

WHEAT PRICE DYNAMICS IN TURKEY: A NONLINEAR ANALYSIS

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ABSTRACT

WHEAT PRICE DYNAMICS IN TURKEY: A NONLINEAR ANALYSIS

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Wheat is an extremely important agricultural commodity, due to its crucial role in everyday nutrition, food security, and in terms of incomes of a large body of farmers worldwide. This study examines the dynamics of wheat prices in Turkey in a framework that allows for regime switching. Due to their simplicity, threshold autoregressive (TAR) models are used to capture the effects of factors such as transaction costs and other institutional arrangements that generate discontinuous adjustment to equilibrium price level. The results are compared with standard linear model estimations. Results indicate that there is strong evidence for asymmetric adjustment of wheat prices in Turkey to the equilibrium price, hence models allowing for regime switching are more preferable over the linear ones. However, the diagnostics of the TAR model reveal that specification of a TAR model allowing for more than two regimes, or a smooth transition autoregressive (STAR) model that allows for smooth transition through a continuum of regimes might be more appropriate.

Keywords: TAR models, cointegration, nonlinear time series, Turkey, wheat prices

ÖZ

TÜRKİYE BUĞDAY FİYATLARININ DOĞRUSAL OLMAYAN DİNAMİKLERİ

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Günlük beslenmedeki yeri, gıda güvenliği açısından önemi ve tarımsal faaliyetler içerisindeki payı, buğdayı oldukça önemli bir tarım ürünü haline getirmektedir. Bu nedenle bu çalışmada, buğday fiyatlarının yurtiçi dinamikleri rejim değişikliklerine izin veren bir model çerçevesinde incelenmiştir. İşlem maliyetleri ve denge fiyatına sürekli yakınsamayı engelleyici başta kurumsal olmak üzere diğer etmenlerin etkileri, Eşik Özbağlanımlı (TAR) modeller kullanılarak açıklanmaya çalışılmıştır. Bulunan sonuçlar, doğrusal model tahminleri ile karşılaştırılmış ve rejim değişikliklerine izin veren doğrusal olmayan modellerin kullanılmasının daha uygun olacağını göstermiştir. Ancak birden fazla rejim değişikliğine izin veren Yumuşak Geçişli Özbağlanımlı (Smooth Transition Autoregressive - STAR) modellerin kullanılması daha iyi sonuçlar verebilir.

Anahtar Kelimeler: Eşik Özbağlanımlı (TAR) model, eşbütünleşme, doğrusal olmayan zaman serileri, Türkiye, buğday fiyatları

To my family

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CHAPTER 1

INTRODUCTION

The recent sharp increases in food prices over the past couple of years has raised serious concerns about the food and nutrition situation of people around the world. This is especially unsettling considering the poor in developing countries. These increases are attributed to rising price trends of agricultural commodities, which are triggered by rising energy prices and subsidized biofuel production, income and population growth, globalization and urbanization on the demand side; and land and water constraints, underinvestment in rural infrastructure and agricultural innovation, lack of access to inputs, and weather disruptions impairing productivity growth in the supply side. Furthermore, climate change risks and rising energy demand is likely to contribute to the increase in prices of agricultural commodities (IFPRI, 2008). In such an environment, a new set of policy actions are in order. Hence, as the first step of policy design, modeling the past and current behavior of agricultural commodity prices takes on a new level of importance.

Economic theory suggests that many important economic variables should display nonlinear and often asymmetric behavior. Downward rigidity in wages

is a common feature of today's many macroeconomic models. It has been also shown in literature that downturns in the business cycles are generally sharper than expansions.¹ Linear models fail to identify and capture these nonlinear phenomena, often leading to inaccuracies in forecasting and policy making.

The "Law of One Price" (LOOP hereafter) hypothesis, basically stating that international arbitrage leads prices of identical or near-identical commodities traded in spatially separated markets to follow similar movements and long-run trends, is a crucial hypothesis that has been studied extensively, with inconclusive results.² The primary reason behind the inconclusive results are believed to be the use of linear models for representing the price of these type of commodities through time. However, the presence of transaction costs and arbitrage boundaries is likely to impinge upon the attainment of smooth and unilinear long-run equilibrium relationships (Mainardi, 2001). Considering the existence of national trade policies, and especially target bands for prices, it is even more likely to find evidence for nonlinear long-run relationships among the prices of similar commodities.

Consider the simplest case, the existence of transaction costs. In this case, agents in an economy act only when the gains to arbitrage are greater than the costs. This creates a discontinuous or a nonlinear adjustment process to long-run equilibrium, leading to the co-existence of two or more separate regimes. Applied to the case of international arbitrage, when the price discrepancies are

¹ For further reference, see Acemoglu and Scott (1997), Cook and Speight (2006) and Sinclair (2010).

² See Taylor (2002), Goldberg and Verboven (2005), Parsley and Wei (1996), Engel and Rogers (1996), Cechetti et al. (2002), Mohanty et al. (1996) for positive evidence in the long run and Asplund and Friberg (2001) and Lamont and Thaler (2003) for examples of violations.

over a certain ‘threshold’ level (that is, gains to trade are greater than the costs), the price gaps are partly removed through international arbitrage. However, in the opposite case (i.e. gains to trade are lower than the costs), the agents in an economy do not engage in arbitrage, which leads to bounded random walk behavior in the local price levels of commodities. In other words, arbitrage opportunities occur only when there is a sufficient gap between prices, so that the potential profit exceeds the cost of trading.

Several nonlinear models have been suggested in the literature to capture the suggested nonlinearities both in theory and in observation.³ These models differ from standard linear econometric models by their assumption of existence of different regimes, within which the time series in hand (for example the price differential) may exhibit different behavior.⁴ Commonly used models in this class are the threshold autoregressive (TAR), smooth transition autoregressive (STAR) and Markov-switching regime models.

The TAR model is defined as a set of different linear autoregressive models, with regime switch occurring due to the movement of threshold variable(s) with respect to fixed threshold(s). While the model is defined as partially linear, the possibility of regime switching implies an overall nonlinear behavior for the time series in hand. The STAR models may be considered as a generalization of the TAR models in that, they assume a continuum of states, bounded within the two extreme regimes, where the time series’ behavior is governed by the distance of the threshold variable to the two extreme regimes. This type of

³ See Enders (2004) for a review.

⁴ Via existence of different means, variances, and autocorrelation and correlation structures.

behavior is captured via a continuous smooth transition function. In the Markov-switching model, contrary to the former models, regime switching occurs due to the exogenous and fixed probabilistic structure of the different states of the time series. No attempt is made to explain why regime changes occur and the timing of these regime switches.

This study, considering the strategic importance of wheat, aims to test the validity of LOOP hypothesis and if this is the case, model wheat prices in Turkey and its possible long-run relationship with US wheat prices. The study concentrates on TAR models due to their simplicity and nature allowing for discrete regime changes with respect to the state of a determined threshold variable. Previous studies on the empirical validity of LOOP include Sarno et al. (2004), where TAR models are utilized. They find strong evidence for nonlinear mean reversion in deviations from the law of one price for nine sectoral real exchange rates for five major industrialized countries since 1974. Mainardi (2001) applies both TAR and STAR models to quarterly wheat prices of three major world suppliers over the period 1973–99 and finds evidence for a band threshold structure for which weakening of the adjustment process is observed in the inner regimes.

This thesis organized as follows: In Chapter 2, price formation in food grain markets and Turkish agricultural policies are discussed. Chapter 3 briefly overviews the econometric concepts and tools that are used to analyze the nonlinear behavior of wheat prices. Chapter 4 describes the data and gives the empirical results of estimated models. Finally, Chapter 5 concludes the thesis.

CHAPTER 2

PRICE FORMATION IN WHEAT MARKETS AND AGRICULTURAL POLICY FRAMEWORK IN TURKEY

2.1 International Price Formation in Wheat Markets

The ‘Law of One Price’ (LOOP) hypothesis states that all identical goods’ prices must converge to only one price⁵ in efficient markets. This hypothesis is based on the crucial assumptions that agents in the economy have full information on the properties of the commodities, and the transaction and transportation costs attached to all commodities are zero. The mechanism that maintains equality of prices is spatial arbitrage. In the absence of transport and transaction costs, the corrective mechanism, arbitrage, is activated when a gap between the prices of identical products occur in two markets, as gains to arbitrage are greater than zero. Hence, traders move products from low price markets towards high price markets until the prices in the two markets are equal, ensuring also that LOOP

⁵ Denominated in the same currency.

holds once more.

Applied to the world grain trade, it is clear that these conditions are unlikely to hold. The presence of geographical distances implies; *(i)* existence of transportation and transaction costs, and non-price factors such as *(ii)* the imperfect homogeneity of the products, *(iii)* a half year asynchronism in harvests in the two hemispheres, *(iv)* multi-national trade agreements and national trade policies, all of which create sustained price differentials in international grain markets. Therefore, it has been argued in literature that what an economist can hope to find is ‘similarity’ or a ‘close association’ between prices of similar goods in spatially or vertically separated markets. Furthermore, this ‘close association’ may not be visible to the naked eye, as presence of transaction costs and arbitrage boundaries is likely to impinge upon the activation of the correction mechanism every time a price discrepancy occurs.

Considering the high volatility exhibited by international grain prices, if one is not sure of what to look for, it is more likely to find evidence against the LOOP hypothesis than to find evidence for it. Due to unforeseen weather conditions and short- and medium- term constraints in supply adjustments to unexpected demand shortfalls or surpluses, agricultural commodity prices tend to exhibit larger fluctuations with respect to other commodities traded internationally, with these fluctuations being at times unrelated to the prevailing international business cycles (Mainardi, 2001). Factors such as political crises, speculative movements, inflation and exchange rate realignments also contribute to the high price volatility in agricultural commodity markets, leading to the impression that grain prices in spatially separated markets are weakly linked.

Wheat, an important staple grain, is considered in this study for its extreme importance due to its many uses, and worldwide cultivation. While it was originally produced in the Fertile Crescent region of the Near East, in 2007, world production of wheat was 607 million tons, making it the third most-produced cereal after maize (784 million tons) and rice (651 million tons) (FAOSTAT, 2009). Wheat grain is a major staple food used to make flour for leavened, flat and steamed breads, biscuits, breakfast cereal, pasta, and for fermentation to make beer, other alcoholic beverages, or biofuel.⁶ These uses also demonstrate that wheat has a strategic importance in terms of food security. For instance, it has been reported by Akder (2007) that 40% of daily energy requirements of a person in Turkey is provided by wheat alone.

There are two major differentiated wheat markets according to different climates and end-uses: the spring type wheat is characterized by its high protein content, while the winter type contains the lowest amount of protein. The Hard Red Winter (HRW) wheat is a hard, brownish, mellow high protein wheat used for bread, hard baked goods and as an adjunct in other flours to increase protein in pastry flour for pie crusts. Some brands of unbleached all-purpose flours are commonly made from hard red winter wheat alone.

It has been shown in literature that international prices are mainly influenced by the US.⁷ ⁸ More particularly, US sets a “price floor to buffer against excess world supply through stockpiling or even to undercut competitors’ subsidies,

⁶ Other uses include (to a limited extent) as a forage crop for livestock, and its straw can be used as a construction material for roofing thatch. For more information, see Britannica (2010).

⁷ See Mohanty et al. (1999) and Sekhar (2002).

⁸ Third largest producer in 2008 after China and India and Canada (FAOSTAT, 2009).

and vice versa in the presence of excess demand. In the case of wheat, since the early 1970s the market has experienced a gradual lessening of the duopolistic or triopolistic power by dominating producer countries, i.e. the United States, Canada, and eventually Australia” (Mainardi, 2001).

2.2 Agricultural Policy Framework in Turkey

Wheat has the largest share in terms of cultivated land⁹ in Turkey. It is grown throughout Turkey, but higher quality crops are cultivated in Central Anatolian Region and its proximity (Çakmak and Akder, 2008), which are characterized by arid to semi-arid soil structure. Considering that alternative crops are quite limited for these regions, it is clear that changes in policies regarding wheat has important welfare implications. Turkey’s share in world wheat production, as shown in Table 2.1 in the years 1979–2008 is 3.5% on average (FAOSTAT, 2009).

Grains, and particularly wheat, have long been subject of governmental measures due also to their strategic importance in terms of food security. The intensities and focuses of these measures have shown volatility in the last century, with high levels of government intervention occurring after traumatic episodes like the Great Depression and World War II. In recent years, movement towards less price distortionary measures for attaining economic efficiency are favored especially in developed countries such as US. However in Turkey, the extent of state intervention in grain markets remained overwhelmingly large until fiscal discipline problems have proved to be too significant to continue so after the crisis of 2001. It has been argued by Kasnakoğlu and Gürkan (1991) that these

⁹ Approximately 40% (Çakmak and Akder, 2008).

policies, while having economic roots and consequences, were also motivated by political processes. This is also supported by the high synchronism between sharp increases in agricultural supports and the electoral cycle as demonstrated by Çakmak et al. (1999).

Table 2.1: Wheat Production in the World and in Turkey, 1979–2008

Period	World		Turkey		Share ^b (%)
	Production (thousand tons)	g ^a (%)	Production (thousand tons)	g (%)	
1979–1983	455,868		16,980	.000	3.72
1984–1988	509,216	11.7	18,520	9.06	3.64
1989–1993	561,400	10.2	19,380	4.64	3.45
1994–1998	572,076	1.90	18,730	−3.35	3.27
1999–2003	578,831	1.18	19,305	3.07	3.34
2004–2008	633,141	9.38	19,505	1.04	3.08

^c Source FAOSTAT (2009).

^a Growth rate

^b Share in world production

The most significant problems of Turkish agriculture have been listed by Çakmak et al. (1999) as

- (i) *Efficiency*: The agricultural sector does not use its current resources (land, labor, capital) efficiently, leading to a low level of production level with respect to its potential.
- (ii) *Policy aims*: The policy aims, as reported in 5-Year Development Plans and Programs, consist of very general statements often juxtaposed with rural development. Furthermore, means to an end have been considered as policy aims. Examples include the reported aim of increasing input productivity, which is a mean for increasing agricultural households' income. Moreover, concepts such as "self-sufficiency" are often used to justify protection measures such as import restrictions, which might result

in more severe problems.

- (ii) *Policy tools:* Agricultural policy tools have lost their effectiveness. This is mostly due to opposing effects of a tool for the targeted economic agents. For example, a common practice to increase the income of agricultural producers is done via increasing the prices of agricultural commodities, thereby transferring some of the consumer surplus to producers. However, when it is considered that many rural households spend a significant share of their income on food, it is clear that the price increase will not result in a solid increase in the income of agricultural producers.

- (iv) *Distribution:* A large share of agricultural supports are done through transfers from consumers to producers via price distortionary measures. The remaining part is financed by tax revenues. Thus, those who spend more on food and other agricultural commodities bear a significant portion of the burden of agricultural policies. Furthermore, the greatest contribution to tax revenues are from payroll employees. Hence, the benefits and costs of agricultural policies are not distributed equally, which is considered as an policy problem.

- (v) *Competitiveness :* The decline in competitiveness of Turkish agriculture is mainly attributed to high factor costs. Labor is a relatively cheaper factor of production with respect to Turkey's competitors, providing Turkey comparative advantage. However technical changes in production favoring use of labor less and capital more results in increasing production costs. Turkey also suffers from problems in marketing its agricultural products, including problems in storage, packaging and transportation. Further-

more, policies of Turkey's trading partners, with the most important one being the European Union (EU), and the greater weight of developed countries in formulation of international regulations also hamper Turkey's competitiveness.

Kasnakoğlu and Çakmak (1998) list agricultural policy tools used in Turkey as;

Regarding production : Support prices or price floors, deficiency payments, subsidies on output, quotas on exports or imports, tariffs, subsidies on inputs, increasing/limiting the cultivated land, improvements in agricultural practices and irrigation techniques, selection of appropriate crops for increasing crop quality, training of farmers, incentives through tax exemptions, advance payments etc.

Regarding marketing : Infrastructural and structural services, marketing and advertisement services.

Domestic producers have been supported for a long time through two main policies aiming to increase their incomes: agricultural price supports via price floors or support prices, procurement and border protection via tariffs (Yıldırım et al., 1998). Grain sector has been supported by high tariffs, direct income support, certificated seeds, fuel, chemical fertilizers, thus it might be argued that grains receive the largest share in supports (Çakmak and Akder, 2008). Until 2001, the government purchases were usually done through a state economic enterprise, Soil Products Office (Toprak Mahsulleri Ofisi, TMO). However, the severe financial crisis of 2001 made the ever-postponed reforms in agricultural policies inevitable as their burden on government expenditures

were not sustainable anymore. However, even without the macroeconomic stabilization program, factors such as new round of negotiations for WTO Agreement on Agriculture and Turkey's candidacy for membership to EU would have forced Turkey to enter into a phase of agricultural policy reform (Çakmak, 2003). These policies have long been criticized for their negative effects on the sector and the whole economy, with benefits of the subsidies going mainly to larger, wealthier farmers while the low-income farmers and consumers bearing the largest share of burden (Çakmak, 2003). Furthermore, the supports have failed to enhance productivity growth and change the crop patterns of farmer towards higher quality crops, such as protein-rich wheat (Yıldırım et al., 1998). Starting with 2001, the agricultural subsidization system has been changed substantially by Agricultural Reform Implementation Program (ARIP). This program, by limiting support policies such as TMO procurements, diminished TMO's influence on regulation of the wheat market. This has increased the influence of commodity exchange boards, owned by the government, in wheat trade in Turkey.¹⁰ In the beginning, ARIP was designed to use direct income supports (DIS) as the only policy tool, decoupled¹¹ per hectare payments¹², to farmers mainly aiming to cushion the effects of the general subsidy reform, along with facilitating transition to efficient production patterns (Çakmak, 2004). However DIS was neither implemented as the only support policy nor at the intended level (Çakmak and Akder, 2008). Throughout the last decade, tariffs have remained as effective as (if not more than) before, which

¹⁰ The most active boards in the grain market are listed as in Edirne, Eskişehir, Konya, Polatlı and Şanlı Urfa (TMO, 2004).

¹¹ Not contingent upon input use or output production decisions of the farmer.

¹² Up to 50 hectares of cultivated land.

are also against WTO Agricultural Trade Agreements commitments of Turkey. Deficiency payments for oilseeds, cotton, olive oil and corn are also implemented under ARIP.

Çakmak (2004) states that ARIP is built on three main themes:

1. Diminishing the government intervention in the output, credit and fertilizer markets and the introduction of DIS.
2. (i) Commercialization and privatization of state economic enterprises, such as TURKSEKER (Turkish Sugar Company) and TEKEL (Turkish Alcohol and Tobacco Company) and
(ii) Restructuring of TMO and quasi-governmental Agricultural Sales Cooperative Unions (ASCUs).
3. One-time alternative crop payments, providing grants to farmers who require assistance in switching out of surplus crops to net imported ones.

While ARIP has eased the strain on the budget resulting from government support purchases, it is argued that ARIP has been ineffective in solving the main problems of Turkish agricultural sector. This is because the problems of Turkish agriculture do not stem from the amount of support to farmers, but as summarized by Çakmak et al. (1999) they are related to the constraints on

Markets : Input¹³ and output¹⁴ markets do not work effectively.

Producers : Lack of organization among producers such as effective unions.

¹³ Land, water and credit.

¹⁴ High transaction costs in some products and regions.

Information : Agricultural trade boards do not provide sufficient information regarding commodity prices and quality.

Rest of the World : World prices not being determined by free trade, presence of quotas, Turkey's commitments to multi-lateral trade agreements.

Wheat prices in Turkey were 40% and 62% higher than those in the US and France, respectively, for the years 1998–2004 (FAOSTAT, 2009), which is mostly attributed to high levels of protection and input prices in agricultural production. Beginning in late 2005, however, the sharp increase in oil prices resulted in increases in input prices for agricultural production as well. Combined with policies that increase domestic prices, such as price supports and tariffs, further loss of competitiveness in the international markets is expected.¹⁵ While not officially stated, the use of such policy tools, indicate a commitment to "self-sufficiency" by protection or "anti-import" tendencies. Akder (2007) shows that self sufficiency is attained on the surface in wheat markets, however, in the same study it is also stated that the while the quantity produced is fully sufficient to meet the domestic demand for wheat, the quality of the processed crops neither meet the standards of "desired" level for domestic use nor required level for exporting. Thus, in order to increase the quality, producers necessarily import higher quality crops, which is contradictory to the intention of "self-sufficiency".

The recent increases in grain prices are expected to be permanent due to factors such as climate change, aridity, the increase in oil prices triggering ethanol and bio-diesel production, and the uncertainty in WTO Agreements.

¹⁵ In such an environment, Çakmak and Akder (2008) suggest DIS as the most favorable policy tool in the short run, coupled with cost decreasing policies in the long-run such as use of less oil dependent technologies.

Thus, in conclusion, it is argued by Çakmak and Akder (2008) that the recent increases in agricultural commodity prices eliminate the need for price supports in Turkey. Furthermore failing to do so implies harming the consumers. It is also stated that when forming new agricultural policies, it should be kept in mind that agricultural policies should also provide sufficient and balanced nutrition. Turkey's best response in this environment would be to keep domestic prices as close as possible to the world prices, and allocate funds to solve the chronic structural problems and stimulate technical improvement in the agricultural sector.

CHAPTER 3

UNIT ROOTS, COINTEGRATION AND NONLINEARITY

3.1 Unit Root Processes

Many econometric time series studies focus on modeling equilibrium relationships as suggested by relevant economic theories. Standard inference methods in time series models assume that variables are stationary (i.e. their mean, variance, and autocovariance are time invariant). However, this is generally not the case in practice. Previous studies have found strong evidence that many observed economic time series are nonstationary processes. Non-stationary processes differ from their stationary counterparts with (i) their time variant means and variances, and (ii) the covariance between the values of the process at two time points depends only on time. Such a time series (as opposed to a stationary one), has no tendency of mean reversion and hence the variance of fluctuations of the series around the mean will approach to infinity. These properties of nonstationary time series make forecasting a futile exercise with standard methods.

One distinguishing property of nonstationary time series is the presence of at least one unit root in the generating process of the series. A classic example of a nonstationary time series is the *random walk model*, often used for modeling asset prices. Consider

$$Y_t = \alpha Y_{t-1} + \varepsilon_t \quad (3.1)$$

where ε_t is a white noise error term and where t is time measured chronologically.

If the initial value (Y_0) is known, (3.1) can be solved as

$$Y_t = \alpha^t Y_0 + \varepsilon_t + \alpha \varepsilon_{t-1} + \dots + \alpha^{t-1} \varepsilon_1 \quad (3.2)$$

If $\alpha = 1$ in equation (3.1)(nonstationarity), the influence of the starting value Y_0 and distant past shocks on the determination of Y_t get the same weight as recent shocks. For $0 < \alpha < 1$, the influence of the initial value as well as the distant past shocks goes to zero as t increases (stationarity). It can be seen that an implication of unit root is the persistence of random past shocks. This persistence dies away in stationary processes, implying that any shock to the system will have a temporary and transitory effect, thereby limiting the uncertainty in the process. Hence, in order to empirically validate the existence of long run equilibrium in a time series variable as suggested by theory, one needs to find evidence against the presence of a unit root in the generating mechanism.

In the presence of nonstationary variables, a regression might have high R^2 and significant t -statistics, but the variables might not have any relationship with economic meaning. These regressions are called *spurious regressions* by Granger and Newbold (1974).¹⁶

¹⁶ According to Granger and Newbold (ibid.), an $R^2 > DW$ is a good rule of thumb to suspect

Due to the aforementioned effects of nonstationarity, many studies attempt to detect the presence of unit roots. There is now a vast amount of unit root tests suggested in the literature. The most influential studies about the test of unit roots are by Dickey and Fuller (1979, 1981). Using the methodology in Dickey and Fuller (1979), Nelson and Plosser (1982) show that many macroeconomic time series contain unit roots.

The Dickey and Fuller¹⁷ (DF) approach for detecting unit roots involves the testing of the null hypothesis that a pure autoregression (of order p) has an autoregressive operator with a single unit root. For order $p = 1$, by subtracting Y_{t-1} from each side of the equation (3.1) we obtain the equivalent form:

$$Y_t - Y_{t-1} = \Delta Y_t = \rho Y_{t-1} + \varepsilon_t \quad (3.3)$$

where $\rho = \alpha - 1$. Thus, testing the hypothesis of a unit root is equivalent to testing the hypothesis $H_0 : \rho = 0$ against $H_1 : \rho < 0$. Dickey and Fuller¹⁸ also consider the following regression equations to test the unit root hypothesis in the presence of deterministic elements β_0 (drift) and $\beta_1 t$ (linear time trend).

$$\Delta Y_t = \beta_0 + \rho Y_{t-1} + \varepsilon_t \quad (3.4)$$

$$\Delta Y_t = \beta_0 + \beta_1 t + \rho Y_{t-1} + \varepsilon_t \quad (3.5)$$

Despite being used frequently, DF type tests are subject of scrutiny for their that the estimated regression is spurious, where DW is Durbin-Watson statistic for detecting autocorrelation.

¹⁷ *ibid.*

¹⁸ *ibid.*

limiting assumptions and relatively low power in detecting unit roots. Attempts to overcome the former weakness include Said and Dickey (1984), use of semi-parametric techniques in Phillips and Perron (1988), and use of instrumental variables in Hall (1989). An important criticism is from Perron (1989), stating that in the presence of structural breaks, DF type test statistics are biased towards nonrejection of a unit root. Following the work of Perron,¹⁹ Zivot and Andrews (2002), Perron (1997), and Lee and Strazicich (2003) provide unit root tests in the presence of structural breaks. Furthermore, KPSS tests are used complementarily with DF type tests.²⁰ By testing both the unit root hypothesis and the stationarity hypothesis, one can distinguish series that appear to be stationary, series that appear to have a unit root, and series for which the data (or the tests) are not sufficiently informative to be sure whether they are stationary or integrated.

3.2 Cointegration

The concept of cointegration was introduced by Granger (1981), and was further elaborated by Engle and Granger (1987), Stock and Watson (1988), Johansen (1988, 1991, 1994), Phillips and Ouliaris (1990) and Johansen and Juselius (1990).

The basic idea behind cointegration is that if all the components of a vector time series process x_t have a unit root, there may exist linear combinations $\xi^T x_t$ without a unit root. These linear combinations may then be interpreted as long-

¹⁹ *ibid.*

²⁰ See Kwiatkowski et al. (1992).

run relations between the components of x_t .²¹ In this case, components of x_t are said to be cointegrated. The concept cointegration is important especially for modeling equilibrium theories involving nonstationary variables, especially if it is considered that the definition of the latter implies instability.

In their seminal work Engle and Granger (1987) consider a set of economic variables in long-run equilibrium given by

$$\beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_n x_{nt} = 0 \quad (3.6)$$

Let β and x_t denote the vectors $(\beta_1, \beta_2, \dots, \beta_n)$ and $(x_{1t}, x_{2t}, \dots, x_{nt})$. Then, the system is in long-run equilibrium when $\beta x_t = 0$. When the system is away from equilibrium, the system is defined in terms of the deviation from long-run equilibrium (called the *equilibrium error*) such that

$$e_t = \beta x_t \quad (3.7)$$

If there is a meaningful equilibrium relation among the components of x_t , it must be the case that the equilibrium error process is stationary.²² Engle and Granger²³ give the following formal definition of cointegration:

Definition 3.2.1 *The components of the vector $x_t = (x_{1t}, x_{2t}, \dots, x_{nt})'$ are said to be cointegrated of order d, b , denoted by $x_t \sim CI(d, b)$ if*

i) All components of x_t are integrated of order d

²¹ Bierens (1997)

²² The generating process of e_t should not contain a unit root, or equivalently for $e_t = \alpha e_{t-1} + u_t$, α should be less than 1 in absolute value.

²³ *ibid.*

ii) There exists a vector $\beta = (\beta_1, \beta_2, \dots, \beta_n)$ such that the linear combination $\beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_n x_{nt}$ is integrated of order $(d - b)$ where $b > 0$.

Most of the cointegration literature focuses on the case in which each variable contains a single unit root, since traditional regression or time series analysis applies when variables are $I(0)$. Furthermore few economic variables are integrated of an order higher than unity.²⁴

3.2.1 Cointegration and Error Correction Mechanism

Stock and Watson (1988) observe that components of x_t share common stochastic trends if they are cointegrated. In this case the equilibrium error process is stationary, which implies that the deviation from long-run equilibrium is temporary in nature. The return of the system from a state of disequilibrium to its long-run equilibrium via movements of some variables have been named as *error correction mechanism*.

It is important to note that the responses of variables to disequilibrium are not captured in the estimated cointegration equation. The notion of error correction actually suggests a dynamic model. In an error correction model (ECM), the short term dynamics of the variables in the cointegrated system are governed by the deviation from equilibrium.

To see the relationship between cointegration and error correction model,

²⁴ Enders (2004)

consider a simple VAR model

$$y_t = a_{11}y_{t-1} + a_{12}z_{t-1} \quad (3.8)$$

$$z_t = a_{21}y_{t-1} + a_{22}z_{t-1} \quad (3.9)$$

whose characteristic equation can be written as

$$\lambda^2 - (a_{11} + a_{22})\lambda + (a_{11}a_{22} - a_{12}a_{21}) = 0 \quad (3.10)$$

It is necessary that one of the characteristic roots of (3.10) is unity while the other is less than unity for the two variables to be $CI(1,1)$, because the restrictions on characteristic roots ensure that each variable has the same stochastic trend, and their differences are stationary. These same restrictions also guarantee that the cointegrating parameter $\beta \neq 0$.²⁵ This finding is known as *Granger representation theorem*, which states that for any set of $I(1)$ variables, error correction and cointegration are equivalent representations. Thus, for $n = 2$, assuming that elements of x_t are $I(1)$ and follow an $AR(p)$ process, one can model both the short-run and the long-run dynamics of variables of system given in (3.7) as

$$\Delta x_{1t} = \alpha_{10} + \gamma_1(e_{t-1}) + \sum_{j=1}^p \alpha_{11}(j)\Delta x_{1,t-j} + \sum_{j=1}^p \alpha_{12}(j)\Delta x_{2,t-j} + \varepsilon_1 \quad (3.11)$$

$$\Delta x_{2t} = \alpha_{20} + \gamma_2(e_{t-1}) + \sum_{j=1}^p \alpha_{21}(j)\Delta x_{1,t-j} + \sum_{j=1}^p \alpha_{22}(j)\Delta x_{2,t-j} + \varepsilon_2 \quad (3.12)$$

3.2.2 Testing for Cointegration

There are various methods for testing for cointegration. The Engle-Granger²⁶ methodology builds on the stationarity of the residuals of the equilibrium

²⁵ For a detailed discussion of this, see Enders (2004).

²⁶ *ibid.*

relationship. The procedure can be broken down into four steps:

- i) Pretesting the variables for their order of integration. Cointegration requires that the variables be integrated of the same order.
- ii) Estimating a static linear model of components of z_t and performing unit root tests on the residuals.²⁷
- iii) Estimation of the ECM.
- iv) Diagnostic checks for testing the adequacy of the ECM.

This method is criticized for several reasons.²⁸ First, the equilibrium error for a set of variables might be found stationary or nonstationary depending on the selection of the left-hand-side variable in analyses involving finite samples. Secondly, the Engle-Granger procedure relies on a two-step estimator, thus “any error introduced by the researcher in Step 1 is carried into Step 2” (Enders, 2004:348). However, for bivariate cases, the Engle-Granger method is perceived as reliable.

The studies by Johansen (1988) and Stock and Watson²⁹ develop tests for cointegration that avoid the problems posed by the Engle-Granger procedure. Furthermore, these tests enable the researcher to test restricted versions of the cointegrating vector(s) as well as finding the number of cointegrating vectors based on the rank of the π matrix, which is defined as

²⁷ If evidence of cointegration is found, the static linear model represents the long-run equilibrium among the variables. If no such evidence is present, the model becomes a candidate for spurious regression.

²⁸ The following discussion is based on Enders (2004).

²⁹ *ibid.*

$$\Delta x_t = (A_1 - I)x_{t-1} + \varepsilon_t = \pi x_{t-1} + \varepsilon_t \quad (3.13)$$

The Johansen procedure involves the following steps:

- i) Pretesting the variables for their order of integration (usually by estimating a vector autoregression using undifferenced data).
- ii) Estimating (3.13) and determining the rank of π .
- iii) Analysis of the cointegrating vector(s) and speed of adjustment coefficients.
- iv) Tests on innovation accounting and causality tests on the ECM.

While the Engle-Granger approach is criticized, it is shown that for bivariate cases many of its major drawbacks become insignificant.

3.3 Nonlinear Time Series Models

Economic theory has long been suggesting that a number of economic variables should behave in a nonlinear fashion.³⁰ Furthermore, studies on many economic variables have found strong evidence for nonlinear behavior.³¹ The concepts of liquidity trap, downward rigidity of wages, target bands, and the observation that downturns in the business cycle are sharper than recoveries are among many cases that conventional econometric models have been unable to illustrate convincingly. This insufficiency of conventional econometric models actually

³⁰ See Barro (1977); Blinder and Fischer (1981); Ball and Romer (1989); Caballero and Engel (1992); Reagan and Weitzman (1982).

³¹ See Neftci (1984) for unemployment, Bae and De Jong (2005) for money demand, Öcal and Osborn (2000) in consumption and production, and Michael et al. (1997) in real exchange rates.

stems from their reliance on linear models. While being extremely useful for approximations, these models are incapable of generating asymmetric behavior.

Several nonlinear models have been suggested in the literature to remedy the insufficiencies of linear models, and to capture the observed asymmetric behavior of economic variables. These models enable a time series to have different states, called regimes, within which they can exhibit different behavior via having different means, variances and correlation structures. Some of the more frequently used models in literature are the threshold autoregressive (TAR) model by Tong (1983), the Markov switching model by Hamilton (1990), and smooth transition autoregressive (STAR) models by Terasvirta (1994). This section aims to introduce TAR and STAR models.

3.3.1 Threshold Autoregressive Models

While the threshold autoregressive (TAR) model was first proposed by Tong (1978), due to the complexity of the suggested procedure by Tong and Lim (1980), it gained popularity after Tsay (1989) suggested a simple method to estimate TAR models. TAR models have been studied extensively in literature (Tong and Lim, 1980; Tong, 1983; Tsay, 1989; Caner and Hansen, 1996).

A TAR model can be basically defined as a piecewise linear autoregressive model in the space of the threshold variable. In a TAR model, behavior of the time series Y_t is governed by the threshold variable r_{t-d} , where r_t is a stationary variable from inside or outside of the model and d is the threshold lag. More formally, given a partition of the space of r_{t-d} as

$$-\infty = \lambda_0 < \lambda_1 < \dots < \lambda_m < \lambda_{m+1} = \infty$$

a TAR model of order p for Y_t can be defined as

$$Y_t = \phi_0^h + \phi_1^h Y_{t-1} + \dots + \phi_p^h Y_{t-p} + \varepsilon_t^h \text{ for } \lambda_{h-1} \leq r_{t-d} < \lambda_h \quad (3.14)$$

$$\varepsilon_t^h \sim iid(0, \sigma^2) \text{ and } h = 1, 2, \dots, m$$

where h denotes the different regimes and λ_h denotes the thresholds separating these regimes. From this definition one can observe that TAR model is actually a regime switching model of the time series Y_t , where behavior of Y_t depends on the state on the system.

Since one confronts mainly with two or three regime cases in practice, it is beneficial to consider a simpler case in more detail. In the two regime case (3.14) becomes

$$Y_t = \begin{cases} \alpha_{10} + \alpha_{11} Y_{t-1} + \dots + \alpha_{1p} Y_{t-p} + \varepsilon_t^1 & \text{if } r_{t-d} > \tau \\ \alpha_{20} + \alpha_{21} Y_{t-1} + \dots + \alpha_{2p} Y_{t-p} + \varepsilon_t^2 & \text{if } r_{t-d} \leq \tau \end{cases} \quad (3.15)$$

$\alpha_{1j} \neq \alpha_{2j}$ for $j = 1, 2, \dots, p$ implies that Y_t governed by different AR processes in different sides of the threshold τ . Thus, while the behavior of Y_t can be adequately represented by a linear model in either sides of the threshold, overall, Y_t process is nonlinear.

Modeling

The TAR model has not gained instant popularity due to several reasons including; (i) the difficulty in identifying threshold variables and estimating the associated threshold values in practice, and (ii) the earlier methods proposed being quite complex. A simple modeling procedure utilizing familiar linear

regression techniques was proposed by Tsay (1989). This procedure can be broken down into four steps:

1. *Specification of an appropriate linear $AR(p)$ model to construct a basis for nonlinear modeling.* This model is estimated using all data points. The order of the AR process can be selected by considering the partial autocorrelation function (PACF) or information criteria like Akaike information criteria (AIC) or Schwarz Bayesian criteria (SBC).
2. *Testing for nonlinearity and in the case of finding evidence for threshold nonlinearity, identification of the threshold variable.* Since threshold behavior is also a nonlinear phenomenon, standard tests for the presence of nonlinearity should be employed. The following tests are frequently used for pretesting for nonlinearity:

(i) McLeod-Li Test³²

(ii) BDS Test³³

(iii) RESET Test³⁴

(iv) Lagrange Multiplier (LM) Tests³⁵

³² McLeod and Li (1983): This test aims to determine if there are significant autocorrelations in the squared residuals from a linear equation, based on the intuition that fitting a linear model inappropriately to the data results in the inherent nonlinearity to be swept into the residuals.

³³ Brock et al. (1996): This is a test for independence and can be used for residual non-linear structure, after linear structure has been removed from the data.

³⁴ Ramsey (1969): This test postulates the null hypothesis of linearity against a general alternative hypothesis of nonlinearity, using the principle that if the residuals from a linear model are independent, they should not be correlated with the regressors used in the estimating equation or with the fitted values.

³⁵ LM tests are generally used to select the proper functional form to use in a nonlinear estimation. This is done by estimating a linear model to get the residuals e_t , estimating an auxiliary regression by regressing e_t on all of the partial derivative $\partial f(\cdot)/\partial \alpha$ where $f(\cdot)$ is the nonlinear functional form and α the parameters of $f(\cdot)$. For further information, see Enders (2004).

For testing threshold nonlinearity and identifying the threshold variable, Tsay³⁶ proposes a test that is based on *arranged autoregression* and predictive residuals. An arranged autoregression is an autoregression with cases rearranged, based on the values of a particular regressor. When estimating an autoregression if the cases are arranged with respect to the threshold variable, threshold behavior can be tested. Equation (3.15) actually illustrates an arranged autoregression with first k observations³⁷ in the first regime and the rest in the second regime. Hence, via arranged autoregression, one can group observations following the similar/same linear AR process, while simultaneously determining the threshold variable (and the delay parameter of the threshold variable). For a given AR order p and TAR process, the estimate of the delay parameter should satisfy

$$\hat{F}(p, d_p) = \max_{v \in S} \{ \hat{F}(p, v) \} \quad (3.16)$$

where $\hat{F}(p, v)$ is the F statistic of the regression of the predictive residuals of the arranged autoregression on the regressors, and S is a set of prespecified positive integer values for d . Hence, possible candidates for the delay parameter should give the most significant results in testing for threshold nonlinearity.

- 3.** *Estimation of the threshold values and number of regimes by using scatterplots.* This procedure generally depends on making inferences on an interval. To see this, assume that the true value of the threshold τ satisfies $Y_{s_i} < \tau < Y_{s_{i+1}}$. Then, any value in the interval $[Y_{s_i}, Y_{s_{i+1}}]$ is as good as

³⁶ *ibid.*

³⁷ The number of observations in one regime essentially depends on the threshold value (in this case τ).

the other in providing an estimate of τ , because they all give the same fitting results for a specified TAR model. Hence, one may search through the sample percentiles, with the only constraint of the threshold being not too close to the 0th or 100th percentiles.³⁸

Once candidates for threshold values are identified, scatterplots of various statistics versus the specified threshold variable should be investigated. Tsay³⁹ uses scatterplot of the standardized predictive residuals versus the threshold variable, or the scatterplot of t ratios of recursive estimates of an AR coefficient versus the threshold variable. For the former, Tsay shows that predictive residuals are biased at the threshold values. The latter scatterplot shows the significance of a particular AR coefficient. Moreover, if the process is linear and the coefficient is significant, t ratios gradually and smoothly converge to a fixed value as the recursion continues. If not, the gradual convergence of the t ratios will be destroyed. Thus, one may expect to see the t ratio to turn, and, perhaps, change direction at the threshold value.

4. *Refinement of the AR order and threshold values, if necessary, in each regime by using linear AR techniques, diagnostic checks on the final model.* Once the number of regimes and the corresponding threshold values are found, the distinct regimes can be estimated utilizing ordinary least squares (OLS). Alternatively, one can construct a single regression for the whole series with indicator functions for different regimes. Once the models are estimated, the validity of the model should be checked via performing tests

³⁸ Since for these extreme points there are not enough observations to provide an efficient estimate.

³⁹ *ibid.*

on presence of autocorrelation, heteroscedasticity, remaining nonlinearity, skewness, kurtosis and normality. One final check is on the forecasting performance of the model.

For finding a consistent estimate of the threshold value, Chan (1993) shows that the sum of squared residuals (SSR) from a TAR model is a function of the threshold value used in the estimation. Accordingly, SSRs of a TAR model are minimized at the true threshold value. Thus a trough in the graph of the SSR versus the threshold value reveals the threshold value. Furthermore, if the graph has several local minima, then the model has several regimes and thresholds.

3.3.2 Threshold Cointegration

In their seminal work Balke and Fomby (1997) introduced the concept of threshold cointegration. The intuition behind threshold cointegration is that, as opposed to the implicit assumption of cointegration, small deviations from the long-run equilibrium may not trigger the error correction mechanism. Equivalently movement toward the long-run equilibrium need not occur in every period, and hence the error correction mechanism may be discontinuous.

There are several arguments in economic theory that validates the assumption of discontinuous adjustment. An example is the case of fixed costs of adjustment preventing economic rational agents from adjusting. Only when the benefits of adjustment exceed the costs (in this case the deviation from the equilibrium exceeds a critical threshold), the economic agents act to move the system back towards the long-run equilibrium. Similarly, even in highly liquid markets, the

presence of transaction costs may create a band in which asset returns diverge where deviations are too small for arbitrage to be profitable. Policy makers also often design policies around targets, and act when deviations from the target are above a predetermined range.

Another criticism against linear cointegration stems from its assumption of symmetrical adjustment. This restriction is too strict for many cases as well. Good examples include the notion of price stickiness, the presence of menu costs, or simply small country versus big country trade effects as suggested by economic theory. The concept of threshold cointegration allows flexibility to the researcher in the case of asymmetric adjustment.

Consider a linear cointegrating relationship. Then the adjustment of the error term is governed by

$$e_t = \alpha e_{t-1} + u_t \quad (3.17)$$

A simple threshold model of three regimes extends the linear adjustment process in (3.17) to

$$e_t = \begin{cases} \mu_l + \alpha_l(L)e_{t-1} + u_t^l & \text{if } e_{t-d} < \theta_l \\ \mu_m + \alpha_m(L)e_{t-1} + u_t^m & \text{if } \theta_l \leq e_{t-d} \leq \theta_u \\ \mu_u + \alpha_u(L)e_{t-1} + u_t^u & \text{if } \theta_u < e_{t-d} \end{cases} \quad (3.18)$$

where for $i=l,m$, and u , $\alpha_i(L)$ are lag polynomials and u_t^i are zero mean random disturbances with standard deviation σ^i . This model is actually identical with (3.15) except that it has three regimes and the threshold variable is the previous value of the dependent variable. Chan (1993) and Tong (1990) call models

exhibiting the latter property as *self-exciting threshold autoregressive* (SETAR) model, in which the governing autoregressive process changes depending on whether the previous value of a time series is above or under a certain threshold value.

For threshold autoregressive processes, the necessary and sufficient conditions for $\alpha_i(L)$ and μ^i that guarantee stationarity are not well understood. There are the studies of Chan and Tong (1985) and Brockwell et al. (1992) that develop a set of sufficient conditions for the general TAR model, however they show that weaker conditions could be possible. For a symmetric TAR where $\alpha_i(L)$ of the outer regimes are the same, Tjostheim (1990) shows that roots of the autoregression in the outer regimes being less than one in absolute value is sufficient for stationarity.

In the case of $\alpha_i(L) = \alpha_i$ and $d = 1$, Chan et al. (1990) show that each one of the following conditions are necessary and sufficient for e_t to be a stationary process:

- (i) $\alpha_l < 1$, $\alpha_u < 1$, and $\alpha_l \alpha_u < 1$;
- (ii) $\alpha_u < 1$, $\alpha_l = 1$, and $\mu_l > 0$;
- (iii) $\alpha_l < 1$, $\alpha_u = 1$, and $\mu_u < 0$;
- (iv) $\alpha_l = \alpha_u = 1$, and $\mu_u < 0 < \mu_l$;
- (v) $\alpha_l \alpha_u = 1$, $\alpha_l < 0$, and $\mu_u + \alpha_u \mu_l > 0$;

These conditions show that the behavior of e_t in the interior regime are irrelevant for its stationarity. What matters is how the autoregressive coefficients and drift

parameters of the outer regimes interact. Furthermore, these conditions also show that just examining the autoregressive coefficients in the outer regimes is not enough. This is especially telling in the fourth case where the outer regime autoregressive coefficients are equal to one, hence contain a unit root, but the drift parameters act so that they push the series back towards the equilibrium band. Note that from these conditions, one can also derive the local or short term dynamics of the model.⁴⁰

Modeling

Balke and Fomby (1997) suggest dividing the problem of determining whether time series in question are threshold cointegrated into two parts. While cointegration is a global characteristic of the time series, threshold behavior can be studied under local characteristics. Thus, one might start by determining whether the time series at hand are cointegrated.⁴¹

It might be argued that existence of discontinuous adjustment to long-run equilibrium might decrease the power of standard unit root tests for cointegration. However, Balke and Fomby⁴² find that these tests are robust to non-linear threshold behavior of the stochastic process, except in models with high persistence, where performance of the standard tests are reduced. High persistence can be induced by (i) high near-unitary autoregressive parameters in the outer regimes, and/or (ii) the relatively wide range of the inner regime.⁴³

⁴⁰ For some specific examples, see Balke and Fomby (1997).

⁴¹ This could be also perceived as an investigation on whether the time series at hand exhibit cointegration "on average".

⁴² *ibid.*

⁴³ Pippinger and Goering (1993)

In these cases nonparametric methods like Bierens (1997) may be more effective at detecting cointegration, especially when using Johansen method to test cointegration.

Once cointegration is detected, examination of the local behavior of the time series (i.e. testing for nonlinear or threshold behavior) should follow. This is done by testing the autoregressive process of equilibrium error for nonlinearity (especially threshold behavior) and if such nonlinearity is detected, constructing an appropriate TAR model for the equilibrium error.

Enders and Granger (1998) modify the standard ADF test to have a threshold autoregression against the null hypothesis of a unit root. In the case of threshold cointegration, their alternative specification is such that

$$\Delta e_t = \begin{cases} \rho_1 e_{t-1} + \varepsilon_t & \text{if } e_{t-d} \geq \tau \\ \rho_2 e_{t-1} + \varepsilon_t & \text{if } e_{t-d} < \tau \end{cases} \quad (3.19)$$

If the system is convergent, then τ is the long-run equilibrium value of the sequence. Whenever e_{t-d} is above its long-run equilibrium value, the adjustment is governed by $\rho_1 e_{t-1}$. It should be noted that the linear adjustment is a special case of (3.19), where $\rho_1 = \rho_2$. To find out whether e_t is stationary while exhibiting asymmetric adjustment, Enders and Granger propose building a nonlinear model along the lines suggested by Chan (1993) and Tsay (1989), and testing this model for

(i) ϕ_μ Test: $\rho_1 = \rho_2 = 0$

(ii) TAR : $\rho_1 = \rho_2$

Once it is established that the time series under consideration are threshold cointegrated, estimated threshold and cointegrating parameters could be plugged into a threshold VECM (TVECM), as Engle and Granger⁴⁴ advocate for the linear case.

Momentum Threshold Autoregressive (M-TAR) Models

Enders and Granger⁴⁵ provide alternative adjustment specifications in their study. Reconsider equation (3.19) in two parts:

$$\Delta e_t = I_t \rho_1 e_{t-1} + (1 - I_t) \rho_2 e_{t-1} + \varepsilon_t \quad (3.20)$$

where I_t is the Heaviside indicator function given by

$$I_t = \begin{cases} 1 & \text{if } e_{t-d} \geq \tau \\ 0 & \text{if } e_{t-d} < \tau \end{cases} \quad (3.21)$$

If equation (3.21) is altered such that the Heaviside indicator depends not on the level of e_{t-d} , but on the previous period's change in e_{t-d} , we obtain the following rule:

$$I_t = \begin{cases} 1 & \text{if } \Delta e_{t-d} \geq 0 \\ 0 & \text{if } \Delta e_{t-d} < 0 \end{cases} \quad (3.22)$$

Replacing (3.21) with (3.22) is “especially valuable when adjustment is asymmetric such that the series exhibits more ‘momentum’ in one direction than the other” (Enders and Granger, 1998). These models are called as momentum

⁴⁴ *ibid.*

⁴⁵ *ibid.*

threshold autoregressive (M-TAR) models. Such a setting allows one to model time series with, for example $|\rho_1| < |\rho_2|$, better since the M-TAR model exhibits little decay for $\Delta e_{t-d} \geq 0$, but substantial decay otherwise. Thus, increases tend to persist but decreases tend to revert quickly. Alternatively, one may specify (3.22) as

$$I_t = \begin{cases} 1 & \text{if } \Delta x_{t-d} \geq 0 \\ 0 & \text{if } \Delta x_{t-d} < 0 \end{cases} \quad (3.23)$$

whenever the adjustment of the time series in question is suspected to be affected by a related time series. These types of models are called as Momentum Threshold Regressive (MTR) models.

3.3.3 Smooth Transition Autoregressive Models

An important criticism on TAR models is that regime switches need not be clear-cut for some processes. To remedy this defect in TAR models, smooth-transition autoregressive (STAR) models have been suggested and studied by Luukkonen et al. (1988); Terasvirta (1994). In these models, regime switching occurs gradually, as the autoregressive parameters change smoothly with respect to a continuous function of the threshold variable. Chan and Tong (1986) proposed that the smooth transition may be modeled via using the cumulative distribution function of a standard normal variable for the transition function. Luukkonen et al. (1988) proposed the family of logistic functions, which contains the single threshold (or equivalently a two regime) TAR model as a special case. Another popular choice for transition functions is the family of exponential functions, which may be viewed as a generalization of the special case of a band

TAR model.

In a STAR setting, parameters are allowed to change slowly. A two regime STAR model of order p is given by

$$y_t = \pi_{10} + \sum_{i=1}^p \pi_{1i} y_{t-i} + (\phi_{20} + \sum_{i=1}^p \phi_{2i} y_{t-i}) * [f(y_{t-d}; \gamma, c)] + \varepsilon_t \quad (3.24)$$

or

$$y_t = \pi' \omega_t + \Theta' \omega_t [F(y_{t-d}; \gamma, c)] + \varepsilon_t \quad (3.25)$$

where $\pi = (\pi_{10}, \dots, \pi_{1p})'$, $\Theta = (\Theta_{20}, \dots, \Theta_{2p})'$ and $\omega_t = (1, y_{t-1}, \dots, y_{t-p}, F(y_{t-d}; \gamma, c))$ is the transition function that is bounded between 0 and 1. These boundaries effectively represent the two extreme regimes. For example, in the first extreme boundary, behavior of y_t is governed solely by the first regime, represented by the coefficients π_t . In the other extreme, behavior of y_t is governed by the second regime, represented by the coefficients $(\pi_t + \Theta_t)$. When the transition function takes a value between 0 and 1, the process becomes a mixture of the two extreme regimes. Hence in the STAR model, there is a continuum of regimes, each associated with a different value of $0 < F(y_{t-d}; \gamma, c) < 1$.

Researchers generally choose either the logistic (3.26) or the exponential (3.27) function for the transition function for their flexibility. In these cases a STAR model is named as LSTAR and ESTAR, respectively.

$$F_L(y_{t-d}; \gamma, c) = (1 + \exp(-\gamma_L(y_{t-d} - c)))^{-1} \text{ with } \gamma_L > 0 \quad (3.26)$$

$$F_E(y_{t-d}; \gamma, c) = 1 - \exp(-\gamma_E(y_{t-d} - c)^2) \text{ with } \gamma_E > 0 \quad (3.27)$$

The parameter γ_i determines the smoothness of change in the value of the transition function, and thus smoothness of the transition from one regime to another. In the extreme case $\gamma \rightarrow \infty$, the logistic function (3.26) approaches the indicator function. Thus, the regime change occurs instantaneously at $y_{t-d} = c$, in which case we obtain a SETAR model. Alternatively, when $\gamma \rightarrow 0$, the logistic function (3.26) approaches to 0.5, reducing the model to a linear AR(p) model with parameters $(\pi_t + .5\Theta_t)$. LSTAR model is used especially for modeling cyclical asymmetries.⁴⁶

The use of ESTAR is more convenient when the adjustment depends on the discrepancy between the current state and the equilibrium, since in the extreme values of y_{t-d} ,⁴⁷ the value of exponential transition function $F_E(y_{t-d}; \gamma, c) \rightarrow 1$, while for $y_{t-d} = c$, $F_E(y_{t-d}; \gamma, c) = 0$. Thus, we obtain a model in which the behavior of the time series depends on the absolute distance of the threshold variable. For $\gamma \rightarrow \infty$ and $\gamma \rightarrow 0$, the value of the exponential function approaches to 1 and 0, respectively.

Modeling

Terasvirta (1994) gives the following method for building a STAR model:

(i) *Construction of an appropriate linear AR(p) model:* Similar to the building of a TAR model, in order to obtain a basis for the nonlinear model, an appropriate AR(p) model is constructed.

(ii) *Test of linearity vs STAR:* Linearity vs. LSTAR, and linearity vs. ESTAR

⁴⁶ See Terasvirta and Anderson (1992) for a detailed discussion.

⁴⁷ $y_{t-d} \rightarrow -\infty$ and $y_{t-d} \rightarrow \infty$.

tests are done utilizing the procedure proposed by Luukkonen et al. (1988). The test against LSTAR involves the approximation of the transition function with a first-order Taylor series approximation around $\gamma_L = 0$ and testing the following obtained auxiliary regression

$$y_t = \beta_0 + \sum_1^p \beta_{1i} y_{t-i} + \sum_1^p \beta_{2i} y_{t-i} y_{t-d} + e_t \quad (3.28)$$

with $H_o : \beta_{2i} = 0$ for $i = 1, \dots, p$. Similarly, by approximating the exponential transition function with a first-order Taylor series approximation, one may test linearity against ESTAR specification by testing the auxiliary regression

$$y_t = \beta_0 + \sum_1^p \beta_{1i} y_{t-i} + \sum_1^p \beta_{2i} y_{t-i} y_{t-d} + \sum_1^p \beta_{3i} y_{t-i} y_{t-d}^2 + e_t \quad (3.29)$$

with $H_o : \beta_{2i} = \beta_{3i} = 0$ for $i = 1, \dots, p$

- (iii) *If linearity is rejected, identification of the transition variable*, by comparing the LM test statistics of the auxiliary regression for various choices of threshold variables, and the delay parameter, d .
- (iv) *Estimation of STAR models*, using nonlinear least squares.
- (v) *Diagnostic tests*, selection of a STAR model (LSTAR vs. ESTAR) via utilizing misspecification tests.
- (vi) *Refinement on the selected model*, by implementing tests for no error autocorrelation, no remaining nonlinearity, parameter consistency, and autoregressive conditional heteroscedasticity (ARCH).

CHAPTER 4

EMPIRICAL RESULTS

4.1 Introduction

This chapter describes the data used in the econometric analysis, and provides the empirical modeling of this data set using nonlinear time series models.

To test for a nonlinear equilibrium relationship between grain prices, statistical information on US and Turkish major producers' export prices of hard red winter (HRW) wheat⁴⁸ are used. Two monthly price series in nominal terms were collected from USDA/ERS (2009)⁴⁹ and PBT (2009),⁵⁰ with samples ranging from 1970 and 1984, respectively, up to 2009 (list of variables in Table 4.1). Wheat price in the US is given in USD/bushel and prices in Turkey are in terms of TL/metric tonnes. All series are seasonally unadjusted. In order to compare these series, Turkish prices are converted into USD using the nominal exchange rates taken from the CBRT (2009)⁵¹, and US export prices are converted into

⁴⁸ Hard, brownish, mellow high protein wheat used extensively for bread, hard baked goods and as an adjunct in other flours to increase protein in pastry flour for pie crusts

⁴⁹ United States Department of Agriculture, Economic Research Service

⁵⁰ Polath Board of Trade

⁵¹ Central Bank of Republic of Turkey

USD/metric tonnes.

It has been shown in literature that grain prices show significant seasonality.⁵² In order to account for this seasonality, several seasonal adjustment methods have been suggested. Most commonly used methods are the X-12 ARIMA,⁵³ developed by the U.S. Census Bureau, and the TRAMO/SEATS⁵⁴ (T/S) package developed by the Bank of Spain. Since it is not fully established which of these methods are superior, in this study, both seasonal adjustment methods will be used in the analysis.

The plan of this chapter is follows. In Section 4.2, wheat prices in Turkey and the US are analyzed and existence of a linear cointegrating relationship is examined, for both seasonally unadjusted and seasonally adjusted data. Section 4.3 investigates the existence of a non-linear cointegrating relationship, and the estimated nonlinear models are examined for their adequacy.

4.2 Linear Equilibrium Relationship Between US and Turkish Wheat Markets

The series we consider in this study is the logarithmic form of the wheat prices in the US and Turkey, at the monthly frequency covering the period January 1988 – December 2007. The series, which are shown in Figure 4.1, suggest non-stationary behavior. This is also supported by the results of several unit

⁵² Flakerud and Johnson (2000)

⁵³ For documentation, see <http://www.census.gov/srd/www/x12a/>

⁵⁴ "Time Series Regression with ARIMA noise, Missing Observations and Outliers / Signal Extraction in ARIMA Time Series", which is a model-based seasonal adjustment method. For documentation, see <http://www.bde.es/servicio/software/econome.htm>

root tests performed on the variables, as shown in Table 4.1. However, the first differences of the logarithmic form exhibit stationarity. Thus, both time series are integrated of order one. After establishing that the time series under

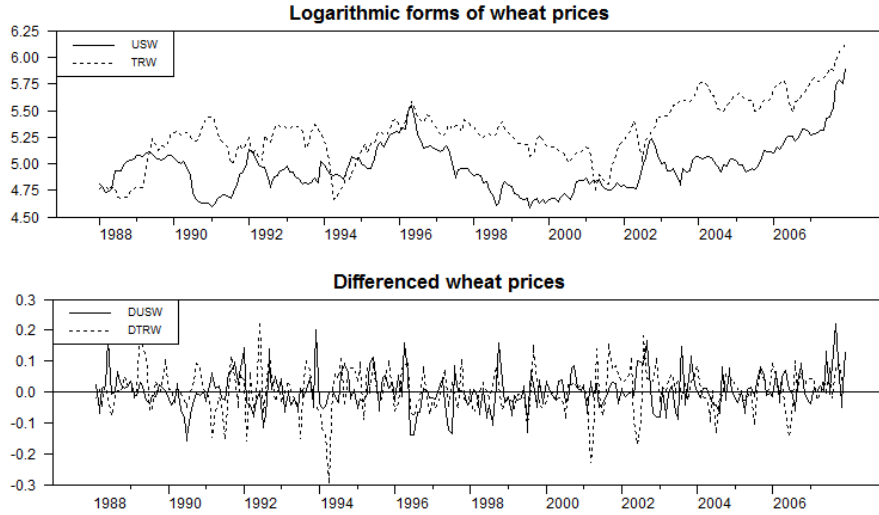


Figure 4.1: Logarithmic and Differenced Logarithmic Wheat Prices

question are $I(1)$ variables, one may look for a cointegrating relationship. In order to test for linear cointegration, we estimate the following equation:

$$\ln(trw)_t = \alpha_0 + \alpha_1 \ln(usw)_t + u_t \quad (4.1)$$

If there is a linear cointegrating relationship between the wheat markets in the US and Turkey, then it should be the case that the residuals from the estimation of equation (4.1) are stationary. To check this, we perform various unit root tests on the residuals, reported in Table 4.1. One might readily argue that existence of outliers might have contributed to the finding of weak evidence

Table 4.1: Unit root tests on HRW wheat prices, adjusted for seasonality

Variable	Lags	ADF			PP		KPSS	
		None	I	I/T	I	I/T	I	I/T
<i>X12A^a</i>								
<i>ln(usw)</i>	(1)	1.12	-.36	-.75	-.09	-.51	1.66**	0.89**
<i>ln(trw)</i>	(1)	1.18	-1.24	-2.13	-1.04	-1.92	5.45**	0.82**
<i>dln(usw)</i>	(0)	-12.46**	-12.51**	-12.59**	-12.67**	-13.28**	0.23	0.16*
<i>dln(trw)</i>	(0)	-13.28**	-13.35**	-13.34**	-13.38**	-13.42**	.10	0.09
<i>u_{t1}</i> ^d	(1)	-2.69**	-2.68	-3.20	-2.53	-3.04	4.44**	0.28**
<i>u_{t2}</i> ^e	(1)	-3.15**	-3.14*	-3.13	-2.98*	-2.98	.29	0.29**
<i>u_{t3}</i> ^f	(3)	-3.45**	-3.44*	-3.45*	-4.03**	-4.03**	.39	0.39**
<i>X12M^b</i>								
<i>ln(usw)</i>	(1)	1.13	-.33	-.73	-.07	-.49	1.66**	0.89**
<i>ln(trw)</i>	(1)	1.18	-1.24	-2.15	-1.04	-1.92	5.46**	0.82**
<i>dln(usw)</i>	(0)	-12.52**	-12.60**	-12.67**	-12.78**	-12.75**	0.22	0.17*
<i>dln(trw)</i>	(0)	-13.21**	-13.29**	-13.28**	-13.31**	-13.36**	.10	0.09
<i>u_{t1}</i>	(1)	-2.70**	-2.69	-3.21	-2.54	-3.04	4.44**	0.28**
<i>u_{t2}</i>	(1)	-3.14**	-3.13*	-3.12	-2.98*	-2.98	.29	0.29**
<i>u_{t3}</i>	(1)	-3.28**	-3.08**	-3.07*	-3.95**	-3.95*	.39	0.39**
<i>T/S^c</i>								
<i>ln(usw)</i>	(1)	1.05	-.52	-.91	-.20	-.60	1.64**	0.88**
<i>ln(trw)</i>	(1)	1.02	-1.68	-2.61	-1.34	-2.21	5.40**	0.80**
<i>dln(usw)</i>	(0)	-12.14**	-12.19**	-12.27**	-12.36**	-12.35**	0.21	0.16*
<i>dln(trw)</i>	(0)	-12.36**	-12.42**	-12.40**	-12.36**	-12.48**	.08	0.08
<i>u_{t1}</i>	(1)	-3.06**	-3.05*	-3.61*	-2.68	-3.18	4.38**	0.28**
<i>u_{t2}</i>	(1)	-3.35**	-3.34*	-3.33	-3.17*	-3.17	.29	0.28**
<i>u_{t3}</i>	(1)	-3.09**	-3.08*	-3.07	-4.01**	-4.01**	.42	0.42**

· Variables in natural logarithms in level and first differenced form. Order of the test given in parantheses (choice based on the highest lag in the autoregressive parameter with significant *t*-statistic and minimum AIC.)

· This row indicates whether the regression includes an intercept or a trend term.

* and ** indicate 5 and 1 percent significance levels, respectively.

^a X12 ARIMA Additive form

^b X12 ARIMA Multiplicative form

^c TRAMO/SEATS

^d *u_{t1}*: Residuals from regression (4.1)

^e *u_{t2}*: Residuals from regression (4.1) with trend term

^f *u_{t3}*: Residuals from regression (4.1) with trend term and dummy variables for outliers

List of Variables

usw: United States HRW, US\$/tonnes: 1988:01-2007:12

trw: Turkey HRW, US\$/tonnes: 1988:01-2007:12

u_{t1}: residuals from regression (4.1) with no trend term or dummy variables for outliers

u_{t2}: residuals from regression (4.1) with trend term

u_{t3}: residuals from regression (4.1) with trend term and dummy variables for outliers

for cointegration. In order to account for these considerations, we examine the residuals from estimation of equation (4.1). The residuals, which are plotted in Figure 4.2, indicate existence of a trend. Hence, we reestimate equation (4.1),

adding a trend term. Table 4.2 presents various statistics of the residuals of this estimation. The results indicate that the distribution is skewed, and does not satisfy normality. Graphical examination of the residuals of the cointegrating

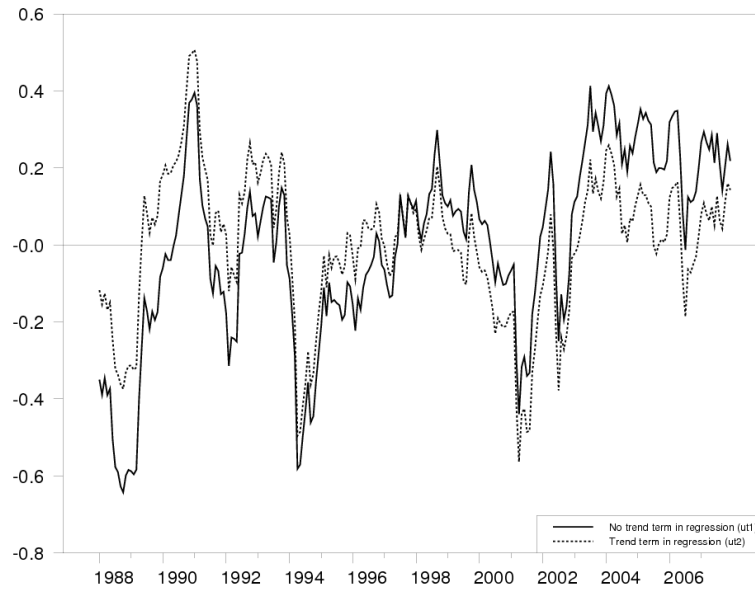


Figure 4.2: Residuals of regressions with and without trend term

relationship indicates that equilibrium error has extreme values in 2001:4, 1991:1, and 1994:4. Statistical analysis reveals that, in 2001:4 equilibrium error deviates from its mean by more than three standard deviation. A more 'flexible' extreme value analysis, i.e. deviation from mean by two and a half standard deviation, brings out 1990:9, 1990:11, 1990:12, 1991:1, 1991:2, 1994:4, and 1994:5 as extreme values, all of which can be explained by exchange rate crises, oil-price shocks, balance-of-payment crises, public sector deficits and financial crises in Turkey. However, addition of dummy variables for these months only improve

the statistics for excess kurtosis in the cointegrating relation. The results of unit root tests on the equilibrium error exhibit substantial improvement, as reported in Table 4.1. The unfavorable results in terms of skewness and normality are not removed by the addition of the mentioned dummies. However, this is to be expected considering that the data from Turkey is highly erratic as Turkey suffered from many exchange rate shocks in the considered period. As stated

Table 4.2: Statistics of Residuals from the Cointegration Regression

Regression	Sample Mean	Std. Error	Statistics			
			<i>t</i> -statistic	Skewness	Kurtosis	Jarque-Bera
<i>X12A</i> ^b						
(4.1) N ^a	-.000	.241	-.000 (1.000)	-.669 (.000)	.043 (.891)	17.953 (.000)
(4.1) T	-.000	.185	-.000 (1.000)	-.473 (.003)	.494 (.123)	11.387 (.003)
(4.1) TD	-.000	.172	-.000 (1.000)	-.464 (.004)	.403 (.209)	10.225 (.006)
<i>X12M</i> ^c						
(4.1) N	-.000	.241	-.000 (1.000)	-.672 (.000)	.049 (.877)	18.079 (.000)
(4.1) T	-.000	.185	-.000 (1.000)	-.473 (.003)	.501 (.118)	11.462 (.003)
(4.1) TD	-.000	.169	-.000 (1.000)	-.518 (.001)	.316 (.324)	11.719 (.003)
<i>T/S</i> ^d						
(4.1) N	-.000	.243	-.000 (1.000)	-.638 (.000)	-.028 (.930)	16.303 (.000)
(4.1) T	-.000	.188	-.000 (1.000)	-.473 (.003)	.382 (.234)	10.392 (.006)
(4.1) TD	-.000	.173	-.000 (1.000)	-.427 (.007)	.157 (.624)	7.529 (.023)

* Significance levels are given in parantheses.

^a This column refers to whether the regression includes a trend term (T) and/or dummy (D) variables for outliers.

^b X12 ARIMA Additive form

^c X12 ARIMA Multiplicative form

^d TRAMO/SEATS

earlier, DF type tests are shown to be biased towards nonrejecting a unit root in the existence of one or several structural breaks in the data. Another reason could be the existence of structural breaks in the cointegrating vector. In order to account for this, Gregory and Hansen (1992) suggest a modified ADF test for investigating the existence of cointegration among variables. The statistics of Gregory-Hansen cointegration tests, reported in Table 4.3, suggest that, when structural breaks are accounted for, there is strong evidence of a cointegrating relationship. It is beneficial to remember at this point that a structural break might also occur in the case of threshold nonlinearity. Hence, existence of neglected nonlinearities in the cointegrating relation should also be investigated, utilizing tests such as McLeod-Li and Tsay Nonlinearity Test. As the Granger

Table 4.3: Gregory Hansen Test Results

Seasonal Adjustment	Model		
	Level Shift(C)	Level shift w/trend (C/T)	Regime Shift (C/S)
<i>X12A</i>	-3.80	-3.62	-4.15
<i>X12M</i>	-3.80	-3.62	-4.15
<i>TRAMO/SEATS</i>	-4.03	-3.89	-4.43

* The given values are the minimum t -statistics obtained from all possible breaks in the cointegrating relationship. See Gregory and Hansen (1996) for calculation of critical values.

representation theorem suggests, after establishing that the $I(1)$ time series in hand are cointegrated, an error correction model can be estimated. This is done by estimating a two variable vector autoregression (VAR) model. The initial VAR model is allowed for a maximum of $p_0 = 18$ lags. According to the minimum AIC and SBC and misspecification tests, a best linear vector ECM

(VECM) model, including only the first lagged terms, is estimated for the data seasonally adjusted with methods mentioned before. The estimated equations are given in Table 4.4.

Table 4.4: Estimated VECM Models for Wheat Prices

	<i>X12A</i>		<i>X12M</i>		<i>T/S</i>	
	<i>trw_t</i>	<i>usw_t</i>	<i>trw_t</i>	<i>usw_t</i>	<i>trw_t</i>	<i>usw_t</i>
Constant	.007 (.004)	.004 (.003)	.007 (.004)	.004 (.003)	.007 (.004)	.004 (.003)
<i>trw_{t-1}</i>	.07 (.061)	.045 (.055)	.071 (.062)	.039 (.056)	.143* (.061)	.003 (.054)
<i>usw_{t-1}</i>	.055 (.072)	.183** (.066)	.056 (.071)	.177** (.066)	-.014 (.072)	.214** (.066)
\hat{u}_{t-1}	-.075** (.021)	-.005 (.019)	-.070** (.021)	-.006 (.019)	-.084** (.022)	-.003 (.019)
D1994:4	-.299** (.056)		-.297** (.056)		-.316** (.058)	
D2001:4	-.172** (.058)		-.169** (.058)		-.174** (.059)	
<i>Statistics</i>						
$\hat{\sigma}^{\varepsilon}$.055	.051	.055	.051	.057	.052
SK	.172	.000	.219	.000	.145	.000
EK	.000	.000	.000	.000	.000	.000
JB	.000	.000	.000	.000	.000	.000
Q(12)	.84	.16	.76	.23	.33	.34
AIC	-70.25	-108.86	-71.21	-106.09	-52.65	-99.06
SBC	-49.42	-94.97	-50.38	-92.19	-31.81	-85.17

Notes: Standard errors in parantheses; ** 1 per cent significance level, * 5 per cent significance level

$\hat{\sigma}^{\varepsilon}$: residual standard deviation, SK : skewness, EK : excess kurtosis, JB : Jarque-Bera test of normality of the residuals, Q(12): Ljung-Box Q-Statistic for no residual autocorrelation

RESET *F*: RESET F test statistic for correct model specification

P-values of tests statistics given for SK, EK, JB, Q(12) and RESET *F*

Diagnostic tests indicate that the estimated VECM suffer from skewed residuals with excess kurtosis and non-normal distribution. Again, these could be attributed to the highly erratic nature of the data. It could also be the case that, the data contains significant nonlinearities such that linear models do not fit the data at all.

In order to test for the presence of neglected nonlinearities in the model, we use several inference methods to test for stochastic non-linearity in the equilibrium error, u_t : McLeod-Li test by McLeod and Li (1983), BDS test by Brock et al. (1996), RESET test by Ramsey (1969), and Tsay Ori-F test by Tsay (1996). The results of these tests, given in Table 4.5, indicate that there is evidence of neglected nonlinearity in the equilibrium error, and hence in the estimated cointegration relationship. In the following section, we try to determine the nature of the nonlinearity.

Table 4.5: Results of Linearity Tests

Test	Data		
	<i>X12A</i>	<i>X12M</i>	<i>T/S</i>
McLeod-Li	290.43 (.000)	295.57 (.000)	299.39 (.000)
RESET	8.87 (.000)	8.59 (.000)	4.12 (.007)
BDS	26.52 (.000)	26.94 (.000)	29.80 (.000)
Tsay Ori-F	2.16 (.001)	2.78 (.000)	3.31 (.001)

* P-values of tests statistics given in parantheses.

4.3 Threshold Equilibrium Relationship Between US and Turkish Wheat Markets

We start by specifying a linear AR model for the equilibrium error term, u_t . The AR model for u_t is parametrized by allowing for a maximum of $p_1 = 15$ lags. The best linear model is selected according to the minimum AIC and SBC criteria and misspecification tests' results. It is worthwhile to note that different seasonal adjustment methods yield slightly different linear models. The

best linear AR models for the equilibrium error are given in Appendix.

After specifying an appropriate AR lag p for u_t , it is possible to test linearity against a threshold alternative. This procedure involves the selection of the threshold lag of u_t , d .⁵⁵ Given the linear AR order p of u_t , an arranged autoregression⁵⁶ is carried out for $d \in [1, 12]$. The results, reported in Table 4.6, indicate that for the data seasonally adjusted with X12A, threshold lag $d = 2$ rejects the null hypothesis of linearity at the 1 per cent significance level. Similarly, for the data adjusted with X12M, $d = 8, 9, 11$ and $d = 7$ reject the null hypothesis of linearity at the 1 and 5 per cent significance level, respectively, while for $d = 2, 3$ this is at the 10 per cent level. For the data adjusted with T/S, $d = 7, 8, 9, 10, 11, 12$ rejects the null hypothesis of linearity at a maximum of 5 per cent significance level.

Table 4.6: P-values of Tsay Arranged Autoregression Test Statistics

	Data		
	<i>X12A</i>	<i>X12M</i>	<i>T/S</i>
1	.945	.197	.347
2	.007	.082	.445
3	.859	.062	.209
4	.834	.402	.127
5	.872	.323	.241
6	.379	.219	.091
7	.399	.034	.013
8	.309	.006	.002
9	.665	.033	.018
10	.930	.367	.042
11	.395	.003	.000
12	.488	.136	.006

Following the determination of threshold lag d , we use Chan's⁵⁷ method of

⁵⁵ The lag for which u_t exhibits nonlinearity, or rejects the null hypothesis of linearity strongest.

⁵⁶ As in Tsay (1989).

⁵⁷ Ibid.

estimating the threshold values and number of regimes, by estimating the model in (3.19), for which testing the null of unit root vs a threshold alternative, for all possible values of τ and selecting those that minimize the SSRs from the fitted model. This procedure is visually supported by a graph of threshold variable versus the corresponding SSRs.

The possible values of the threshold are initially searched in an interval that omits the first and the last 15 per cent of data to obtain efficient estimates. The threshold is reestimated omitting the first and the last 10 per cent of the data, as the number of observations left out of the regression are still adequate when 20 per cent of the data are omitted.

Once the threshold values τ and number of regimes k are determined, the following model is estimated for a given p ⁵⁸ :

$$\Delta u_t = I_t \rho_1 u_{t-1} + (1 - I_t) \rho_2 u_{t-1} + \sum_{i=0}^p \Delta u_{t-i} + \varepsilon_t \quad (4.2)$$

$$I_t = \begin{cases} 1 & \text{if } u_{t-d} \geq \tau \\ 0 & \text{if } u_{t-d} < \tau \end{cases} \quad (4.3)$$

For the threshold lags $d = 2$, and 3 we are able to reject the null hypothesis $\rho_1 = \rho_2 = 0$ for the X12A data, indicating that the equilibrium error is stationary. Once it is found that the equilibrium error is convergent, we test existence of threshold behavior via the null of $\rho_1 = \rho_2$. For the X12A data, we are able to find thresholds away from the end-points of the considered interval, and for which the null hypothesis is rejected at 1 per cent significance level. For comparison,

⁵⁸ Determined by various information criteria such as AIC and SBC and misspecification tests.

estimates of standard ADF test is also given in Table 4.7. For X12M data with $d = 2$, the null of $\rho_1 = \rho_2$ is rejected on 10 per cent significance level. For T/S data and $d = 7$, we find evidence of nonlinear behavior at the 5 per cent significance level. However, since a threshold delay of 7 is considered rather late and since the estimation results of both the X12M and the T/S data are not satisfactory, results of these estimations are not reported.

Table 4.7: Threshold Model Estimates of the Equilibrium Error

	TAR ($d = 2$)*	ADF
ρ_1	-.303 (-4.29) ^a	-.120 (-3.45)
ρ_2	-.063 (-1.61)	NA
Δu_{t-1}	.216 (-3.37)	-.182 (-2.82)
AIC	143.39	145.98
SBC	157.28	152.89
ϕ_μ ^b	10.56 (.000)	NA
$\rho_1 = \rho_2$ ^c	8.84 (.003)	NA
Q(12) ^d	9.10 (.694)	10.42 (.579)

* $\hat{\tau} = .1875$

^a Entries in this row are t statistic for the null hypothesis $\rho_1 = 0$.

^b Entries in this row are the sample F statistics for $H_o : \rho_1 = \rho_2 = 0$.

^c Entries in this row are the sample F statistics for $H_o : \rho_1 = \rho_2$.

^d Q(12) is the Ljung-Box statistic that the first twelve residual autocorrelations are jointly equal to 0.

Significance levels are given in parantheses.

The positive finding of nonlinear stationarity of the equilibrium error justifies the estimation of a threshold error correction model (TECM) for the X12A data. Using the consistent estimates of the threshold τ , fitted equations are then estimated as in Table 4.8. Diagnostic tests reveal that the estimated model is adequate.

An important implication of the TECM is the possibility of modeling Turkish market adequately with past data from both the Turkish market and the US market. Results show that, in the short run, agents in the Turkish market are influenced significantly both by the recent price deviations both in Turkey (1-2 months) and US (4-5 months) and the price deviations occurred in the last year in the mentioned markets. Similarly, in the long run, agents in the Turkish market act as to keep a certain balance between the US and Turkish wheat prices, which is indicated by the negative and significant coefficients of the equilibrium error.

While Turkish market dynamics can be modeled with the TECM, little can be said for the US market. Estimation results indicate that Turkish wheat market dynamics are insignificant for the US wheat market. This is also consistent with Turkey being a relatively small country in wheat production with respect to the US, and hence being ineffective in world wheat price formation. As the final step, the general approach in comparing models is to compare the forecasts of the ECM and TECM with respect to the actual data. However, it is argued by Nieto (2008) that threshold models with a sharp cutoff (as opposed to a STAR model) aren't appropriate for forecasting, as sharp cutoff models such as TAR can not distinguish between cutoff values in between the two data values at which the optimal break is located. This makes forecasting a futile exercise. Nieto⁵⁹ suggests a procedure obtaining the predictive distributions for the variables of interest and, then, in obtaining samples from them via Monte Carlo simulation, in order to estimate their means and their variances. However, this is beyond

⁵⁹ *ibid.*

Table 4.8: TECM Estimates of Wheat Prices

	$\Delta(TRW_t)$	$\Delta(USW_t)$
constant	.006 (.004) ^a	.004 (.003)
$z_{positive}$ ^b	-.035 (.052)	-.028 (.043)
$z_{negative}$	-.090** (.027)	-.009 (.023)
$\Delta(TRW_{t-1})$.108** (.065)	
$\Delta(TRW_{t-12})$	-.171* (.065)	
$\Delta(USW_{t-1})$.148 ⁺ (.078)	.182** (.066)
$\Delta(USW_{t-4})$	-.0196*	
$\Delta(USW_{t-12})$		-.198** (.066)
Q(12) ^a	.940	.748
AIC	-51.39	-127.58
SBC	-27.42	-110.45

^a Standard errors are given in parantheses.

** 1 per cent significance level, * 5 per cent significance level, + 10 per cent significance level

^b $z_{pos} = I_{t-1}u_{t-1}$
 $z_{neg} = (1 - I_{t-1})u_{t-1}$

the scope of this study.

Momentum Threshold Autoregressive Model

The finding that Turkish wheat prices have a significant relationship with the US prices, while the converse does not hold, motivates the direct investigation of threshold behavior of Turkish wheat prices with respect to the US prices. This analysis involves the estimation of MTAR model, specified by equation (3.22) in Chapter 3, for the price spread defined as the difference between Turkish and US prices.

The estimations are done for the X12A and X12M data for which threshold behavior was found meaningful. The results of the MTAR estimation, reported

in Table 4.9, indicate that the price differentials exhibit momentum threshold autoregressive behavior. The adjustment appears to be asymmetric such that the attractor is stronger for negative changes in the price differential.

Table 4.9: MTAR Model Estimate of the Price Differential

	<i>X12A</i>	<i>X12M</i>
ρ_1	-.043 (-1.36)	-.042 (-1.31)
ρ_2	-.105 (-3.06)	-.107 (-3.12)
$\Delta spread_t$.132 (2.02)	.136 (2.08)
$\hat{\sigma}^\varepsilon$.058	.049
AIC	87.54	86.08
SBC	97.96	96.49
ϕ_μ	5.56 (.004)	5.66 (.004)
$\rho_1 = \rho_2$	1.79 (.182)	1.97 (.161)
Q(12)	16.94 (.152)	16.83 (.156)

Discussion

It has been shown in this chapter that wheat markets in Turkey and in the US have a cointegrating relationship, and that this long-run relationship can be better modeled by a nonlinear model, such as the TAR and the MTAR model. However, diagnostics of the threshold models reveal that these models too have some deficiencies. These might be due to the erratic behavior of the data, especially considering that prices in Turkey are multiplied with the exchange rate to obtain prices denominated in the same currency, USD. The inherent

nonlinearities in the exchange rate considered in a more comprehensive model⁶⁰ is expected to perform better in this sense. Another explanation could be the possible existence of more than two regimes. In this case, estimation of a model allowing for a continuum of thresholds, like the STAR model as suggested by Terasvirta (1994), might be more appropriate. However, this is beyond the scope of this study.

⁶⁰ This requires estimation of a multivariate TAR model. See Tsay (1998) for further information.

CHAPTER 5

CONCLUSION

Over the last two decades, interest in nonlinear time series has been steadily increasing which stems from the inadequacy of linear models in capturing the observed behavior of many economic time series. This thesis mainly focuses on modeling the wheat prices in Turkey with respect to the US from the perspective of the Law of One Price (LOOP) hypothesis, with a model allowing for nonlinear dynamics due to existence of arbitrage preventing factors such as transaction costs.

This study also provides a survey of the important time series concepts like stationarity, unit roots and cointegration. This is followed by a survey of the most commonly used nonlinear models in the literature, namely the threshold autoregressive (TAR) and the smooth transition autoregressive (STAR) models, and the concepts of threshold cointegration are discussed. The empirical studies are based on the TAR model due to its simplicity and sharp-regime switching behavior.

The empirical studies consider the monthly prices of hard red winter (HRW)

type wheat for the period 1988:1–2007:12 in Turkey and in the United States. The results indicate that there is convincing evidence for the existence of a nonlinear long-run equilibrium relationship between the two markets, generated by the Turkish market adjusting to the deviations from the long-run equilibrium asymmetrically. While the diagnostics of both the error correction model (ECM) and its threshold counterpart (TECM) indicate some problems, the latter seems to be more preferable than the ECM, considering that the convincing evidence towards asymmetric behavior, as well as the lower residual variances produced by the TECM.

The findings related to the asymmetrical nature of the cointegrating relationship are consistent with the general literature and in line with the common wisdom concerning the LOOP hypothesis and the asymmetrical responses of large vs. small countries, considering that Turkey's role as a price-taker in the international wheat markets. The low performance of TECM could be due to the erratic behavior of the exchange rate, which is used to convert prices in Turkey into US Dollars. A model examining the exchange rate separately is expected to be more revealing and comprehensive in this sense. Furthermore, the possible existence of more than one threshold (i.e. more than two regimes) for the equilibrium error might have contributed to the poor diagnostics. If this is indeed the case, then modeling the equilibrium error with models allowing for continuum of regimes, such as smooth transition autoregressive (STAR) models, would be more appropriate. The estimated MTAR models indicate that the adjustment of the price differential shows more persistence for negative changes in the previous period. It has to be also considered that a longer data set might

produce better results.

To sum up, we conclude that HRW wheat prices in Turkey can be modeled better allowing for nonlinear structures in the generating mechanisms of the long-run equilibrium relationship. This finding is important on the following grounds. First, use of linear models are expected to fail in identifying and capturing the evident nonlinear behavior of the wheat prices, and often leading to inaccuracies in forecasting and policy making, as they demonstrate the average responses of the whole time series. Secondly, the existence of threshold behavior implies the need for regime-specific policies.

REFERENCES

- ACEMOGLU, D. AND A. SCOTT (1997): “Asymmetric business cycles: Theory and time-series evidence,” *Journal of Monetary Economics*, 40, 501–33.
- AKDER, A. (2007): “Tarım Envanteri ve Alternatif Ürünler Geliştirilmesi,” Tech. rep., İstanbul Ticaret Odası.
- ÇAKMAK, E. (2003): “Evaluation of the past and future agricultural policies in Turkey: are they capable to achieve sustainability,” *Options Méditerranéennes, Sér. A*, 52, 155–65.
- ÇAKMAK, E., ed. (2004): *Structural Change and Market Opening in Agriculture: Turkey Towards EU Accession*, Brussels – 27 September 2004: CEPS and EFPP Workshop on ‘Strategy for EU and Turkey in the Pre-Accession Period’.
- ÇAKMAK, E. AND H. AKDER, eds. (2008): *Türkiye’de Tarım ve Gıda: Gelişmeler, Politikalar ve Öneriler*, İstanbul: TÜSİAD.
- ÇAKMAK, E., H. KASNAKOĞLU, AND H. AKDER (1999): *Tarım Politikalarında Yeni Denge Arayışları ve Türkiye*, İstanbul: TÜSİAD.
- ASPLUND, M. AND R. FRIBERG (2001): “The law of one price in Scandinavian Duty-Free Stores,” *American Economic Review*, 91, 1072–83.
- BAE, Y. AND R. DE JONG (2005): “Money Demand Function Estimation by Nonlinear Cointegration,” Ohio State University Department of Economics, mimeo.
- BALKE, N. S. AND T. B. FOMBY (1997): “Threshold Cointegration,” *International Economic Review*, 38, 627–645.
- BALL, L. AND D. ROMER (1989): “Are prices too sticky?” *Quarterly Journal of Economics*, 104, 507–24.
- BARRO, R. (1977): “Long-term contracting, sticky prices, and monetary policy,” *Journal of Monetary Economics*, 3, 305–16.
- BIERENS, H. J. (1997): “Nonparametric Cointegration Analysis,” *Journal of*

- Econometrics*, 77, 379–404.
- BLINDER, A. AND S. FISCHER (1981): “Inventories, rational expectations, and the business cycle,” *Journal of Monetary Economics*, 8, 277–304.
- BRITANNICA (2010): “Wheat, Online Encyclopaedia Britannica,” Accessed: June 2010 from <http://www.britannica.com/EBchecked/topic/641558/wheat>.
- BROCK, W., W. DECHERT, J. SCHEINKMAN, AND B. LEBARON (1996): “A Test for Independence Based on the Correlation Dimension,” *Econometric Reviews*, 15, 197–235.
- BROCKWELL, P., J. LIU, AND R. TWEEDIE (1992): “Testing Stationarity Against the Unit Root Hypothesis,” *Econometric Reviews*, 12, 1–32.
- CABALLERO, R. AND E. ENGEL (1992): “Price Rigidities, Asymmetries, and Utput Fluctuations,” NBER Working Papers 4091.
- ÖCAL, N. AND D. OSBORN (2000): “Business Cycle Non-linearities in UK Consumption and Production,” *Journal of Applied Econometrics*, 15, 27–43.
- CBRT (2009): “Daily Exchange Rates,” Tech. rep., Central Bank of Republic of Turkey, accessed : September 2009 from <http://evds.tcmb.gov.tr>.
- CECHETTI, S., M. NELSON, AND R. SONORA (2002): “Price level convergence among Unites States Cities: Lessons for the European Central Bank,” *International Economic Review*, 43, 1081–99.
- CHAN, K. (1993): “Consistency and Limiting Distribution of the Least Squares Estimator of a Threshold Autoregressive Model,” *The Annals of Statistics*, 21, 520–33.
- CHAN, K., J. PETRUCCELLI, H. TONG, AND S. WOOLFORD (1990): “A Multiple Threshold AR(1) Model,” *Journal of Applied Probability*, 22, 267–79.
- CHAN, K. AND H. TONG (1985): “On the Use of Deterministic Lyapunov Functions for the Ergodicity of Stochastic Difference Equations,” *Advances in Applied Probability*, 17, 666–78.
- (1986): “On Estimating Thresholds in Autoregressive Models,” *Journal of Time Series Analysis*, 7, 179–90.
- COOK, S. AND A. SPEIGHT (2006): “International Business Cycle Asymmetry and Time Irreversible Nonlinearities,” *Journal of Applied Statistics*, 33, 1051–65.

- DICKEY, D. AND W. FULLER (1979): “Distribution of the Estimators for Autoregressive Time Series with a Unit Root,” *Journal of the American Statistical Association*, 74, 427–431.
- (1981): “Likelihood Ratio Tests for Autoregressive Time Series with a Unit Root,” *Econometrica*, 49, 1057–1072.
- ENDERS, W. (2004): *Applied Econometric Time Series, 2nd Edition*, New Jersey, USA: John Wiley.
- ENDERS, W. AND C. GRANGER (1998): “Unit-Root Tests and Asymmetric Adjustment with an Example Using the Term Structure of Interest Rates,” *Journal of Business and Economic Statistics*, 16, 304–11.
- ENGEL, C. AND J. ROGERS (1996): “How wide is the border?” *American Economic Review*, 86, 1112–25.
- ENGLE, R. AND C. GRANGER (1987): “Co-Integration and Error Correction: Representation, Estimation and Testing,” *Econometrica*, 55, 251–276.
- FAOSTAT (2009): “Crop Production,” Tech. rep., Food and Agriculture Organization of the United Nations, accessed: June 2010 from www.faostat.org.
- FLASKERUD, G. AND D. JOHNSON (2000): “Seasonal Price Patterns for Crops,” mimeo.
- GOLDBERG, P. AND F. VERBOVEN (2005): “Market Integration and Convergence to the Law of One Price: Evidence from The European CarMarket,” *Journal of International Economics*, 65, 49–73.
- GRANGER, C. (1981): “Some properties of time series and their use in econometric model specification,” *Journal of Econometrics*, 16, 121–30.
- GRANGER, C. AND P. NEWBOLD (1974): “Spurious Regressions in Econometrics,” *Journal of Econometrics*, 2, 111–120.
- GREGORY, A. AND B. HANSEN (1992): *Residual Based Tests for Cointegration in Models with Regime Shifts*, Queens University: Kingston.
- HALL, A. (1989): “Testing for a Unit Root in the Presence of Moving Average Errors,” *Biometrika*, 76, 49–56.
- HAMILTON, J. (1990): “Analysis of Time Series Subject to Changes in Regimes,” *Journal of Econometrics*, 45, 39–70.

- IFPRI (2008): “High Food Prices: The What, Who, and How of Proposed Policy Actions,” Tech. rep., International Food Policy Research Institute.
- JOHANSEN, S. (1988): “Statistical Analysis of Cointegrating Vectors,” *Journal of Economic Dynamics and Control*, 12, 231–54.
- (1991): “Estimation and hypothesis testing of cointegrated vectors in Gaussian vector autoregressive models,” *Econometrica*, 59, 1551–80.
- (1994): “The role of constant and linear terms in cointegration analysis of nonstationary variables,” *Econometric Reviews*, 13, 205–30.
- JOHANSEN, S. AND K. JUSELIOUS (1990): “Maximum Likelihood Estimation and Inference on Cointegration with Application to the Demand for Money,” *Oxford Bulletin of Economic and Statistics*, 52, 169–209.
- KASNAKOĞLU, H. AND E. ÇAKMAK (1998): “The Fiscal Burden on Distribution of Costs and Benefits of Agricultural Support Policies in Turkey,” Tech. rep., World Bank Technical Paper No:470, Washington, D.C.
- KASNAKOĞLU, H. AND A. GÜRKAN (1991): “The Political Economics of Agricultural Price Support in Turkey: An Empirical Assessment,” *Public Choice*, 70, 277–98.
- KWIATKOWSKI, D., P. PHILLIPS, P. SCHMIDT, AND Y. SHIN (1992): “Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?” *Journal of Econometrics*, 54, 159–78.
- LAMONT, O. AND R. THALER (2003): “The law of one price in financial markets,” *Journal of Economic Perspectives*, 17, 191–202.
- LEE, J. AND M. STRAZIČIČ (2003): “Minimum LM Unit Root Test with Two Structural Breaks,” *Review of Economics and Statistics*, 85, 1082–89.
- LUUKKONEN, R., P. SAIKKONEN, AND T. TERASVIRTA (1988): “Testing Linearity Against Smooth Transition Autoregressive Models,” *Biometrika*, 75, 491–99.
- MAINARDI, S. (2001): “Limited Arbitrage in International Wheat Markets: Threshold and Smooth Transition Cointegration,” *The Australian Journal of Agricultural and Resource Economics*, 45, 335–60.
- MCLEOD, A. AND W. LI (1983): “Diagnostic Checking ARMA Time Series Models Using Squared Residual Correlations,” *Journal of Time Series*

Econometrics, 4, 269–73.

MICHAEL, P., A. NOBAY, AND D. A. PEEL (1997): “Transaction Costs and Nonlinear Adjustment in Real Exchange Rates: An Empirical Investigation,” *Journal of Political Economy*, 105, 862–79.

MOHANTY, S., S. D.B., E. PETERSON, AND M. W.H. (1996): “Law of One Price in International Commodity Markets: A Fractional Cointegration Analysis,” Iowa State University, mimeo.

MOHANTY, S., W. MEYERS, AND D. SMITH (1999): “A Reexamination of Price Dynamics in International Wheat Market,” *Canadian Journal of Agricultural Economics*, 47, 21–29.

NEFTCI, S. N. (1984): “Are Economic Time Series Asymmetric Over the Business Cycle?” *Journal of Political Economy*, 92, 307–28.

NELSON, C. AND C. PLOSSER (1982): “Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications,” *Journal of Monetary Economics*, 10, 193–162.

NIETO, F. (2008): “Forecasting with univariate TAR models,” *Statistical Methodology*, 5, 263–76.

PARSLEY, D. AND S. WEI (1996): “Convergence to the Law of One Price without Trade Barriers or Currency Fluctuations,” *Quarterly Journal of Economics*, 111, 1211–36.

PBT (2009): “Average Monthly Prices of Anatolian HRW Wheat,” Tech. rep., Polatlı Board of Trade, accessed : September 2009 from <http://www.polatliborsa.org.tr/tr/BugdayFrames.htm>.

PERRON, P. (1989): “The Great Crash, The Oil Price Shock, and the Unit Root Hypotheses,” *Econometrica*, 55, 277–301.

——— (1997): “Further Evidence on Breaking Trend Functions in Macroeconomic Variables,” *Journal of Econometrics*, 80, 355–85.

PHILLIPS, P. AND S. OULIARIS (1990): “Asymptotic properties of residual based tests for cointegration,” *Econometrica*, 58, 165–93.

PHILLIPS, P. AND P. PERRON (1988): “Testing for a Unit Root in Time Series Regression,” *Biometrika*, 71, 599–607.

PIPPINGER, M. AND G. GOERING (1993): “A Note on the empirical power of

- unit root tests under threshold processes,” *Oxford Bulletin of Economics and Statistics*, 55, 473–81.
- RAMSEY, J. (1969): “Tests for Specification Errors in Classical Linear Least-Squares Regression Analysis,” *Journal of the Royal Statistical Society*, 31, 350–71.
- REAGAN, P. AND M. WEITZMAN (1982): “Asymmetries in Price and Quantity Adjustments by the Competitive Firm,” *Journal of Economic Theory*, 27, 410–20.
- SAID, S. AND D. DICKEY (1984): “Testing for Unit Roots in ARMA Models of Unknown Order,” *Biometrika*, 71, 599–607.
- SARNO, L., M. TAYLOR, AND I. CHOWDHURY (2004): “Nonlinear Dynamics in Deviations from the Law of One Price: A Broad-based Empirical Study,” *Journal of International Money and Finance*, 23, 1–25.
- SEKHAR, C. (2002): “Price formation in worldwheat markets– implications for policy,” *Journal of Policy Modeling*, 25, 85–106.
- SINCLAIR, T. (2010): “Asymmetry in the Business Cycle: Friesdman’s Plucking Model with Correlated Innovations,” [Http://www.bepress.com/snede/vol14/iss1/art3](http://www.bepress.com/snede/vol14/iss1/art3).
- STOCK, J. AND M. WATSON (1988): “Testing for Common Trends,” *Journal of the American Statistical Association*, 83, 1097–1107.
- TAYLOR, A. (2002): “A Century of Purchasing Power Parity,” *Review of Economics and Statistics*, 84, 139–50.
- TERASVIRTA, T. (1994): “Specification, Estimation and Evaluation of Smooth Transition Autoregressive Models,” *Journal of the American Statistical Association*, 89, 208–18.
- TERASVIRTA, T. AND H. ANDERSON (1992): “Characterizing Nonlinearities in Business Cycles Using Smooth Transition Autoregressive Analysis,” *Journal of Applied Econometrics*, 7, 119–36.
- TJOSTHEIM, D. (1990): “Non-linear Time Series and Markov Chains,” *Advances in Applied Probability*, 22, 587–611.
- TMO (2004): “Hububat Raporu,” Tech. rep., Tarım Mahsulleri Ofisi, accessed : June 2010 from [http : //www.tmo.gov.tr/uploads/yayinlar/hububat_raporu.pdf](http://www.tmo.gov.tr/uploads/yayinlar/hububat_raporu.pdf).

- TONG, H. (1978): *On a Threshold Model in Pattern Recognition and Signal Processing*, Amsterdam: Sijhoff and Noordhoff.
- (1983): “A Note on a Delayed Autoregressive Process in Continuous Time,” *Biometrika*, 70, 710–12.
- (1990): *Nonlinear Time Series: A Dynamical System Approach*, Oxford, UK: Oxford University Press.
- TONG, H. AND K. LIM (1980): “Threshold Autoregression, Limit Cycles and Cyclical Data,” *Journal of the Royal Statistical Society*, 42, 245–92.
- TSAY, R. (1996): “Nonlinearity Tests for Time Series,” *Biometrika*, 73, 461–66.
- TSAY, R. S. (1989): “Testing and Modeling Threshold Autoregressive Processes,” *Journal of the American Statistical Association*, 84, 231–40.
- (1998): “Testing and Modeling Multivariate Threshold Models,” *Journal of the American Statistical Association*, 93, 1118–1202.
- USDA/ERS (2009): “Wheat Yearbook,” Tech. rep., United States Department of Agriculture, Economic Research Service, accessed: September 2009 from <http://www.ers.usda.gov/Data/Wheat/WheatYearbook.aspx>.
- YILDIRIM, T., W. FURTAN, AND A. GÜZEL (1998): “Türkiye Buğday Politikasının Teorik ve Uygulamalı Analizi,” Tech. rep., Tarımsal Ekonomi Araştırma Enstitüsü, Ankara.
- ZIVOT, E. AND D. ANDREWS (2002): “Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis,” *Journal of Business and Economic Statistics*, 20, 25–44.

APPENDIX

Table .1: Estimated Linear AR Models for Equilibrium Error

	Data		
	<i>X12A</i>	<i>X12M</i>	<i>T/S</i>
Constant	.003 (.005)	.003 (.005)	.002 (.005)
u_{t-1}	.775** (.059)	.720** (.061)	.703** (.064)
u_{t-2}	.169** (.058)	.224** (.059)	.322** (.074)
u_{t-3}			-.042 (.069)
u_{t-4}			-.052 (.061)
$\hat{\sigma}^{\varepsilon}$.078	.078	.079
Q(12)	.195	.268	.116
AIC	99.66	100.59	114.11
SBC	120.49	121.42	145.28

* Standard errors are given in parantheses.