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Conventional monetary policy and the degree of interest rate pass through in the long run: a non-normal approach

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Abstract

We investigate the long-run pass through of the federal funds rate to the prime rate from February 1987 to February 2015. Unlike previous studies that rely on conventional cointegration tests, this study employs cointegration tests based on the "residual augmented least squares" (RALS). The RALS cointegration tests have been shown to gain power when using a linear model in the presence of non-normal errors. The results indicate a significant cointegrating relation between the federal funds rate and the prime rate with incomplete interest rate pass through.

Keywords: Monetary policy, interest rate pass through, cointegration analysis, non-normal errors, RALS

JEL classification: E52, E43, E58, C12, C22

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1. Introduction

According to the conventional monetary transmission mechanism, changes in the federal funds rate operate through the financial system to the real economy after the quantity of money demanded equals the current supply that banks make available. (Bernanke, 1988) For example, suppose the Federal Reserve increases the supply of money in the U.S. economy. The immediate effect of this action is the Fed adds reserves to the banking system thereby reducing the interest rate on federal funds.

In the long run, however, a fall in the federal funds rate is also supposed to stimulate new spending. When the Fed increases the stock of reserves, banks issue more deposits, make more loans, and purchase more open market securities. The increase in the supply of loans and demand for bonds by banks leads to a fall in bank loan and open market interest rates. Consequently, the degree of interest rate pass through in the long run between bank loan rates and the federal funds rate is a simple and direct measure of this channels potency.

While the literature on the immediate effect of changes in the federal funds rate on interest rates is quite extensive, much less attention has been paid to the long-run effect on bank loan rates.[1] For example, once known as the "favored customer" loan rate, the prime rate is now used as an interest rate floor in the pricing of many types of adjustable rate bank loans.[2] As such, the prime rate is a suitable proxy for the marginal lending rate in the bank loan portfolio.

Following the literature, we measure interest rate pass through in the long run by testing for the existence of a common stochastic trend between the prime rate and the conventional

[1] Some notable exceptions include, Scholnick (1999), Payne (2006a), Payne (2006b), and Payne (2007) which all measure the degree of interest rate pass through in the long run between residential mortgage rates and the federal funds rate. Moreover, the cointegration relationship between the federal funds and prime rate has been examined in Atesoglu (2003) and Payne and Waters (2008).

[2] For example, short-term corporate loans, credit card loans, small business loans, private student loans, and adjustable rate mortgages are all loans that can reference the prime rate.

instrument of monetary policy in the U.S., the federal funds rate. (Bernanke and Blinder, 1992) In contrast, however, we introduce the recently developed “residual augmented least squares” (RALS) cointegration tests proposed by Lee et al. (2015) in our analysis for two important reasons.

First, in comparison to conventional nonlinear cointegration tests, the RALS cointegration tests avoid the common practice of pre-specifying a particular density function or functional form. Given that tests based on linear models will lose power in the presence of nonlinearity, the conventional approach is to assume the precise form of the nonlinearity. However, this method can be complicated due to nuisance parameter issues in non-linear functions, potential power loss due to misspecification, and proper selection of non-linear estimation techniques. Distinctively, however, the RALS testing procedures are free of these problems.

Second, the new tests utilize information in non-normal errors that have been ignored in the literature on testing for cointegration. As pointed out in Lee et al. (2011), popular nonlinear tests assuming a particular nonlinear functional form with normal errors tend to suffer from power loss in the presence of non-normal errors, unlike linear based tests. However, the RALS estimator gains power when using a linear model in the presence of non-normal errors. To the best of our knowledge, this is the first empirical study that applies the information in non-normal errors to the monetary transmission mechanism.

The rest of the paper proceeds as follows. The next section outlines the traditional approach for testing for a cointegrating relationship between the prime and federal funds rates along with the RALS methodology. The third section presents the empirical results along with a discussion of the results. The fourth and final section concludes.

2. Methodology

We begin this section with a discussion of a simple cointegrated VAR (1) model, $y_t = (p_t, f_t)'$.[3] Here p_t denotes the prime rate and f_t denotes the federal funds rate. We then introduce the single equation cointegration test used in our analysis.

The general VAR(1) model for y_t is:

$$y_t = \gamma + \Gamma y_{t-1} + \epsilon_t \tag{1}$$

where $\epsilon_t \sim iid(0, \Omega)$ and $\Omega = \begin{bmatrix} \sigma_{pp} & \sigma_{pf} \\ \sigma_{fp} & \sigma_{ff} \end{bmatrix}$. Equation (1) can be rewritten as:

$$\Delta y_t = \gamma + \mathrm{B} y_{t-1} + \epsilon_t \tag{2}$$

where $\mathrm{B} = \Gamma - \mathrm{I}$. With the normalized cointegrating vector of $(1, -\beta_f)'$, equation (2) can be represented as the vector error correction model (VECM).

$$\Delta p_t = \gamma_p + \alpha_p\left(p_{t-1} - \beta_f f_{t-1}\right) + \epsilon_{pt} \tag{3a}$$

$$\Delta f_t = \gamma_f + \alpha_f\left(p_{t-1} - \beta_f f_{t-1}\right) + \epsilon_{ft} \tag{3b}$$

[3] In general, one may consider VAR(p) representation; we suppress Δy_{t-1}, Δy_{t-2}, $\cdots$, Δy_{t-p} for ease of exposition.

By assuming weakly exogenous f_t with respect to $(\alpha_p, \beta_f)'$, the coefficient on the error correction term, α_f, becomes 0. Then, α_p and β_f can be efficiently estimated from the following conditional error correction model (ECM):

$$\Delta p_t = \gamma_p + \delta\left(p_{t-1} - \beta_f f_{t-1}\right) + \varphi\Delta f_t + e_t \tag{4}$$

where $\delta = \alpha_p$, $\varphi = \sigma_{pp}^{-1}\sigma_{pf}$, and e_t is uncorrelated with ϵ_{ft}.

One useful representation of the conditional ECM in (4) is the conditional autoregressive distributed lag (ADL) model proposed by Banerjee et al. (1998):

$$\Delta p_t = \gamma_p + \alpha_p p_{t-1} + \lambda f_{t-1} + \varphi\Delta f_t + e_t \tag{5}$$

where $-\alpha_p\beta_f = \lambda$. This ADL model has been widely adopted in the literature due to it having important testing advantages over other representations.[4] For example, the ADL test tends to be correctly sized and more powerful than other single equation based tests. In addition, the ADL test is free from a nuisance parameter issue unlike conditional ECM tests (see Zivot, 2000).

In their landmark paper, Engle and Granger (1987; EG) suggested a residual based cointegration test. The EG cointegration test is based on the *t*-statistics given by the null hypothesis of $\delta = 0$ in the following Augmented Dickey-Fuller (ADF) regression:

$$\Delta\hat{u}_t = \delta\hat{u}_{t-1} + e_t \tag{6}$$

[4] For example, see Li and Lee (2010) and Banerjee et al. (2016).

where $\hat{u}_t$ is the residual from the least squares estimation (LS) of the following long-run regression:[5]

$$p_t = d_t + \phi f_t + u_t \tag{7}$$

where d_t denotes a deterministic term which possibly includes either a constant ($d_t = \alpha$) or a constant and linear trend ($d_t = \alpha + \varrho t$).

When estimating the interest rate pass through in the long run between the prime rate and the federal funds rate, the deterministic term only includes the intercept.[6] The intercept, α, is interpreted as a constant loan intermediation margin and the slope coefficient, ϕ, infers the degree of interest rate pass through in the long run from the federal funds rate to the prime rate.

Although the EG test is easy to implement and quite intuitive, its weaknesses are well documented. According to Kremers et al. (1992) and Ericsson and MacKinnon (2002), the EG testing regression given by (6) imposes an assumption that constrains the identicalness of the short-run parameter (φ) and the long-run parameter (β_f). As this so-called common factor restriction is diminished in practice (i.e., the long-run and short-run coefficients are different from each other), the EG tests tend to lose power. To circumvent this issue, Lee and Lee (2015) propose a modification of the EG test by augmenting equation (6) with its first differenced independent regressor.

$$\Delta\hat{u}_t = \delta\hat{u}_{t-1} + \kappa\Delta f_t + e_t^* \tag{8}$$

[5] Also known as the cointegration regression. (Engle and Granger, 1987)
[6] For example, see Frexias and Rochet (1997) and Payne and Waters (2008).

$$= \delta \hat{u}_{t-1} + e_t \tag{8'}$$

where $\hat{u}_t$ is the residual from the LS estimation given by (7).

Although these approaches to testing for cointegration are all well cited, they ignore potentially useful information if the errors are non-normal. For example, more often than not it is assumed that the error term is normally distributed. Yet, this assumption is not necessary for the asymptotic properties of tests for cointegration to hold in general. Hence, it would be worthwhile if one can utilize certain properties from non-normal errors to improve performances of a testing procedure. Recently, Lee and Lee (2015) proposed a simple modification of single equation based cointegration tests by doing just that.[7] Specifically, the "residual augmented least squares" (RALS) cointegration tests exploit the second and third moments of residual series $\hat{e}_t$ obtained from conventional cointegration tests by constructing a new term, $\widehat{w}_t$.

$$\widehat{w}_t = h(\hat{e}_t) - \widehat{K} - \hat{e}_t \widehat{D}_2, \qquad t = 1, \cdots, T \tag{9}$$

where $h(\hat{e}_t) = [\hat{e}_t^2, \hat{e}_t^3]'$, $\widehat{K} = \frac{1}{T}\sum_{t=1}^{T} h(\hat{e}_t)$, and $\widehat{D}_2 = \frac{1}{T}\sum_{t=1}^{T} h'(\hat{e}_t)$. By letting $\widehat{m}_j = \frac{1}{T}\sum_{t=1}^{T} \hat{e}_t^j$ where $j = 2, 3$, the newly added term $\widehat{w}_t$ can be represented by:

$$\widehat{w}_t = [\hat{e}_t^2 - \widehat{m}_2, \hat{e}_t^3 - \widehat{m}_3 - 3\widehat{m}_2 \hat{e}_t]'. \tag{10}$$

We can thus describe the RALS ADL and RALS EG2 cointegration tests as follows: [8]

$$\Delta p_t = d_t + \delta p_{t-1} + \lambda f_{t-1} + \varphi \Delta f_t + \widehat{w}_t{}'\psi + v_t \tag{11}$$

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[7] Im and Schmidt (2008) introduced the procedure in the OLS framework and the idea was adapted to tests for stationarity by Im et al. (2014) and Meng et al. (2013).

[8] The simulation results of Lee et al. (2015) show that the RALS ECM test shows size distortions and the power of the RALS ADL and RALS EG2 tests tend to dominate that of the RALS EG test; therefore, we only consider the RALS ADL and RALS EG2 test in our experiment.

$$\Delta \hat{u}_t = c + \delta \hat{u}_{t-1} + \kappa \Delta f_t + \hat{w}_t{}' \psi + v_t \tag{12}$$

where d_t denotes a deterministic term which includes either a constant ($d_t = \alpha$) or a constant and linear trend ($d_t = \alpha + \varrho t$), c is a constant, and $\hat{u}_t$ is the residual from the LS estimation (7). In more general cases, lags of Δp_t and Δf_t are allowed to control for possible serial correlation in v_t. Similarly, lags of $\Delta \hat{u}_t$ are allowed in the RALS EG2 regression given by (12).

The first and second terms in $\hat{w}_t$ are constructed based on the moment conditions implying no heteroscedasticity and zero normalized kurtosis that arise as properties of the normal distribution. Under non-normal distributions, these conditions yield non-negligible stationary terms that can be considered as stationary covariates as suggested by Hansen (1995). Accordingly, augmenting these terms into each testing regression reduces the magnitude of error variance in the testing regression and results in a more powerful test.

When implementing the RALS ADL and EG2 tests, the null hypothesis of no cointegration is tested against the alternative of the presence of cointegration. That is,

$$H_0: \delta = 0 \qquad \text{against} \qquad H_1: \delta < 0.$$

The null hypothesis is tested using the *t*-ratio obtained from equations (11) and (12) respectively. As pointed out in Lee et al. (2015), critical values of the two RALS cointegration tests depend on a long run correlation coefficient of ρ^2:

$$\rho^2 = \frac{\sigma_{ev}^2}{\sigma_{ee}\sigma_{vv}} \tag{13}$$

where $\Omega = \begin{pmatrix} \sigma_{ee} & \sigma_{ev} \\ \sigma_{ve} & \sigma_{vv} \end{pmatrix}$. To find the appropriate critical values, the nuisance parameter in the limiting distributions has to be estimated using the following nonparametric technique:

$$\widehat{\Omega} = \begin{pmatrix} \hat{\sigma}_{ee} & \hat{\sigma}_{ev} \\ \hat{\sigma}_{ve} & \hat{\sigma}_{vv} \end{pmatrix} = \sum_{k=-\xi}^{\xi} W(\tfrac{k}{\xi}) \tfrac{1}{T} \sum_{t=k+1}^{T} \hat{V}_t \hat{V}'_{t-k}, \tag{14}$$

where $W(\cdot)$ is a Bartlett or Parzen kernel weight function, ξ is a bandwidth parameter and $\hat{V}_t = (\hat{e}_t, \hat{v}_t)$. For the RALS ADL and RALS EG2 tests, $\hat{V}_t = (\hat{e}_t, \hat{v}_t)$ is constructed from the residuals from (5) and (11) or (8′) and (12) respectively. The empirical critical values (T=100) for various range of ρ^2 is given in Lee et al. (2015) and it can be interpolated with respect to a certain value of ρ^2.

3. Data and empirical results

This section presents the estimation results for the long-run interest rate path through of the federal funds rate to the prime rate. The variables we use in our estimation are the monthly prime interest rate and the effective federal funds rate.[9] Our sample is from February 1987 to February 2015. Each observation was collected and published by the Federal Reserve Board of Governors in its H.15 release. Figure 1 is a time series graph of the prime rate and federal fund rate over our full sample.

[Insert Figure 1]

Clearly, the prime rate and the federal funds rate display similar patterns over time. Although each variable exhibits its individual characteristics, the stable tendency of co-movement is undeniable. To test the hypothesis of co-movement formally, we carry out cointegration analysis between the two interest rates. We begin with the augmented Dickey–

[9] Both interest rates are averages of daily figures.

Fuller (ADF) and Phillips–Perron (PP) unit root tests. The results are reported in Table 1. The model with a constant (C) and the model that includes both a constant and trend (CT) reveal that the two variables are both integrated of order one. Consequently, it is safe to say that statistically, both the prime and federal funds rates exhibit unit root behavior and their first differences are stationary, which are necessary conditions for applying tests for cointegration.

[Insert Table 1]

Testing for cointegration is performed over three different sample periods. For comparison, our first regime is from 1987:02 to 2005:10 which is the same sample used by Payne and Waters (2008). The second and third sample we use covers 1987:02 to 2008:12 and 1987:02 to 2015:02. Breaking our sample into these two periods allows us to measure the impact of the zero lower bound on the long run relationship between the two rates.[10]

[Insert Table 2]

Four different single equation based cointegration tests as described in Section 2, namely ECM, ADL, EG, and EG2 were carried out for comparison. To ensure no serial correlation in the residual for each testing regression given by (4), (5), (6) and (8), the number of lags is chosen based on the t-statistics approach as is standard in literature. In ECM and ADL tests, lags of Δp_t and Δf_t are selected by specific to general methods to minimize the loss of efficiency that may be caused by including a large number of additional terms. For the EG and EG2 tests, lags of $\Delta \hat{u}_t$ are selected by general to specific methods with the maximum number of lag of 12.

[10] On December 16, 2008 the Federal Open Market Committee established a target range for the federal funds rate of zero to a quarter percent.

Panel (B) of Table 2 presents the estimation results of equation (7). As defined earlier, the intercept represents the loan intermediation margin and averages 3.28% over our full sample. The slope estimate, the measure of long-run pass through, is 0.88. Comparing the estimated slopes over the three samples we can conclude that the degree of long-run pass through is less than 1. This result implies incomplete pass through from the federal funds rate to the prime rate as found by Atesoglu (2003). However, we can see from the EG results in Panel (A) that there is insufficient statistical evidence to reject the null hypothesis of no cointegration at the 1, 5, and 10 percent levels. Furthermore, a cointegration relationship is not supported by any other conventional test used.

The non-rejection by conventional tests could be attributed to low power from the omission of on-going nonlinearities, structural breaks, or asymmetric adjustments of the series. As a result, many researchers consider procedures that allow for potential nonlinearity or structural breaks. However, it is not easy to distinguish clearly between any non-linear structure and non-normality in the data. In fact, it is appropriate to say that the use of non-normal errors, because they can reflect at least partly neglected nonlinearity, is an approach robust to the type of misspecification that can arise in this situation. In this sense, one should prefer a linear testing procedure that improves testing power by exploiting existing information about non-normality, instead of assuming a prior that specifies the type of nonlinearity. Following this line of argument, we, therefore, apply the RALS cointegration tests of Lee et al. (2015).

Implementing the RALS ADL cointegrating methodology is done in the following manner. We firstly obtain the residuals from the ADL testing equation given in (5) and construct the newly added term $\widehat{w}_t$ which is described in (9) and (10). By augmenting $\widehat{w}_t$ to (5), the RALS ADL testing regression in (11) is obtained. In order to find the appropriate critical value, we estimate the squared long-run correlation coefficient in (13) via the nonparametric technique in (14) with the two residual series from (5) and (11). [11]

[Insert Table 3]

To ensure no serial correlation, the number of lags included for each test is determined the same way as conventional tests. The results of the RALS ADL and EG2 tests are reported in Table 3. The RALS ADL model provides noticeably different results. Based on the computed *t*-statistics, the RALS ADL rejects the null hypothesis of no cointegration over all three samples.

Based on the sample period 1, Payne and Waters (2008) concluded that the federal funds rate and prime rate were cointegrated but only after allowing an endogenous break in the nonlinear momentum threshold cointegration model. They then reasoned that non-rejection of the conventional cointegration test is related to its low power property caused by neglecting a non-linearity or structural changes in the data. As a result, they assume asymmetric nonlinearity and choose to model the cointegrating relationship using the Enders-Skilos (2001) momentum threshold autoregressive model.

The RALS testing approach introduces a way to increase the power of conventional cointegration tests in the presence of non-normal errors while avoiding to take a stand on the specific non-linearity form or to require any specific non-linear estimation technique. Using the RALS cointegration tests we obtained the following result for sample 1:

[11] Note that an analogous RALS EG2 testing regression can be obtained. The only difference between the two tests is that the residual used to construct $\widehat{w}_t$ is obtained from the equation (8′), which is same as EG regression of (6).

$$\Delta p_t = 0.172 - \underset{(-3.605)}{0.054}\, p_{t-1} + \underset{(3.880)}{0.050} f_{t-1} + \underset{(22.927)}{0.747}\, \Delta f_t - \underset{(-1.427)}{0.389}\, \hat{w}_{1t} + \underset{(10.091)}{8.779}\, \hat{w}_{2t}$$

$$+ \textstyle\sum_{i=1}^{3} \Delta f_{t-i} + \sum_{i=1}^{3} \Delta p_{t-i}$$

The coefficient of the variable p_{t-1} has a *t*-statistic of -3.605. Note that the critical value for the RALS ADL test depends on the long-run correlation coefficient estimate of 0.677. Moreover, from Table 4, the 1%, 5%, and 10% critical values are -3.856, -3.238, and -2.907, respectively. Hence, we can reject the null hypothesis at the 5% level and conclude that the variables are cointegrated.[12] Contrary to the results from the conventional cointegration tests, our empirical findings provide significant support for the long-run interest rate path through over all considered sample periods.

4. Conclusion

In order for conventional monetary policy to be effective, changes in the policy rate must pass through in the long run to the bank loan and open market rates. Thus the degree of long-run pass through is important because it measures the influence of policy actions on the economy.

This study measures the degree of interest rate pass through in the long run by testing the stochastic co-movement between the federal funds rate and prime rate from 1987 to 2015. Using four different established cointegration tests, namely the ECM, ADL, EG, and EG2 tests, we are

[12] One may have a question why the RALS EG2 test performs worse than RALS ADL test. As pointed out in Lee and Lee (2015), the EG2 regression becomes more powerful when the common factor restriction (CFR) holds. As the CFR becomes invalid, the newly added differenced term becomes redundant and we cannot expect significant efficiency gains. It seems the CFR varies across data and that the power of the EG2 test becomes more evident in a certain type of data.

unable to reject the null hypothesis of no cointegration. However, the results from cointegration tests exploiting information embedded in non-normal errors lead to an alternative conclusion. Specifically, the support for co-movement between the federal funds rate and prime rate irrespective of the regime considered. Thus we are not only able to find a significant cointegration relationship between these two interest rates, but also are able to confirm the degree of interest rate pass through in the long run is less than one.

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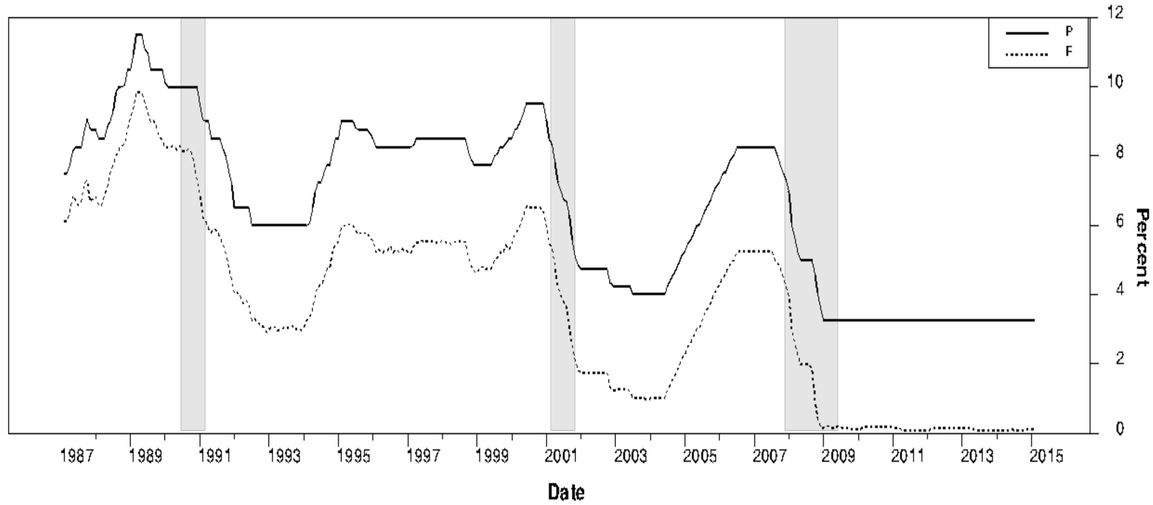
Figure 1 Prime rate and federal funds rate, February 1987 to February 2015



*Note: Figure 1 plots the prime rate (p_t) and the federal funds rate (f_t) from February 1987 to February 2015. The shaded lines are NBER recession dates.

Table 1 Unit root tests

Variable	ADF(C)	ADF(CT)	PP(C)	PP(CT)
p_t	−1.367	−2.680	−0.846	−2.235
Δp_t	−4.065***	−7.309***	−9.678***	−9.711***
f_t	−1.382	−2.557	−0.873	−2.032
Δf_t	−4.017***	−7.235***	−9.494***	−9.503***

*Note: Critical values of the ADF and Philips-Perron tests with a constant, denoted by ADF(C) and PP(C), are (1%) −3.46, (5%) −2.87, and (10%) −2.57. Critical values of the ADF and Philips-Perron tests with a constant and trend, denoted by ADF(CT) and PP(CT), are (1%) −3.99, (5%) −3.43, and (10%) −3.14. ***, **, and * signify rejections at 1%, 5%, and 10%, respectively.

Table 2 Conventional tests

(A)			
Tests	$t_{\hat{\delta}}$	lags	
Period 1			
ECM	-1.612	3 (2.056)	3 (2.052)
ADL	-2.739	3 (-2.040)	3 (-1.898)
EG	-1.921	11 (-3.121)	
EG2	-1.776	11 (-3.158)	
Period 2			
ECM	-1.278	3 (2.177)	3 (-2.135)
ADL	-3.140	3 (2.209)	3 (-1.964)
EG	-3.069	4 (2.254)	
EG2	-3.002	4(2.196)	
Period 3			
ECM	-1.768	3 (3.128)	3 (-2.724)
ADL	-3.367*	3 (3.090)	3 (-2.553)
EG	-3.311	4 (1.738)	
EG2	-3.456*	4(1.686)	

(B)			
	α	f_t	R^2
Period 1	3.48***	0.841***	0.961
	(57.13)	(73.89)	
Period 2	3.50***	0.843***	0.962
	(64.36)	(80.77)	
Period 3	3.28***	0.881***	0.98
	(103.42)	(127.97)	

*Note on Panel (A): The third and fourth column of the table show numbers of lag included and *t*-statistics for the last lagged regressors are reported in the parenthesis. In case of ADL and ECM tests, the third and fourth columns contain number of Δp_t and Δf_t, respectively. In case of EG and EG2 tests, number of $\Delta \hat{u}_t$ is included in the third column. The 1%, 5%, and 10% critical values for ECM, ADL, EG, and EG2 when *T*=500 are: -4.103, -3.527, -3.208; -4.095, -3.520, -3.200; -4.306, -3.767, -3.468, and -4.103, -3.527, -3.208, respectively. ***, **, and * signify rejections at 1%, 5%, and 10%, respectively. *Note on Panel (B): *t*-statistics of estimated coefficients in long-run regression are reported in the parenthesis. ***, **, and * signify rejections of the null hypothesis at 1%, 5%, and 10%, level respectively.

Table 3 RALS cointegration tests

Tests	$t_{\hat{\delta}}$	lags		$\hat{\rho}^2$
Period 1				
RALS ADL	-3.605**	3 (2.540)	3 (-2.594)	0.677
RALS EG2	-1.543	11 (-2.688)		0.714
Period 2				
RALS ADL	-4.042***	3 (2.694)	3 (-2.561)	0.677
RALS EG2	-1.707	4 (-2.864)		0.714
Period 3				
RALS ADL	-4.727***	3 (3.862)	3 (-3.333)	0.677
RALS EG2	-1.998	4 (-2.841)		0.714

*Note: The third and fourth column of the table show numbers of lag included and *t*-statistics for the last lagged regressors are reported in the parenthesis. In case of RALS ADL, the third and fourth columns contain number of Δp_t and Δf_t, respectively. In case of RALS EG2, number of $\Delta \hat{u}_t$ is included in the third column. ***, **, and * signify rejections at 1%, 5%, and 10%, respectively.

Table 4 Critical values for RALS cointegration tests (*T*= 500)

		RALS ADL			RALS EG2		
Model	ρ^2	1%	5%	10%	1%	5%	10%
	0.1	-2.968	-2.277	-1.907	-3.066	-2.374	-2.028
	0.2	-3.185	-2.531	-2.169	-3.372	-2.697	-2.343
	0.3	-3.398	-2.734	-2.371	-3.560	-2.904	-2.559
	0.4	-3.533	-2.885	-2.526	-3.692	-3.066	-2.745
C	0.5	-3.678	-3.017	-2.675	-3.851	-3.227	-2.905
	0.6	-3.749	-3.122	-2.782	-3.922	-3.336	-3.020
	0.7	-3.856	-3.238	-2.907	-4.066	-3.459	-3.156
	0.8	-3.936	-3.339	-3.014	-4.160	-3.571	-3.266
	0.9	-4.032	-3.434	-3.106	-4.242	-3.680	-3.375
	1.0	-4.095	-3.520	-3.200	-4.303	-3.763	-3.465
	0.1	-2.968	-2.277	-1.907	-3.066	-2.374	-2.028
	0.2	-3.185	-2.531	-2.169	-3.372	-2.697	-2.343
	0.3	-3.398	-2.734	-2.371	-3.560	-2.904	-2.559
	0.4	-3.533	-2.885	-2.526	-3.692	-3.066	-2.745
CT	0.5	-3.678	-3.017	-2.675	-3.851	-3.227	-2.905
	0.6	-3.749	-3.122	-2.782	-3.922	-3.336	-3.020
	0.7	-3.856	-3.238	-2.907	-4.066	-3.459	-3.156
	0.8	-3.936	-3.339	-3.014	-4.160	-3.571	-3.266
	0.9	-4.032	-3.434	-3.106	-4.242	-3.680	-3.375
	1.0	-4.095	-3.520	-3.200	-4.303	-3.763	-3.465

*Note: Model C and CT denotes a model with a constant and a model with a constant and trend, respectively.