me to establish if the arbitrage alters levels and distributions of the price differences. So, first, I evaluate if price differences tend to be equal or smaller than the arbitrage costs, and compare the median values through a semi-parametric 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 through 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 the arbitrage eliminates (unexploited) profitable opportunities.

Formal non-parametric tests of equality of median values and equal distribution are applied. The Kruskal-Wallis test is a rank sum statistics that allows one to test for equality of median values across different samples. The Kolmogorov-Smirnov test is a non-parametric test of equality of probability distributions. The test quantifies the distance between the empirical cumulative distribution function (CDF) of two different samples, and it may be used to evaluate the distance (and optential 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, 2001):

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

where $\alpha$ is the estimated median value, and the $E[\pi_t^T]$ 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 if price differences tend to be larger (positive coefficient) or smaller (negative coefficient) than the arbitrage costs. In order 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 the specified one.

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 sub-samples of positive and negative values. The estimates on the entire sample allow me to conclude on the global behavior of price series, while the the estimates on positive values will allow to conclude on how profitable arbitrage opportunities of different magnitudes are differently exploited. The autoregressive model is as follows:

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

where $\tau$ is the quantile at which the model is evaluated, $\theta_0$ and $\theta_1$ are the estimated coefficients with the inverse of 1 - $\theta_1$ representing the speed of reversion, and $h = \frac{ln(0.5)}{ln(\hat{\theta}_1)}$ representing the half life (the number of periods required to achieve a 50 % adjustment toward the equilibrium). I consider three values of $\tau$ : 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 interquantiles coefficient ([.25-.75]) and test for statistical significance. Intuitively, the larger profitable arbitrage opportunities should be exploited faster than the smaller ones, and therefore the higher the quantile, the faster the reversion of price differentials should be. The quantile autoregression model should reveal lower estimated coefficients $\theta_1$) 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 the larger the profit opportunities, the faster their elimination (via arbitrage) should be (Figure 1).

The specification I adopt shares analogies with the threshold cointegration model proposed by Balke and Fomby (1997). Let me 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 variable Profitabe trade ($E[\pi_t^T]^+$) 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, the negative values of the variable Profitabe trade ($E[\pi_t^T]^-$) corresponds 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 ($\theta_1$) are inversely related to the speed of reversion: if $\theta_1$ converges to zero, the mean reversion is immediate, and therefore the arbitrage opportunities are exploited immediately; if $\theta_1$ converges to one , the local persistence is strong and therefore the arbitrage opportunities tend to last longer; if $\theta_1$ is above one the time series show a locally explosive tendency which would imply that the 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 tonnes. The export prices are nearest position, so they are indicative and do not constitute actual market price (IGC, 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 contains a large share of missing values.

More specifically, the dataset includes freight rates (priced in US $ per tonnes) for the following markets: US Gulf (USA), Rouen (France) and Hamburg (Germany) for wheat; Adelaide (Australia), Rouen and Hamburg for barley; Bangkok (Thailand), Chi Minh (Vietnam) and Karachi (Pakistan) for rice. Data span for a ten years period, from April 2005 to May 2014, and are available at weekly frequency. The dataset contains no missing or few missing data for three price series (0.8% for Australian price of barley, 2.5% for German price of barley, and 5.2% for Vietnamese price of rice) which have been opportunely treated through interpolation.

The dataset also includes, for the selected countries and commodities, information on the annual stock levels collected from the USDA and on the monthly trade flows, collected from the UNCOMTRADE database.

## Empirical Results

The preliminary analysis shows that the three regimes are not always occurring for the six markets 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 out of three regimes. The share of price differences exceeding the freight costs is generally larger in regime one than in regimes two and three; 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 one with respect to the regimes two and three: 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 the regimes one and two are compared to the regime three: the 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: when spatial or temporal arbitrage is occurring prices tend to differ by less than arbitrage costs, as implied by the LOP. Interestingly, for rice, price differences tend to be much larger than arbitrage costs. A deeper investigation reveals that when direct trade is conspicuous in both directions[x] 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 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 conclude on 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 test by Cumby and Huizinga (1992) cannot be rejected in regime I for most market pairs. 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 induces serial correlation. 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

[x] This is the case, for wheat markets, for France-USA pair, and, for rice, for the Pakistan-Vietnam and the Pakistan-Thailand pairs.

differences are serially correlated only for 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 in that storage is linking prices of the same market over time, but it does not link prices of 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 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. A further evidence of the role of arbitrage on serial correlation come from the analysis on the whole sample: the null hypothesis of no serial correlation is rejected very often. Differently, when arbtrage is considered, the differences on serial correlation are detected. In short, the price differences tend to not 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 conclude on the validity of the LOP.

As for the quantile autoregression model, a statistical significant autoregressive coefficient (lower than one 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 few cases the estimated coefficients exceed one, indicating that arbitrage opportunities are not exploited (and indeed favor further opportunities of profitable arbitrage). However, these exceptions are related to lower quantiles (.25), thus they are related to small arbitrage opportunities. In addition, the local unit roots (i.e. the local explosive behavior) is more evident in the three cases in which trade is bilateral[xi]: reasonably, it is relatively more difficult to make profitable arbitrage if it is need to forecast incoming and outgoing trade flows, than forecasting only outgoing trade flows.

As far 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: larger deviations are eliminated faster than small ones. Intuitively a large deviation means that the arbitrage opportunities are large, and 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 (.25-.75) are statistically significant (see columns 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

[xi]Again, this is the case, for wheat markets, for France-USA pair, and, for rice, for the Pakistan-Vietnam and the Pakistan-Thailand pairs.

ones in that the coefficients estimated at lower quantiles (.25) is larger than the coefficients estimated at higher quantiles (.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 (.25) are larger than the coefficients estimated at higher quantiles (.75)[xii]. Again, a richer set of information is important to empirically validate of the LOP.

[xii] Indeed, the same evidence is also found for the inside regime.

## 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 the validity of the LOP has been usually investigated ignoring 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 which includes weekly data on prices and transaction costs, as well as data on trade flows and stock levels. I use non-parametric tests and quantile regressions to highlight the price dynamics when arbitrage is occurring, and to conclude on the validity of the Law. As pointed by Goodwin et al. (1990), the inclusion of data on transaction costs results in a lower tendency 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 the price differences tend to be smaller than the arbitrage costs when arbitrage is occurring. Second, the serial correlation in price differences, observed throughout the entire sample, is less evident when spatial arbitrage is occurring, and it dies out in few weeks. Third, the arbitrage tends to eliminate unexploited profit opportunities, and the larger profit opportunities are exploited quicker than the smaller opportunities, especially when the spatial arbitrage is occurring.

Several key messages may be derived from the present analysis: first, the empirical validity of the Law may be better proved when the statistical inference is coupled with the observations of data on trade and storage; second, the quantile regression is a promising tool to investigate 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, the 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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## Methodological Appendix
## On spatio-temporal 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 will 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 $t+1$ (cfr. previous studies such as Goodwin et al., 1990; Coleman, 2009). The arbitrage conditions can be stated as follows:

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

(2) $E_t[P^i_{t+1}|\Omega_t] - E_t[P^j_{t+1}|\Omega_t] = E_t[T^{ij}_t|\Omega_t]$ 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 $j$, $E_t[T^{ij}_t]$ are expected unit cost to ship from $i$ to $j$ at time $t$, $X^{ij}_t$ is the quantity traded from $i$ to $j$, $\Omega_t$ is the information set[xiii]. 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 <u>expected</u> prices at the final location, although the expected prices will differ from the <u>realized</u> price for a "forecast" error term ($\epsilon^P_t \overset{iid}{\sim} (0, \sigma^2)$), assumed to be iid with zero mean[xiv]. Notationally this means that $E_t[P^i_{t+1}|\Omega_t] = P_{t+1} + \epsilon^P_{t+1}$, that is price expectations differ by realized price for a zero mean error term. In a more compact notation, we may rewrite the trade arbitrage conditions for the two markets as follows:

(3) $(E_t[P^i_{t+1}|\Omega_t] - E_t[P^j_{t+1}|\Omega_t] - T_t) \cdot X_t = 0$

where $X_t$ represents the traded quantity. Since there is no reason to transfer goods among the two locations if there is not a price gap, conditions (1) and (2) 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,

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

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

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:

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

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

where $k_t$ represents the cost to store goods for one period, $\delta$ is the depreciation rate, $r$ is the interest rate, $S_t$ 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 it is constant over time ($k_t = k\ \forall t > 0$). Noting that $E_t[P^i_t|\Omega_t] = P^i_t$, and $E_t[k_t|\Omega_t] = k_t = k$, the expressions 4 and 5 greatly simplify. In sum, I only assume that storage costs and expected future prices are known, while realized future prices are uncertain[xv].

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 (4) and (5) suggest that storage will not occur if prices at time $t+1$ and time $t$ are expected to differ by less than storage costs[xvi]. To have a clearer picture, I rewrite the above conditions[xvii] as follows:

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

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 substitutes strategies[xviii].

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

(7) $|E_t[P^i_{t+1}|\Omega_t] - E_t[P^j_{t+1}|\Omega_t]| \leq T$ for $X_t > 0$

However, as long as $T > k$, that is spatial arbitrage is more costly than temporal arbitrage, it will be not profitable to store the imported good.

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[xv] For simplicity we set $r$ and $\delta$ equal zero. The results are not sensitive to this assumption, which is in line with literature on storage (cfr. Wright and Williams, 1984). Moreover, we assume there will not be convenience yield.

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

[xvii] For simplicity we only write them for market $i$.

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

Therefore, condition (8) is also valid[xix]:

(8) $|E_t[P^i_{t+1}|\Omega_t] - E_t[P^j_{t+1}|\Omega_t]| \leq T - k$ for $X_t > 0$ and $S_t > 0$

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.

[xix] This result is also shown by Coleman (2009)

# Tables and Figures

Table 1: Number of deviations per regime

| Markets pair | Regime I | | Regime II | | Regime III | |
|---|---|---|---|---|---|---|
| | $X > 0, S > 0$ | | $X = 0, S > 0$ | | $X = 0, S = 0$ | |
| Wheat: FRA - USA | 52 | | 52 | | na | |
| | [44.2%] | [22] | [46.1%] | [21] | | |
| Wheat: GER - USA | na | | 138 | | na | |
| | | | [14.4%] | [17] | | |
| Barley: FRA - AUS | 52 | | 152 | | 307 | |
| | [46.2%] | [7] | [13.3%] | [9] | [51.0%] | [15] |
| Barley: GER - AUS | na | | 203 | | 305 | |
| | | | [5.2%] | [4] | [9.6%] | [11] |
| Rice: PAK - VIE | 52 | | 103 | | 46 | |
| | [86.5%] | [29] | [49.5%] | [16] | [44.2%] | [18] |
| Rice: PAK - THA | 104 | | na | | 12 | |
| | [80.7%] | [76] | | | [19.2%] | [5] |

FRA, USA, GER, AUS, PAK and VIE stand, repectively, for France, United States of America, Germany, Australia, Pakistan and Vietnam. na stands for not available. The first line of the table reports the number of observations per each regime, while in squared parentheses are reported 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

| Markets pair | Adjustment | All Sample | I vs II | I vs III | II vs III |
|---|---|---|---|---|---|
| Wheat: FRA - USA | 1 week | .468 | .339 | | |
| | 4 weeks | .425 | .779 | | |
| Wheat: GER - USA | 1 week | | | | |
| | 4 weeks | | | | |
| Barley: FRA - AUS | 1 week | .001 | .159 | .557 | .000 |
| | 4 weeks | .001 | .002 | .547 | .001 |
| Barley: GER - AUS | 1 week | .001 | | | .001 |
| | 4 weeks | .001 | | | .001 |
| Rice: PAK - VIE | 1 week | .001 | .115 | .011 | .058 |
| | 4 weeks | .001 | .007 | .135 | .001 |
| Rice: PAK - THA | 1 week | .000 | | .000 | |
| | 4 weeks | .001 | | .000 | |
| N. of rejections | 1 week | 4 out of 5 | 0 out of 3 | 1 out of 3 | 2 out of 3 |
| N. of rejections | 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% |

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

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Table 3: Two-sample Kolmogorov-Smirnov test for equality of distribution functions

| Markets pair | Adjustment | I vs II | I vs III | II vs III |
|---|---|---|---|---|
| Wheat: FRA - USA | 1 week | .417 | | |
| | 4 weeks | .349 | | |
| Wheat: GER - USA | 1 week | | | |
| | 4 weeks | | | |
| Barley: FRA - AUS | 1 week | .103 | .458 | .000 |
| | 4 weeks | .004 | .607 | .000 |
| Barley: GER - AUS | 1 week | | | .001 |
| | 4 weeks | | | .001 |
| Rice: PAK - VIE | 1 week | .011 | .001 | .021 |
| | 4 weeks | .000 | .252 | .000 |
| Rice: PAK - THA | 1 week | | .000 | na |
| | 4 weeks | | .000 | |
| N. of rejections | 1 week | 0 out of 3 | 2 out of 3 | 2 out of 3 |
| N. of rejections | 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 % |

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

Table 4: Median regression analysis

| Markets pair | Regime I | | Regime II | | Regime III | |
|---|---|---|---|---|---|---|
| Wheat: FRA - USA | -.095 | $.268^{+}$ | .039 | .041 | | |
| | [.115] | [.146] | [.136] | [.154] | | |
| Wheat: GER - USA | | | $-.816^{**}$ | $-.693^{**}$ | | |
| | | | [.089] | [.096] | | |
| Barley: FRA - AUS | $-.930^{**}$ | $-.666^{**}$ | $-1.022^{**}$ | $-.847^{**}$ | $-.544^{**}$ | $-.588^{**}$ |
| | [.179] | [.196] | [.085] | [.098] | [.084] | [.076] |
| Barley: GER - AUS | | | $-1.204^{**}$ | $-1.065^{**}$ | $-.780^{**}$ | $-.663^{**}$ |
| | | | [.085] | [.075] | [.071] | [.069] |
| Rice: PAK - VIE | $.405^{**}$ | $.163^{**}$ | .120 | $.606^{**}$ | .064 | .001 |
| | [.075] | [.177] | [.152] | [.126] | [.246] | [.250] |
| Rice: PAK - THA | $1.813^{**}$ | $1.875^{**}$ | | | $.124^{*}$ | $.178^{*}$ |
| | [.156] | [.125] | | | [.052] | [.077] |

Standard errors in squared brackets. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$ , $^{**}$ $p < 0.01$
The first and second column for each regime report, respectively, results for profitable trade 1 and profitable trade 4.

Table 5: Serial correlation tests - profitable trade 1

| Markets pair | Adjustment | All Sample | Regime I | Regime II | Regime III |
|---|---|---|---|---|---|
| Wheat: FRA - USA | 1 week | .000 | .014 | .019 | |
| | 4 weeks | .000 | .432 | .727 | |
| Wheat: GER - USA | 1 week | .000 | | .606 | |
| | 4 weeks | .228 | | .737 | |
| Barley: FRA - AUS | 1 week | .001 | .073 | .194 | .075 |
| | 4 weeks | .102 | .539 | .615 | .217 |
| Barley: GER - AUS | 1 week | .000 | | .016 | .134 |
| | 4 weeks | .429 | | .960 | .324 |
| Rice: PAK - VIE | 1 week | .000 | .001 | .001 | .002 |
| | 4 weeks | .023 | .333 | .626 | .249 |
| Rice: PAK - THA | 1 week | .000 | .000 | | .047 |
| | 4 weeks | .000 | .005 | | .767 |
| N. of rejections | 1 week | 6 out of 6 | 2 out of 4 | 1 out of 5 | 1 out of 4 |
| N. of rejections | 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 % |

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

| Markets pair | Adjustment | All Sample | Regime I | Regime II | Regime III |
|---|---|---|---|---|---|
| Wheat: FRA - USA | 1 week | .000 | .011 | .162 | |
| | 4 weeks | .002 | .078 | .699 | |
| Wheat: GER - USA | 1 week | .000 | | .558 | |
| | 4 weeks | .353 | | .891 | |
| Barley: FRA - AUS | 1 week | .000 | .093 | .387 | .000 |
| | 4 weeks | .426 | .573 | .630 | .447 |
| Barley: GER - AUS | 1 week | .000 | | .081 | .005 |
| | 4 weeks | .481 | | .528 | .492 |
| Rice: PAK - VIE | 1 week | .000 | .001 | .000 | .002 |
| | 4 weeks | .000 | .151 | .080 | .298 |
| Rice: PAK - THA | 1 week | .000 | .000 | | .026 |
| | 4 weeks | .000 | .108 | | .356 |
| N. of rejections | 1 week | 6 out of 6 | 2 out of 4 | 1 out of 5 | 3 out of 4 |
| N. of rejections | 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 % |

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

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Table 7 : Quantile autoregression ($\theta_1$ estimates and interquantiles estimates)

| | Quantiles | | | IQ [.25-.75] | IQ [.25-.75] | IQ [.25-.75] |
|---|---|---|---|---|---|---|
| Markets pair | 0.25 | 0.50 | 0.75 | Whole Sample | $E[\pi_t^T] < 0$ | $E[\pi_t^T] > 0$ |
| Wheat: FRA - USA | 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: GER - USA | 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: FRA - AUS | 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: GER - AUS | 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: PAK - VIE | 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: PAK - THA | 1.02** | 0.98** | 0.92** | -0.11** | 0.02 | -0.10** |
| | (0.02) | (0.01) | (0.01) | (0.02) | (0.01) | (0.02) |

(100 bootstrapped) s.e in squared brackets. $^+$ $p < 0.10$, $^*$ $p < 0.05$ , $^{**}$ $p < 0.01$

Table 8 Half lives by quantiles (expressed in weeks)

| | 0.25 | 0.50 | 0.75 |
|---|---|---|---|
| Wheat: FRA - USA | $\infty$ | 3.1 | 1.4 |
| Wheat: GER - USA | 13.5 | 3.1 | 1.6 |
| Barley: FRA - AUS | 6.6 | 2.3 | 1.2 |
| Barley: GER - AUS | 5.9 | 2.4 | 1.4 |
| Rice: PAK - VIE | 6.5 | 4.3 | 2.2 |
| Rice: PAK - THA | $\infty$ | 22.7 | 8.3 |

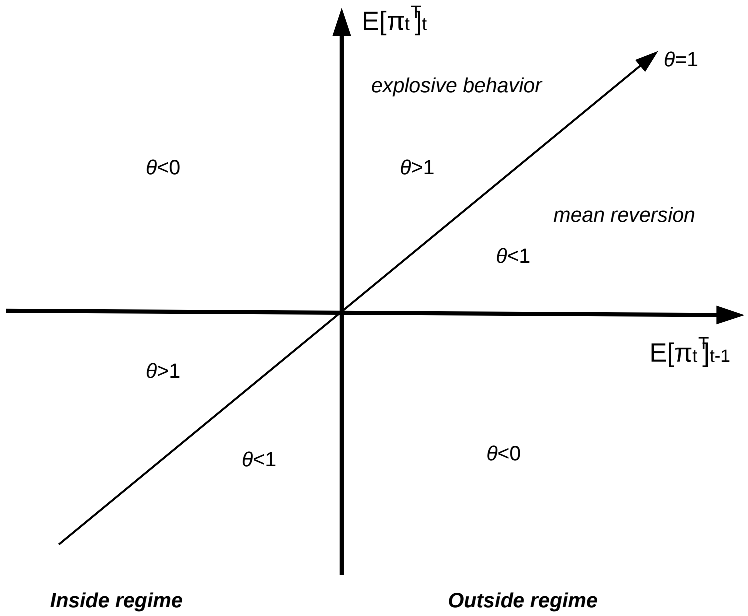



Figure 2: Quantile Autoregression on $E[\pi_t^T]$

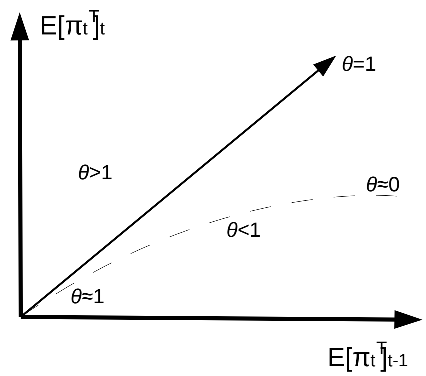
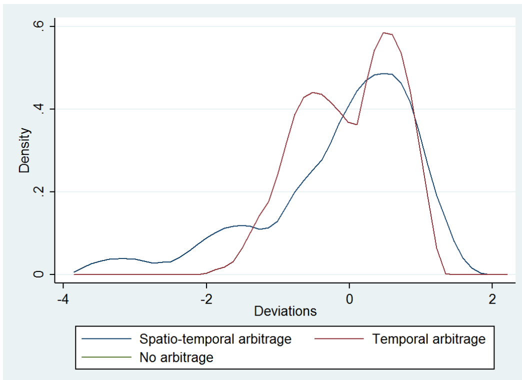
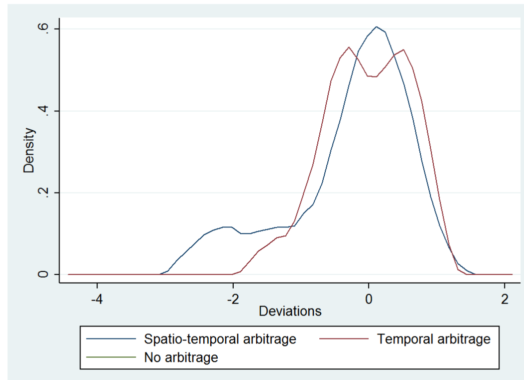



Figure 3: Quantile Autoregression on $E[\pi_t^T]$

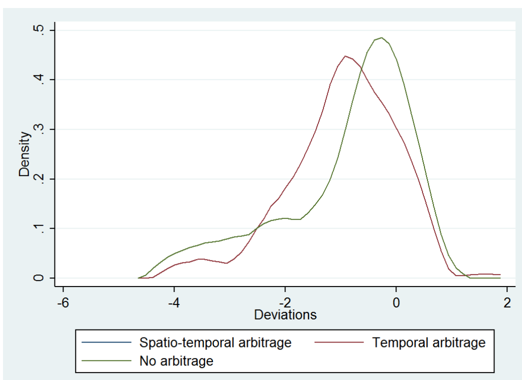
# Graphical appendix - Not intended for publication



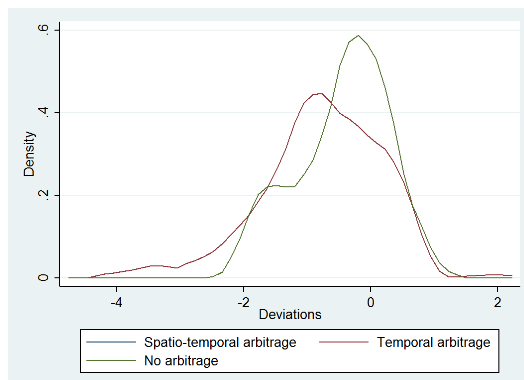

(a) Wheat: FRA - USA




(b) Wheat: FRA - USA

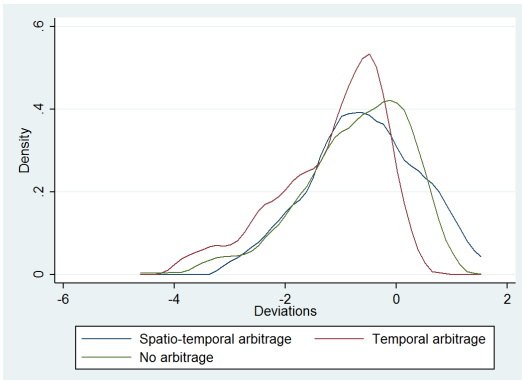



(c) Wheat: GER - USA

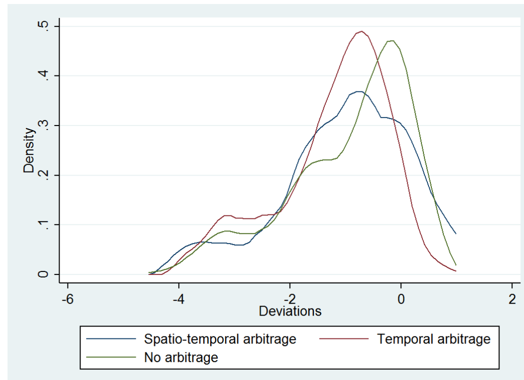



(d) Wheat: GER - USA

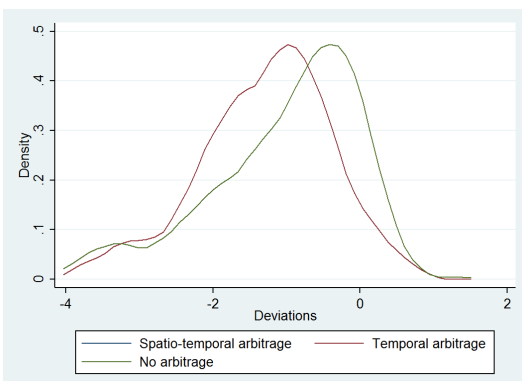
Figure 4: The figures on the left refer to profitable trade with 1 week adjustment period; the figures on the right refer to profitable trade with 4 weeks adjustment period. The blue, red and green lines are, respectively, for regime one (spatio-temporal arbitrage), two (temporal arbitrage) and three (no arbitrage).



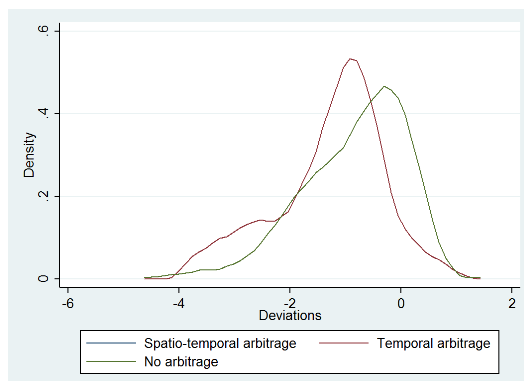

(a) Barley: FRA - AUS




(b) Barley: FRA - AUS

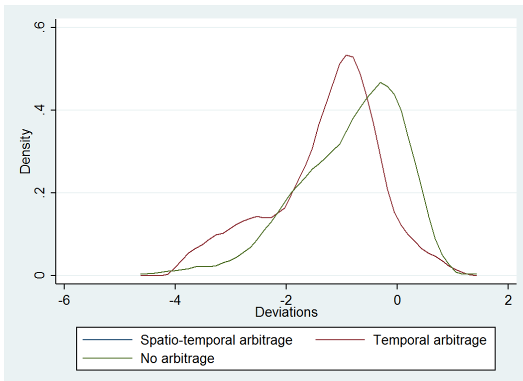



(c) Barley: GER - AUS

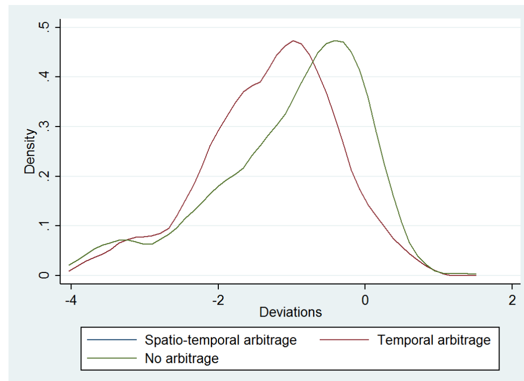



(d) Barley: GER - AUS

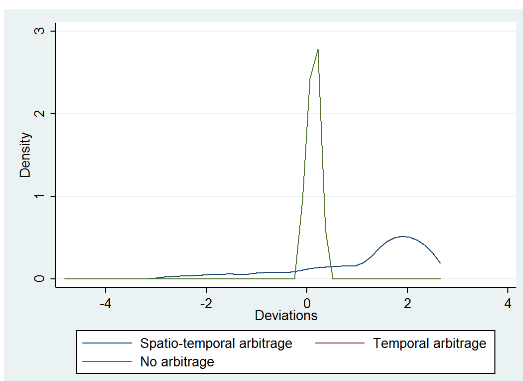
Figure 5: The figures on the left refer to profitable trade with 1 week adjustment period; the figures on the right refer to profitable trade with 4 weeks adjustment period. The blue, red and green lines are, respectively, for regime one (spatio-temporal arbitrage), two (temporal arbitrage) and three (no arbitrage).



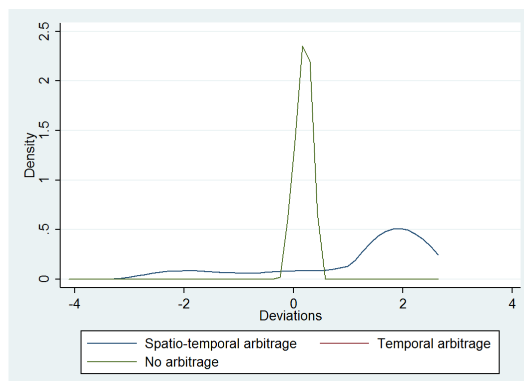

(a) Rice: PAK - VIE




(b) Rice: PAK - VIE

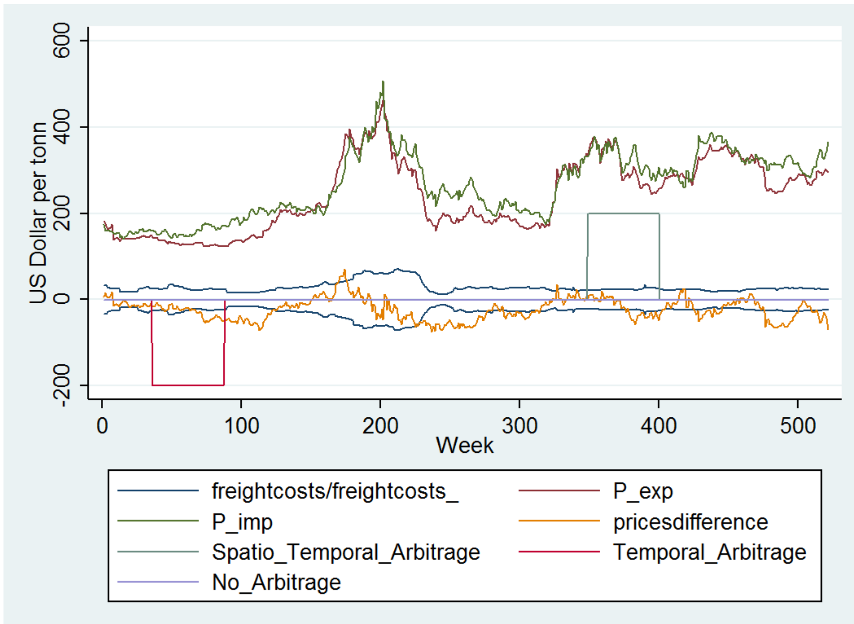



(c) Rice: PAK - THA

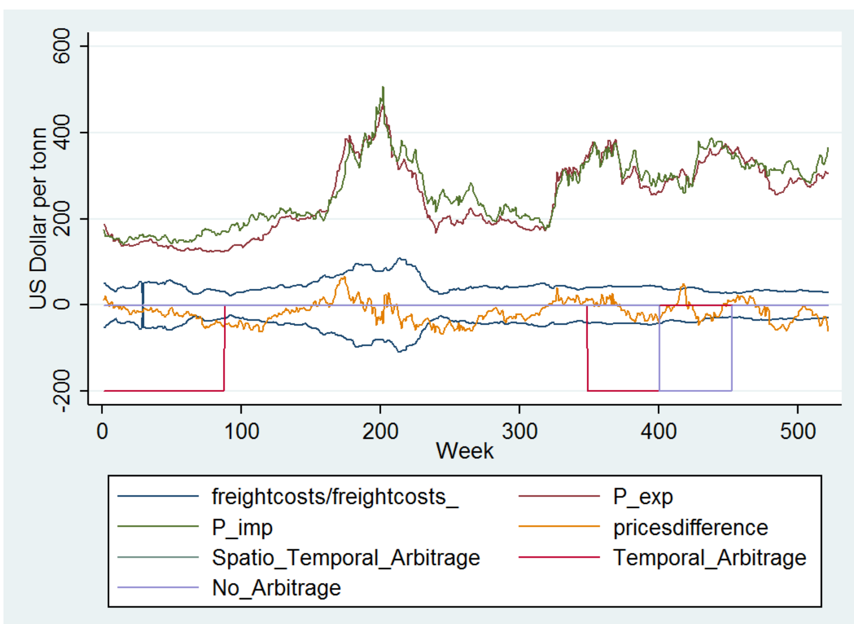



(d) Rice: PAK - THA

Figure 6: The figures on the left refer to profitable trade with 1 week adjustment period; the figures on the right refer to profitable trade with 4 weeks adjustment period. The blue, red and green lines are, respectively, for regime one (spatio-temporal arbitrage), two (temporal arbitrage) and three (no arbitrage).

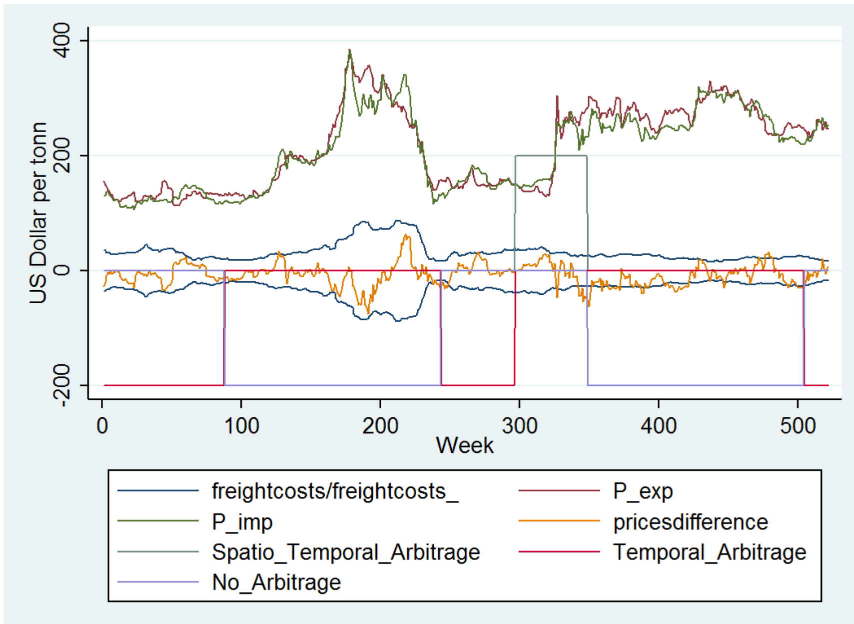



(a) Wheat: FRA - USA

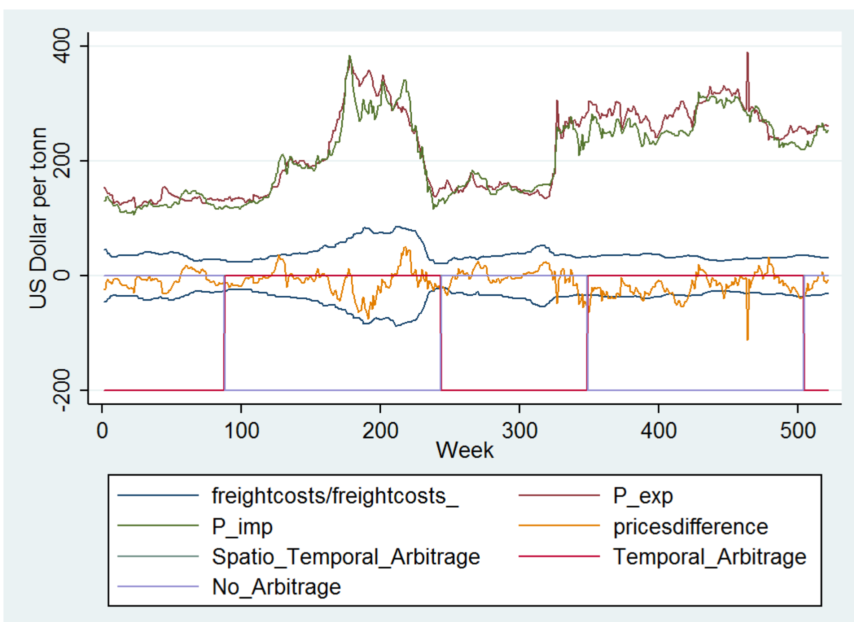



(b) Wheat: GER - USA

Figure 7: The plots show import and export prices, price differences and regimes: spatio-temporal arbitrage, temporal arbitrage, and no arbitrage.

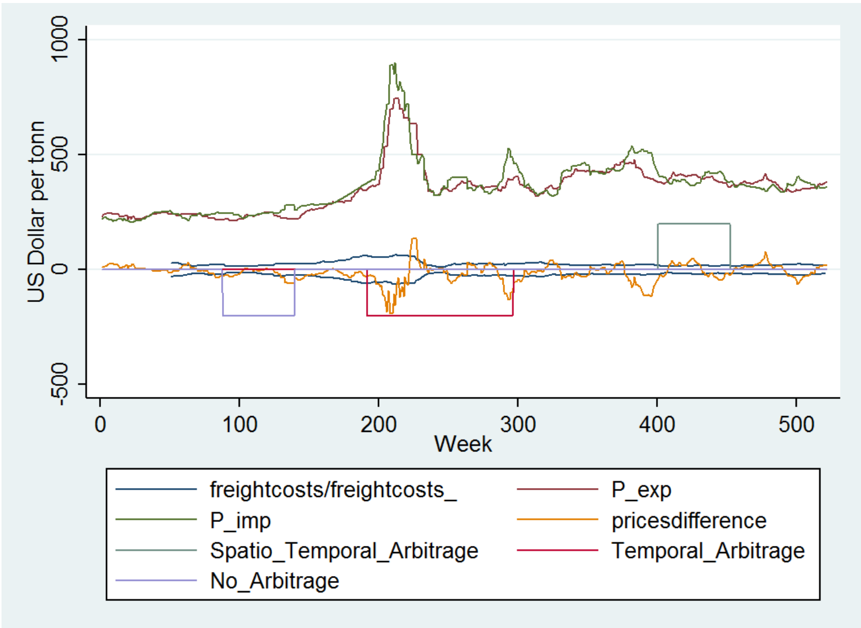



(a) Barley: FRA - AUS

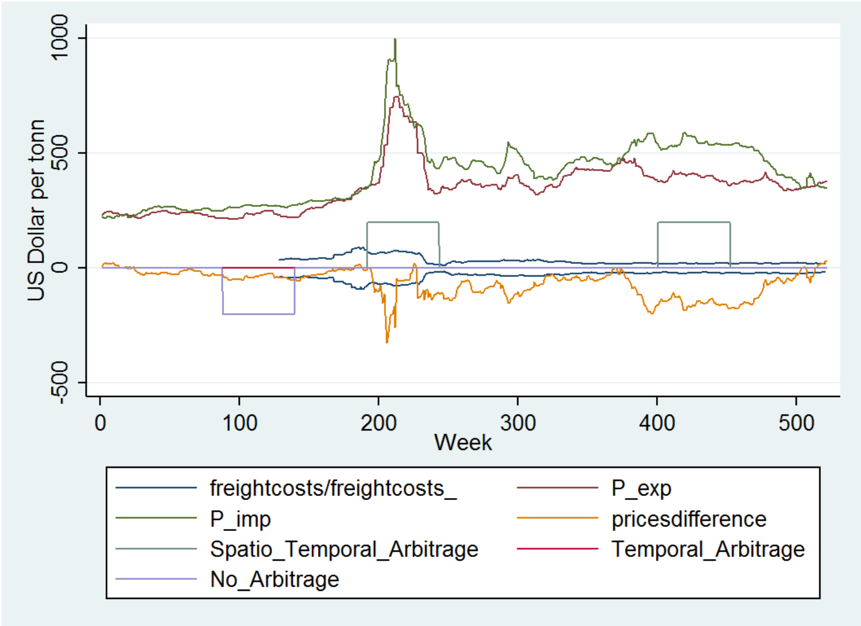



(b) Barley: GER - AUS

Figure 8: The plots show import and export prices, price differences and regimes: spatio-temporal arbitrage, temporal arbitrage, and no arbitrage.




(a) Rice: PAK - VIE




(b) Rice: PAK - THA

Figure 9: The plots show import and export prices, price differences and regimes: spatio-temporal arbitrage, temporal arbitrage, and no arbitrage.