Three Essays on Applied Economics

by

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Abstract

This dissertation consists of three essays in housing, trade, and time series econometrics. The first essay empirically investigates cointegrating relation between housing prices and economic fundamental variables in the US housing market. Employing simple yet rigorous econometric techniques, the present paper finds strong evidence in favor of cointegrating relations in most US states when both the demand and supply side fundamental variables are included in the cointegrating regression. This casts doubt on the previous empirical work that reported weak or no cointegrating relation of housing prices with mostly demand-side fundamental variables, which may have a misspecification problem. Further, cointegrating vector estimates seem consistent with economic theories only when both side fundamental variables are used.

The second essay estimates exchange rate elasticities of US cotton exports to China, Indonesia, Thailand, South Korea, and Taiwan, five textile producing cotton importers with floating or regularly adjusting exchange rates since the 1970s. A model is developed with US exports depending on the exchange rate, US production cost, mill use, and cotton inventories. The role of inventories in cotton consumption is examined in Southeast and East Asia countries with Asian financial crisis. Aggregating the five importers disguises exchange rate effects. The lesson is that exchange rate effects should be examined for each separate market. Changes in rates of depreciation have stronger effects than changes in exchange rates in the present sample.

The third essay evaluates relative forecast performances of two bias-correction methods.

The least squares (LS) estimator suffers from significant downward bias in autore-gressive models that include an intercept. By construction, the LS estimator yields the best in-sample t among a class of linear estimators notwithstanding its bias. Then, why do we need to correct for the bias? To answer this question, we evaluate the usefulness of the two popular bias correction methods, proposed by Hansen (1999) and So and Shin (1999), by comparing their out-of-sample forecast performances with that of the LS estimator. We find that bias-corrected estimators overall outperform the LS estimator. Especially, Hansen's grid bootstrap estimator combined with a rolling window method performs the best.

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CHAPTER 1

THE EXCHANGE RATE, US COTTON EXPORTS, AND COTTON INVENTORIES OF ASIAN TEXTILE PRODUCERS

I. INTRODUCTION

One of the principles of international economics is that currency appreciation should lower demand for exports. The present paper examines the evidence for US cotton exports to five major textile producing importers during the floating exchange rate era. A novel model of the textile producing cotton warehouse stock allows mill use as an exogenous demand variable. The effects of the Asian financial crisis also examined.

Currencies have depreciated for most developing countries including China, Indonesia, South Korea, Taiwan, and Thailand, the five textile producers in the present paper. Sample selection is based on five textile producer floating or regularly adjusting exchange rates beginning with the earliest bilateral US cotton export data in 1978 and extending through 2010. The patterns of currency depreciation differ suggesting a trade weighted exchange rate would conceal information. Although the yuan exchange rate is fixed, China is included in the sample since it has become the largest US cotton importer, averaging 15% of US exports over the sample period and reaching 26% in 2010.

Other importers such as Turkey and Pakistan are not included in the sample. Turkey imported 17% of US exports in 2007 and averaged 7% since 1986 with an upward trend. The lira has been fixed with little variation relative to the dollar. Pakistan was the next largest importer of US cotton in 2008 at 6% and has recently increased imports while averaging 4% of US exports since 2000, but the rupee has been fixed. US exports account for stationary averages of 39% of total cotton imports into Indonesia, 54% into South Korea, 35% into Taiwan, and 29% into Thailand over the sample period.

The dollar has appreciated relative to these currencies over the 33 years of the sample period, a total of 83% relative to the Chinese yuan, 85% to the Indonesian rupiah, 90% Korean won, 64% Taiwanese Dollar, and 67% to the Thai baht. Depreciation raises importer currency prices for US cotton. The empirical issue is whether US exports diminish as a result. The market context is increasing demand for cotton in these developing textile producers along with falling US production cost. Importers may, however, be able to avoid their depreciating currency or they may have stocks of cotton, cash, or credit that allow undisrupted imports.

The present model includes the stock of cotton inventories that textile producers maintain as insurance against price changes and exchange rate variation. In the model, cotton is supplied from the US as well as another source insensitive to the dollar exchange rate. Falling production cost increases US export supply.

The present paper utilizes a model of imperfect substitutes between US cotton and cotton from the other source independent of the dollar exchange rate. Underlying cotton market conditions include falling US production cost and increasing mill use, variables included in the model. Regression analysis includes error correction models and the effect of the Asian financial crisis of 1997.

The sensitivity of cotton exports to exchange rates might be expected to vary by importer. The present study uncovers differences among these five countries. With average exchange rates, depreciation of one currency might lower exports while importers in another currency might be less sensitive and dominate the aggregate effect. Aggregated export data and average exchange rates may conceal differences in underlying bilateral relationships.

There are differences in these five importer markets but the bilateral exchange rates have no impacts on US exports, consistent with the literature. An increase in the rate of depreciation, however, lowers imports due to diminished purchasing power of local currency. The wealth of the textile producers is diminished by an increase in the rate of depreciation. In response they reduce operations and import less cotton. This effect of an increase in rate of depreciation on cotton trade is novel to the literature.

II. THE LITERATURE ON EXCHANGE RATES, EXPORTS, AND INVENTORIES

According to last 2010 marketing year USDA reports world cotton trade climbed 2.5 million bales to 38.4 million. The US is the largest cotton exporter followed by the African euro zone, India, Uzbekistan, Australia, and Brazil. In 2010 US raw cotton exports were 15.3 million bales up 3.3 million from 2009 marketing year. US global market shares have declined recently as described by Hudson and Ethridge (2000) but the US still accounts for about one fifth of world exports as described by Jolly, Jefferson-Moore, and Traxler (2005). Cotton is a major agricultural commodity in the US Southeast. The recent low cotton prices are due to the continued high levels of global production described by Meyer (2002).

There is some literature on the effect of the exchange rate on cotton exports. The USDA (2001) describes trends in the exchange rate and the US share of the world cotton market but does not examine the econometrics. Similarly, a report by the Cotton Research and Development Corporation (2003) stresses the critical nature of the exchange rate for Australian cotton producers but does not include econometric analysis. Schuh (1974) examines the effects of exchange rates on cotton trade during the pre Bretton Woods era of fixed but occasionally adjusting exchange rates. Raines (2002) focuses on the effect of the exchange rate on US textile trade during the 1990s floating exchange rates, but finds minimal impacts. Shane, Roe, and Somwaru (2006) find no effect of the exchange rate on aggregate US cotton exports although they do find effects for other commodities.

Similarly, Awokuse and Yuan (2006) find exchange rate volatility affects US poultry exports, and Xie, Kinnucan, and Myrland (2009) find exchange rate effects on domestic prices and exports of farmed Salmon in Norway. Almarwani, Jolly, and Thompson (2007) find dollar appreciation lowers some agricultural exports but the impacts vary across countries and commodities. For US cotton market shares, they find an exchange rate elasticity of 0.34 for Australia and 0.63 for Argentina. Their data set extends from 1961 to 2000 while the present data set focuses on floating exchange rates beginning in 1978 and extends to 2007. There has been work published in recent years focused primarily on the impact of subsidies for cotton production. Agricultural policy support is critical for the cotton market and the effects of subsidies are examined by Pan, Fadiga, Mohanty, and Welch (2007) and Schmitz, Rossi, and Schmitz (2007). The interplay of subsidies and exchange rates is an area for future research, both theoretical and empirical.

The present study utilizes bilateral exchange rates rather than an average exchange rate, focuses on export levels rather than market shares, and analyzes the impact of the rate of appreciation as well as appreciation. The present study also finds changes in the level of the exchange rate have weaker effects than changes in the rate of depreciation. Exchange rate sensitivity also varies considerably across the three cotton importer markets. Their trade weighted exchange rate is insignificant to their aggregate imports.

III. A MODEL OF THE IMPORTED COTTON MARKET

The general link between the exchange rate and exports is developed by Thompson (2005). The present model assumes the market equilibrium for cotton is determined by cotton demand for textile production and by supply from US exports and from the rest of the world. The focus is on the effect of the exchange rate on market equilibrium US exports. Demand and supply functions are assumed linear.

The demand for cotton in textile production is based on maintaining two stocks for mill operations, a stock of cotton W for input, and a stock of domestic currency B. Assuming all cotton input is imported, the stock of cotton changes according to

$$\Delta W = X + S - M$$

where X is imports from the US, S is imports from other sources, and M is mill use. Higher mill use M lowers the stock of cotton as ΔW falls, and would increase import demand to maintain W. The timing of cotton purchases X and S do not necessarily match mill use M suggesting a nonzero varying stock W.

The two sources X and M are imperfect substitutes. The quantities of each purchase may be small relative to W with many purchases made during the year, the period of observation in the present data. Over the course of a year

$$\Delta W = 0 \text{ and } X + S = M.$$

Total potential US imports X_p are assumed to be less than M suggesting purchases from both sources. Depreciation relative to the dollar increases the relative price of US cotton, decreases US exports X, and decreases relative exports X/S.

Regarding the other stock, cash B is maintained to pay local expenses L and for for imported cotton, and changes according to

$$\Delta B = R - L - (P/E)X + (P/E_S)S$$

where R is revenue from selling textiles, L is local expenses, P is the international price of cotton in dollars, E is the \$/rupiah exchange rate, and E_S is the rupiah exchange rate with other sources assumed constant. The other source could also be domestic. Depreciation relative to the dollar lowers E and raises the local price P* for a given US price P since P* = P/E. Depreciation relative to the dollar induces substitution toward the other source S and X/S falls. Both X and S fall due to the higher costs of operation but X falls more.

Depreciation also lowers the dollar value EB of the stock of cash reserves, a wealth diminishing effect, according to $B\Delta E < 0$. The hypothesis is that this lost wealth diminishes mill operations and further lowers cotton demand in the mills.

US cotton supply X is increasing function of the local price where $P = P_\$/E$, $P_\$$ is the dollar price, E is the local \$/currency exchange rate. Dollar appreciation, a decrease in E, lowers X. Alternative supply S is insensitive to the dollar exchange rate. Textile producer cotton demand D is a decreasing function of the local currency price based on textile demand. Higher textile prices or mill investment would increase mill use U. Demand is also sensitive to local currency depreciation that reduces the purchasing power of textile producer stock B of local currency.

The Asian cotton market, the identity between supply and demand, can be written as:

$$W_t + U_t + X_t = W_{t-1} + A_t + M_t \quad (1)$$

where W_t is ending inventory, W_{t-1} is beginning inventory, U_t is domestic consumption, X_t is exports, A_t is domestic production, M_t is imports. The identity can be expressed by the demand for domestic consumption and the demand for exports to represent current demand (D_t). In the same way, the total of beginning inventory, domestic production, and imports reveals current supply (S_t). The identity then takes the following form:

$$S_t - D_t - \Delta W_t = 0 \quad (2)$$

Following Isengildina-Massa and MacDonald (2009) each variable in the identity is a function of a set of explanatory variables;

$S_t = b(E_{t-1}(p_t), z_t)$ Supply

$D_t = g(p_t, y_t)$ Demand

$W_t = h(p_t, w_t)$ Inventory

where p_t is the inflation adjusted price, $E_{t-1}(p_t)$, is the period t-1 expectation of p_t, and z_t, y_t, and w_t are exogenous variables affecting supply, demand, and inventory. Westcott and Hoffman (1999) specify price in forecasting models as a function of the stocks-to-use ratio. Stocks-to-use ratio can be introduced in (3) dividing through by $g(p_t, y_t)$:

$$S_t - g(p_t, y_t) - h(p_t, w_t) = 0 \tag{3}$$

$$\frac{S_t}{g(p_t, y_t)} - 1 = \frac{h(p_t, w_t)}{g(p_t, y_t)} = r(p_t, w_t, y_t) = W/U \tag{4}$$

where r denotes the ratio of stock-to-use.

The amount of cotton input, U, equals the quantity of cotton purchased Q^e minus the cotton that added to the stock of inventories ΔW

$$U = Q^e - \Delta W$$

The change in cotton over time equals the change in produced minus the change in addition to inventory stocks

$$\Delta U = \Delta Q^e - \Delta^2 W$$

Price elasticity of cotton demand in use is

$$\eta^{cot} = \frac{\%\Delta U}{\%\Delta P} = \frac{\frac{\Delta Q^e - \Delta^2 W}{Q^e_{t-1} - \Delta W_{t-1}}}{\%\Delta P}$$

The linear demand for cotton is

$$D = a_0 - a_1 P + a_2 U - a_3 N + a_4 W \tag{5}$$

where D is the quantity of bales demanded, U is bales of mill use, and N is the rate of appreciation or depreciation ΔE/E. Parameters are positive and signs of expected effects are indicated. Dollar appreciation, a decrease in E, lowers quantity demanded. Higher mill use U increases demand D to maintain the warehouse W but a_2 might not equal one given spare warehouse capacity.

An increase in the dollar price of cotton P lowers quantity of US exports demanded in coefficient a_1. Mill operation could continue at the same level given a nonzero cotton inventory W. Similarly, a fall in P leads to an increase in the quantity of cotton demanded without necessarily increasing textile output but with temporary stockpiling of cotton in W.

An increase in mill use M raises demand for cotton in the coefficient a_2 to maintain the cotton input stock W. The demand coefficients are not a concern of the present paper but a_2 should be close to one.

Depreciation of the local currency relative to the dollar (a decrease in E) lowers cotton demand in the coefficient a_3 due to the higher local price of US cotton. This price effect of depreciation is examined in the literature.

An exchange rate effect not examined in the literature is the effect of a change in the rate of appreciation $N = \Delta E/E$ on the purchasing power of cash balances B. Generally N is negative in the data indicating local currency depreciation. An increase in the rate of depreciation -N diminishes the wealth of cash balances, lowering the purchasing power of producer cash reserves. Producers holding cash reserves B anticipate depreciation but an increase in the rate of depreciation unexpectedly lowers wealth. The coefficient a_4 on the rate of depreciation N is this wealth diminishing effect on cotton demand due to the change $B\Delta E$ in the dollar value of cash reserves.

The quantity of US cotton exports is a function of unit cost of production C as well as the price of cotton

$$X = -b_o + b_1 P_\$ - b_2 C$$

To relate US supply to the local currency price P the effect of E is separated into

$$X = -b_o + b_3E + b_4P - b_2 lnC \tag{6}$$

where X is bales exported and C is the US cost of production per bale.

The supply of cotton from the rest of the world is a function of price only,

$$S = -c_o + c_1P. \tag{7}$$

Equilibrium in the importing country market is pictured in Figure 1 where quantity demanded D equals total quantity supplied, the horizontal sum of quantities supplied from the two sources, D = X + S. Substitute (5), (6), and (7) equilibrium market P is function of four exogenous variables.

$$\mathrm{P}^e = b_o + b_1E + b_2W - b_3C. \tag{8}$$

Substitute the equilibrium price P^e into the US export function (6) to find the reduced form

$$\mathrm{X}^e = a_o + a_1E + a_2W - a_3C. \tag{9}$$

Estimated equation signs of coefficients follow from the underlying demand and supply relations. Dollar appreciation lowers US supply X and also lowers demand D due to the wealth reduction of cash balances leading to the lower X^e.

$$\mathrm{P}^e = \overset{(+)}{d_o} + \overset{(?)}{d_1E} + \overset{(+)}{d_2W} + \overset{(+)}{d_3C} \tag{10}$$

where $d_0 = (a_0 + b_0 + c_0)/\alpha > 0$, $d_1 = (a_3 - b_1)/\alpha$, $d_2 = a_2/\alpha > 0$, $d_3 = b_2/\alpha > 0$, and $\alpha = a_1 + b_1 + c_1$. Dollar appreciation lowers supply from the US but also lowers demand making the effect of E on P^e ambiguous. The effects of M and C on P^e are positive.

Substitute the equilibrium price P^e into the US cotton export function (6) to find the reduced form equilibrium US exports X^e as a function of the three exogenous variables,

$$X^e = \overset{(?)}{\alpha_0} + \overset{(+)}{\alpha_1} E + \overset{(+)}{\alpha_2} W + \overset{(-)}{\alpha_3} C \tag{11}$$

where $\alpha_0 = b_1 d_0 - b_0$, $\alpha_1 = b_1(1 + d_1)$, $\alpha_2 = b_1 d_2 > 0$, and $\alpha_3 = b_1 d_3 - b_2$. Note the positive exchange rate effect in α_1 since $d_1 = (a_3 - b_1)/(a_1 + b_1 + c_1) > -1$ reduces to $a_1 + a_3 + c_1 > 0$. Similarly α_3 is shown to be negative.

An exchange rate effect not considered in the literature is the effect of a change in the rate of local currency depreciation, $N = -\Delta E/E$. The present depreciation rates are stationary and highly variable while exchange rates have smooth trends. To test sensitivity of exports to depreciation rates, equilibrium exports X^e are also estimated as

$$X^e = \alpha_0 + \alpha_1 N + \alpha_2 W + \alpha_3 C. \tag{12}$$

Summarizing, depreciation decreases US supply X and local demand D, lowering cotton purchases Q^e and US exports X^e. An increase in the depreciation rate N has the same effects. An exogenous increase in warehouse W decreases cotton demand D lowering X^e. Lower US production cost C increases US supply X resulting in an increase in X^e.

The effects of changes in the exogenous variables in (10) are shown in Figure 1. Depreciation or a fall in the exchange rate E raises the local price of cotton and lowers demand, and the equilibrium level of US exports X^e falls. An increase in the depreciation rate -N also lowers demand by reducing the purchasing power of cash reserves. Increased mill use M increases demand for cotton and raises equilibrium US exports X^e. Lower production cost increases US supply X and raises exports X^e.

Figure 1

Figure 2 shows the effects of local currency depreciation. Demand falls with price in US dollars. Equilibrium US exports X^e fall, as do price P^e, total quantity Q^e, and quantity supplied from other sources S^e. As constructed, the supply of X is more elastic and X^e/S^e falls. The regression analysis effectively holds the other exogenous variables constant.

Figure 2

IV. DATA SERIES IN THE COTTON EXPORT MODEL

The dollar has appreciated relative to the Chinese yuan, Indonesian rupiah, Korean won, Taiwan dollar and Thai baht as shown by the series in Figure 3 but the patterns and timing differ. For the Chinese yuan rate E_C there was a fairly consistent depreciation over the three decades although the rate of depreciation slowed in 1986. This smooth exchange rate trend appears easy to predict.

Figure 3

The E_I rate of the Indonesian rupiah has depreciated more steadily than the other two with sharp falls in 1980, 1986, and especially 1996 during the Asian financial crisis. Since then the rupiah has been stable. Only consistent rate of the South Korean won E_K has been steady over the sample period except a slight fall during the Asian financial crisis. The E_W of the Taiwanese dollar has also followed same sharp depreciations as the Indonesian rupiah and the

Thai baht. Since the financial crisis Taiwanese dollar has maintained its steadiness for the last decade.

The E_T rate of the Thai baht had sharp depreciations in 1980, 1983, and 1996 but has been stable aside from those three collapses. Such sharp depreciations are hard on traders with contracts for delivery. For instance, the 30% baht depreciation in 1983 might appear innocuous in the series but raised the baht price of US cotton by that percentage. An importer who had signed a contract to purchase 1000 bales of US cotton at $1000 per bale would have paid for 1.68 million baht in 1982 but would have had to pay 2.40 million in 1983. The baht collapsed by 46% in 1996. On the face of the five patterns, the Thai baht might have been the most disruptive of US cotton exports depending on purchaser behavior.

Figure 4 shows the appreciation rates for the three currencies. The mean depreciation rates are -2.2%, -3.1%, -0.4%, -0.02%, and -0.07 for the CH yuan, ID rupiah, KR won, TW dollar, and TH baht and the standard deviations are larger than the means. These depreciation rates all prove stationary. The high depreciation rate and high standard deviation in Indonesia might be particularly disruptive.

Figure 4

Figure 5 shows US cotton exports in thousands of bales. There has been growth in all five series except South Korea but the patterns are different. Chinese imports M_C have fluctuated until the 1990s but since 2001 cotton imports have risen and China has become the largest cotton importer in the world. Taiwanese imports M_W have been fairly steady with some growth during the 1990s. There were sharp falls in 1983, 1989, and 2001 that are not apparently related to the Taiwanese dollar exchange rate that depreciated steadily over the entire period except for the 1974 collapse.

Figure 5

Indonesian cotton imports from US M_I have a much more dramatic pattern with periods of rapid growth but collapses in 1983, 1991, and 1994. The 1983 collapses of exports and the rupiah coincide. The 30% increase in the price of US cotton could have led to defaults on contracts and must have diminished spot transactions but such single occurrences do not verify the theory. The 1980 rupiah collapse had no apparent effect on US exports, and the 1996 rupiah collapse occurred during the sharp decline in US exports that began two years earlier.

Thai imports M_T were fairly stable before increasing after 2000 and have had considerable ups and downs over the years. The baht collapses in 1980 and 1996 occurred during years when exports were falling, and the 1983 collapse is consistent with the subsequent decline in exports. Finally South Korean imports have been constantly decreasing since 1978 when they have been the top cotton importer from US. Over the sample period they have also been affected by the market fluctuations but their steady downsizing textile sector is easy to observe in the data.

Figure 6 shows the increased mill use that would increase demand for US imports in the three importing countries. Mill use in Bangladesh M-BN was level until 1987 and then grew steadily until 1999 before increasing its growth. Mill use in Indonesia M-IN increased growth in 1986 but fell off in 1993 and has been erratic since. Mill use in Thailand M-TH began a sharp increase in 1984 before entering a period of decline in 1991 that lasted until 1998.

Figure 6

Figure 7 shows the falling unit cost of production for US cotton. The data is the cents per bale "farm price" inflated to 2007. The assumption is that the farm price is competitive and covers the cost of production. The falling cost per bale would increase US supply in Figure 1 and increase US exports.

Figure 7

Finally Figure 8 shows the falling mill delivered price of US cotton. Again the data is the cents per bale "mill delivered price" inflated to 2007. The same assumption can be applied here that the mill delivered price is competitive. The falling mill delivered price per bale would decrease US supply in Figure 1 and increase US exports.

Figure 8

V. STATIONARITY ANALYSIS

A preliminary question is the order of integration of the variables in (9) that would suggest the form of variables for regression analysis. Fundamental applied time series techniques are developed by Enders (2004). If the series are integrated of the same order they may be cointegrated indicating a long term dynamic equilibrium relationship.

Ordinary least squares regression assumes variables have constant means while stationary variables at least have a tendency toward a long term dynamic equilibrium. Economic variables that are not stationary might be difference stationary, as is the case with the present data. An innovation in applied time series is the error correction model ECM that considers transitory partial adjustment relative to a long term dynamic equilibrium.

Recent examples of applied time series analysis on related topics include Byard, Chen, and Thompson (2007) on US tomato imports, Copeland and Thompson (2007) on US tariffs and wages, and Upadhyaya and Thompson (1998) on exchange rate effects on local manufacturing industries in Alabama.

Stationarity analysis for the natural logs of all variables for five countries follows. Variables are transformed into natural logs to estimate elasticities directly. The autoregressive AR1 model is $\ln E_t = a_0 + a_1 \ln E_{t-1} + e_t$ where $\ln E_t$ is the natural log of the exchange rate and e_t is white noise. If $a_1 < 1$ then the series converges to the dynamic equilibrium $a_0/(1 - a_1)$ and is stationary in levels. The $/yuan rate is stationary with its long period of steady depreciation in Figure 1. There is no evidence of residual autocorrelation in the correlation coefficient ρ and no evidence of heteroskedasticity in the ARCH test with one lag. The other two exchange rates are not stationary.

Table 1

Table 1 reports stationarity analysis for the natural logs transformed variables. The five exchange rates are difference stationary according to the augmented Dickey-Fuller ADF test $\Delta \ln E_t = a_0 + a_1 \ln E_{t-1} + a_2 t + a_3 \Delta \ln E_{t-1} + e_t$ with the critical a_1 variable equal to zero according to the DF statistic and all coefficients equal to zero by φ tests. There is no evidence of residual autocorrelation or heteroskedasticity making the differences $\Delta \ln E_t$ stochastic as suggested in Figure 2. The exchange rates $\ln E_t$ are then random walks.

First column in Table 1 reports stationarity analysis for the natural logs of US cotton exports to the five countries. Exports to China are stationary as suggested by Figure 2 as are exports to Thailand. The five series are also difference stationary although the a_1 statistic for exports to Bangladesh is marginally significant. The next column in Table 1 reports the difference stationary tests on warehousing variable. Exchange rate appreciation, a test of I(2) second order integration of the exchange rates. Appreciation rates are not I(1) processes. Differences are stationary but second differences are not. Variables in an error correction model should be integrated of the same order and appreciation rates should not be included with levels of variables that are I(1) in a cointegration model.

Summarizing, natural logs of variables are nonstationary but almost all are difference stationary. The I(1) difference stationary random walk series can be expected to produce spurious regressions in levels but reliable statistics in difference regressions, and may be cointegrated. Currency depreciation rates are stationary but not difference stationary. An error correction model may be run in on the model (9) with the level of the exchange rate but not with the appreciation rate.

VI. REGRESSION MODEL RESULTS

The estimated reduced form equation for US exports with the exchange rate lnE in (9) is

$$\ln X^e = \alpha_0 + \alpha_1 \ln W/U + \alpha_2 \ln E + \alpha_3 \ln C + \varepsilon \tag{13}$$

where ε is a white noise residual. Table 2 reports estimates of (13).

* Table 2 *

For South Korea and Indonesia, only the stock-to- use has effect but possible residual correlation discounts those effects. However while the effect is positive in South Korea, it is negative in Indonesia. This may be associated with the warehouse cost and the level of the textile industry in both countries. For Taiwan the model has very weak results. Except forTaiwan, cost has effect in all countries. In China, Indonesia, and Thailand, an increase in the unit cost of cotton decreases the import levels. The exchange rate has a positive effect in Taiwan and a negative effect in Thailand. The series are co-integrated by Engle-Granger tests suggesting adjustment relative to the dynamic equilibrium in each market.

Table 3 reports the related ECM error correction models

$$\Delta \ln X^e = \beta_0 + \beta_1 \Delta \ln E + \beta_3 \Delta \ln M + \beta_4 \ln \Delta C + \gamma \varepsilon_{-1} + e \tag{14}$$

where ε_{-1} refers to the lagged residual from (13).

* Table 3 *

The ECM for Taiwan has a strong 1.15 transitory exchange rate elasticitiy β_2. For Thailand the transitory exchange rate elasticitiy β_2 is -0.56. Error correction adjustments are 1.11 = 1.21 x 0.92 for the exchange rate E for Taiwan and -0.88 = 0.55 x -1.60 for Thailand. Transitory stock-to-use ratio elasticity is also significant for Indonesia with -0.35. Error correction adjustment for Indonesia is -0.26. The exchange rate effect is insignificant with "gray area" residual correlation. Nevertheless, the strong transitory and nearly elastic error correction effects indicate exports to Taiwan and Thailand are sensitive to the exchange rate. Warehouse also has some part in import decision in Indonesia.

For Indonesia there is a hint of a transitory exchange rate effect. The error correction adjustment implies a significant mill use elasticity of 0.47 with standard error 0.23. For Thailand there are no transitory adjustments or adjustments relative to the dynamic equilibrium in spite of the significant error correction process.

The Asian financial crisis of 1997 may play a role in these markets. The banking systems had been government owned, but were privatized following the crisis. For China, Indonesia, South Korea, and Taiwan, the crisis had no impact on US cotton exports in unreported regression results. For Thailand the crisis strongly affects US cotton exports in Table 4. The crisis dummy and its interaction with the exchange rate are significant. Explanatory power almost doubles compared to Table 4. There is "gray area" residual correlation and the series are co-integrated leading to an error correction model.

* Table 4 *

The related ECM is reported in the second row of Table 4. There are no transitory effects in the difference coefficients but a strong error correction coefficient $\gamma = -0.61$ in (14). These variables robustly adjust relative to the dynamic equilibrium with error correction exchange rate elasticities 0.61 times those in the first row of Table 4. The derived pre-crisis error correction elasticity for the exchange rate and its standard error are 9.64 (3.36) while the post-crisis elasticity 0.46 (4.92) is insignificant. The crisis itself leads to a 1.1% increase in exports to Thailand evaluated at the mean lnE of -3.4 according to $\partial \ln X/\partial D_{97} = 0.61 \times [-9.02+ (2.70 \times -3.4)]$.

For the depreciation rate, the estimated model in Table 5 is

$$\ln X^e = \alpha_0 + \alpha_1 N + \alpha_3 \ln M + \alpha_4 \ln C + \varepsilon \qquad (15)$$

where N is in level from since it is a percentage change, $N = \Delta \ln E$.

* Table 5 *

For Indonesia every unit decrease in N or1% baht depreciation lowers US exports to Thailand by 2.10%. The -9.4% mean depreciation rate for Thailand and its 18.4% standard deviation suggest the substantial range of effects from 6.7% to -20.6%. In China there is a hint of a stronger effect. In Indonesia, South Korea, and Taiwan the depreciation model explains no export variation. Co-integration is not tested since the depreciation rate is not difference stationary.

In unreported regressions, the financial crisis dummy and its interaction with N reveal only one significant difference from Table 5 although explanatory powers are slightly higher. For Indonesia there is a strong 2.06 depreciation rate effect post-crisis but no pre-crisis effect making the 0.74 effect in Table 5 an average of the lack of a pre-crisis effect and the strong post-crisis effect.

* Table 6 *

Table 6 reports a strong depreciation rate effect of 1.01 for South Korea and 0.32 for Indonesia with levels of independent variables. Results for the other two countries with lags are similar to results without lags. An increase of one unit in the depreciation rate lowers exports to South Korea by 1.01% and to Indonesia 0.3%. In an unreported regression with the crisis dummy variable, the effect in Thailand is 9.22 pre-crisis and 1.73 post-crisis.

Finally we pool the five countries to observe whether they contain similar characteristics in importing US cotton for their textile industry. Regression on pooled data is reported in three different tables. Table 7 reports exchange rate model pooled data. Pooled regressions with the exchange rate, lagged exchange rate, and depreciation rate reveal no effects but the countries are different as indicated by the dummy variables in Tables 7, 8, and 9.

* Table 7 *

In Table 7 the exchange rate has an elasticity of -0.24 post-crisis. Exports to the three countries increased 27% due to the crisis evaluated at the mean N of -5.4%. Some credit must go to banking reform. In Table 8 only the lagged depreciation rate effect post-crisis is reported. The lagged depreciation rate has an elasticity of 3.49 following the Asian crisis although gray area residual correlation discounts this effect.

* Table 8 *

Table 9 reports only four-country pooled data regression results without China. This is tested to observe the exchange rate effects in South Korea, Indonesia, Taiwan, and Thailand without an outlier in the dataset. Results reveal significant exchange rate and post-crisis exchange rate effects.

* Table 9 *

Since the models in Table 8 and Table 9 yield large standard errors (small T-Stats), we can take this as a signal that these five textile producing countries are not all that homogenous. Instead a more advanced approach in Panel Regression family for instance like Random Effects Model may be more appropriate to use in this case. However that approach would be a different topic for a future study.

VII. CONCLUSION

There are no apparent effects of bilateral exchange rates on US cotton exports for China, Indonesia, South Korea, Taiwan, and Thailand in the present model. Depreciation or its threat must lead cotton importers to hedge or pursue other ways to avoid exposure with forward contracts, dollars as inventory currency, transactions in foreign currencies, and foreign bank accounts. An increase in the depreciation rate of Indonesia, however, clearly lowers US exports. There is also an apparent similar effect in Bangladesh. An increase in the depreciation rate in Thailand, however, has no effect on US exports.

A novel finding of the present paper is that rates of depreciation have stronger effects than exchange rates themselves. A change in the rate of depreciation diminishes the wealth of cash balances. This wealth effect is more robust before the Asian financial crisis In Indonesia.

There is a hint of a stronger effect in Bangladesh. The wealth effect surfaces in Thailand the following year. While textile producers may hedge or use foreign bank accounts to avoid currency risk, the rate of local currency depreciation has a negative impact.

More smoothly adjusting exchange rates would diminish abrupt changes in critical rates of depreciation. The Asian financial crisis marked a move away from government owned banking systems leading to weaker impacts of depreciation rates.

The present model can be applied to other commodities. The wealth reducing effect of an increase in the depreciation rate can be examined for other commodities and countries. The present results suggest effects may vary across importers.

The global cotton market consists of numerous exporters and importers. A complete model would include interrelated trade flows and bilateral exchange rates of each. The present paper focuses on US exports but may be a precursor to a more complete model. Ideally, data on bilateral cotton exports and imports would lead to a more complete model of the international market including the effects of bilateral exchange rates and, more critically perhaps, depreciation rates.

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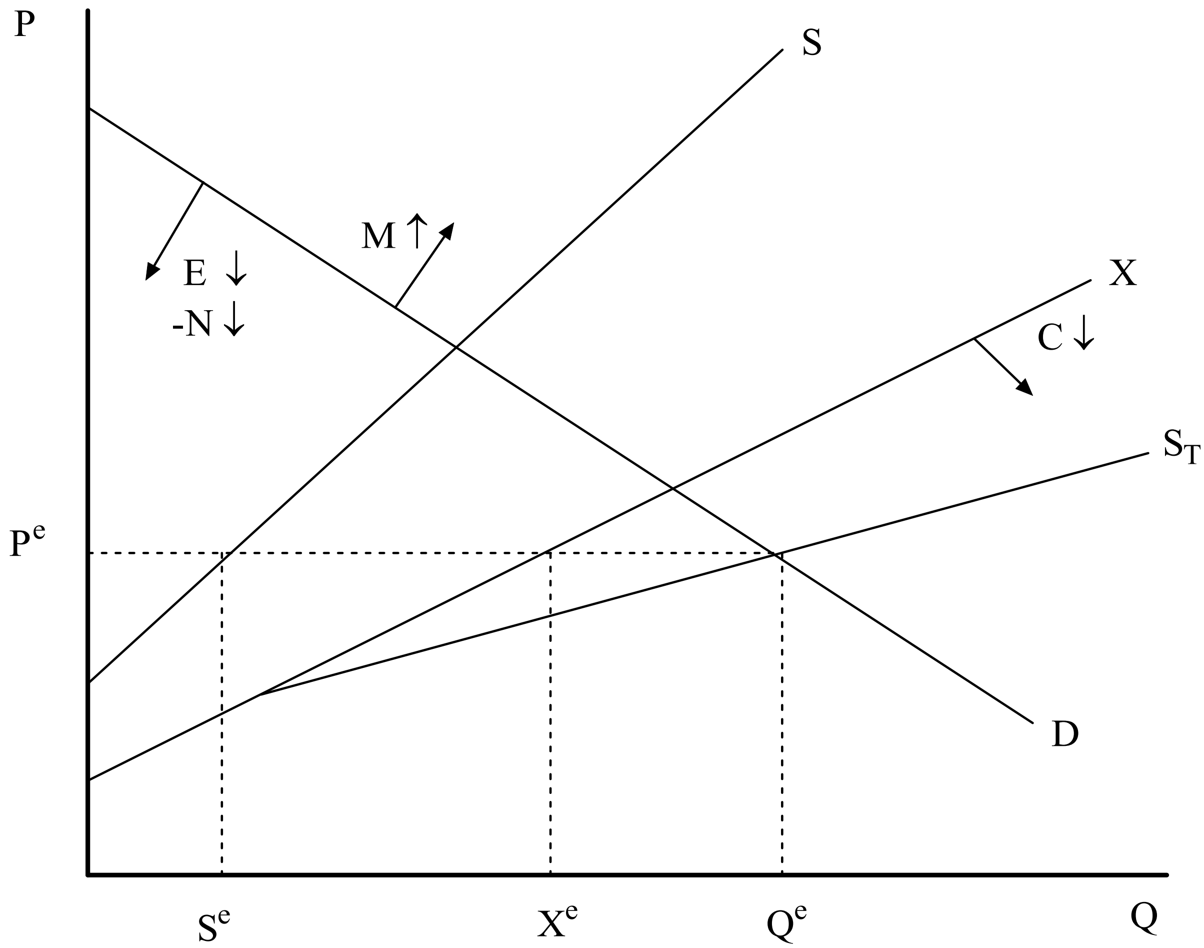

Figure 1. The market for cotton in the importing country

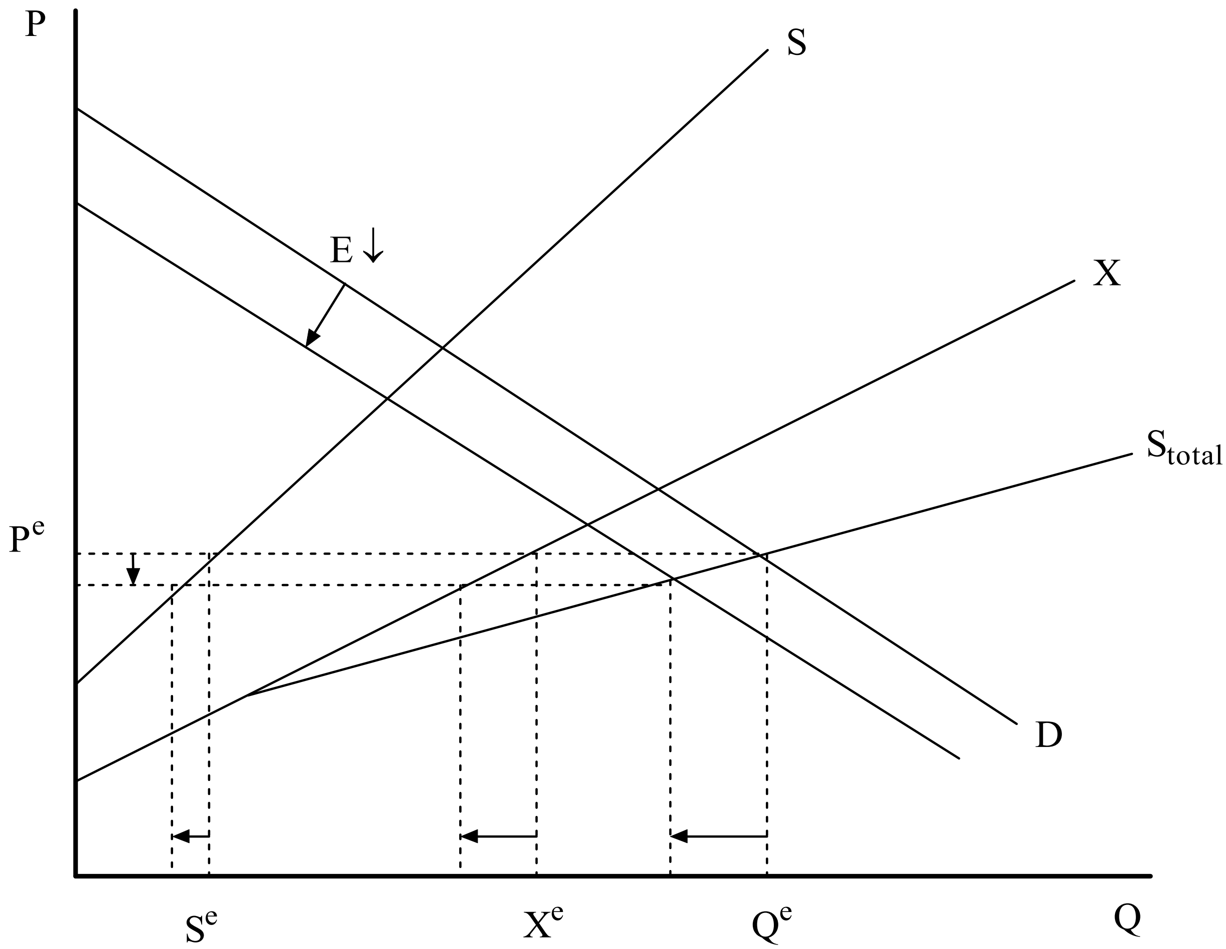

Figure 2. Depreciation of the local currency relative to the dollar

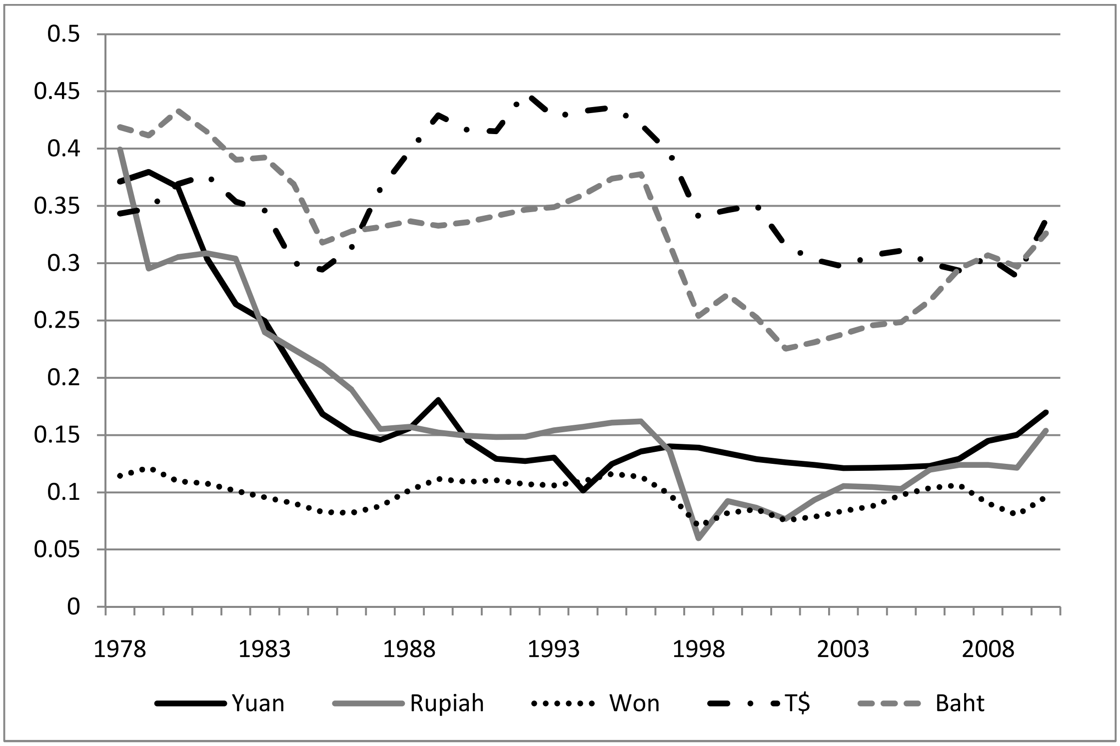

Figure 3. US dollar exchange rates of the CH yuan, ID rupiah, KR won, TW dollar, TH baht

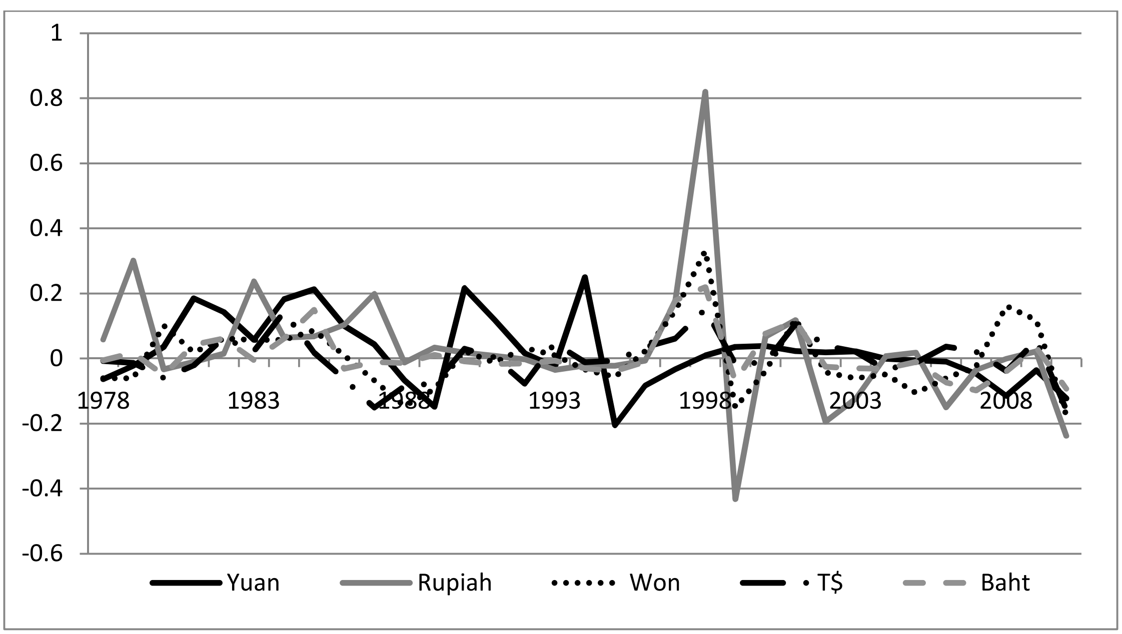

Figure 4. Depreciation Rates of the Importing Currencies

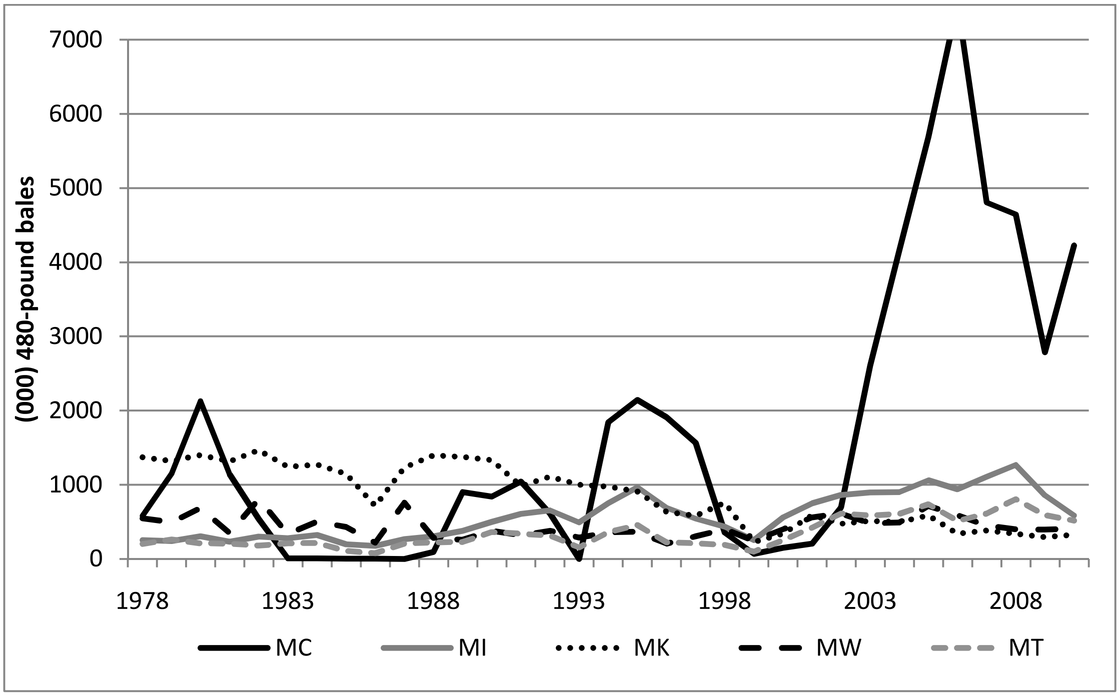

Figure 5. China, Indonesia, S. Korea, Taiwan, and Thailand Imports from US

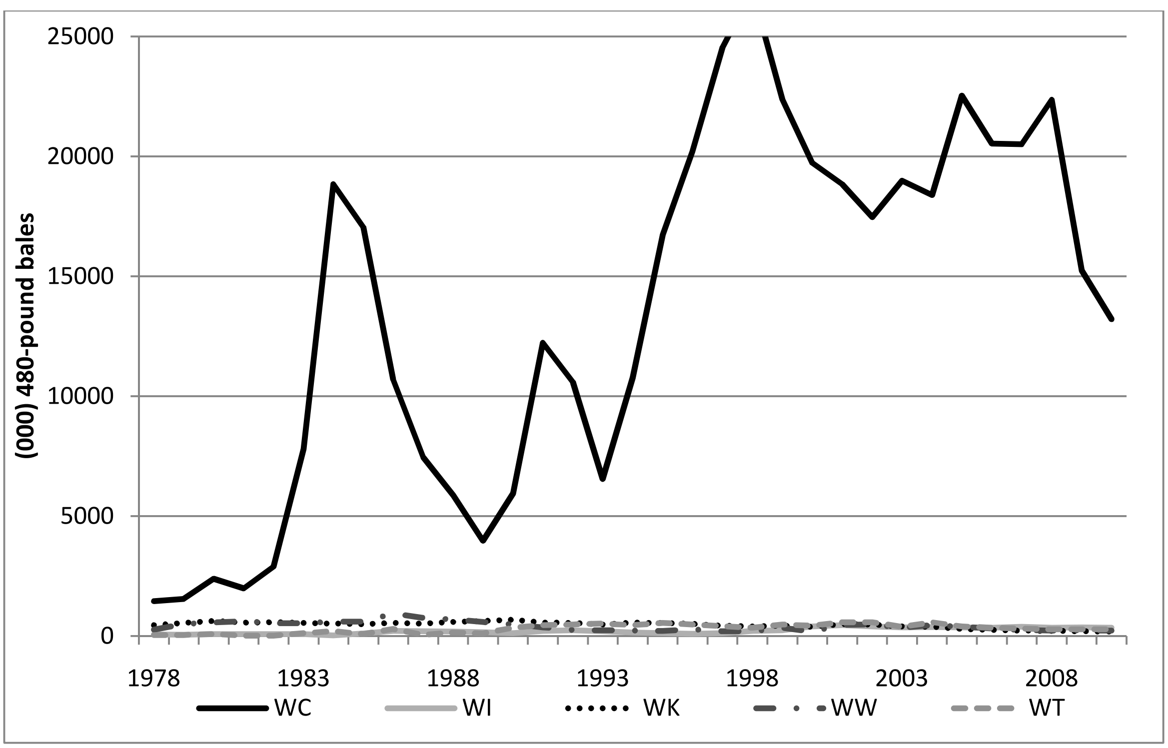

Figure 6. Warehouse Stock Use in 1000s of Bales

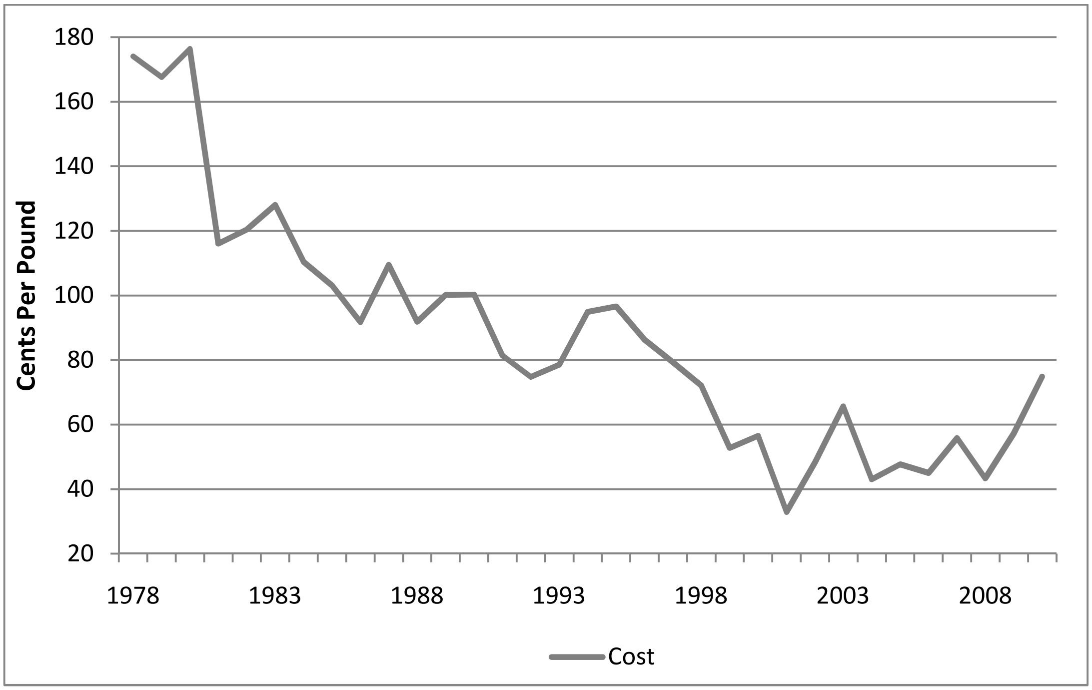

Figure 7. Unit Cost of Producing US Cotton

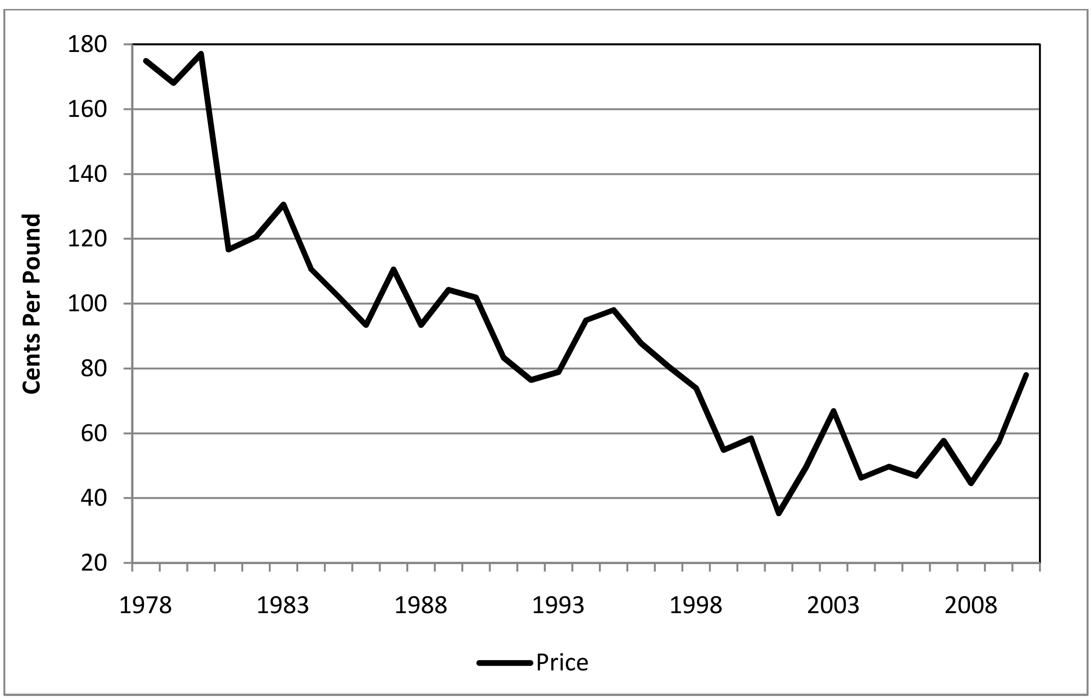

Figure 8. Mill delivered Price of US Cotton

Table 1. Stationarity Analysis

	M_C	W_C	E_C	N_C
China	t = -2.98* φ = 3.69* ρ = -.066* ARCH = 1.85	t = -3.37* φ = 6.09* ρ = .066 ARCH = 0.09	t = -1.34 φ = 4.01 ρ = -.097 ARCH = 2.33	t = -4.57* φ = 10.22* ρ = -.074* ARCH = 2.64
	M_I	W_I	E_I	N_I
Indonesia	t = -2.73* φ = 2.63 ρ = -.029 ARCH = 1.03	t = -3.31* φ = 3.92 ρ = -.033 ARCH = 1.28	t = -1.05 φ = 1.52 ρ = -.012 ARCH = 0.05	t = -5.18* φ = 16.41* ρ = .020 ARCH = 0.02
	M_K	W_K	E_K	N_K
S. Korea	t = -3.15* φ = 5.17* ρ = -.010 ARCH = 0.02	t = -1.55 φ = 2.62 ρ = -.021 ARCH = -0.86	t = -2.99 φ = 3.36 ρ = .042 ARCH = 0.61	t = -4.64 φ = 8.26 ρ = .028 ARCH = 1.55
	M_W	W_W	E_W	N_W
Taiwan	t = -2.67* φ = 9.75* ρ = -.150 ARCH = -0.22	t = -2.31* φ = 3.87* ρ = .086 ARCH = 2.14	t = -1.94* φ = 1.74 ρ = -.044 ARCH = -0.88	t = -2.86* φ = 4.62* ρ = -.005 ARCH = -0.58
	M_T	W_T	E_T	N_T
Thailand	t = -3.36* φ = 3.96 ρ = .003 ARCH = 0.31	t = -1.86* φ = 3.16* ρ = .008 ARCH = 2.91	t = -1.47 φ = 1.59 ρ = .001 ARCH = 3.17	t = -3.91* φ = 6.45* ρ = .049 ARCH = 2.90
	C			
US Cotton Cost	t = -2.12* φ = 3.13* ρ = -.043 ARCH = -0.56			
	P			
Cotton Mill Price	t = -1.92* φ = 2.18 ρ = -.040 ARCH = -0.36			

Table 2. Import-Exchange Rate Model

	constant	W/U	E	C		DW > 1.74 EG < -3.60
M_C	21.57* (1.97)	-0.81 (-0.92)	-1.24 (-0.53)	-3.20* (-1.97)	EG -3.43*	R^2 .166 DW 1.11 ARCH 0.63
M_I	15.26*** (4.57)	-0.50*** (-3.35)	-0.40 (-1.52)	-1.49*** (-5.28)	EG -4.45*	R^2 .685 DW 1.55 ARCH -0.74
M_K	6.29* (1.70)	0.99** (2.38)	-0.27 (-0.58)	0.77*** (4.03)	EG -3.96*	R^2 .716 DW 1.35 ARCH 0.52
M_W	3.19 (1.26)	0.17 (0.96)	0.92* (1.70)	-0.01 (-0.03)	EG -7.33*	R^2 .228 DW 2.52 ARCH 0.85
M_T	17.82*** (3.59)	-0.06 (-0.41)	-1.60* (-1.69)	-1.54*** (-3.58)	EG -4.01*	R^2 .431 DW 1.36 ARCH -0.55

Table 3. Exchange Rate Error Correction Model

ECM	constant	ΔW/U	ΔE	ΔC	γ residual	DW > 1.74 EG < -3.60
M_C	0.09 (0.23)	1.10 (1.03)	-3.41 (-0.84)	-0.15 (-0.06)	-0.56*** (-3.17)	R^2 .312 DW 2.11* ARCH 1.06
M_I	0.02 (0.43)	-0.35** (-2.66)	0.04 (0.15)	-0.19 (-0.63)	-0.52*** (-3.24)	R^2 .341 DW 1.73* ARCH 1.21
M_K	-0.02 (-0.35)	0.54 (1.03)	0.28 (0.51)	0.42 (1.27)	-0.54*** (-2.80)	R^2 .276 DW 1.94* ARCH -0.30
M_W	-0.01 (-0.21)	-0.04 (-0.19)	1.15 (1.37)	-0.09 (-0.24)	-1.21*** (-6.40)	R^2 .630 DW 1.93* ARCH 0.39
M_T	0.04 (0.53)	-0.06 (-0.54)	-0.56 (-0.51)	0.15 (0.32)	-0.55*** (-3.46)	R^2 .339 DW 1.95* ARCH -0.08

Table 4. Exchange Rates and the Asian Financial Crisis

	constant	**W/U**	**E**	**C**	**D_{97}**	**$D_{97}E$**	**DW > 1.74** **EG < -3.60**
M_T	25.37*** (3.92)	-0.03 (-0.25)	-3.83** (-2.60)	-1.57*** (-3.32)	-9.02* (-1.58)	2.70* (1.65)	R^2 .505 DW 1.46* ARCH -0.43 EG -4.15*
ECM	**constant**	**ΔW**	**ΔE**	**ΔC**	**γ residual**		
M_T	0.03 (0.52)	-0.03 (-0.29)	-0.75 (-0.69)	0.12 (0.26)	-0.61*** (-3.56)		R^2 .351 DW 1.96 ARCH -0.54

Table 5. Import-Depreciation Model

	constant	W/U	N	C		DW > 1.74 EG < -3.60
M_C	14.68*** (2.98)	-0.95 (-1.38)	-5.45 (-1.31)	-2.15* (-1.82)	EG -3.91*	R^2 .205 DW 1.32 ARCH 0.69
M_I	10.25*** (14.83)	-0.43*** (-2.91)	-0.03 (-0.08)	-1.12*** (-7.08)	EG -3.53*	R^2 .660 DW 1.12 ARCH -0.32
M_K	4.25*** (3.62)	0.99** (2.39)	0.12 (0.22)	0.82*** (4.61)	EG -3.69*	R^2 .713 DW 1.23 ARCH 1.40
M_W	7.29*** (9.72)	0.36** (2.27)	0.56 (0.65)	-0.19 (-1.27)	EG -7.58*	R^2 .163 DW 2.55 ARCH 0.89
M_T	9.37*** (10.37)	-0.07 (-0.49)	-2.10* (-1.83)	-0.87*** (-3.85)	EG -4.18*	R^2 .440 DW 1.44 ARCH -0.42

Table 6. Depreciation Rate Error Correction Model

ECM	constant	ΔW/U	ΔN	ΔC	γ residual	DW > 1.74 EG < -3.60
M_C	0.05 (0.13)	0.78 (0.82)	0.82 (0.30)	0.63 (0.27)	-0.55*** (-3.41)	R^2 .362 DW 2.02 ARCH 0.68
M_I	0.03 (0.60)	-0.34*** (-2.90)	0.32** (2.23)	-0.11 (-0.41)	-0.47*** (-3.50)	R^2 .437 DW 1.75* ARCH -0.21
M_K	-0.02 (-0.42)	0.37 (0.77)	1.01** (2.76)	0.36 (1.20)	-0.42*** (-2.48)	R^2 .409 DW 1.87* ARCH 0.13
M_W	-0.01 (-0.25)	0.15 (0.72)	0.65 (0.94)	-0.15 (-0.42)	-1.19*** (-6.23)	R^2 .619 DW 1.99* ARCH 0.66
M_T	0.04 (0.64)	0.03 (0.30)	0.94 (1.34)	0.34 (0.92)	-0.61*** (-4.63)	R^2 .499 DW 1.88* ARCH 0.49

Table 7. Pooled Sample with Exchange Rates and the Asian Financial Crisis

	constant	**W/U**	**E**	**C**	**D_I**	**D_K**	**D_W**	**D_W**	**D_{97}**	**$D_{97}E$**	**DW 1.85**
X	3.16 (1.20)	-0.26 (-1.27)	0.70 (1.39)	0.18 (0.68)	-4.18 (-1.19)	-2.49 (-0.97)	-0.94 (-1.14)	-1.48* (-1.62)	1.70*** (3.35)	-0.24*** (-3.18)	R^2 .161 DW 0.85 ARCH 5.25 EG -6.64*

Table 8. Pooled Sample with Lagged Depreciation Rate and the Asian Financial Crisis

	constant	**W/U**	**N_{-1}**	**C**	**D_I**	**D_K**	**D_W**	**D_T**	**D_{97}**	**$D_{97}N_{-1}$**	**DW 1.85**
X	5.59*** (2.78)	-0.06 (-0.34)	-5.34*** (-3.66)	0.06 (0.13)	0.21 (0.55)	0.47 (1.50)	-0.14 (-0.46)	-0.46 (-1.32)	0.52 (1.50)	3.49** (1.96)	R^2 .194 DW 1.04 ARCH 3.96 EG -7.46*

Table 9. Pooled Sample less China with Exchange Rates and the Asian Financial Crisis

	constant	**W/U**	**E**	**C**	**D_K**	**D_W**	**D_T**	**D_{97}**	**$D_{97}E$**	**DW 1.85**
X	-2.11 (-0.82)	0.14 (1.42)	1.04*** (4.19)	-0.06 (-0.33)	2.14*** (4.49)	5.12*** (3.85)	4.76*** (3.66)	0.28 (1.07)	-0.10** (-2.44)	R^2 .426 DW 0.73 ARCH 4.33 EG -5.31*

CHAPTER 2

HOUSING PRICES AND FUNDAMENTALS: THE ROLE OF A SUPPLY SHIFTER

I. INTRODUCTION

Housing investment behavior and housing prices studies have become more attractive since one of the first indicators of 2007-2010 financial crisis, the US subprime mortgage financial crisis. Over the past four years millions of foreclosures were filed and home sales continue to fall. In early 2005 housing prices reached the highest levels, by 2006 and 2007 began their steep decline and thereafter caused problems to home owners in refinancing. This bursting housing bubble has been referred as the most significant risk to the US economy. Summers (1981) and Poterba (1985) argue that the outward shift in the demand curve for housing is due to the impact of high levels of inflation that increase the interest rate subsidy on home mortgages. Glaeser (2004) points out that although demand-side analysis has dominated the housing literature to understand booms and busts in housing prices we need to understand housing supply. He furthers that the common combination of rising real housing prices since the late ‘70s and amounts of construction forces us to consider the housing supply.

The present paper tests cointegration between housing prices and fundamentals in the US single family occupied housing market with a model that includes building cost as a supply shifter. Most of the conventional tests focus on the demand side of this relationship. Other demand side fundamentals used as explanatory variables across states with annual data from 1975 to 2009 are real income per capita and population.

** *Figure 1* **

The impact of building cost on housing prices is visible in the sample data. Figure 1 shows data series from 1890 for real home prices, building cost index, population, and long term interest rates movements from Robert J. Shiller website. Population has been growing steadily in all states. Real income per capita has been increasing in nearly all of the states since the late 1970s. Figure 2 shows income per capita for California, Florida, New York, Pennsylvania, Illinois, and Texas. Income has continued to grow with an average of 35% in these states since 1975.

** *Figure 2* **

Although real housing prices vary in most states, there has been a steady increase in almost all populous states starting from 1997. This increase has been referred as a “bubble”. In some of the populous states, bubble has averaged a lot more. Figure 3 shows real housing prices for the same selected six states. Since 1975 housing prices increased on average 11% in California, 9% in Florida, 7% in New York, 4% in Pennsylvania, 3.5% in Illinois, and 2% in Texas. However by the end of 2007 these rises have ended and began a steep decline in most states.

** *Figure 3* **

The importance of the present study lies in finding cointegration from a single equation. However as Banarjee (1999) points out especially in small samples cointegration tests are considered to have relatively low test power. The present study demonstrates that the issue of power may not be critical to finding cointegration rather it is a correctly specified model. Gallin (2006) uses both univariate and more powerful panel-data tests for cointegration and rejects it, employing to construction wage as a supply shifter. Wages are highly correlated with income, however, and may include only demand side information. In addition, wages add little to the explanation and may hide the supply side information. In the present study, we use a building cost index. Building costs are assumed competitive between states. This is more helpful in reflecting supply side information such as oil price movements than construction wages.

Moreover the paper underlines the significance of obtaining the correct signs of the estimated coefficients from univariate cointegration tests. Persistent movement among these cointegrating variables with correct signs then suggest that in the long run the housing market will reach a dynamic equilibrium and the relation among the states without cointegration is only bubbles.

The sample is single family housing price. Index is selected for the 50 states and DC. Annual data begin with the earliest available state data from 1975 and extend through 2009. Regarding the time horizon, Shiller and Perron (1985) argue more observations holding the time span fixed does not increase the power of tests. Our results, therefore, should satisfy the reader in having a finite sample of 36 observations for this time series empirical study.

Organization of the paper is as follows. Section two is the literature review. In section two we explain the model and econometric methods for the cointegration. Section four reports the regression results and interpretation. Section five is the conclusion.

II. LITERATURE REVIEW

The previous studies (Abraham and Hendershott 1996, Capozza, Hendershott, Mack, and Mayer 2002, Meen 2002) indicate a common thought in the housing market that even if housing prices and income move in different directions in the short-run, the steady relationship between two variables will eventually push them toward their long-run equilibrium. Most of the studies focus on finding cointegration by using powerful tests, panel regression or different sample sets. Further these studies have not mentioned the significance of obtaining correct signs in the coefficients of cointegrating variables. Although the importance of building costs has been discussed slightly in the literature the correct definition as a supply shifter has not been explained sufficiently well. There are many variables that contribute to building costs from land prices to steel, and from transportation cost to labor cost. If housing prices increase with general prices then real housing prices in the long-run are expected to be stationary. [1]

As Meen (2002) points out, in the short-run with inelastic housing supply, a positive demand shock will temporarily increase housing prices. However, when prices go above the equilibrium, this relation will follow the change in the building cost levels. Most of the following literature report cointegration only from demand side. Malpezzi (1999) tests and formulates two-equation models of housing prices in many different ways and confirms that changes in housing prices are cointegrated with income. Abraham and Hendershott (1996) estimate 30 MSAs and confirm cointegration between housing prices and income. In an another MSA study, Mikhed and Zemick (2009) use several fundamental variables to explain housing prices and find that prior to 2006 there had been a price bubble. Their univariate tests also indicate a decline in the prices for these MSAs. Holly, Pesaran, and Yamagata (2006) find in

[1] Here Meen (2002) states that changes in house prices can be forecasted partly and they are not random walk.

their panel study for 49 states over 29 years that housing prices are cointegrated with fundamentals (real income). Another study on dynamics of housing prices outside of US in Singapore by Hin and Cuervo (1999) find that there is a cointegration between housing prices and fundamentals such as real GDP and the prime lending rate.

Capozza, Hendershott, Mack, and Mayer (2002) is the one of the few studies where supply shifter construction cost is used in a city-level panel study for 62 Metropolitan Statistical Areas (MSA) in the US. Authors test real housing price dynamics and find correlation with the fundamentals such as city size, real income growth, population growth, and real construction costs. Galin (2006) is the only study where housing prices are not cointegrated with income in a city-level panel of 95 MSAs over 23 years. The author states that even powerful tests are not significant enough to reject the null hypothesis of no cointegration.

The univariate regression results from state level sample in the present paper noticeably demonstrate that in the US housing market there is cointegration between house prices and fundamentals in some states when we incorporate both demand and supply shifters. The approach in this study is confirming these results without relying on panel study which requires stronger assumptions. We simply finalize the results by only single equation in all states. Furthermore our findings not only support cointegration in most states but also explain the significance of obtaining the correct signs in the equation. However, there is no significant evidence when we employ only demand shifters income and population.

III. THE HOUSING MARKET MODEL

The relationship of the housing price and fundamentals can be seen by analyzing housing supply and demand. The proposed quantity of owner-occupied housing demand depends on the real price of house P, real income per capita Y, population L, and other stochastic demand shifters ε_d. The housing supply depends on the real price of house P, building cost C, population POP, and other stochastic supply shifters ε_s:

$$Q_d = D(P, Y, POP;\ \varepsilon_d) \tag{1}$$

$$Q_s = S(P, C;\ \varepsilon_s) \tag{2}$$

The housing price and the quantity of house demanded can be written as a function of exogenous variables:

$$P = P(Y, POP, C;\ \varepsilon_d;\ \varepsilon_s) \tag{3}$$

Solution for the proposed model will be a log-linearized where the log of housing price is related to the logs of the rest of the derived variables. Coefficients of this log-linearized model are assumed unchanged and other unobserved components of the model are assumed stationary. Housing price and fundamentals are cointegrated with unit roots. The relationship in (3) will depend on the elasticities of supply and demand. The idea will be testing for cointegration. There may be many reasons why such a cointegrating relationship may not exist. Unstable price elasticities of supply, rapid changes in demographics may affect the price elasticity of demand or local taxes may not be stationary.

A long-run equilibrium relationship between the housing prices and fundamentals such as income would require cointegration. To elaborate the theory, we follow Poterba (1984) and Topel and Rosen (1988). The model assumes housing is proportional to the stock of housing, indicated by K_t. The demand for housing can be shown as

$$R_t = -\alpha K_t + \Phi_t, \tag{4}$$

where R_t is the rental rate for a unit of housing and Φ_t is a vector of demand shifters. For simplicity assume that Φ_t follows a random walk:

$$\Phi_t = \Phi_{t-1} + u_t$$

A straightforward approach to explain the structural model of the housing market is the present-value model where the amount of rent should equal the user cost of housing. Gallin (2006) suggests that if taxes, maintenance, and the risk premium are ignored one may write the housing price as

$$P_t = R_t + \beta E_t P_{t+1}, \tag{5}$$

where P_t is the price of housing, E_t is the expectations operator conditional on information available at time t, and β is the discounte rate. Substituting (4) into (5) yields

$$P_t = -\alpha K_t + \Phi_t + \beta E_t P_{t+1}, \tag{6}$$

According to Gallin (2006) in the short run if K_t is fixed then new investments can be written as

$$I_t = \gamma P_t + \omega_t, \tag{7}$$

where ω_t is the vector of housing supply shifters. The law of motion for capital:

$$K_t = (1 - \delta)K_{t-1} + I_{t-1}, \text{ implies}$$

$$P_t = \frac{-\alpha\gamma}{1-(1-\delta)L} P_{t-1} + \beta E_t P_{t+1} + \Phi_t + \frac{-\alpha}{1-(1-\delta)L} \omega_{t-1}, \tag{8}$$

where L is the lag operator.

We can show that a solution to (8) has real roots for reasonable values for α and γ

$$P_t = a\emptyset_t + b(L)u_t + d(L)\omega_t, \tag{9}$$

where u_t is the housing prices. Assuming $b(1) < 0$ and $d(1) < 0$ in (9) housing prices, demand shifters, and supply shifters are cointegrated in the model, if ω_t elements have unit roots. In other words, housing prices are cointegrated with stochastic demand shifters in Φ_t.

IV. EMPIRICAL RESULTS

A. Augmented Engle-Granger (AEG) τ test

Based on the theory above we can continue with cointegration tests for state-level housing prices and fundamentals. The hypothesized regression is

$$x_{0,t} = \alpha + \delta t + \sum_{m=1}^{M} \beta_m x_{m,t} + e_t, \quad (10)$$

where $m = 1, \ldots, M$ indexes $I(1)$ variables and $t = 1, \ldots, T$ indexes time. If the residuals e_t are stationary, then it can be concluded that the x's are cointegrated. We follow augmented Engle-Granger (AEG) τ test for cointegration as in Engle and Granger (1987), a two-step procedure. First estimated residuals $\hat{e}_t$ are obtained by estimating (10) with ordinary least squares. The next step is to do an ADF τ test on the residuals.

Real housing prices, real income per capita, and population for all states come from St. Louis FRED database. Average national building cost is obtained from Robert J. Shiller's website. The building cost index mixes 20-city average steel, cement, and lumber prices as a materials component, and includes 20-city average skilled and unskilled labor wages. Over the sample period building cost index has an average of 84.5 and standard error of 1.23.

*** Table 1 ***

Table 1 reports results of three different AEG τ tests run for three different models. In the first column income is the only explanatory variable. Having only one variable, cointegration is confirmed only in five states, California, Hawaii, Maine, Maryland, and South Dakota. In the middle column, two demand shifter fundamentals income and population are incorporated. Results do not change as expected with more demand shifters in the equation. California, DC, Iowa, Maryland, and South Dakota are the significant states with cointegration. No other state is reported as significant. In the last column population is dropped and a supply shifter building cost is added with the demand shifter income to test the housing price and fundamentals relationship. Results change dramatically compared to other one-variable and two-variable models' cointegration tests. Cointegration is confirmed in twenty states, including populous states such as Arizona, Florida, Georgia, and North Carolina.

B. Canonical Cointegrating Regression (CCR)

Park's (1992) CCR method estimates the cointegrating vector, with a number of advantages. The main idea of CCR is to implement least square estimation via transformed variables using the long-run covariance matrix of $\eta_t = [\varepsilon_t \ u_t]$, so that the LS estimator is asymptotically efficient. CCR is as efficient as the ML procedure of Johansen (1988) but is robust to distributional assumptions because it is nonparametric.[2]

** *Table 2* **

Table 2 reports the first model using CCR cointegration regression where housing price is a function of only one demand shifter, income. CCR cointegration is displayed in H(p,q) column under the null hypothesis of cointegragtion. Except in Arkansas, Iowa, Missouri, Oklahoma,

[2] Johansen Test was also employed for this study. Cointegration is confirmed at least in one variable in 32 states only.

South Dakota, and West Virginia cointegration is confirmed in almost all states. However it is seen in the coefficient column that the demand shifter income is either insignificant in nine states or has the wrong sign in thirteen states. This is not expected in this study regardless of the cointegration results.

** *Table 3* **

Table 3 reports the next model where two demand shifter income and population are employed. On the contrary of the expectation of explaining the function with only demand side, cointegration is not confirmed in seventeen states. Under the coefficient column in thirty eight states demand shifters both or separately has the wrong signs. Populous states like Pennsylvania, Georgia, Michigan, and Illinois are some of the examples. While one expects to see income per capita to have positive sign in model 2 but in these states it has negative sign although cointegration is confirmed. Some information is still hidden in this model when two demand shifters are used.

** *Table 4* **

Finally in the last table we employ one demand shifter income and one supply shifter building cost in explaining house prices. The results again change dramatically in this model as with the Augmented Engle Granger test. Cointegration is confirmed for almost all states except in California, Michigan, South Dakota, Texas, and Wisconsin. Also coefficients are now significant and have the correct signs for the most states. Failing to confirm cointegration especially in California and Texas is expected because of the large housing markets in metropolitan cities Los Angeles, San Francisco, Houston, and Dallas. This evidently suggests bubbles in housing market. However without relying on panel study which requires stronger assumptions, the model as a whole explains this hidden information by including building cost in a single equation for each state.

V. CONCLUSION

Choosing the right supply and demand shifters is a critical part of the study of housing market dynamics. In order to reflect more supply information, the current study incorporates building cost to test the relationship between housing prices and fundamentals in the US single family housing market at the state level. This study confirms that housing prices and fundamentals are linked by a long-run equilibrium relationship in most states. Cointegration is tested with Augmented Engle Granger and canonical cointegrating regression test for the analysis in three different models for each of the states.

There is no significant evidence to support cointegration when only demand shifters are employed in the housing market model. The present paper reveals that even with low power univariate regression methods there is cointegration between housing prices and fundamentals in most states when both supply and demand shifters are incorporated. The previous literature has been improved with deterministic and correctly specified work by using a finite small sample. Persistent movements among variables have provided much stronger cointegration results determined by the fundamentals.

When the model including both demand and supply shifters is specified more correctly, cointegration is confirmed in most states. In the states such as California, Michigan, South Dakota, Texas, and Wisconsin with no cointegration, the relationship between housing prices and fundamentals are nothing but bubbles. The present paper also suggests that the housing market will eventually reach equilibrium in the long run.

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Table – 1 Augmented Engle/Granger Univariate Cointegration Test Results

ADF Test Statistics			
STATES	**Y**	**Y-POP**	**Y-BC**
Alabama	-1.170	-1.280	-4.970***
Alaska	-3.100	-3.110	-3.270
Arkansas	-1.250	-2.180	-4.490**
Arizona	-1.820	-1.510	-3.930*
California	-3.520**	-3.680*	-3.510
Colorado	-1.620	-1.620	-3.730*
Connecticut	-2.460	-2.720	-2.430
Delaware	-2.370	-2.820	-3.080
D.C.	-3.030	-3.940*	-2.840
Florida	-2.910	-2.040	-4.080**
Georgia	-0.620	-2.360	-3.910*
Hawaii	-3.800**	-3.820*	-3.770*
Idaho	-1.150	-1.240	-3.960*
Illinois	-1.560	-2.600	-2.830
Indiana	-1.640	-2.280	-2.940
Iowa	-2.630	-4.130**	-2.210
Kansas	-1.890	-1.460	-2.610
Kentucky	-1.490	-2.110	-4.820***
Louisiana	-1.700	-1.740	-3.050
Maine	-3.290*	-3.300	-3.060
Maryland	-3.870**	-3.910*	-3.550
Massachusetts	-3.030	-3.040	-3.050
Michigan	-2.600	-2.840	-3.950*
Minnesota	-1.490	-1.980	-3.200
Missouri	-1.340	-3.130	-4.410**
Mississippi	-1.100	-1.230	-5.370***

Notes: Critical Values for 35 sample-size are calculated from MacKinnon (2010); for 2 variables -4.228, -3.516, -3.168, for 3 variables -4.732, -3.994, -3.633, for 1%, 5%, and 10% respectively.

Table – 1 contd. Augmented Engle/Granger Univariate Cointegration Test Results

ADF Test Statistics			
STATES	**Y**	**Y-POP**	**Y-BC**
Montana	-2.770	-2.970	-4.130**
North Carolina	-1.160	-3.450	-4.360**
North Dakota	-1.230	-1.790	-5.440***
Nebraska	-1.220	-2.080	-2.280
Nevada	-3.000	-2.650	-3.380
New Hampshire	-2.540	-2.400	-2.780
New Jersey	-2.760	-2.750	-2.760
New Mexico	-1.840	-2.020	-2.600
New York	-2.210	-2.160	-2.390
Ohio	-1.960	-3.060	-2.280
Oklahoma	-1.510	-1.820	-2.940
Oregon	-1.900	-2.010	-3.300
Pennsylvania	-2.520	-2.760	-2.950
Rhode Island	-2.940	-3.020	-2.650
South Carolina	-1.520	-2.80	-3.330
South Dakota	-3.970**	-4.520**	-7.110***
Tennessee	-1.350	-2.900	-4.830***
Texas	-1.520	-1.490	-2.020
Utah	-1.970	-1.900	-3.760*
Virginia	-2.240	-2.140	-3.210
Vermont	-1.790	-2.290	-2.560
Washington	-2.390	-2.390	-2.920
Wisconsin	-1.760	-1.750	-4.150**
West Virginia	-1.070	-2.490	-3.660*
Wyoming	-1.560	-1.560	-3.520

Notes: Critical Values for 35 sample-size are calculated from MacKinnon (2010); for 2 variables -4.228, -3.516, -3.168, for 3 variables -4.732, -3.994, -3.633, for 1%, 5%, and 10% respectively.

Table – 2 Model 1 CCR Results (1-inp)

CCR Cointegration Results		
	Coeff. (St. Err.)	**H(p,q)**
STATES	**Model 1**	**Stat (p-value)**
Alabama	-0.140 (0.190)	1.600 (0.210)***
Alaska	2.240 (0.310)	0.240 (0.630)***
Arkansas	-0.360 (0.340)	4.260 (0.040)
Arizona	0.100 (0.550)	0.520 (0.470)***
California	2.150 (0.170)	0.460 (0.500)***
Colorado	0.790 (0.280)	1.050 (0.310)***
Connecticut	0.530 (0.460)	0.560 (0.450)***
Delaware	1.090 (0.250)	0.050 (0.820)***
District of Columbia	1.550 (0.620)	0.580 (0.450)***
Florida	-0.070 (0.270)	1.410 (0.240)***
Georgia	0.300 (0.040)	1.460 (0.230)***
Hawaii	2.800 (0.430)	0.680 (0.410)***
Idaho	0.580 (0.140)	0.050 (0.810)***
Illinois	0.850 (0.170)	0.030 (0.870)***
Indiana	-0.050 (0.170)	0.480 (0.490)***
Iowa	0.200 (0.970)	6.400 (0.010)
Kansas	-0.400 (0.970)	2.270 (0.130)***
Kentucky	0.200 (0.260)	0.730 (0.390)***
Louisiana	-0.350 (0.560)	1.160 (0.280)***
Maine	0.940 (0.230)	0.000 (0.970)***
Maryland	0.920 (0.120)	0.000 (0.980)***
Massachusetts	1.140 (0.230)	0.500 (0.480)***
Michigan	0.910 (0.200)	0.020 (0.890)***
Minnesota	0.650 (0.160)	0.140 (0.710)***
Missouri	-0.160 (0.210)	10.060 (0.000)
Mississippi	-0.370 (0.350)	0.200 (0.650)***

Notes: Stat and p-values in H(p,q) column with three asterisks indicate significant critical values for the corresponding states. (Under the null hypothesis of cointegration p-values > 10% are significant)

Table – 2 contd. Model 1 CCR Results (1-inp)

CCR Cointegration Results		
	Coeff. (St. Err.)	**H(p,q)**
STATES	**Model 1**	**Stat (p-value)**
Montana	1.590 (0.490)	0.150 (0.700)***
North Carolina	0.340 (0.040)	0.060 (0.800)***
North Dakota	0.730 (0.450)	2.560 (0.110)***
Nebraska	0.130 (0.420)	2.470 (0.120)***
Nevada	0.590 (0.290)	0.550 (0.460)***
New Hampshire	0.330 (0.170)	1.480 (0.220)***
New Jersey	0.900 (0.260)	0.130 (0.720)***
New Mexico	0.500 (0.520)	0.410 (0.520)***
New York	1.830 (0.360)	1.810 (0.180)***
Ohio	-0.140 (0.310)	2.430 (0.120)***
Oklahoma	-0.700 (1.510)	3.940 (0.050)
Oregon	1.810 (0.090)	0.650 (0.420)***
Pennsylvania	0.700 (0.330)	0.000 (0.950)***
Rhode Island	1.270 (0.250)	1.160 (0.280)***
South Carolina	0.390 (0.000)	0.860 (0.350)***
South Dakota	0.530 (0.150)	4.220 (0.040)
Tennessee	-0.050 (0.150)	2.520 (0.110)***
Texas	-1.130 (0.440)	0.030 (0.870)***
Utah	0.670 (0.400)	0.830 (0.360)***
Virginia	0.630 (0.100)	0.060 (0.810)***
Vermont	0.570 (0.210)	0.150 (0.70)***
Washington	1.610 (0.190)	0.030 (0.860)***
Wisconsin	0.750 (0.370)	0.100 (0.750)***
West Virginia	-0.130 (0.680)	3.050 (0.080)
Wyoming	0.650 (0.580)	1.880 (0.170)***

Notes: Stat and p-values in H(p,q) column with three asterisks indicate significant critical values for the corresponding states. (Under the null hypothesis of cointegration p-values > 10% are significant)

Table – 3 Model 2 CCR Results (2-inp)

CCR Cointegration Results			
	Coeff. (St. Err.)		H(p,q)
STATES	Y	POP	Stat (p-value)
Alabama	-2.170 (0.890)	5.350 (2.210)	1.320 (0.250)***
Alaska	2.250 (0.240)	0.180 (0.080)	0.000 (0.950)***
Arkansas	-3.780 (0.830)	6.580 (1.540)	0.010 (0.930)***
Arizona	2.690 (0.410)	-0.830 (0.400)	0.090 (0.770)***
California	0.840 (0.370)	0.530 (0.290)	1.440 (0.230)***
Colorado	3.540 (0.850)	-2.360 (0.820)	3.370 (0.070)
Connecticut	-0.910 (0.740)	10.230 (3.660)	0.060 (0.810)***
Delaware	0.720 (0.740)	0.230 (0.850)	0.700 (0.400)***
DC	1.880 (0.200)	2.590 (0.540)	0.380 (0.540)***
Florida	6.540 (1.170)	-4.050 (0.940)	7.080 (0.010)
Georgia	-1.000 (0.360)	0.920 (0.320)	2.210 (0.140)***
Hawaii	3.510 (0.550)	-0.140 (0.480)	0.220 (0.640)***
Idaho	0.580 (0.910)	-0.040 (0.700)	0.240 (0.630)***
Illinois	-0.200 (0.490)	2.990 (1.570)	0.640 (0.420)***
Indiana	-1.020 (0.490)	2.190 (1.090)	0.020 (0.880)***
Iowa	-0.690 (0.170)	7.270 (0.790)	10.370 (0.000)
Kansas	6.240 (1.070)	-13.200 (2.270)	3.090 (0.080)
Kentucky	-1.090 (0.390)	3.400 (0.980)	1.360 (0.240)***
Louisiana	0.520 (0.530)	-0.100 (1.030)	2.310 (0.130)***
Maine	2.030 (1.220)	-3.230 (3.650)	0.230 (0.630)***
Maryland	1.280 (0.550)	-0.330 (0.930)	1.440 (0.230)***
Massachusetts	2.180 (0.140)	0.040 (1.160)	1.220 (0.270)***
Michigan	-1.380 (0.390)	6.250 (0.960)	0.110 (0.740)***
Minnesota	-0.050 (1.110)	1.650 (2.060)	7.220 (0.010)
Missouri	-2.180 (0.570)	4.460 (1.150)	3.110 (0.080)
Mississippi	-0.900 (1.190)	1.780 (3.610)	0.970 (0.330)***

Notes: Stat and p-values in H(p,q) column with three asterisks indicate significant critical values for the corresponding states. (Under the null hypothesis of cointegration p-values > 10% are significant)

Table – 3 contd.   Model 2 CCR Results (2-inp)

CCR Cointegration Results			
	Coeff. (St. Err.)		**H(p,q)**
STATES	**Y**	**POP**	**Stat (p-value)**
Montana	2.770 (0.540)	-2.760(0.940)	10.140 (0.000)
North Carolina	-1.120 (0.180)	1.500 (0.180)	1.300 (0.260)***
North Dakota	0.530 (0.410)	2.580 (2.150)	4.990 (0.030)
Nebraska	-2.580 (0.680)	8.540 (2.230)	10.860 (0.000)
Nevada	2.060 (0.390)	-0.420 (0.100)	5.590 (0.020)
New Hampshire	4.120 (1.360)	-5.810 (2.360)	5.500 (0.020)
New Jersey	2.120 (0.220)	-1.430 (0.680)	1.680 (0.200)***
New Mexico	2.780 (0.660)	-2.140 (0.590)	0.970 (0.330)***
New York	1.990 (0.260)	0.410 (1.410)	0.060 (0.810)***
Ohio	-1.420 (0.360)	6.940 (1.580)	5.050 (0.030)
Oklahoma	1.400 (0.730)	-2.940 (1.200)	15.430 (0.000)
Oregon	1.680 (1.010)	-0.500 (1.460)	0.130 (0.720)***
Pennsylvania	-0.490 (0.400)	7.560 (3.050)	0.020 (0.880)***
Rhode Island	0.690 (0.500)	2.910 (1.640)	0.000 (0.970)***
South Carolina	-1.810 (0.360)	2.620 (0.470)	0.700 (0.400)***
South Dakota	-0.290 (0.530)	3.020 (1.950)	4.820 (0.030)
Tennessee	-1.730 (0.480)	2.990 (0.710)	5.580 (0.020)
Texas	2.570 (0.610)	-2.240 (0.480)	2.070 (0.150)***
Utah	2.420 (0.800)	-0.880 (0.540)	0.540 (0.460)***
Virginia	1.580 (0.090)	-1.160 (0.330)	1.650 (0.200)***
Vermont	2.740 (0.410)	-5.430 (1.030)	1.020 (0.310)***
Washington	1.800 (0.890)	-0.210 (0.850)	0.280 (0.590)***
Wisconsin	1.450 (1.110)	-0.710 (2.350)	0.430 (0.510)***
West Virginia	0.930 (0.120)	7.120 (0.450)	4.340 (0.040)
Wyoming	0.880 (0.230)	-0.940 (0.400)	3.480 (0.060)

Notes: Stat and p-values in H(p,q) column with three asterisks indicate significant critical values for the corresponding states. (Under the null hypothesis of cointegration p-values > 10% are significant)

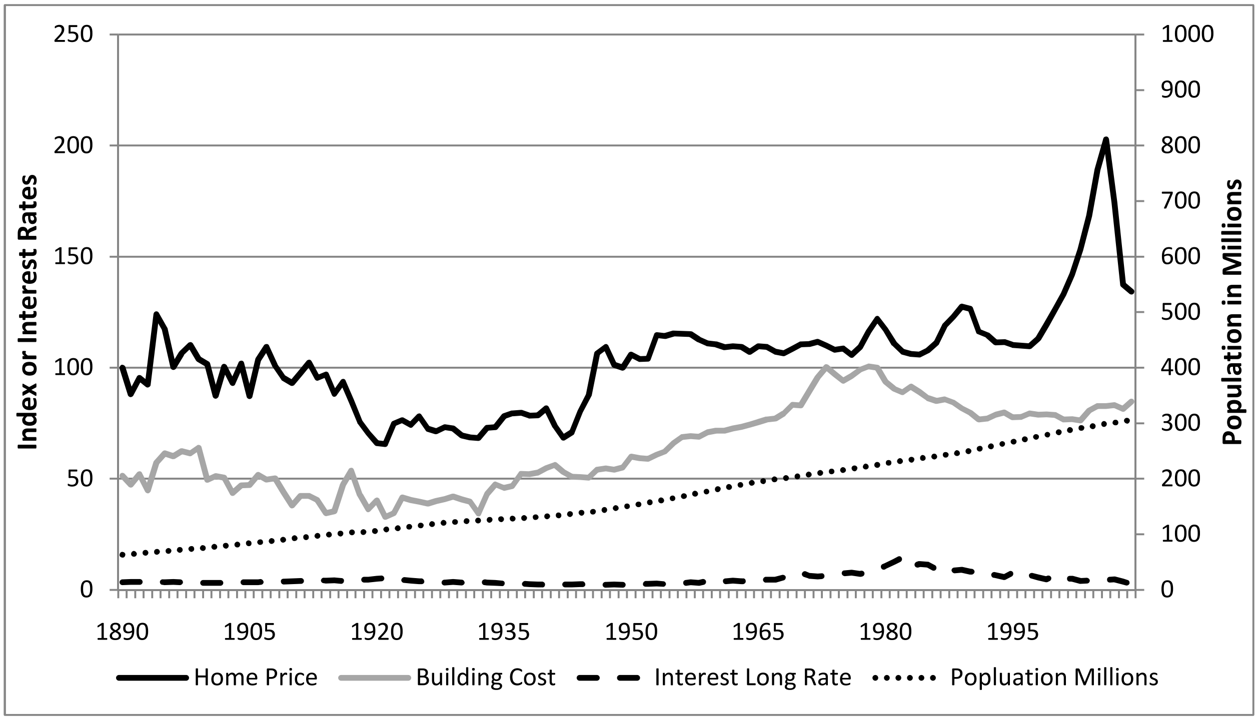

Figure 1. US Real home price, building cost, interest rates, and population

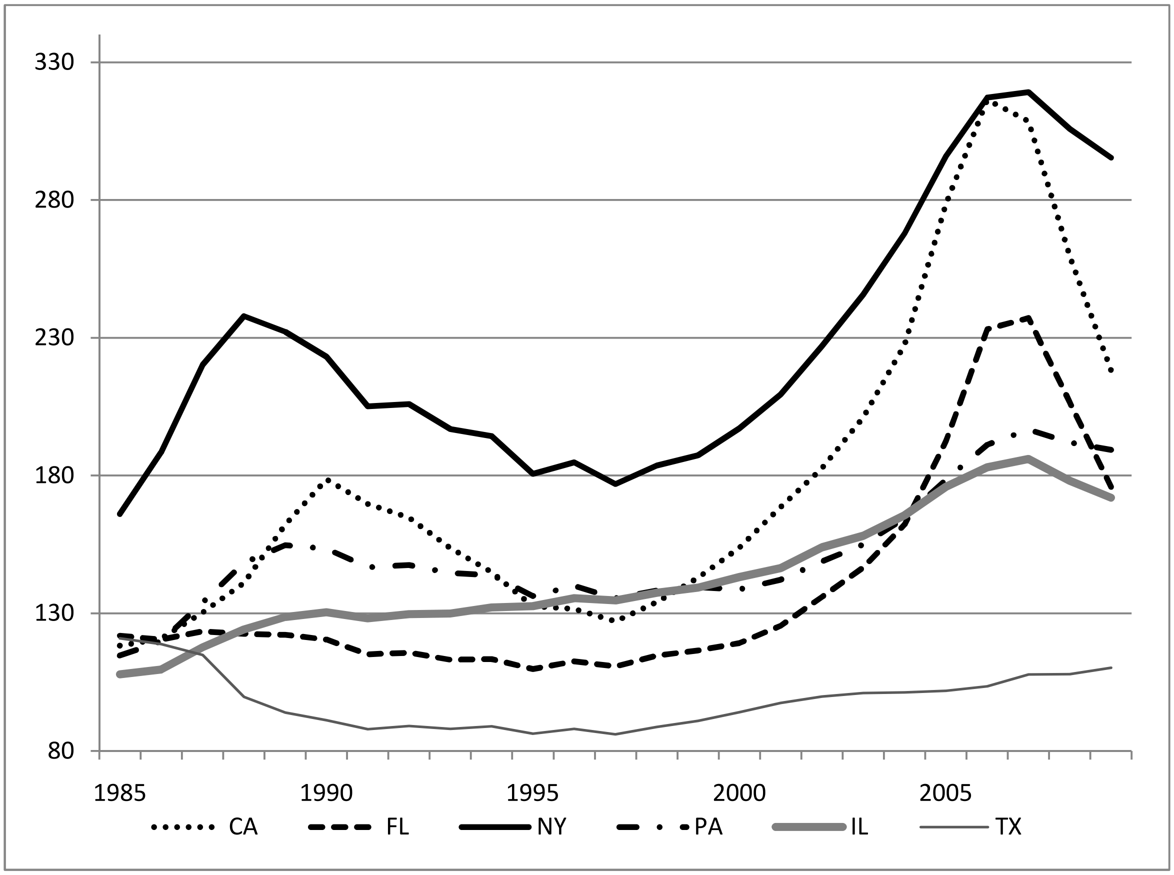

Figure 2. Real housing price index for selected states

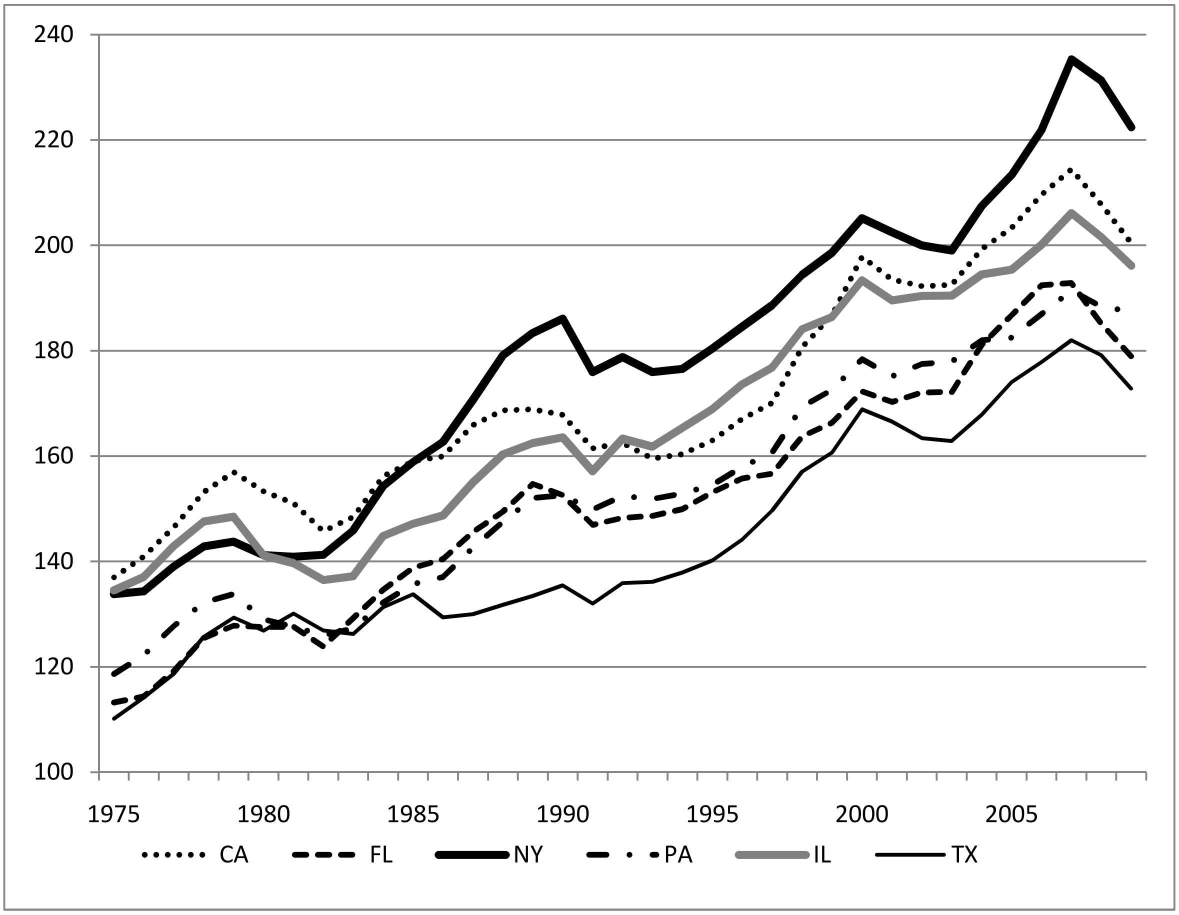

Figure 3. Nominal per capita income for selected states

CHAPTER 3

BIAS CORRECTION AND OUT-OF-SAMPLE FORECAST ACCURACY

I. INTRODUCTION

It is a well-known statistical fact that the least squares (LS) estimator for autoregressive (AR) processes suffers from serious downward bias in the persistence coefficient when the stochastic process includes a non-zero intercept and/or deterministic time trend. The bias can be substantial especially when the stochastic process is highly persistent (Andrews, 1993).

Since the seminal work of Kendall (1954), an array of bias-correction methods has been put forward. To name a few, Andrews (1993) proposed a method to obtain the exactly median-unbiased estimator for an AR(1) process with Gaussian errors. Andrews and Chen (1994) extends the work of Andrews (1993) to get approximately median-unbiased estimator for higher order AR(p) processes. Hansen (1999) developed a nonparametric bias correction method, the grid bootstrap (GT), which is robust to distributional assumptions. The GT method has been actively employed by many researchers, among others, Kim and Ogaki (2009), Steinsson (2008), Karanasos et al. (2006), and Murray and Papell (2002).

An alternative approach has been also proposed by So and Shin (1999) who develop the recursive mean adjustment (RMA) estimator that belongs to a class of (approximately) mean-unbiased estimators. The RMA estimator is computationally convenient to implement yet powerful and used in the work of Choi et al. (2008), Sul et al. (2005), Taylor (2002), and Cook (2002), for instance.

By construction, the LS estimator provides the best in-sample t among the class of linear estimators notwithstanding its bias.[3] A natural question then arises: Why do we need to correct for the bias? We attempt to find an answer by comparing the out-of-sample forecast performances of the bias-correction methods with that of the LS estimator. We apply the GT and the RMA approaches along with the LS estimator for quarterly commodity price indices for the period of 1974.QI to 2008.QIII, obtained from the Commodity Research Bureau (CRB). We find that both bias correction methods overall outperform the LS estimator. Especially, Hansen's GT estimator combined with a rolling window method performed the best.

Organization of the paper is as follows. In Section 2, we explain the source of bias and how each method corrects for biases. We also briefly explain how we evaluate the relative forecast performances. Section 3 reports our major empirical findings and Section 4 concludes.

II. BIAS-CORRECTION METHODS

We start with a brief explanation of the source of the bias in the LS estimator for an autoregressive process. Consider the following AR(1) process.

$$y_t = c + \rho y_{t-1} + \varepsilon_t, \tag{1}$$

where $|\rho| < 1$ and ε_t is a white noise process. Note that estimating by the LS estimator is

[3] Recall that the LS estimator is obtained by minimizing the sum of squared residuals.

equivalent to estimating the following.

$$(y_t - \bar{y}) = \rho(y_{t-1} - \bar{y}) + \varepsilon_t, \tag{2}$$

where $\bar{y} = T^{-1} \sum_{j=1}^{T} y_j$.

The LS estimator for ρ is unbiased only when $E\,[\varepsilon_t |\, \rho(y_{t-1} - \bar{y})] = 0$. This exogeneity assumption, however, is clearly violated because ε_t is correlated with y_j, for $j = t, t + 1, \ldots, T$, thus with $\bar{y}$. Therefore, the LS estimator for AR processes with an intercept creates the mean–bias. The bias has an analytical representation, and as Kendall (1954) shows, the LS estimator $\hat{\rho}_{LS}$ is biased downward.

There is no analytical representation of the median–bias. Monte Carlo simulations, however, can easily demonstrate that the LS estimator produces significant median–bias for ρ when ρ gets close to unity (see Hansen, 1999).

When ε_t is serially correlated, it is convenient to express (1) as follows.

$$y_t = c + \rho y_{t-1} + \textstyle\sum_{j=1}^{k} \beta_j \, \Delta y_{t-1} + u_t, \tag{3}$$

where u_t is a white noise process that generates ε_t.

For Hansen's (1999) GT method, we define the following grid-t statistic.

$$t_N\,(\rho_i) = \frac{\hat{\rho}_{LS} - \rho_i}{se\,(\hat{\rho}_{LS})},$$

where $\hat{\rho}_{LS}$ is the LS point estimate for ρ, $se\,(\hat{\rho}_{LS})$ denotes the corresponding LS standard error, and ρ_i is one of M fine grid points in the neighborhood of $\hat{\rho}_{LS}$. Implementing LS estimations for B bootstrap samples at each of M grid points, we obtain the $\alpha\%$ quantile function estimates $q^*_{N,\alpha}(\rho_i) = q^*_{N,\alpha}\big(\rho_i, \varphi(\rho_j)\big)$, where φ denotes nuisance parameters such as βs that are functions of ρ_i. After smoothing quantile function estimates, the (approximately) median-unbiased estimate is obtained by,

$$\hat{\rho}_G = \rho_i \in R, s.t.\ t_N(\rho_i) = \tilde{q}^*_{N,50\%}(\rho_i),$$

where $\tilde{q}^*_{N,50\%}(\rho_i)$ is the smoothed 50% quantile function estimates obtained from $q^*_{N,\alpha}$. To correct for median–bias in β_j estimates, we treat other βs as well as ρ as nuisance parameters and follow the procedures described above.

So and Shin's (1999) RMA estimator utilizes demeaning variables using the partial mean instead of the global mean $\bar{y}$. Rather than implementing the LS for (2), the RMA estimator is obtained by the LS estimator for the following regression equation.

$$\left(y_t - \overline{y}_{t-1}\right) = \rho\left(y_{t-1} - \overline{y}_{t-1}\right) + \mu_t,$$

where $\overline{y}_{t-1} = (t-1)^{-1} \sum_{j=1}^{t-1} y_j$ and $\eta_t = \varepsilon_t - (1-\rho)(t-1)^{-1} \sum_{j=1}^{t-1} y_j$.

Note that the error term η_t is independent of $\left(y_{t-1} - \overline{y}_{t-1}\right)$, which results in bias reduction for the RMA estimator $\hat{\rho}_R$. For a higher order AR process such as (3), the RMA estimator can be obtained by treating βs as nuisance parameters as in Hansen's (1999) GT method. We use a conventional method proposed by Diebold and Mariano (1995) to evaluate the out-of-sample forecast accuracy of each bias-correction method relative to that of the LS estimator. Let $y^1_{t+h|t}$ and $y^2_{t+h|t}$ denote two competing (out-of-sample) h-step forecasts given information set at time *t*. The forecast errors from the two models are,

$$\varepsilon^1_{t+h|t} = y_{t+h} - y^1_{t+h|t}, \qquad \varepsilon^2_{t+h|t} = y_{t+h} - y^2_{t+h|t}$$

For the Diebold-Mariano test, define the following function.

$$d_t = L\left(\varepsilon^1_{\mathrm{t+h|t}}\right) - L\left(\varepsilon^2_{\mathrm{t+h|t}}\right),$$

where $L\left(\varepsilon^j_{\mathrm{t+h|t}}\right), j = 1, 2$ is a loss function.[4] To test the null of equal predictive accuracy,

$H_0 : Ed_t = 0$, the Diebold-Mariano statistic (DM) is defined as,

$$DM = \frac{\overline{d}}{\sqrt{\widehat{Avar}(\overline{d})}}$$

where $\bar{d}$ is the sample mean loss differential,

$$\bar{d} = \frac{1}{T - T_0} \sum_{t=T_0+1}^{T} d_t,$$

$\widehat{Avar}(\overline{d})$ is the asymptotic variance of $\bar{d}$,

$$\widehat{Avar}\left(\overline{d}\right) = \frac{1}{T - T_0} \sum_{j=-q}^{q} k(j, q)\hat{\Gamma}_j,$$

$k(.)$ denotes a kernel function where $k(.) = 0,\ j > q$, and $\hat{\Gamma}_j$ is j^{th} autocovariance function estimate.[5] Under the null, DM has the standard normal distribution asymptotically.

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[4] One may use either the squared error loss function, $\left(\varepsilon^j_{\mathrm{t+h|t}}\right)^2$, or the absolute error loss function, $|\varepsilon^j_{\mathrm{t+h|t}}|$.

[5] Following Andrews and Monahan (1992), we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.

III. EMPIRICAL RESULTS

We use quarterly commodity price indices, CRB Spot Index and its six sub-indices, obtained from the Commodity Research Bureau (CRB) for the period of 1974 to 2008.[6] We noticed a structural break of these series in 1973, the year of the demise of the Bretton Woods system (see Figure 1). Since our main objective is to evaluate relative forecast performances of competing estimators, we use observations starting from 1974.Q1 instead of using a dummy variable for the Bretton Woods era.

Table 1 reports our estimates for the persistence parameter in (3). We find that both the RMA and the GT methods yield significant bias-corrections. For example, the estimate for the Spot Index increases from 0.950 (LS) to 0.969 (RMA) and 0.975 (GT). This is far from being negligible because corresponding half-life estimates are 3.378, 5.503, and 6.844 years, respectively. Note also that median-unbiased estimates by the GT are not restricted to be less than one, because the GT is based on the local-to-unity framework and allows even mildly explosive processes.[7]

We evaluate the out-of-sample forecasting ability of the three estimators, the LS, the RMA, and the GT, with two alternative forecasting methods. First, we utilize first 69 out of 139 observations to obtain h-step ahead forecasts. Then, we keep forecasting recursively by adding one observation in each iteration until we forecast the last observation. Second, we obtain h-step ahead forecasts using first 69 observations, then keep forecasting with a rolling window by

[6] In order to reduce noise in the data, we converted monthly frequency raw data to quarterly data by taking end-of-period values. Alternatively, one may use quarterly averages. Averaging time series data, however, creates time aggregation bias as pointed by Taylor (2001).

[7] When the true data generating process is $I(1)$, one may use AR models with differenced variables, then correct for biases. Median/Mean bias for such models, however, tends to be small, because differenced variables often exhibit much weaker persistence. Since we are interested in evaluating the usefulness of bias-corrected estimators, we do not consider such models.

adding and dropping one observation in each iteration, maintaining 69 observations, until we reach the end of full sample. We report our results in Tables 2 and 3.

Overall, we find that both bias-correction methods outperform the LS estimator with an exception of the Textile Sub-Index. No matter what methods are employed, the ratios of root mean squared prediction errors (RMSPE), LS/RMA and LS/GT, are mostly greater than one, which implies higher prediction precision of these methods relative to the LS estimator. For example, 4-period (1 year) ahead out-of-sample forecasts for the Spot index by the LS, RMA, and GT with the recursive method yield 0.104, 0.099, and 0.102 RMSPEs, respectively (see Table 2). Because the ratio LS/RMA (1.050) is greater than LS/GT (1.018) and both ratios are greater than 1, the RMA performs the best and the LS is the worst for this case. The corresponding Diebold-Mariano statistic shows that the RMA outperforms the LS at the 5% significance level. The evidence of superior performance of the GT is weaker than the RMA because corresponding p-value is 0.185, that is, significant only at the 20% significance level. When we use the rolling window method for 4-period ahead Spot Index forecasts, the grid bootstrap works the best and the LS performs the worst. The GT is superior to the LS at the 1% significance level, while the RMA outperforms the LS at the 5% level.

Another interesting finding is that a long memory is not necessarily good because forecast performance seems better with the rolling window method. It is easy to see the RMSPEs for each estimator are much smaller when we employ the rolling window strategy rather than the recursive method.[8] Especially, Hansen's GT estimator combined with the rolling window method performs the best because the associated RMSPEs are the smallest in majority cases.

[8] We implemented same analysis for the sample period of 1974.Q1 to 2005.Q4 to see whether recent persistent movements of commodity indices significantly affected our results. We found very similar results.

IV. CONCLUDING REMARKS

This paper evaluates relative forecast performances of two bias-correction methods, the RMA and the GT, to the LS estimator without bias-correction. When an intercept or an intercept and and linear time trend are included in AR models, the LS estimator for the slope coefficient is downward-biased. Despite the bias, the LS estimator provides the best in-sample fit among a class of linear estimators. We attempt to find some justification of using these bias-correction methods by comparing the out-of-sample forecast accuracy of the methods with that of the LS estimator. Using the CRB Spot Index and its six sub-indices, we find that both methods overall outperform the LS estimator. Especially, Hansen's GT performs the best when it is combined with the rolling window strategy.

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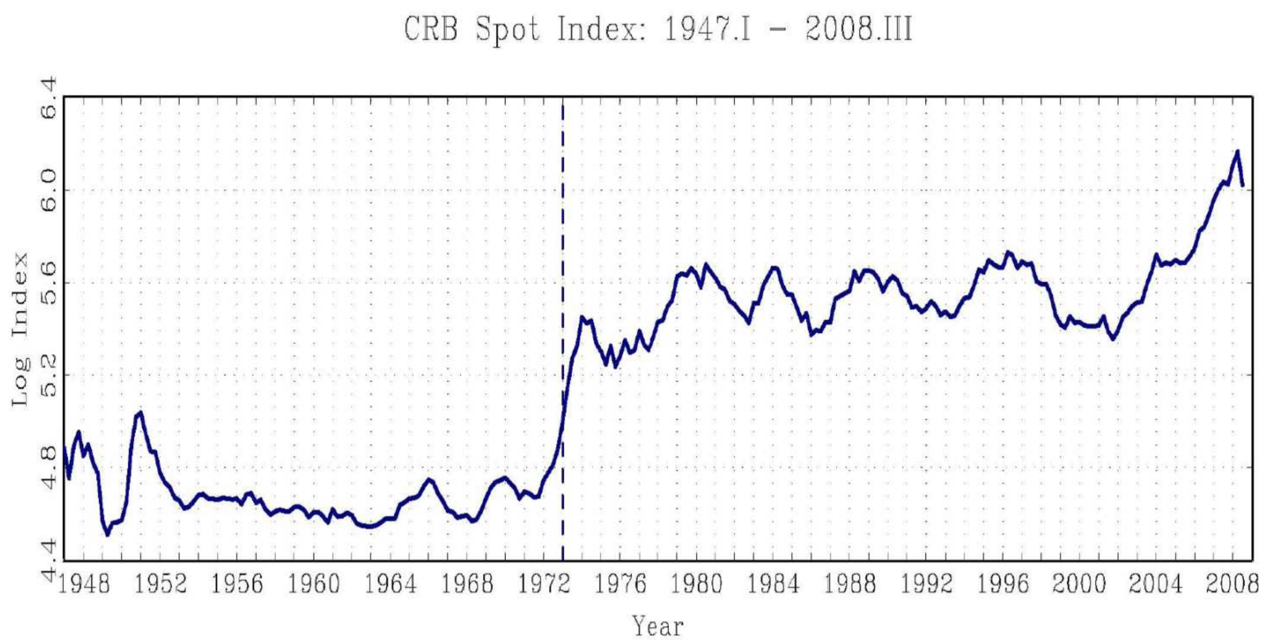
Figure 1. CRB Historical Data



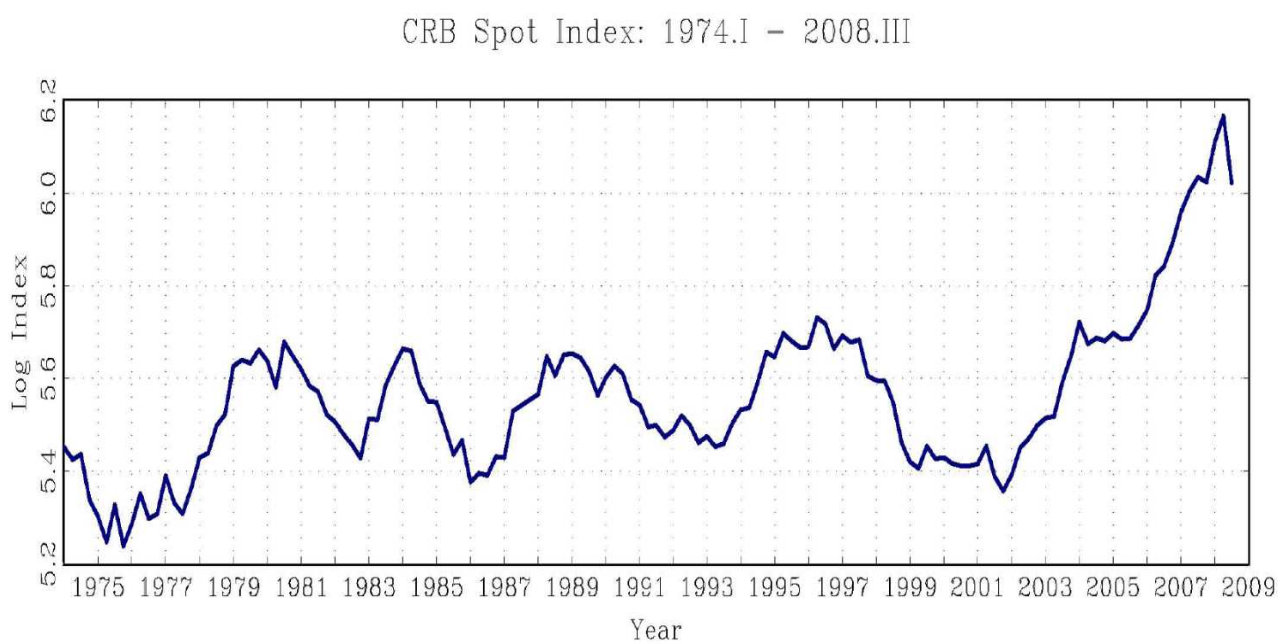


Figure 2. Quarterly Forecasts

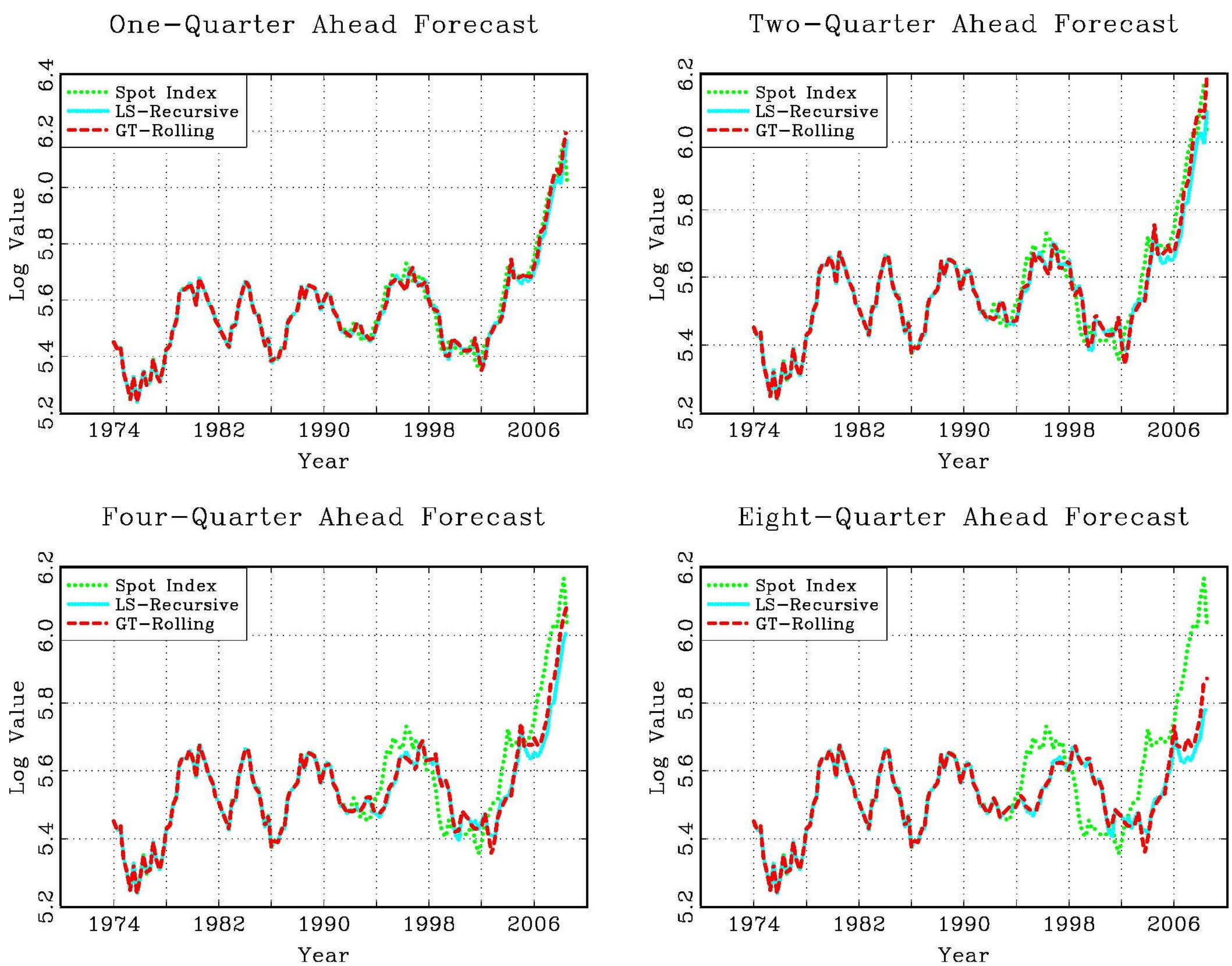


Figure 3. Commodity Data Index

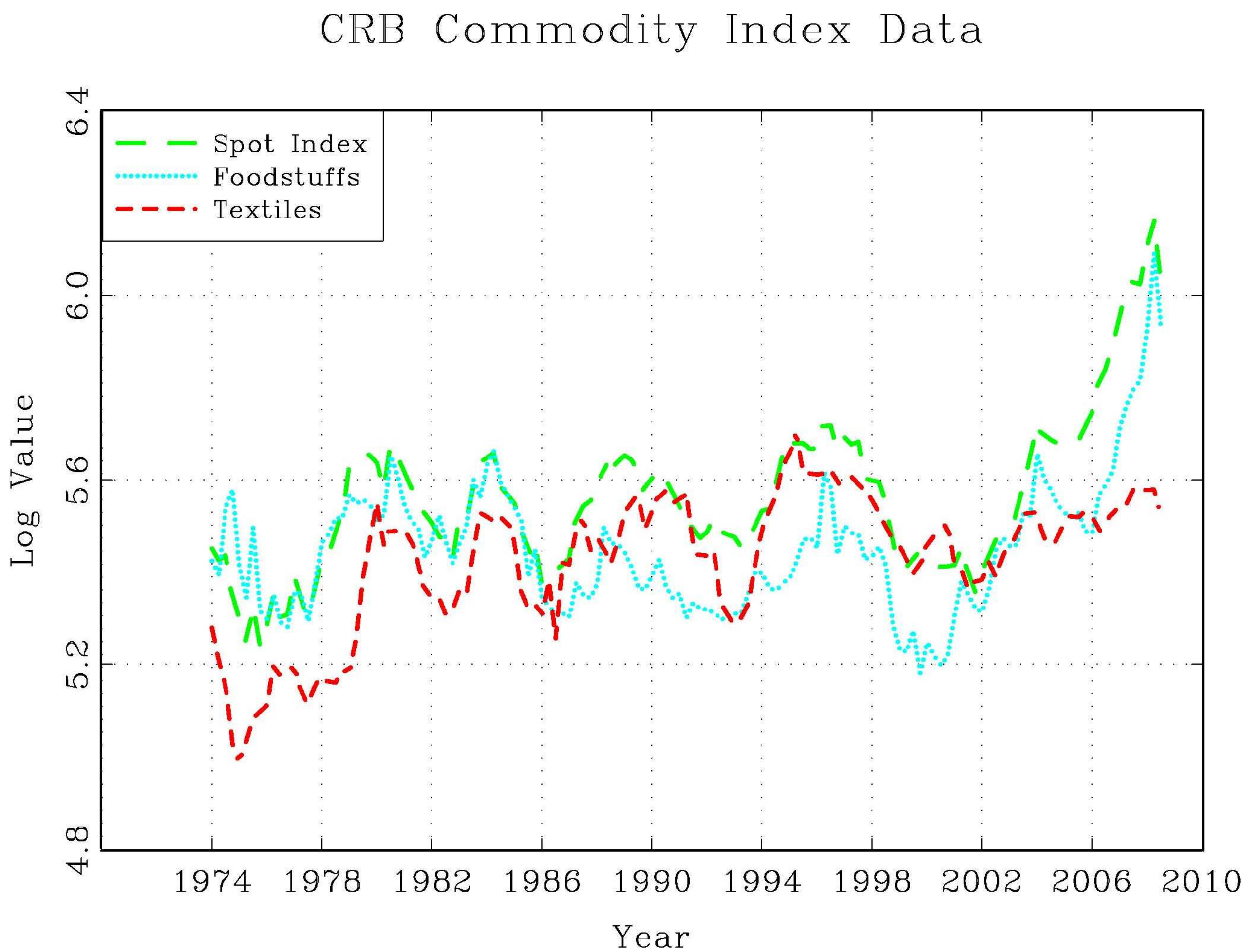


Figure 4. ADF-t Statistics

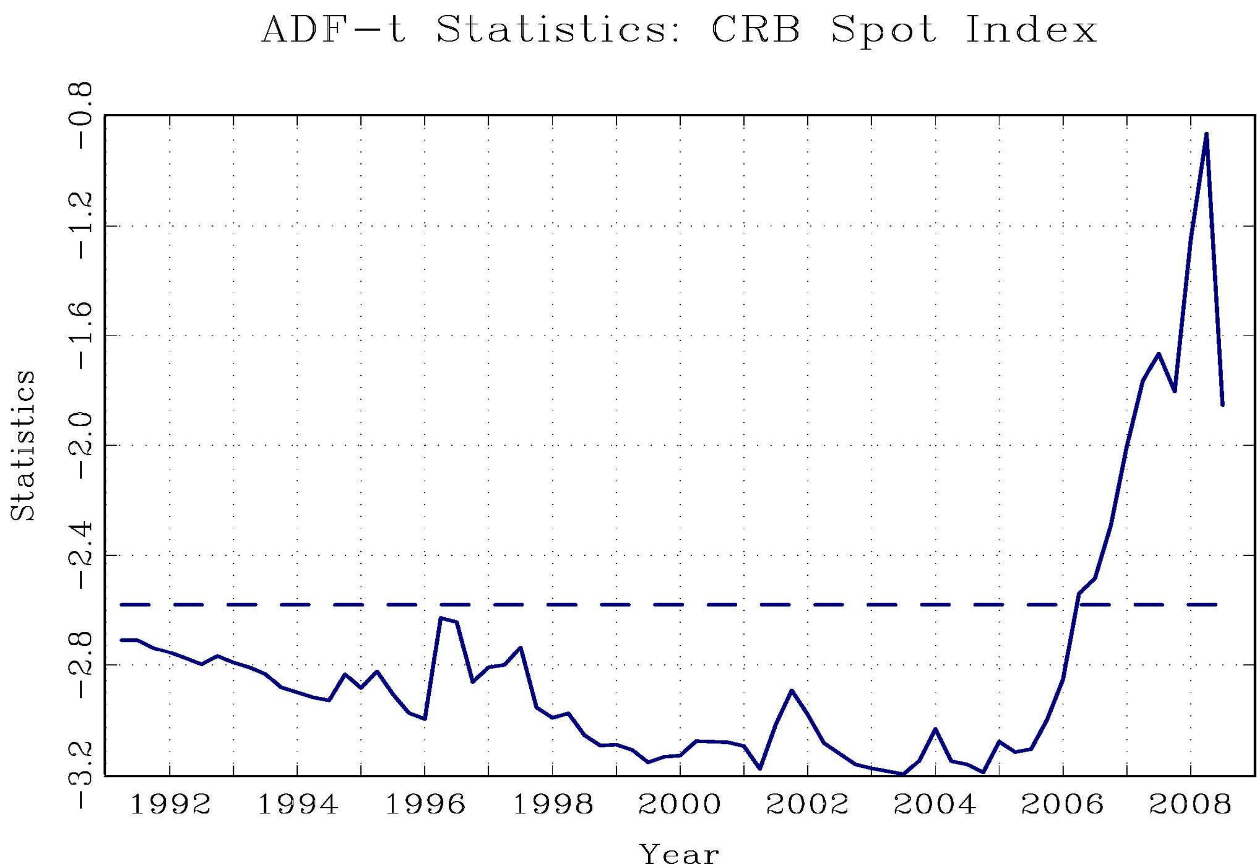


Figure 5. ADF-t Statistics from Rolling Window Est.

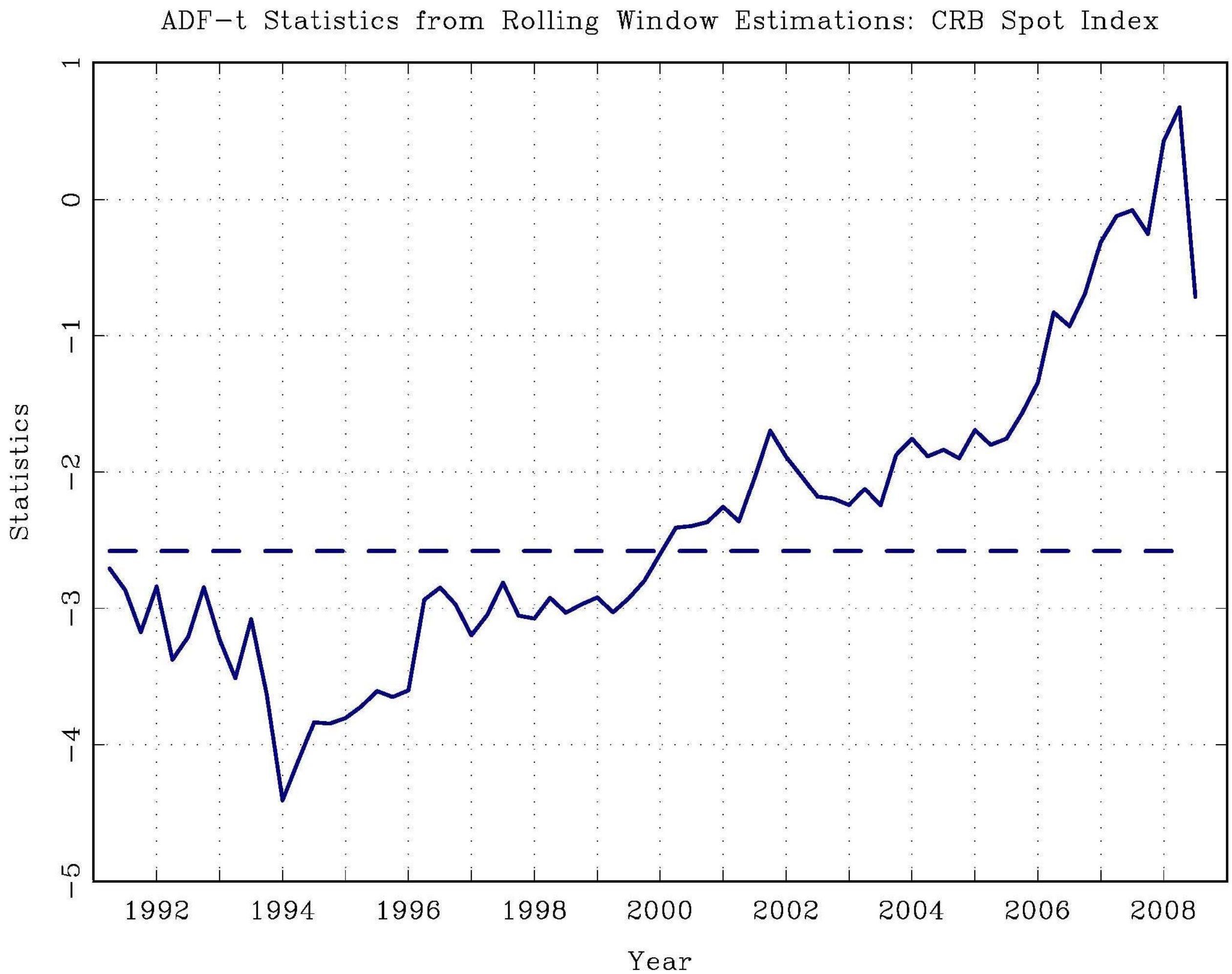


Table 1. Persistence Parameter Estimation Results

Index	ρL	CI	ρR	CI	ρG	CI
Spot	0.950	[0.856,0.972]	0.969	[0.872,0.985]	0.975	[0.910,1.022]
Livestock	0.933	[0.770,0.966]	0.972	[0.795,0.986]	0.990	[0.875,1.044]
Fats&Oil	0.933	[0.776,0.965]	0.951	[0.800,0.985]	0.997	[0.864,1.049]
Foodstuff	0.952	[0.813,0.976]	0.977	[0.836,0.993]	1.008	[0.890,1.049]
Raw Industrials	0.940	[0.847,0.966]	0.969	[0.863,0.979]	0.955	[0.907,1.009]
Textiles	0.917	[0.807,0.951]	0.947	[0.824,0.967]	0.932	[0.874,1.003]
Metals	0.963	[0.870,0.981]	0.974	[0.887,0.993]	0.996	[0.929,1.024]
Index	HL_L	CI	HL_R	CI	HL_G	CI
Spot	3.378	[1.114,6.102]	5.503	[1.265,11.47]	6.844	[1.837, ∞]
Livestock	2.499	[0.663,5.010]	6.102	[0.755,12.29]	17.240	[1.298, ∞]
Fats&Oil	2.499	[0.683,4.864]	3.449	[0.777,11.47]	57.680	[1.185, ∞]
Foodstuff	3.523	[0.837,7.133]	7.447	[0.967,24.70]	∞	[1.487, ∞]
Raw Industrials	2.801	[1.044,5.010]	5.503	[1.176,8.165]	3.764	[1.775, ∞]
Textiles	2.000	[0.808,3.449]	3.182	[0.895,5.164]	2.461	[1.287, ∞]
Metals	4.596	[1.244,9.033]	6.578	[1.445,24.70]	43.240	[2.353, ∞]

Note: i) The number of lags (k) was chosen by the general-to-specific rule as recommended by Ng and Perron (2001). ii) ρL, ρR, and ρG denote the least squares (LS), recursive mean adjustment (RMA, So and Shin 1999), and grid bootstrap (GT, Hansen 1999) estimates for persistence parameter, respectively. iii) 95% confidence intervals (CI) were constructed by 10,000 nonparametric bootstrap simulations for the LS and RMA estimators, and by 10,000 nonparametric bootstrap simulations on 30 grid points over the neighborhood of the LS estimate for the GT estimator. iv) HL_L, HL_R, and HL_G denote the corresponding half-lives in years, calculated by $(\ln(0.5)/\ln(\rho))/4$.

Table 2. Recursive Out-of-Sample Forecast Results

Index	*h*	$RMSPE_L$	$RMSPE_R$	$RMSPE_G$	LS/RMA	LS/GT	DM_R	DM_G
Spot	1	0.045	0.044	0.045	1.031	1.004	1.183 (0.237)	0.180 (0.857)
	2	0.066	0.063	0.064	1.059	1.033	1.808 (0.071)	1.310 (0.190)
	3	0.084	0.078	0.081	1.065	1.029	2.555 (0.011)	1.544 (0.122)
	4	0.104	0.099	0.102	1.050	1.018	2.421 (0.015)	1.324 (0.185)
	6	0.141	0.138	0.139	1.026	1.012	1.456 (0.145)	0.917 (0.359)
	8	0.176	0.174	0.176	1.01	0.999	0.708 (0.479)	0.097 (0.923)
	12	0.218	0.221	0.220	0.985	0.992	1.135 (0.256)	0.796 (0.426)
Live	1	0.082	0.079	0.081	1.035	1.012	1.561 (0.119)	1.182 (0.237)
	2	0.118	0.110	0.115	1.066	1.025	2.598 (0.009)	2.585 (0.010)
	3	0.128	0.124	0.127	1.035	1.012	2.064 (0.039)	1.450 (0.147)
	4	0.144	0.138	0.142	1.039	1.011	2.683 (0.007)	1.839 (0.066)
	6	0.178	0.172	0.174	1.034	1.021	1.810 (0.070)	2.027 (0.043)
	8	0.197	0.194	0.196	1.012	1.006	0.789 (0.43)	0.797 (0.425)
	12	0.216	0.212	0.213	1.019	1.011	1.442 (0.149)	1.506 (0.132)
Fats	1	0.110	0.109	0.11	1.003	0.995	0.397 (0.692)	0.360 (0.719)
	2	0.159	0.157	0.156	1.013	1.018	1.712 (0.087)	1.780 (0.075)
	3	0.174	0.173	0.172	1.008	1.011	1.294 (0.196)	1.543 (0.123)
	4	0.193	0.192	0.192	1.001	1.003	0.230 (0.818)	0.458 (0.647)
	6	0.245	0.246	0.247	0.994	0.992	1.082 (0.279)	1.608 (0.108)
	8	0.271	0.273	0.276	0.993	0.983	1.436 (0.151)	3.713 (0.000)
	12	0.283	0.287	0.29	0.986	0.976	2.516 (0.012)	4.771 (0.000)
Food	1	0.063	0.062	0.062	1.027	1.029	1.521 (0.128)	1.113 (0.266)
	2	0.090	0.088	0.087	1.032	1.040	2.172 (0.030)	3.458 (0.001)
	3	0.105	0.103	0.103	1.017	1.022	1.532 (0.125)	2.116 (0.034)
	4	0.124	0.122	0.121	1.015	1.020	1.326 (0.185)	1.864 (0.062)
	6	0.157	0.156	0.156	1.003	1.004	0.299 (0.765)	0.559 (0.576)
	8	0.179	0.181	0.180	0.991	0.995	0.921 (0.357)	0.670 (0.503)
	12	0.197	0.201	0.201	0.980	0.981	1.381 (0.167)	1.637 (0.102)

Table 2. contd. Recursive Out-of-Sample Forecast Results

Index	*h*	$RMSPE_L$	$RMSPE_R$	$RMSPE_G$	LS/RMA	LS/GT	DM_R	DM_G
Raw	1	0.049	0.047	0.048	1.028	1.009	1.053 (0.292)	0.721 (0.471)
	2	0.076	0.072	0.074	1.057	1.021	1.800 (0.072)	1.444 (0.149)
	3	0.097	0.092	0.095	1.056	1.023	2.639 (0.008)	1.642 (0.101)
	4	0.122	0.118	0.121	1.036	1.010	2.235 (0.025)	0.963 (0.335)
	6	0.162	0.157	0.159	1.030	1.015	1.980 (0.048)	1.339 (0.181)
	8	0.200	0.196	0.199	1.019	1.004	1.668 (0.095)	0.544 (0.586)
	12	0.256	0.259	0.256	0.990	1.000	1.058 (0.290)	0.024 (0.981)
Text	1	0.037	0.037	0.037	0.993	0.989	0.450 (0.653)	0.935 (0.350)
	2	0.056	0.056	0.056	0.997	0.999	0.115 (0.908)	0.072 (0.943)
	3	0.074	0.075	0.074	0.99	0.994	0.532 (0.595)	0.448 (0.654)
	4	0.089	0.091	0.090	0.978	0.985	1.776 (0.076)	1.962 (0.050)
	6	0.109	0.113	0.112	0.964	0.973	2.240 (0.025)	2.417 (0.016)
	8	0.121	0.125	0.124	0.969	0.971	2.230 (0.026)	3.389 (0.001)
	12	0.130	0.132	0.134	0.981	0.973	1.087 (0.277)	2.521 (0.012)
Metal	1	0.087	0.085	0.086	1.020	1.014	1.878 (0.060)	0.612 (0.540)
	2	0.139	0.135	0.134	1.031	1.034	2.296 (0.022)	1.283 (0.199)
	3	0.187	0.181	0.178	1.033	1.046	3.540 (0.000)	3.078 (0.002)
	4	0.226	0.223	0.221	1.016	1.024	2.565 (0.010)	2.102 (0.036)
	6	0.309	0.303	0.301	1.019	1.025	2.546 (0.011)	2.458 (0.014)
	8	0.376	0.373	0.372	1.008	1.011	1.759 (0.079)	2.268 (0.023)
	12	0.493	0.495	0.495	0.996	0.997	0.952 (0.341)	1.312 (0.189)

Note: i) Out-of-sample forecasting was recursively implemented by sequentially adding one additional observation from 69 initial observations toward 139 total observations. ii) The number of lags (k) was chosen by the general-to-specific rule recommended by Ng and Perron (2001). iii) h denotes the forecast horizon (quarters). iv) RMSPEL, RMSPER, and RMSPEG denote the root mean squared prediction errors (RMSPE) for the Least Squares (LS), Recursive Mean Adjustment (RMA), and grid bootstrap (GT) estimators, respectively. v) LS/RMA and LS/GT are RMSPEL/RMSPERand RMSPEL/RMSPEG, respectively. vi) DMR and DMG denote Diebold-Mariano (1995) asymptotic test statistics for the pairs of estimators, LS-RMA and LS-GT. Null hypothesis is equal prediction accuracy. p-values from an asymptotic standard normal distribution are in parenthesis.

Table 3. Rolling Window Out-of-Sample Forecast Results

Index	*h*	$RMSPE_L$	$RMSPE_R$	$RMSPE_G$	LS/RMA	LS/GT	DM_R	DM_G
Spot	1	0.045	0.044	0.044	1.006	1.01	0.328 (0.743)	0.473 (0.636)
	2	0.065	0.062	0.062	1.039	1.054	1.833 (0.067)	1.778 (0.075)
	3	0.079	0.076	0.074	1.046	1.066	2.296 (0.022)	3.348 (0.001)
	4	0.097	0.094	0.093	1.034	1.046	2.116 (0.034)	3.267 (0.001)
	6	0.134	0.13	0.129	1.032	1.043	1.633 (0.102)	2.648 (0.008)
	8	0.169	0.166	0.165	1.02	1.026	1.429 (0.153)	2.509 (0.012)
	12	0.213	0.211	0.212	1.013	1.008	1.136 (0.256)	0.997 (0.319)
Live	1	0.083	0.082	0.083	1.014	1.008	1.162 (0.245)	0.303 (0.762)
	2	0.119	0.115	0.112	1.03	1.058	2.046 (0.041)	2.145 (0.032)
	3	0.126	0.123	0.122	1.026	1.039	2.387 (0.017)	1.683 (0.092)
	4	0.14	0.138	0.135	1.02	1.036	1.531 (0.126)	2.075 (0.038)
	6	0.17	0.168	0.164	1.012	1.036	1.347 (0.178)	3.026 (0.002)
	8	0.185	0.184	0.18	1.008	1.026	0.844 (0.399)	2.309 (0.021)
	12	0.194	0.195	0.186	0.992	1.041	0.761 (0.446)	3.731 (0.000)
Fats	1	0.11	0.11	0.108	1.001	1.011	0.094 (0.925)	0.461 (0.645)
	2	0.158	0.158	0.153	1.005	1.037	0.433 (0.665)	1.338 (0.181)
	3	0.173	0.173	0.167	1.001	1.035	0.132 (0.895)	1.892 (0.058)
	4	0.192	0.193	0.188	0.994	1.018	0.821 (0.411)	1.246 (0.213)
	6	0.248	0.253	0.251	0.98	0.989	2.277 (0.023)	1.354 (0.176)
	8	0.277	0.284	0.282	0.973	0.981	3.933 (0.000)	2.412 (0.016)
	12	0.293	0.304	0.298	0.964	0.981	4.006 (0.000)	2.469 (0.014)
Food	1	0.062	0.062	0.061	1.01	1.016	0.945 (0.345)	0.793 (0.428)
	2	0.085	0.082	0.08	1.034	1.069	2.068 (0.039)	2.226 (0.026)
	3	0.1	0.098	0.095	1.018	1.057	1.483 (0.138)	3.073 (0.002)
	4	0.117	0.115	0.111	1.016	1.055	1.373 (0.170)	2.824 (0.005)
	6	0.153	0.152	0.148	1.007	1.032	0.656 (0.512)	2.396 (0.017)
	8	0.176	0.179	0.173	0.985	1.019	1.873 (0.061)	1.318 (0.187)
	12	0.198	0.203	0.195	0.975	1.015	2.284 (0.022)	1.263 (0.207)

Table 3. contd. Rolling Window Out-of-Sample Forecast Results

Index	*h*	$RMSPE_L$	$RMSPE_R$	$RMSPE_G$	LS/RMA	LS/GT	DM_R	DM_G
Raw	1	0.048	0.048	0.047	1.007	1.021	0.388 (0.698)	0.828 (0.408)
	2	0.078	0.076	0.074	1.014	1.049	0.516 (0.606)	1.417 (0.156)
	3	0.093	0.093	0.09	1.004	1.035	0.201 (0.841)	1.858 (0.063)
	4	0.12	0.119	0.116	1.007	1.034	0.522 (0.601)	2.206 (0.027)
	6	0.159	0.159	0.156	1	1.02	0.016 (0.987)	1.286 (0.198)
	8	0.198	0.197	0.194	1.005	1.019	0.417 (0.677)	2.252 (0.024)
	12	0.255	0.253	0.255	1.006	1.001	0.669 (0.504)	0.158 (0.875)
Text	1	0.037	0.037	0.037	1.017	1.002	0.745 (0.457)	0.213 (0.832)
	2	0.058	0.056	0.057	1.029	1.009	1.203 (0.229)	0.563 (0.573)
	3	0.074	0.073	0.074	1.01	0.999	0.482 (0.629)	0.066 (0.947)
	4	0.087	0.088	0.088	0.99	0.991	1.004 (0.316)	1.408 (0.159)
	6	0.106	0.108	0.108	0.985	0.985	1.211 (0.226)	1.633 (0.103)
	8	0.117	0.118	0.119	0.986	0.981	1.562 (0.118)	2.521 (0.012)
	12	0.121	0.123	0.124	0.985	0.979	1.221 (0.222)	2.284 (0.022)
Metal	1	0.083	0.084	0.083	0.998	1.006	0.127 (0.899)	0.282 (0.778)
	2	0.133	0.134	0.132	0.997	1.014	0.111 (0.912)	0.454 (0.650)
	3	0.171	0.17	0.165	1.004	1.035	0.369 (0.712)	2.439 (0.015)
	4	0.215	0.215	0.21	1.003	1.028	0.440 (0.660)	2.909 (0.004)
	6	0.293	0.292	0.288	1.002	1.019	0.214 (0.831)	1.471 (0.141)
	8	0.366	0.365	0.359	1.003	1.02	0.565 (0.572)	2.422 (0.015)
	12	0.489	0.491	0.488	0.995	1.001	1.017 (0.309)	0.155 (0.877)

Note: i) Out-of-sample forecasting was implemented by sequentially adding one additional observation and dropping one observation in each iteration, maintaining 69 observations. ii) The number of lags (k) was chosen by the general-to-specific rule recommended by Ng and Perron (2001). iii) h denotes the forecast horizon (quarters). iv) RMSPEL, RMSPER, and RMSPEG denote the root mean squared prediction errors (RMSPE) for the Least Squares (LS), Recursive Mean Adjustment (RMA), and grid bootstrap (GT) estimators, respectively. v) LS/RMA and LS/GT are RMSPEL/RMSPER and RMSPEL/RMSPEG, respectively. vi) DMR and DMG denote Diebold-Mariano (1995) asymptotic test statistics for the pairs of estimators, LS-RMA and LS-GT. Null hypothesis is equal prediction accuracy. p-values from an asymptotic standard normal distribution are in parenthesis.