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International Mobility of Capital in the United States: Robust Evidence from Time-Series Tests

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Abstract: This study examines the relationship between domestic saving and investment and measures the international mobility of capital in the United States. The long-run model, “with” and “without” structural breaks, is estimated using several single-equation and system estimators to assess the robustness of results and take an exhaustive account of the methodological and measurement issues. The results provide dominant support for the long-run relationship between domestic saving and investment. The estimates of the slope parameter on saving above zero and the dominant support for cointegration between saving and investment across estimators vindicate the validity of intertemporal budget constraint and suggest the sustainability of current account deficits. The numerical magnitude of the slope parameter on saving is consistently low across estimators. The results showing the low slope parameter on saving resonate with the observed high mobility of capital. The estimates of the model with structural breaks reinforce the dominant support for the long-run relationship between domestic saving and investment. The inclusion of these structural breaks in the model generally reduces the numerical magnitude of the slope parameter on saving and suggests the high mobility of capital.

Keywords: saving, investment, capital mobility, cointegration, structural breaks

JEL Classification: E21, E22, F21, F32, F41

1 Introduction

The international mobility of capital remains an area of unresolved controversy in the open economy macroeconomics. The Mundell-Fleming model (Mundell 1962, 1963; Fleming 1962) postulates the perfect mobility of capital and frictionless integration of international financial markets. The influential paradigm pioneered

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by Feldstein and Horioka (1980) provides a contrary dimension to current account (saving minus investment) and suggests the imperfect mobility of capital and the near-autarkic behaviour of international capital markets. Feldstein and Horioka (FH) find high long-run correlations between domestic saving and investment for the OECD countries, and they interpret these results in terms of the immobility of capital and imperfect integration of international capital markets. The high saving-investment (SI) correlations (small size of current accounts) in the wake of high mobility of capital, as manifested by large capital flows, competitive returns on financial assets and persistent current account imbalances in the OECD countries, marked an unresolved puzzle. Obstfeld and Rogoff (2000) characterise high SI correlations and high mobility of capital as one of the six major puzzles in the international macroeconomics. The micro-founded intertemporal optimization approach to current account that came into vogue almost contemporaneously with the FH strand, since the early-1980s, generally accepts the findings of numerically high and statistically significant SI correlations in FH strand, but it develops several theoretical channels to explain these correlations in the wake of high mobility of capital; see Singh (2007) for a survey. It views high SI correlations as the corollary of current account solvency constraint, rather than as an index of capital immobility. The intertemporal budget constraint may not allow the countries to run high and perpetual current account deficits, and the solvency constraint requires the long-run relationship between domestic saving and investment. The SI correlations, thus, tend to be high, regardless of the degree of capital mobility and financial openness of the economy.

The econometric methodology remains central to the empirical findings and, as such, a part of the FH puzzle could be ascribed to the methodological and measurement problems surrounding the SI correlations. The endogeneity of saving, omitted variables model mis-specification bias, serial-correlation of residuals and the heteroscedasticity of residual variance could induce bias in SI correlations, as the unobserved and unspecified factors that affect investment could also contemporaneously affect the behaviour of saving.¹ The time-averaged SI series used in FH cross-sectional regressions may induce bias in SI correlations and possibly lead to the rejection of capital mobility. The endogeneity of regressors makes the standard least squares estimates biased and inconsistent, and overturns the statistical inference. The efficiency of the instrumental

¹ The degree of the omitted variables model mis-specification bias, however, may depend on the relationship between omitted variables and regressors included in the model. Such bias sometimes may only be a small sample problem, if the omitted variables are $I(0)$ and the regressors included in the model are $I(1)$. The model mis-specification bias may tend to become negligible or close to null in the large samples.

variables (IV) or generalised method of moments estimators, commonly used to alleviate endogeneity, hinges heavily on the quality (weak or strong) and validity (orthogonality) of instruments. The instruments that are weakly related to endogenous regressors (weak instruments) and are non-orthogonal to the Gaussian disturbances (invalid instruments) can still produce biased and inconsistent estimates. The weak instruments may yield biased two-stage least squares (2SLS) estimates even in large samples (Bound, Jaeger, and Baker 1995; Staiger and Stock 1997). When several regressors in a model are instrumented, then the validity requirements for the instruments used for endogenous regressors become even more stringent (Staiger and Stock 1997). It is, in fact, difficult to find appropriate instruments that are strongly correlated with endogenous regressors, but are uncorrelated with the Gaussian disturbances. The paradigm shift in time-series econometrics since the late-1980s fashioned the use of several optimal estimators developed in both single-equation and vector autoregression (VAR)-based system settings. These estimators resolve the problems of “spurious regression,” serial-correlation and long-run endogeneity, and provide efficient parameter estimates.

Most time-series studies examining SI correlations have implicitly assumed a temporally stable and time-invariant parameter vector and, thus, have estimated the long-run model without allowing structural breaks in the cointegrating vector (Miller 1988; Leachman 1991; Coakley, Kulasi, and Smith 1996; Jansen 1996; Coiteux and Olivier 2000; Levy 2000; De Vita and Abbott 2002; Caporale, Panopoulou, and Pittis 2005; Nell and Santos 2008). The financial markets are vulnerable to the speculative (systematic or stochastic) expectations (rational or irrational) of international investors and, as such, are susceptible to the structural breaks and regime switches. The possibilities of structural breaks become particularly pronounced when the relationship between the model series is examined over a longer time-horizon. The structural breaks reduce the power of cointegration tests and weaken the robustness of statistical evidence obtained from the standard one-regime models with time-invariant parameters. A few studies that attempt to account for structural breaks (Sarno and Taylor 1998a, 1998b; Evans, Kim, and Oh 2008) employ the standard estimators/tests that assume a single structural break and/or implicitly rely on the assumption that the post-breakdown periods are relatively long and on the asymptotics in which the length goes to infinity with the sample size. The cointegration breakdowns could occur even over the short time periods such as at the end of the sample.

This study examines the relationship between domestic saving and investment and measures the international mobility of capital in the United States. The persistent current account deficits, reserve-currency characteristic of the U.S. dollar and the commonly observed high preferences for the U.S. financial assets

are among the key catalysts that contributed to the mobility of capital into the U.S. The episodes of economic and financial crises ranging from the Great Depression of the early-1930s to the recent global financial crises of the late-2000s consistently suggest that the economic states (booms and recessions) of the goods and financial markets in the U.S. have significant bearing on the states of the goods and financial markets in the world economy. The evidence obtained from the U.S., as such, would be a useful approximation to the international mobility of capital and the integration of financial markets. The novelty of the study merits attention on two counts. First, most studies estimating FH model have drawn conclusions from the estimates of a single or select estimators and such a reliance could lead to biased assessment in terms of both statistical inference and magnitudes of the long-run parameters. The study estimates the model using several single-equation and system estimators to assess the robustness of results and take an encompassing account of the methodological and measurement issues. Second, the study estimates the model “with” and “without” structural breaks to discern the possible dispersion in the magnitude of the slope parameter on saving across regimes. The remainder of the study is structured as follows. Section 2 specifies the model. Section 3 presents the empirical results. Section 4 sums up the conclusions.

2 The Model

The reduced-form bi-variate FH model is estimated to examine the long-run relationship between domestic saving and investment and measure the international mobility of capital.

$$[I/Y]_t = \alpha + \beta[S/Y]_t + \varepsilon_t; \quad t \in [1, \dots, T] \quad [1]$$

In model [1], the saving, S , is measured in terms of the gross saving, investment, I , in terms of the gross capital formation (gross fixed capital formation plus inventories) and output, Y , in terms of the gross domestic product (GDP); all at current prices. The ratios of saving, $[S/Y]$, and investment, $[I/Y]$, are expressed in percent, and hence represent the respective rates of saving and investment (hereafter saving and investment or SI). The $\partial[I/Y]/\partial[S/Y] = \beta \in [0, 1]$ is the slope parameter on saving and it shows the proportion of incremental saving retained and invested in the country of origin. The residual term, $\varepsilon_t \sim (0, \sigma_\varepsilon^2)$, follows the usual Gaussian iid properties. Model [1] is estimated on annual data from the United States for the period 1948–2007. All the data are sourced from the CDROM version of the International Financial Statistics, International Monetary Fund.

The macroeconomic identity, $Y = C + I + G + (X - M)$, rearranged as, $(S - I) = (X - M)$, suggests that the current account is in (i) deficit when $(S - I) = (X - M) < 0$, (ii) surplus when $(S - I) = (X - M) > 0$ and (iii) balance when $(S - I) = (X - M) = 0$; where Y denotes output (GDP), C consumption, G government spending, and the X exports and M imports of goods and services. The identity, $(S - I) = (X - M)$, can be represented as, $I = S - (X - M)$, and, by dividing both sides by Y , as, $I/Y = S/Y - (X - M)/Y$. This suggests that the domestic investment in an open economy is financed by both domestic saving, S , and foreign saving, S^* , such that $I = S - (X - M) = S + S^*$; where $S^* = -(X - M) = \text{CAD}$ and that CAD denotes the current account deficit. The higher the proportion of saving retained in the domestic economy, the lower the proportion is borrowed from or lent to the international financial markets. In a complete financial autarky with $\beta = 1$ in model [1] and $(S - I) = (X - M) = 0$, all domestic investment is financed by domestic saving, S , and there are no borrowing and lending across countries and, as such, no international mobility of capital. On a diametrically opposite end of the spectrum with $\beta = 0$ in model [1] and $I = -(X - M) = \text{CAD} = S^*$, all domestic investment is financed by foreign saving, S^* , and implied borrowing from the international capital markets. There is, thus, a frictionless mobility of capital and the perfect integration of domestic capital market into the world pool of capital. The intermediate state with $0 < \beta < 1$ characterises the current account imbalances, $(X - M) \neq 0$, and the moderate mobility of capital. The $\beta = 0.5$, for example, implies that a half of the increment in domestic investment is financed by the increment in domestic saving and the remaining half is financed by the borrowing from the international financial markets. The study considers the mobility of capital as (i) high when β is low, $0 \leq \beta < 0.50$, (ii) moderate when β is moderate, $0.50 \leq \beta < 0.75$ and (iii) low when β is high, $0.75 \leq \beta \leq 1$.

3 Empirical Results

3.1 Unit Root Tests

The unit root tests are first performed to examine the time-series properties of the model series. Such an analysis assumes particular importance for the FH model, as, *prima facie*, it may seem puzzling to recognise the $I(d)$ property of the ratio of two possibly $I(d)$ series of saving (and investment) and GDP; where the order of integration $d \geq 1$ (Levy 2000). Since the rates of saving and investment

are bounded between zero and one, these rates may be persistent, rather than $I(1)$ processes. It is, however, a common practice to model such bounded persistent series as $I(1)$, rather than stationary, process (Kejriwal 2008). Nicolau (2002) argues that while it is not possible to say that these bounded time-series are random walks, some of these series behave just like random walks. The paths of these bounded random walks are almost indistinguishable from the usual random walks, although these are stochastically bounded by an upper and lower finite limit. Cavaliere (2005) develops an asymptotic theory for the integrated and near-integrated time-series with some constrained range, and shows that the presence of such constraints can lead to drastically different asymptotics. Kejriwal (2008) simulates the critical values corresponding to the bounded unit root distribution for a set of sample countries, and finds that the critical values are the same as those of the standard unit root tests. Hence, the 0–1 bounds on the saving and investment shares are not constraining in any way (Kejriwal 2008).

The results suggest that the augmented Dickey-Fuller (ADF) (Dickey and Fuller 1981) test does not reject the null hypothesis of a unit root in the level series of both saving and investment in the model with drift and no trend (Table 1). The ADF test rejects the null for saving, but not for investment, in the model with drift and trend. The ADF test rejects the null hypothesis in the differenced series of (i) both saving and investment in the model with drift and (ii) only saving in the model with drift and trend. The Phillips-Perron (PP) (Phillips and Perron 1988) test rejects the null hypothesis for the level series of (i) investment, but not saving, in the model with drift and (ii) both saving and investment in the model with drift and trend. The PP test rejects the null for the differenced series of saving and investment in the model estimated with drift as well as with drift and trend. The KPSS (Kwiatkowski, Phillips, Schmidt, and Shin 1992) test rejects the contrary null hypothesis of no unit root in the level series of saving and investment in the model estimated with drift, but not with trend. The KPSS test does not reject the null in the differenced series. The ADF and PP tests have low power, while the KPSS test has a tendency to over-reject the null hypothesis in small samples. The asymptotically powerful DF-GLS, PT, DF-GLSu and QT tests (Elliott, Rothenberg, and Stock 1996; Elliott 1999), based on the generalised least squares (GLS), are carried out to cross-examine the evidence and assess the robustness of results. While the evidence obtained from the GLS-based point optimal tests is somewhat mixed, these tests generally point towards $I(1)$ properties of the model series (Table 1).

The one-regime unit root tests become mis-specified and are not very informative of non-stationarity in the presence of structural breaks in the underlying series. These tests are biased towards non-rejection of the null hypothesis of a unit root, if the underlying series contains a structural break (Perron 1989).

Table 1: Unit root tests without structural breaks.

Series	Conventional Tests			GLS-Based Point Optimal Tests			
	H ₀ : Unit root	H ₀ : No Unit root		DF-GLS(k)	PT (k)	DF-GLSu(k)	H ₀ : Unit root
		PP [lw = 4]	KPSS [lw = 4]				
Level series							
Model I: Drift and No Trend							
I/Y	-3.96*	0.528**	-3.94* (1)	1.26 (1)	-3.91** (1)	2.34 (1)	
S/Y	-1.70	1.074*	-0.24 (2)	17.47* (2)	-0.89 (2)	19.39** (2)	
Model II: Drift and Trend							
I/Y	-4.54*	0.062	-5.06* (1)	3.13 (1)	-5.24** (1)	1.68 (1)	
S/Y	-3.88**	0.141	-4.84* (1)	4.07 (1)	-4.98** (1)	2.23 (1)	
Differenced series							
Model I: Drift and No Trend							
ΔI/Y	-9.95*	0.051	-3.00* (1)	3.86* (1)	-6.98** (1)	2.13 (1)	
ΔS/Y	-9.58*	0.059	-1.27 (2)	17.31* (2)	-4.20** (2)	4.26 (2)	
Model II: Drift and Trend							
ΔI/Y	-9.99*	0.044	-5.26* (1)	5.78* (1)	-6.83** (1)	2.16* (1)	
ΔS/Y	-9.86*	0.040	-1.82 (10)	245.56* (10)	-1.69 (10)	101.25** (10)	

Notes: (1) * and ** indicate the statistical significance and implied rejection of the null hypothesis at 1% and 5% levels, respectively. The critical values are given in (i) Davidson and MacKinnon (1993) for the ADF and PP tests, (ii) Kwiatkowski, Phillips, Schmidt, and Shin (1992) for the KPSS test and (iii) Elliott, Rothenberg, and Stock (1996) and Elliott (1999) for the DF-GLS, PT, DF-GLSu and QT tests; (2) The figures in round parentheses are the number of lags. The truncation lags in ADF test are selected using the Akaike information criterion and those in GLS-based point optimal tests using the modified Akaike information criterion (MAIC) of Ng and Perron (2001). The PP test is performed using the spectral estimation lag windows (lw) of lw = 1 and lw = 4. Similarly, the KPSS test is performed using the lag windows (lw) of lw = 1 and lw = 4 for the residual variance of the Newey-West estimator (Newey and West 1987). The results obtained under both the lag windows provided similar evidence for the null hypothesis. The results are, therefore, reported only for one of the lag windows (lw = 4) for the PP and KPSS tests.

The stationary series may erroneously appear to be non-stationary due to the false non-rejection of the null hypothesis. Perron (1989) provides a test for the null hypothesis of a unit root in the presence of a exogenously determined structural break in the series at the known location. The estimates from the Perron (1989) test, however, could be biased in favour of the rejection of the null hypothesis, as the break-point is not treated as data-dependent and unknown under the alternative hypothesis (Zivot and Andrews 1992). The study uses the endogenous structural break unit root tests of Zivot and Andrews (1992), Lumsdaine and Papell (1997) and Lee and Strazicich (2003, 2004) to test the null hypothesis of a unit root and determine the break-points endogenously from the data. These tests involve the estimation of the model for different break dates using the recursive (rolling or sequential) approach, and then performing the grid-search to locate the most significant break-point, $\pi \in \Pi \subset (0, 1)$, endogenously from the data. The observations are trimmed symmetrically from both beginning and end of the sample space, and the trimmed interval of $\Pi = \{0.15 \times T, 0.85 \times T\}$ is used to perform the grid-search and locate the break-point.

The Zivot-Andrews test tests the joint null hypothesis of a unit root with no structural break against the alternative hypothesis of a one-time break in the series. It sets $y(t) = \alpha + y(t-1) + \varepsilon(t)$ as the null model and uses the minimum t-test statistic (highest absolute t-test, $|t|$, statistic) to test the null hypothesis of a unit root with no structural break. The one-time break, however, could be inadequate and lead to the loss of information in the presence of multiple breaks in the series. Ben-David, Lumsdaine, and Papell (2003) argue that just as the failure to allow one break can cause non-rejection of the unit root null by the ADF test, the failure to allow for two breaks, if they exist, can cause non-rejection of the unit root null by the tests which only incorporate one break. They further argue that allowing for more breaks does not necessarily mean more rejections of the unit-root hypothesis, because the critical value increases in absolute value with the inclusion of more breaks (Ben-David, Lumsdaine, and Papell 2003). Lumsdaine and Papell (1997) extend the Zivot-Andrews test to accommodate up to two structural breaks in the series at the unknown locations. The Lumsdaine-Papell test allows structural breaks only under the alternative hypothesis and not under the null hypothesis analogous to the Zivot-Andrews test. It follows that the rejection of the null hypothesis in both Zivot-Andrews and Lumsdaine-Papell tests does not necessarily imply the rejection of the unit root per se, but would imply the rejection of a unit root without breaks (Lee and Strazicich 2003). The assumption of no break under the null hypothesis often leads to “spurious rejections” of the null hypothesis. Lee and Strazicich (2003, 2004) develop the minimum Lagrange Multiplier (LM)

unit root tests and allow up to two structural breaks under the null hypothesis.² The break-point is determined where the LM t-statistic, obtained from all the possible regressions, is at its minimum (maximum in absolute, $|t|$, term). The study performs the Lee-Strazicich test for both one and two structural breaks, using the “break model.” The results obtained from the structural break unit root tests generally do not reject the null hypothesis of a unit root for the level series, but reject the null hypothesis for the first-differenced series (Table 2). These results provide dominant support for I(1) properties of the model series.

3.2 Tests for Cointegration and the Long-Run Estimates

Most time-series studies have implicitly assumed a temporally stable and time-invariant parameter vector and, thus, have estimated the long-run model without allowing structural breaks in the cointegrating vector (Miller 1988; Leachman 1991; Coakley, Kulasi, and Smith 1996; Jansen 1996; Coiteux and Olivier 2000; Levy 2000; De Vita and Abbott 2002; Caporale, Panopoulou, and Pittis 2005; Nell and Santos 2008). The study first undertakes the base-line analysis and estimates the long-run model in a standard one-regime setting without structural breaks. The model is estimated using (i) the OLS-based estimator of Engle and Granger (OLSEG) (1987), generalized method of moments (GMM) estimator of Hansen (1982), dynamic OLS (DOLS) estimator of Saikkonen (1991) and Stock and Watson (1993), non-linear least squares (NLLS) estimator of Phillips and Loretan (1991) and the fully-modified OLS (FMOLS) estimator of Phillips and Hansen (1990) in a single-equation setting and (ii) the maximum-likelihood system estimator of Johansen (1991) and the over-parameterized level-VAR estimator of Toda and Yamamoto (1995) in a VAR-based system setting. The use of several estimators is intended to assess the robustness of results across methodologies.

2 Lee and Strazicich (2003, 2004) allow for (i) an abrupt change in level, but no change in trend rate, in the “crash model” (denoted as Model A) and (ii) simultaneous changes in both level and trend in the “break model” (denoted as Model C). The asymptotic null distribution of the two-break LM unit root test (i) is invariant to the location ($\lambda = T_B/T$) and magnitude of structural break in the model with one-time change in level (Model A) and (ii) depends on the location ($\lambda = T_B/T$) of structural break in the model with a change in both level and trend (Model C). The critical values in Model C (model with intercept and trend break) are symmetric around λ and $(1-\lambda)$. The study performs the Lee-Strazicich tests, for both one and two structural breaks, using the “break model” (Model C).

Table 2: Unit root tests with structural breaks.

Series	One structural break			Two structural breaks	
	Zivot-Andrews	Lumsdaine-Papell	Lee-Strazicich	Lumsdaine-Papell	Lee-Strazicich
Level series					
Model I: Drift and No Trend					
I/Y	-5.14 (0)	-5.14 (0)	-4.31* (0)	-5.51 (1)	-4.42 (1)
	[1988]	[1987]	[1984]	[1987, 1995]	[1984, 1992]
S/Y	-4.10 (3)	-4.10 (3)	-4.37* (3)	-4.23 (3)	-4.70 (3)
	[1985]	[1984]	[1985]	[1960, 1984]	[1985, 1999]
Model II: Drift and Trend					
I/Y	-5.30 (0)	-5.28 (0)	-4.05 (0)	-6.02** (0)	-5.78** (9)
	[1990]	[1989]	[1989]	[1976, 1994]	[1974, 1989]
S/Y	-4.13 (3)	-4.10 (3)	-4.39 (9)	-4.94 (3)	-5.49 (3)
	[1985]	[1984]	[1983]	[1977, 1996]	[1983, 1995]
Differenced series					
Model I: Drift and No Trend					
$\Delta I/Y$	-6.57* (3)	-6.57* (3)	-2.79 (0)	-7.10* (3)	-3.32 (0)
	[1982]	[1981]	[1979]	[1975, 1993]	[1981, 1989]
$\Delta S/Y$	-8.43* (1)	-8.43* (1)	-2.17 (0)	-8.73* (1)	-2.90 (1)
	[1994]	[1993]	[1985]	[1970, 1993]	[1982, 1989]
Model II: Drift and Trend					
$\Delta I/Y$	-6.62* (3)	-6.60* (3)	-3.44 (0)	-7.83* (3)	-4.49 (6)
	[1996]	[1995]	[1966]	[1975, 1993]	[1966, 1981]
$\Delta S/Y$	-8.52* (1)	-8.53* (1)	-3.59 (3)	-9.26* (1)	-4.79 (10)
	[1994]	[1993]	[1968]	[1981, 1999]	[1968, 1983]

Notes: (1) * and ** indicate the statistical significance at 1% and 5% levels, respectively. The critical values are given in Zivot and Andrews (1992), Lumsdaine and Papell (1997), and Lee and Strazicich (2003, 2004). The critical values depend upon the location of the break-point in the model with trend break in the Lee-Strazicich test (see Lee-Strazicich 2003); (2) The figures in square brackets are the break-points (years); (3) The figures in round parentheses are the number of lags; (4) The lag-length, k , is determined using (i) the Akaike information criterion in the Zivot-Andrews and Lumsdaine-Papell tests and (ii) the general-to-specific approach in the Lee-Strazicich test. The lags are sequentially dropped from the end in the general-to-specific approach, and the significance level of 10% is used as the minimum cut-off to trim the lags.

3.2.1 Standard OLSEG and RLS Estimates

The two-step OLSEG estimator sequentially involves the estimation of a static regression model in levels, $Y(t) = \alpha + \beta X(t) + \varepsilon(t)$, and then the estimation

of an auxiliary, $\varepsilon(t) = \gamma\varepsilon(t-1) + \nu(t)$, or augmented auxiliary, $\Delta\varepsilon(t) = \gamma\varepsilon(t-1) + \sum_{i=1}^k \zeta(i)\Delta\varepsilon(t-i) + \nu(t)$, regression to perform unit root tests on $\varepsilon(t)$ and test $H_0: \varepsilon(t) \sim I(1)$ (no cointegration among $I(1)$ variables) against $H_1: \varepsilon(t) \sim I(0)$ (cointegration among $I(1)$ variables). The study estimates model [1] in levels and performs the ADF and PP unit root tests on $\varepsilon(t)$ to test the null hypothesis of no cointegration against the alternative hypothesis of cointegration between saving and investment. The ADF test is performed using an autoregressive (AR) lag of $k=2$ (as suggested by the Akaike information criterion). The PP test is performed using the lag window (lw) of $lw=4$. The OLS estimates of model [1] and the ADF and PP test statistics for the null hypothesis of a unit root in $\varepsilon(t)$ and the implied null hypothesis of no cointegration between saving and investment are as follows.

$$[I/Y]_t = 12.6363 + 0.4012 [S/Y]_t \quad [2]$$

$$(14.04) \quad (8.39)$$

$$\bar{R}^2 = 0.54; \quad CRDW = 0.91[0.48]$$

$$ADF = -3.4779[-3.34]; \quad PP = -4.1456[-3.34]$$

$$H_0: \beta = 0, \quad t = 8.39; \quad H_0: \beta = 1, \quad t = -12.52$$

The figures in round parentheses are the t-ratios and in square brackets the 5% critical values for the null hypothesis of a unit root in $\varepsilon(t)$ for the ADF, PP (Davidson and Mackinnon 1993) and CRDW (Sargan and Bhargava 1983) tests. Both ADF and PP tests consistently reject $H_0: \varepsilon(t) \sim (1)$ in favour of $H_1: \varepsilon(t) \sim (0)$ and suggest the equilibrium relationship between saving and investment.³ The use of 5% critical values from Phillips and Ouliaris (1990) provides similar evidence. The magnitude of the long-run slope parameter on saving differs from both zero and unity in that the t-ratios reject both $H_0: \beta = 0$ and $H_0: \beta = 1$. The OLSEG estimates, thus, provide consistent support for the equilibrium relationship between the model series.

The equilibrium residuals measure the distance between the actual and forecast series of the model. Another way to test cointegration is to map the movements in the residual process of a cointegrating regression (Xiao 1999; Xiao and Phillips 2002). If the given series are cointegrated, then the residuals of a cointegrating regression should be stable with long-run movements within some critical bounds. Xiao (1999) and Xiao and Phillips (2002) argue that the cumulative sum (CUSUM) of

³ The PP test is also performed using the lag window of $lw=1$. The $PP = -4.2964[-3.34]$ statistic, based on the model with $lw=1$, does not reject the null hypothesis of a unit root in the residuals of model [2]. These results consistently support the cointegrating relationship between saving and investment.

recursive residuals test of Brown, Durbin, and Evans (1975) can be applied to the residuals of a regression to directly test the null hypothesis of cointegration. The study estimates the model using recursive least squares (RLS) to map the time-profile of the disequilibrium residuals and trace the temporal-trajectories of the model parameters. The time-trajectories of both CUSUM and CUSUM of squared residuals (CUSUMSQ) remain well within the 5% critical bounds (Figure 1). The sequential F statistics are scaled by 5% critical value such that the value larger than unity implies rejection and that less than unity the acceptance of the null hypothesis of model stability. The F statistics remain well below the critical unity grid and suggest the temporal stability of the recursive residuals, except for two spikes that cross the critical unity grid. The estimated residuals normally remain within the critical boundaries (Figure 1). The intercept, α , and slope, β , parameters move within the standard error confidence bands and seem temporally stable.

3.2.2 Optimal Single-Equation Estimates

The standard OLS estimates become biased and inefficient in the presence of non-orthogonality of regressors and serial-correlation of residuals. The “super-consistency” property of OLS indeed allows one to omit $I(0)$ regressors from the cointegrating model and asymptotically ignore the problems of endogeneity and serial-correlation.⁴ In small samples, however, the OLS estimates remain biased and have inferential problems for the significance of long-run parameters. The bias is often substantial (Banerjee, Dolado, Galbraith, and Hendry 1993; Inder 1993) and the t statistics of cointegrating coefficients are generally not valid for statistical inference. The commonly used method to alleviate endogeneity is the IV or GMM estimator of Hansen (1982). The GMM has desirable properties in large samples. The standard moment conditions in a linear regression, $y = X\beta + \mu$, require that $E[\mu\mu'] = I\sigma^2$, $E[X'\mu] = E[X'(y - X\beta)] = 0$ and $V[X'\mu] = [X'X]\sigma^2$; where E is the expectation operator, X the matrix of exogenous variables and μ the vector of residuals. The OLS estimators are obtained by minimizing $\mu'\mu = (y - X\beta)'(y - X\beta)$. The OLS parameter estimates should satisfy the moment condition in terms of the orthogonality (zero correlation) between exogenous variables and residual term, such that $E[X'\mu] = 0$. This moment condition, $E[X'\mu] = 0$, could either come from the assumptions about variables or/and be derived from the first-order conditions of an optimization problem. The

⁴ The OLS estimators of a regression are “super-consistent” when the model series are cointegrated. Instead of approaching their true values at a rate proportional to $n^{-1/2}$, the OLS estimates will approach them at a rate proportional to n^{-1} (Davidson and Mackinnon 1993).

Figure 1: Recursive least squares estimates and the temporal stability of the model.

condition is operationalized by replacing the expectation operator, E , by the sample average, $T^{-1} \sum_{t=1}^T X'_t(y_t - X_t\beta) = 0$.

If the orthogonality condition is not satisfied such that $E[X'\mu] \neq 0$, then it is essential to replace X by some instrument set, Z , and minimize $E[Z'\mu]$ so that $E[Z'\mu] = 0$ and $V[Z'\mu] = [Z'Z]\sigma^2$; where matrix Z is assumed to have the same dimension as matrix X . The IV estimators, $\hat{\beta}_{IV} = (Z'X)^{-1}Z'y$, are obtained by setting $Z'\mu = 0$ or $Z'(y - X\beta) = 0$. If there are more moment conditions than the number of parameters, then the system of equations becomes algebraically over-identified and cannot be solved. This situation arises because the lagged (twice-lagged, thrice-lagged, ...) variables tend to be the weak instruments, and it often becomes necessary to have a large set of moment conditions. Sargan (1958) develops the generalised instrumental variables estimator and suggests minimizing $(y - X\beta)'Z(Z'Z)^{-1}Z'(y - X\beta) = \mu'Z(Z'Z)^{-1}Z'\mu$. The matrix $(Z'Z)^{-1}$ serves to weight the orthogonality conditions. The weighting matrix comes into operation when the dimensions of Z are larger than the dimensions of X . Hansen (1982) shows that a more efficient estimator can be obtained by replacing $(Z'Z)^{-1}$ by the optimal weighting in terms of the inverse of the matrix, $MCOV(z\mu) = \sum_{k=-L}^L \sum_{t=1}^T Z'_t\mu_t\mu_{t-k}Z_{t-k}$. Hansen (1982) suggests the use of $J \sim \chi^2(n-p)$ statistic to test the moment conditions and examine the non-orthogonality of regressors to the residual process; where n is the number of instruments and p the number of parameters. The study performs the GMM estimation using the optimal weights suggested by Hansen (1982).

An optimal alternative to using GMM is to introduce an explicit AR(1) specification for $X(t)$ along with the stochastic model for the relationship between $Y(t)$ and $X(t)$. The triangular representation of the cointegrated system of Phillips (1991), with $I(1)$ series of $Y(t)$ and $X(t)$ and $I(0)$ series of $\mu(t)$, suggests that the OLS estimator of β is consistent, but not generally fully efficient,

$$Y(t) = \alpha + \beta X(t) + \mu(t) \quad [3]$$

$$\Delta X(t) = \eta(t) \quad [4]$$

The asymptotic distribution of OLS estimator depends on various nuisance parameters engendered by serial-correlation in $\mu(t)$ and by correlation between $\mu(t)$ and innovation term for $\Delta X(t)$ in model [4]. The $\mu(t)$ and $\eta(t)$ are cross-correlated not only contemporaneously, but also at various leads and lags. Phillips (1991) suggests using the following representation for $\mu(t)$,

$$\mu(t) = \sum_{j=-k}^k \delta(j)\eta(t-j) + \xi(t) \quad [5]$$

The $\xi(t)$ in model [5] is not correlated with $\eta(t-j)$, $\forall j \in [-k, k]$. The cointegrating model [3] can be augmented with the leads and lags of $\Delta X(t)$ to resolve the

problem of cross-correlation between $\mu(t)$ and $\eta(t)$ (Phillips and Loretan 1991; Saikkonen 1991; Stock and Watson 1993). By substituting model [4] into model [5] and then substituting the resulting transform into model [3], the leads and lags cointegration estimator can be represented as

$$Y(t) = \alpha + \beta X(t) + \sum_{j=-k}^k \delta(j) \Delta X(t-j) + \xi(t) \quad [6]$$

Since $\xi(t)$ is not correlated with $\eta(t)$ in model [5], it will also be uncorrelated with $\Delta X(t)$ in model [6]. The $\Delta X(t)$ asymptotically eliminates the effect of endogeneity of $X(t)$ on the distribution of OLS estimator of β . If $\xi(t)$ is independently and identically distributed, then the standard distribution theory can be used to perform inference on OLS parameter estimates. While the leads and lags of $\Delta X(t)$ resolve the problem of endogeneity of $X(t)$, they do not necessarily eliminate all the serial-correlation and heteroscedasticity in $\xi(t)$. Stock and Watson (1989, 1993) suggest using GLS to estimate model [6]. The GLS estimates of standard errors and variance-covariance matrix could be used to construct the asymptotically valid χ^2 hypothesis tests on β . Phillips and Loretan (1991) argue that due to persistence in the effects of innovations arising from unit roots in the system, the lags of $\Delta X(t)$ are generally not an adequate proxy for the past history of $\mu(t)$ and they suggest using a parametric correction in model [6] to account for the potential serial-correlation in $\xi(t)$. The requisite information set for valid conditioning is better modelled by using lagged equilibria than by using lagged differences of the dependent variable, and they recommend augmenting model [6] with the lagged levels of $[Y(t) - \alpha - \beta X(t)]$,

$$Y(t) = \beta_0 + \beta X(t) + \sum_{j=-k}^k \delta(j) \Delta X(t-j) + \sum_{j=1}^k \varphi(j) [Y(t-j) - \alpha - \beta X(t-j)] + \zeta(t) \quad [7]$$

The $\zeta(t)$ is serially uncorrelated and model [7] can be estimated using non-linear least squares (NLLS). The NLLS estimator of β is asymptotically efficient and the estimates of variance-covariance matrix have the standard limiting distribution. The NLLS variance-covariance matrix can be used to perform the hypothesis test on β in a standard manner.

Phillips and Hansen (1990) develop the fully-modified OLS (FMOLS) estimator to resolve the problems of endogeneity-bias and serial-correlation, and obtain the efficient estimates of the model parameters. The FMOLS estimator starts with the standard OLS regression and then, analogous to the Phillips-Perron (Phillips and Perron 1988) unit root test, makes a non-parametric correction to account for the endogeneity-bias and serial-correlation that may show up in the OLS residuals. The estimates of the long-run parameters and the associated t-statistics are, thus, adjusted to correct for the bias arising from

the endogeneity of regressors and serial-correlation of residuals. The FMOLS estimator is super-consistent and is asymptotically both unbiased and normally distributed (Park and Phillips 1988; Phillips and Hansen 1990; Hansen and Phillips 1990). The t -statistics of the long-run coefficients are asymptotically normally distributed, and the standard limiting distributions can be used to perform the statistical inference in the FMOLS estimates.

The DOLS and NLLS estimations require the determination of the optimal lags and leads structures of the dynamic regressors. The Akaike information criterion (AIC) pointed towards an unduly large lags and leads structure of $k\{-9, 0, +9\}$, while the Schwarz information criterion (SIC) suggested a relatively parsimonious structure of $k\{-4, 0, +4\}$ for the DOLS estimator. The model with DOLS is estimated using the parsimonious lags and leads structure of $k\{-4, 0, +4\}$ as suggested by SIC. The AIC and SIC consistently suggested $k\{-1, 0, +1\}$ for the model with NLLS, and the Ljung-Box portmanteau (LB-Q) statistic (Ljung and Box 1978) did not reject the null hypothesis of no serial-correlation in the model residuals. The NLLS estimation is, therefore, carried out using $k\{-1, 0, +1\}$. The estimations are also carried out using the higher lags and leads structure of $k\{-5, 0, +5\}$ for the DOLS and $k\{-2, 0, +2\}$ for the NLLS estimator so as to assess the robustness of results. The standard errors of the parameters from DOLS and NLLS estimators are adjusted using the heteroscedasticity and autocorrelation consistent (HAC) estimator of Newey and West (1987). The GMM, DOLS, FMOLS and NLLS estimates of the model consistently suggest the positive and significant long-run effects of domestic saving on investment (Table 3). The J -statistics in GMM do not reject the null hypothesis of no correlation between the regressors and the residual term. The long-run slope parameter on saving ranges between 0.31 and 0.37, and the t -ratios reject both $H_0 : \beta = 0$ and $H_0 : \beta = 1$ at 1% level across all the estimators. The numerically low magnitudes of the slope parameter on saving (0.31–0.37), consistently across all the estimators, point towards the high mobility of capital. The results are robust to the variations in instrument set in GMM and the model structures in DOLS, FMOLS and NLLS estimations (see Annexure 1).

The conventional CUSUM and CUSUMSQ tests used to map the time-profile of the disequilibrium residuals become biased and inefficient when the model residuals are autocorrelated and regressors are characterised by endogeneity. Xiao and Phillips (2002) use the FMOLS estimator to resolve the problem of serial-correlation and endogeneity. They construct the cumulative sum (CS_n) and moving sum (MS_n) test statistics to test the direct null hypothesis of “cointegration” against the alternative hypothesis of “no cointegration” among $I(1)$

Table 3: Optimal single-equation estimates of the long-run model.

Regressor	Dependent variable: $[I/Y]_t$							
	GMM		DOLS		FMOLS		NLLS	
	GMM1	GMM2	$k\{-4, 0, +4\}$	$k\{-5, 0, +5\}$	$lw = 1$	$lw = 4$	$k\{-1, 0, +1\}$	$k\{-2, 0, +2\}$
Constant	14.17 (9.60)	14.27 (10.29)	13.03* (19.78)	13.30* (21.57)	13.66* (13.18)	13.82* (10.81)	14.19* (7.42)	14.57* (6.27)
$[S/Y]_t$	0.32* (4.24)	0.31* (4.44)	0.37* (10.37)	0.36* (10.82)	0.35* (6.28)	0.34* (4.97)	0.33* (3.34)	0.31* (2.59)
	$J=1.04$ [0.31]	$J=0.0023$ [0.96]	—	—	—	—	$\varphi = 0.70^*$ (10.76)	$\varphi = 0.32^*$ (6.30)
Null Hypothesis								
t-ratios								
$H_0 : \beta = 0$	4.24*	4.44*	10.37*	10.82*	6.28*	4.97*	3.34*	2.59*
$H_0 : \beta = 1$	-9.01*	-9.88*	-17.66*	-19.24*	-11.66*	-9.65*	-6.78*	-5.76*
New CUSUM and MOSUM Tests								
CS_n								
	0.7191	0.8229	0.9221	1.0042	1.0416	0.9757	0.5883	0.5594
Bandwidth Parameter								
MS_n								
$h = 0.1$	1.1140	1.1467	1.1586	1.2006	0.9696	0.9911	0.6885	0.8052
$h = 0.2$	1.2489	1.3636	1.6010	1.4374	1.2315	1.2301	0.7870	0.8592
$h = 0.3$	1.1464	1.0646	1.4535	1.2652	1.1598	1.1144	0.6633	0.6293
$h = 0.4$	0.9561	0.8229	0.9007	1.0656	0.9984	0.9409	0.7762	0.7461
$h = 0.5$	0.6974	0.8212	0.8654	0.9425	0.9491	0.8871	0.5958	0.5197

Notes: (1) The figures in round parentheses are the t-ratios; (2) The figures in square brackets corresponding to the J -statistics are the p-values; (3) * indicates the statistical significance at 1% level; (4) The critical values for the CS_n statistic are 2.326 (at 1% level) and 1.842 (at 5% level) (see Xiao and Phillips 2002; Table 1; p.49); (5) The parameters of the lag, contemporaneous and lead first-differenced dynamic regressors of $k\{-4, 0, +4\}$ and $k\{-5, 0, +5\}$ used in DOLS and of $k\{-1, 0, +1\}$ and $k\{-2, 0, +2\}$ used in NLLS estimations do not carry any economically meaningful interpretation and are, therefore, not reported to conserve space. The lw denotes the lag window. The φ is the coefficient of the lagged level term of model [7]; (6) The GMM estimation is carried out using the Bartlett lag window. The instrument set comprises a constant and two lags of $[S/Y]$ in GMM1, and a constant and five lags of $[S/Y]$ in GMM2.

variables. The study uses the optimal residuals obtained from all the GMM, DOLS, FMOLS and NLLS estimates of the long-run model to construct the cumulative sum, $CS_n = \max_{k=1, \dots, n} \sqrt{1/\hat{\omega}_{u,x}^2 n} \left| \sum_{t=k}^n \hat{\varepsilon}_t \right|$, and moving sum, $MS_n = \max_{k=1, \dots, n - [nh]} \sqrt{1/\hat{\omega}_{u,x}^2 n} \left| \sum_{t=k}^{k+[nh]} \hat{\varepsilon}_t \right|$, test statistics and perform the new

cumulative sum (CUSUM) and moving sum (MOSUM) tests; where $\hat{\varepsilon}_t$ represents the optimal residuals of the equilibrium relationship among the model variables, $\hat{\omega}_{u,x}^2$ is a semi-parametric kernel estimator of $\omega_{u,x}^2$ and $0 < h < 1$ is the bandwidth parameter for the moving window (see Xiao 1999; Xiao and Phillips 2002). The new CUSUM and MOSUM tests, based on optimal residuals, overcome the problem of endogeneity of regressors and serial-correlation of residuals and provide efficient estimates, as compared to the conventional CUSUM and CUSUMSQ tests based on the standard OLS recursive residuals. The results suggest that the CS_n statistics do not reject the direct null hypothesis of cointegration and cross-validate the equilibrium relationship between saving and investment (Table 3).⁵

3.2.3 Maximum-Likelihood System Estimates

The maximum-likelihood (ML) system estimator of Johansen (1991) estimates the k^{th} order vector autoregression model and takes a system-based account of endogeneity.

$$\begin{bmatrix} \Delta[I/Y]_t \\ \Delta[S/Y]_t \end{bmatrix} = \Gamma_1 \begin{bmatrix} \Delta[I/Y]_{t-1} \\ \Delta[S/Y]_{t-1} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \times \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \times \begin{bmatrix} [I/Y]_{t-1} \\ [S/Y]_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad [8]$$

Model [8] can be reparameterized as

$$\Delta X(t) = \sum_{i=1}^{k-1} \Gamma(i) \Delta X(t-i) + \tilde{\Pi} X(t-1) + \mu + \varepsilon(t) \quad [9]$$

The $\Gamma(i) = - \left[I - \sum_{i=1}^{k-1} \Pi(i) \right]$, $\tilde{\Pi} = - \left[I - \sum_{i=1}^k \Pi(i) \right]$ and $\Pi = \alpha\beta'$ in model [9]. The $X' = [I/Y, S/Y]$ is a $p \times 1$ vector of p number of $I(1)$ variables, μ is a vector of constants, and $\varepsilon(t)$ is a p -dimensional vector of disturbances with zero-mean and covariance matrix Σ [i.e. $\varepsilon(t) \sim (0, \Sigma)$]. Model [9] is estimated using $k=2$, as suggested by the likelihood ratio (LR) test (Sims 1980).

The asymptotic λ -trace and the λ -trace adjusted for small-sample (Johansen 2000, 2002) consistently reject the null hypothesis of $r=0$ (but not $r \leq 1$) and

⁵ Since the cumulative sum in CS_n statistic is replaced by the moving sum in MS_n statistic, the critical values for MS_n statistic should intuitively be in the vicinity of the critical values for CS_n . By this analogy, the MS_n statistics generally do not reject the direct null hypothesis of cointegration between saving and investment.

Table 4: Maximum-likelihood system estimates of the long-run model.

Panel I: $X' = [I/Y \ S/Y]; [VAR \ lag \ k = 2]$									
Eigenvalues	λ -trace Rank Test					λ -max Rank Test			
	H_0	H_1	λ -trace	λ -trace@	95 % CV	H_0	H_1	λ -max	95 % CV
0.248	$r = 0$	$r \geq 1$	17.10**	16.45**	15.41	$r = 0$	$r = 1$	16.54**	14.07
0.010	$r \leq 1$	$r = 2$	0.56	0.54	3.84	$r \leq 1$	$r = 2$	0.56	3.76
Long-run parameters of the first cointegrating vector normalised on I/Y									
LR Test of:	I/Y					S/Y			
	1					95 % χ^2 value			
Exclusion Restrictions	15.19* (0.00)					-0.295			
Weak Exogeneity	14.58* (0.00)					5.66** (0.02)			
						6.09* (0.01)			
Panel II: Lag Structures and the λ -trace and λ -max Rank Tests: A Sensitivity Analysis									
k	Eigenvalues			λ -trace Rank Test			λ -max Rank Test		
	H_0	H_1		λ -trace	λ -trace@	H_0	H_1	λ -max	
k = 1	0.318	$r = 0$	$r \geq 1$	24.94**	24.58**	$r = 0$	$r = 1$	22.61**	
	0.039	$r \leq 1$	$r = 2$	2.33	2.32	$r \leq 1$	$r = 2$	2.33	
k = 3	0.219	$r = 0$	$r \geq 1$	14.34	13.54	$r = 0$	$r = 1$	14.10**	
	0.004	$r \leq 1$	$r = 2$	0.25	0.24	$r \leq 1$	$r = 2$	0.25	
k = 4	0.233	$r = 0$	$r \geq 1$	14.99	13.75	$r = 0$	$r = 1$	14.84**	
	0.003	$r \leq 1$	$r = 2$	0.14	0.14	$r \leq 1$	$r = 2$	0.14	
k = 5	0.139	$r = 0$	$r \geq 1$	8.29	8.29	$r = 0$	$r = 1$	8.26	
	0.001	$r \leq 1$	$r = 2$	0.03	0.03	$r \leq 1$	$r = 2$	0.03	

Notes: (1) The r denotes the number of cointegrating vectors; (2) @ λ -trace statistics corrected for small sample; (3) The figures in round parentheses are the p-values; (4) * and ** indicate the statistical significance and implied rejection of the null hypothesis at 1% and 5% levels, respectively. Some of the p-values are on the border line of critical region and, thus, strictly do not reject the null hypothesis at the indicated level of significance; (5) CV denotes the critical value.

suggest the presence of one cointegrating vector (Table 4). The long-run parameter on S/Y is statistically significant and dimensionally consistent with the estimates obtained from the single-equation estimators. The χ^2 statistic rejects the null hypothesis of zero-restriction on the parameter of S/Y and suggests the significant long-run effects of domestic saving on investment. The results are, however, sensitive to the use of lag structures in the VAR model. Both asymptotic λ -trace and λ -trace adjusted for small-sample reject the null hypothesis of no cointegration in the models estimated with lags $k=1$ and $k=2$, but not in the models estimated with lags $k=3$, $k=4$ and $k=5$ (Table 4). The presence of cointegration does not necessarily imply that the estimated parameters are temporally stable. The test of parameter constancy, based on recursive estimation, is performed to map the temporal stability of the cointegrating vector (Hansen and Johansen 1993, 1999). The recursive estimation is carried out starting with a base sample of 1950 and then sequentially increasing the sample through 2007. The recursive test statistics, $X(t)$ and $R1(t)$, are scaled by 5% critical value, such that the value less than unity implies the acceptance and that larger than unity the rejection of the null hypothesis hypothesis of constancy of β vector. Both $X(t)$ and $R1(t)$ statistics remain well below the critical unity grid, and do not reject the null hypothesis of constancy of β vector (Figure 2).

3.3 Tests for Granger Non-Causality

3.3.1 Vector Error-Correction Estimates

The estimates of the cointegrating model show only the steady-state equilibrium relationship and do not provide any information on the short-run dynamics. The Granger Representation Theorem (Engle and Granger 1987) postulates that if $y(t)$ and $x(t)$ sequences of a given regression in levels, $y(t) = \alpha + \beta x(t) + \varepsilon(t)$, are $I(1)$ and are cointegrated, then $\Delta y(t) = y(t) - y(t-1)$, $\Delta x(t) = x(t) - x(t-1)$ and the common stochastic process $\varepsilon(t) = y(t) - \alpha - \beta x(t)$ are all $I(0)$ and, in such case, there exists a valid error-correction representation of the time-series. The error-correction model resolves the problem of “spurious regression” without losing long-run information contained in the level variables. The study estimates the vector error-correction model (VECM) to measure the speed-of-adjustment towards steady-state equilibrium and test the null hypothesis of Granger non-causality.

$$\Delta[I/Y]_t = \pi + \sum_{i=1}^k \varphi(i) \Delta[I/Y]_{t-i} + \sum_{i=1}^k \lambda(i) \Delta[S/Y]_{t-i} + \alpha_1 z(t-1) + v_1(t) \quad [10]$$

$$\Delta[S/Y]_t = \tau + \sum_{i=1}^k \zeta(i) \Delta[S/Y]_{t-i} + \sum_{i=1}^k \varsigma(i) \Delta[I/Y]_{t-i} + \alpha_2 z(t-1) + v_2(t) \quad [11]$$

Figure 2: ML estimates and the recursive test of beta constancy.

The $z(t-1)$ is the lagged error-correction term and $\alpha_i \in [0, -1]$, $\forall i = 1, 2$, measures the speed-of-adjustment towards steady-state equilibrium. The lagged error-correction term, $z(t-1)$, in model [10] and model [11] is obtained from the cointegrating vector of the long-run model estimated using alternatively the OLSEG, DOLS, FMOLS, NLLS and ML estimators. The higher (lower) the speed-of-adjustment, the lower (higher) would be the dispersion from long-run equilibrium and implied lower (higher) would be the mobility of capital. The significant parameter of the lagged error-correction term is relatively a more efficient method for rejecting the null hypothesis of no cointegration and determining the equilibrium relationship, as compared to the static OLSEG which does not account for the model dynamics (Kremers, Ericsson, and Dolado 1992). The standard limiting distributions can be used to test the significance of the error-correction parameter. The first-differenced dynamic regressors and $z(t-1)$ are the two possible sources of non-causality in VECM. The saving causes investment, if $H_0 : \sum_{i=1}^k \lambda(i) = 0$ or $H_0 : \alpha_1 = 0$ in model [10] is rejected, but $H_0 : \sum_{i=1}^k \zeta(i) = 0$ or $H_0 : \alpha_2 = 0$ in model [11] is not rejected. The investment causes saving, if $H_0 : \sum_{i=1}^k \zeta(i) = 0$ or $H_0 : \alpha_2 = 0$ in model [11] is rejected, but $H_0 : \sum_{i=1}^k \lambda(i) = 0$ or $H_0 : \alpha_1 = 0$ in model [10] is not rejected. The saving and investment are characterised by bi-directional causality, if $H_0 : \sum_{i=1}^k \lambda(i) = 0$ or $H_0 : \alpha_1 = 0$ in model [10] and $H_0 : \sum_{i=1}^k \zeta(i) = 0$ or $H_0 : \alpha_2 = 0$ in model [11] are rejected. The short-run dynamic models [10] and [11] in first-differences are augmented with the lagged error-correction term, $z(t-1)$, obtained from the long-run model estimated alternatively with (i) OLSEG (Model I), (ii) DOLS (Model II), (iii) FMOLS (Model III), (iv) NLLS (Model IV) and (v) ML (Model V) estimators, and, as such, five variants of VECM are estimated to test the null hypothesis of Granger non-causality and take an encompassing account of the adjustment process towards steady-state equilibrium (Table 5).

The results remain consistent across all the VECMs, and suggest the significant effects of lagged disequilibrium (Model I to Model V, Table 5). The VECMs reinforce the evidence obtained from the long-run models and point towards the equilibrium relationship between domestic saving and investment. The t -statistics reject $H_0 : \alpha_1 = 0$ consistently across all the estimates, and cross-validate the cointegrating relationship. The speed-of-adjustment towards steady-state equilibrium is quite fast, ranging between 60 % to 63 % per annum. The implied departure from equilibrium $\{1 - \alpha\}$ ranges between 37 % to 40 %, and it points towards the high mobility of capital. The Jarque – Bera $\sim \chi^2$ statistic does not reject the null hypothesis of normality in favour of the non-normal alternative. The VECMs consistently suggest bi-directional causality with stronger evidence for the effects of saving on investment, as compared to the feedback effects of investment on saving. The causality comes mainly from the “disequilibrium adjustments,” rather than the “short-run dynamics.”

Table 5: Vector error-correction models and the Granger non-causality [VAR lag k = 2].

Regressor	Model I		Model II		Model III		Model IV		Model V	
	[OLSEG-Based $z(t-1)$]		[DOLS-Based $z(t-1)$]		[FMOLS-Based $z(t-1)$]		[NLLS-Based $z(t-1)$]		[ML-Based $z(t-1)$]	
	$ I/Y _t$	$[S/Y]_t$	$ I/Y _t$	$[S/Y]_t$	$ I/Y _t$	$[S/Y]_t$	$ I/Y _t$	$[S/Y]_t$	$ I/Y _t$	$[S/Y]_t$
Constant	7.45* (0.00)	3.53*** (0.07)	8.07* (0.00)	3.92*** (0.06)	8.47* (0.00)	4.21*** (0.06)	8.72* (0.00)	4.40*** (0.07)	8.96* (0.00)	4.62*** (0.07)
$\sum_i^k \Delta I/Y _{t-i}$	0.70*** [4.33]	0.55 [1.96]	0.71*** [4.57]	0.56 [2.10]	0.707*** [4.59]	0.57 [2.19]	0.70*** [4.50]	0.569 [2.23]	0.68*** [4.22]	0.565 [2.25]
$\sum_i^k \Delta[S/Y]_{t-i}$	-0.75*** [4.56]	-0.60*** [3.23]	-0.73*** [4.56]	-0.59*** [3.20]	-0.710*** [4.47]	-0.58*** [3.11]	-0.69*** [4.35]	-0.573*** [3.01]	-0.66*** [4.07]	-0.556*** [2.81]
$z(t-1)$	-0.60* (0.01)	-0.29*** (0.04)	-0.62* (0.01)	-0.31*** (0.04)	-0.63* (0.01)	-0.32*** (0.04)	-0.63* (0.01)	-0.33*** (0.05)	-0.62* (0.02)	-0.33*** (0.06)
	(0.00)	(0.06)	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)	(0.06)

Table 5: (continued)

Regressor	Model I				Model II				Model III				Model IV				Model V			
	[OLSEG-Based $z(t-1)$]		[DOLS-Based $z(t-1)$]		[DOLS-Based $z(t-1)$]		[FMOLS-Based $z(t-1)$]		[NLLS-Based $z(t-1)$]		[NLLS-Based $z(t-1)$]		[ML-Based $z(t-1)$]		[ML-Based $z(t-1)$]		[ML-Based $z(t-1)$]		[ML-Based $z(t-1)$]	
	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$	$ t/Y _t$	$ S/Y _t$
$\bar{R}^2$	0.24	0.17	0.25	0.18	0.25	0.18	0.25	0.18	0.25	0.18	0.25	0.18	0.25	0.18	0.26	0.18	0.26	0.18	0.26	0.18
DW	2.11	1.95	2.12	1.95	2.12	1.95	2.11	1.95	2.11	1.95	2.11	1.94	2.11	1.94	2.11	1.94	2.11	1.94	2.11	1.94
LB-Q (14)	15.21	25.74	15.29	26.00	15.29	26.00	15.11	25.85	15.11	25.85	14.82	25.49	14.13	24.50	14.13	24.50	14.13	24.50	14.13	24.50
	(0.36)	(0.03)	(0.36)	(0.03)	(0.36)	(0.03)	(0.37)	(0.03)	(0.37)	(0.03)	(0.39)	(0.03)	(0.44)	(0.04)	(0.44)	(0.04)	(0.44)	(0.04)	(0.44)	(0.04)
Skewness	-0.27	0.05	-0.24	0.07	-0.24	0.07	-0.23	0.07	-0.23	0.07	-0.21	0.08	-0.19	0.09	-0.19	0.09	-0.19	0.09	-0.19	0.09
	(0.42)	(0.87)	(0.46)	(0.84)	(0.46)	(0.84)	(0.50)	(0.82)	(0.50)	(0.82)	(0.52)	(0.81)	(0.56)	(0.80)	(0.56)	(0.80)	(0.56)	(0.80)	(0.56)	(0.80)
Kurtosis (excess)	-0.17	-0.35	-0.13	-0.33	-0.13	-0.33	-0.11	-0.31	-0.11	-0.31	-0.09	-0.30	-0.08	-0.28	-0.08	-0.28	-0.08	-0.28	-0.08	-0.28
	(0.80)	(0.62)	(0.85)	(0.63)	(0.85)	(0.63)	(0.88)	(0.65)	(0.88)	(0.65)	(0.89)	(0.67)	(0.91)	(0.69)	(0.91)	(0.69)	(0.91)	(0.69)	(0.91)	(0.69)
Jarque-Bera	0.74	0.31	0.61	0.30	0.61	0.30	0.51	0.28	0.51	0.28	0.45	0.27	0.37	0.25	0.37	0.25	0.37	0.25	0.37	0.25
	(0.69)	(0.85)	(0.74)	(0.86)	(0.74)	(0.86)	(0.77)	(0.87)	(0.77)	(0.87)	(0.80)	(0.87)	(0.83)	(0.88)	(0.83)	(0.88)	(0.83)	(0.88)	(0.83)	(0.88)

Notes: (1) The $z(t-1)$ is the lagged error-correction term, and it is obtained from the cointegrating vector of the long-run model estimated using alternatively the (i) OLSEG (Model I), (ii) DOLS (Model II), (iii) FMOLS (Model III), (iv) NLLS (Model IV) and (v) ML (Model V) estimators; (2) The figures in square brackets are the F-statistics and those in round parentheses are the associated p-values; (3) *, ** and *** indicate the statistical significance at 1 %, 5 % and 10 % levels, respectively. Some of the p-values are on the border line of critical region and, thus, strictly do not reject the null hypothesis at the indicated level of significance; (4) LB-Q denotes the Ljung-Box Portmanteau statistic (see Ljung and Box 1978); (5) The Jarque-Bera $\sim \chi^2$ statistic (see Jarque and Bera 1980) is for the null hypothesis of normality of residuals.

The impulse response and variance decomposition analyses are carried out on all the VECMs (Model I to Model V) to trace the time-profile and map the response trajectories of $\Delta[I/Y]$ $\{\Delta[S/Y]\}$ to the shocks to the innovations of $\Delta[S/Y]$ $\{\Delta[I/Y]\}$. The results for the impulse response functions and variance decomposition analyses remain consistent across all the VECMs and are, therefore, reported only for one VECM based on the cointegrating vector obtained from the ML system estimator (Model V, Table 6). The impulse response functions are constructed using the estimated parameters and, since each parameter is estimated imprecisely, these functions also contain errors (Enders 2004). The standard error bands around the impulse response functions are constructed to account for the parameter uncertainty inherent in the estimation process and map the width of the prediction intervals. The Monte Carlo simulations are performed using 10,000 draws and the analysis is carried out for a time horizon of 10 years. Both impulse response functions and decompositions of variance consistently suggest that $\Delta[I/Y]$ [DGDIRATE] and $\Delta[S/Y]$ [DGDSRATE] show larger responses to the shocks to their own innovations than to the shocks to the cross innovations of other series in the system (Figure 3, Table 6). The innovations of DGDSRATE explain around 12% of the variations in the innovations of DGDIRATE, while the innovations of DGDIRATE explain around 40% of the variations in the innovations of DGDSRATE. The innovation accounting reinforces the evidence obtained from VECM and suggests the bi-directional causality between saving and investment. The effects of saving on investment seem stronger than the feedback effects of investment on saving.

Table 6: Vector Error-Correction Model and the Decomposition of Variance [based on ML-based VECM; VAR lag $k = 2$].

Period	DGDIRATE			DGDSRATE		
	S.E.	DGDIRATE	DGDSRATE	S.E	DGDIRATE	DGDSRATE
1	0.89	100.00	0.00	0.99	60.31	39.69
2	0.92	94.84	5.16	1.02	61.57	38.43
3	0.96	87.78	12.22	1.07	56.48	43.52
4	0.96	87.71	12.30	1.08	56.47	43.53
5	0.96	87.54	12.46	1.08	56.25	43.75
10	0.96	87.50	12.50	1.08	56.23	43.77

Notes: (1) S.E. denotes the standard errors; (2) Cholesky ordering: $[\Delta[I/Y] \Delta[S/Y]]$.

Figure 3: Impulse response functions and the standard error bands (based on ML-based VECM; VAR lag $k=2$).

3.3.2 Over-Parameterized Level-VAR Estimates

The VECM approach to testing Granger non-causality builds sequentially on the (i) pretesting of model series for unit root(s), (ii) determining of cointegration rank and (iii) eventually the testing of zero-restrictions on the parameters of the short-run dynamic and long-run lagged disequilibrium regressors. The unit root tests used to determine the I(d) properties of the model series are known to have low power in small samples. The subsequent cointegration tests conditioned on the unit root pre-tests and that non-causality tests conditioned sequentially on the cointegration pre-tests could potentially contain a pre-test bias. The over-parameterized level-VAR estimator of Toda and Yamamoto (1995) (TY) by-passes all the pretesting requirements and is applicable to all VAR systems characterised by a stationary (around a deterministic trend) or integrated or cointegrated process of an arbitrary order. The TY estimator involves the (i) estimation of the level-VAR model of order k augmented artificially with extra $d_{\max}$ lags, and then the (ii) testing of zero-restrictions on the parameters of first k lagged (but not all lagged) regressors to draw long-run Granger causal inference; where $d_{\max}$ is the maximal order of integration of the system series. The VAR lag-length, k , can be determined using the usual model selection criteria and lag-length selection tests.

$$\begin{bmatrix} [I/Y]_t \\ [S/Y]_t \end{bmatrix} = \omega + \sum_{i=1}^k \xi(i) \begin{bmatrix} [I/Y]_{t-i} \\ [S/Y]_{t-i} \end{bmatrix} + \sum_{i=k+1}^{d_{\max}} \xi(i) \begin{bmatrix} [I/Y]_{t-i} \\ [S/Y]_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon(1t) \\ \varepsilon(2t) \end{bmatrix} \quad [12]$$

The ω is a vector of intercept terms, $\sum_{i=1}^{q=[k+d_{\max}]} \xi(i)$ a matrix of long-run parameters and ε a vector of white-noise residuals with usual Gaussian iid properties. The $d_{\max}$ lag(s) augmentation represents the artificial over-loading of the true lag-length, k , and the implied over-parameterization of the level-VAR model. The level-VAR model [12] can be reparameterized as

$$X(t) = \sum_{i=1}^{q=[k+d_{\max}]} \Xi(i)X(t-i) + \Omega + \varepsilon(t) \quad [13]$$

Under the null hypothesis of zero-restrictions on the parameters of each variable in vector $X' = [I/Y \ S/Y]$ for lags one to k , the Wald statistic has an asymptotic χ^2 distribution with usual degrees of freedom. The AIC suggested lags $k=5$, while the SIC suggested lags $k=2$ for the VAR model. The study uses lags $k=2$ (as suggested by SIC) and estimates three sets of over-parameterized level-VAR models; (i) one based on $d_{\max}=0$ and implied $q=[k+d_{\max}]=[2+0]=2$ lags, (ii) second based on $d_{\max}=1$ and implied $q=[k+d_{\max}]=[2+1]=3$ lags, and (iii) third based on $d_{\max}=2$ and implied $q=[k+d_{\max}]=[2+2]=4$ lags of the VAR model. The estimates of these over-fitted VAR models are used to

compute the joint F-statistics for the null hypothesis of zero-restrictions on the parameters of regressors up to first $k=2$ lags (ignoring extra $d_{\max}$ lags loadings). The over-parameterized level-VAR models are also estimated using $k=3$ lags and implied (i) $q=[k + d_{\max}]=[3 + 0]=3$ lags, (ii) $q=[k + d_{\max}]=[3 + 1]=4$ lags and (iii) $q=[k + d_{\max}]=[3 + 2]=5$ lags of the VAR model so as to determine the robustness of results.

The joint F statistics computed for first $k=2$ lags [in the model with $q=[k + d_{\max}]=[2 + 0]=2$ lags] reject the null hypothesis of zero restrictions on the parameters of the lagged regressors of (i) $[S/Y]_t$ in the model with $[I/Y]_t$ as the regressand and (ii) $[I/Y]_t$ in the model with $[S/Y]_t$ as the regressand (Table 7). The F statistics for first $k=3$ lags [in the model with $q=[k + d_{\max}]=[3 + 0]=3$ lags] reject the null hypothesis (at 10% level) of zero restrictions on the parameters of the lagged regressors of $[S/Y]_t$ in the model with $[I/Y]_t$ as the regressand. The zero-restrictions are not rejected for the parameters of the lagged regressors of $[I/Y]_t$ in the model with $[S/Y]_t$ as the regressand. The F statistics do not reject the null hypothesis of zero restrictions on the parameters of the distributed lagged regressors of (i) $[S/Y]_t$ in the model with $[I/Y]_t$ as the regressand and (ii) $[I/Y]_t$ in the model with $[S/Y]_t$ as the regressand in all the remaining models with over-parameterizations based on $d_{\max}=1$ and $d_{\max}=2$ (see off-diagonal elements, Table 7). The zero restrictions are rejected (at 1% level) for the parameters of the autoregressive regressors in all the models estimated with over-parameterizations set at $d_{\max}=0$, $d_{\max}=1$ and $d_{\max}=2$ (see diagonal elements, Table 7). The sensitivity analysis undertaken further to ascertain the robustness of results suggests that the models estimated using the higher lag structures of $k=4$ and $k=5$ consistently do not provide any support for the long-run Granger-causal nexus between domestic saving and investment (see Annexure 2). It needs to be recognised that the TY estimator suffers from the loss of power and tends to be inefficient, given that it is based on an intentionally over-fitted VAR system.

3.4 Structural Breaks

The model estimated in a one-regime and parameter-invariant setting provides useful information so long as there are no structural breaks in the relationship among variables. The long-run relationship and model parameters, however, may change either suddenly at a given date or smoothly over time. If a change occurs in the population regression function during the sample period, then the regression over the full-sample would estimate the relationship that holds “on average” in that the regression estimates would combine two different periods. The “average” regression function in the model with structural break can be quite different

Table 7: Over-parameterized level-VAR estimates and the long-run Granger non-causality [F-statistics].

Regressor	Maximal order of integration (dmax) of the model series						Dependent variable
	dmax = 0		dmax = 1		dmax = 2		
	$[I/Y]_t$	$[S/Y]_t$	$[I/Y]_t$	$[S/Y]_t$	$[I/Y]_t$	$[S/Y]_t$	
$[I/Y]_t$ $[S/Y]_t$	VAR Lags: $q = [k + dmax] = [2 + 0] = 2$; Zero-Restrictions for first $k = 2$ Lags		VAR Lags: $q = [k + dmax] = [2 + 1] = 3$; Zero-Restrictions for first $k = 2$ Lags		VAR Lags: $q = [k + dmax] = [2 + 2] = 4$; Zero-Restrictions for first $k = 2$ Lags		
	8.03* (0.00) 4.96* (0.01)	5.01* (0.01) 58.70* (0.00)	8.94* (0.00) 0.59 (0.56)	0.15 (0.86) 14.91* (0.00)	7.48* (0.00) 0.64 (0.53)	0.11 (0.90) 14.37* (0.00)	
$[I/Y]_t$ $[S/Y]_t$	VAR Lags: $q = [k + dmax] = [3 + 0] = 3$; Zero-Restrictions for first $k = 3$ Lags		VAR Lags: $q = [k + dmax] = [3 + 1] = 4$; Zero-Restrictions for first $k = 3$ Lags		VAR Lags: $q = [k + dmax] = [3 + 2] = 5$; Zero-Restrictions for first $k = 3$ Lags		
	6.03* (0.00) 2.37*** (0.08)	0.96 (0.42) 40.01* (0.00)	5.25* (0.00) 0.55 (0.65)	0.34 (0.80) 14.87* (0.00)	4.85* (0.01) 0.79 (0.51)	0.48 (0.70) 13.93* (0.00)	

Notes: (1) The figures in round parentheses are the p-values; (2) * and *** indicate the statistical significance at 1% and 10% levels, respectively. Some of the p-values are on the border line of critical region and, thus, strictly do not reject the null hypothesis at the indicated level of significance.

from the true regression function at the end of the sample, depending on the location and magnitude of the break-point. The structural breaks reduce the power of standard cointegration tests and weaken the robustness of statistical evidence obtained from one-regime models without structural breaks. This section allows structural breaks in the cointegrating vector and cross-examines the evidence obtained from the standard base-line model without structural breaks. The analysis is carried out using the (i) standard tests for model instability (Hansen 1992; Quandt 1960; Andrews 1993, 2003; Andrews and Ploberger 1994), (ii) test for cointegration with one structural break (Gregory and Hansen 1996), (iii) tests for multiple structural breaks (Bai and Perron 1998, 2003; Kejriwal and Perron 2008, 2010), (iv) test for cointegration with multiple structural breaks (Johansen, Mosconi, and Nielsen 2000), and the (v) new tests for cointegration breakdowns over the short time periods (Andrews and Kim 2006).

3.4.1 Standard Tests for Model Instability

The parameter instability tests of Hansen (1992) test the null hypothesis of constant parameters against the alternative that the parameters follow a martingale. Hansen (1992) develops the test statistics denoted as (i) L to test the stability of the individual coefficients of a regression model, (ii) Lc to test the joint stability of the regression coefficients and (iii) σ_ε^2 to test the stability of the regression residuals.⁶ These tests are valid for both static and dynamic regression models. The Lc statistic is asymptotically robust to heteroscedasticity. The OLS estimates of the model juxtaposed with the Hansen test statistics for the null hypothesis of parameter stability are as follows.

$$\begin{aligned}
 [I/Y]_t &= 12.6363 + 0.4012[S/Y]_t \\
 &\quad (14.04) \quad (8.39) \\
 \text{Hansen L} &= 0.48 \quad 0.44 \\
 \text{Statistics} &\quad \{0.05\} \quad \{0.06\}
 \end{aligned}
 \tag{14}$$

$$\bar{R}^2 = 0.54; \text{Hansen Joint Lc} = 0.90 \{0.08\}; \text{Hansen } \sigma_\varepsilon^2 = 0.11\{0.54\}$$

The figures in round parentheses in model [14] are the t-ratios and in curly brackets are the p-values. The L statistics generally reject the null hypothesis of stability and point towards the instability of both intercept and slope parameters.

⁶ For a further discussion on L, Lc and σ_ε^2 test statistics, see Hansen (1992). Hansen (1992) excludes the unit root process and deterministic trends. Therefore, the results from the Hansen tests applied to the FH model with non-stationary processes may be interpreted with caution and be treated as only indicative.

The L_c statistic weakly rejects the joint null hypothesis of model stability, while the σ_ε^2 statistic does not reject the stability of the residual variance.

A limitation of the tests developed in Hansen (1992) is that these tests simply test the null hypothesis of constancy, and do not provide any information on the timing of structural break. Similarly, the limitation of the conventional Chow test (Chow 1960) alternative is that it tests the structural break only at the known location.⁷ Nevertheless, if the break date is unknown, then the recursive Chow test can be used to test for structural break at every possible point and grid-search the break-point from some bounded space, $\Pi = (\pi_0, \pi_1)$. If the null hypothesis of no structural break is rejected more than once during the grid-search, then the highest rejection of the null hypothesis, as suggested by the global maxima of the test statistic, $\text{Sup-F} = \max[F(\pi_0), F(\pi_0 + 1), \dots, F(\pi_1)]$, can be used to determine the point of structural break, $\pi \in \Pi \subset (0, 1)$, that occurs under the alternative hypothesis. The Supremum (Sup) F statistic based on the recursive sequence of Chow tests is equivalent to the Quandt Likelihood-Ratio (QLR) (Quandt 1960) statistic or approximately the Sup-Wald statistic such that $\text{Sup-Chow} = \text{QLR} = \max[F(\pi_0), F(\pi_0 + 1), \dots, F(\pi_1)] = \text{Sup-F}$. The use of F tests at every possible break-point, however, invalidates the traditional F and χ^2 distributions, and these distributions cannot be used to perform statistical inference for the Sup-Chow or Sup-F test.

Andrews (1993, 2003) and Andrews and Ploberger (1994) derive the asymptotic (large sample) null distributions and provide the critical values for the Supremum Wald, LM and LR test statistics. The asymptotic critical values depend on the (i) number of parameters, k , that are allowed to break (change) under the alternative hypothesis and the (ii) sub-sample interval over which the test statistics are computed. Andrews (1993) considers the parametric model indexed by the parameters (β_t, δ_0) for $t = 1, 2, \dots$ and suggests that the $\text{Sup}_{\pi \in \Pi} W_T(\pi)$, $\text{Sup}_{\pi \in \Pi} LM_T(\pi)$ and

$\text{Sup}_{\pi \in \Pi} LR_T(\pi)$ tests can be used to test the null hypothesis of parameter stability (no structural break) against the alternative hypothesis of a one-time change at an unknown point.

⁷ The timing of structural break in the long-run relationship among variables may not strictly coincide with the timing of the policy changes and economic shocks (systematic or stochastic), given that the adjustment process may not be instantaneous and the economic agents normally take time to recognise and adjust to the shocks. The speed-of-adjustment depends on several factors such as the magnitudes of the policy and economic shocks, rigidities in the goods and financial markets and the process of expectation (adaptive or rational) formation among the economic agents. For a survey of the literature on the detection and dating of structural breaks, especially if the exact break-point is unknown, see Hansen (2001).

$$H_0: \beta_t = \beta_0 \text{ for all } t \geq 1; \quad H_1(\pi): \beta_t = \begin{cases} \beta_1(\pi) & \text{for } t = 1, \dots, T\pi \\ \beta_2(\pi) & \text{for } t = T\pi + 1, \dots, T \end{cases}; \quad \pi \in \Pi \subset (0, 1)$$

The $T\pi$ is the time of change in the parameter and, for simplicity, $\pi \in \Pi \subset (0, 1)$, rather than $T\pi$, is referred to as the point of structural change. In the case of the tests of pure structural change, no parameter, δ_0 , appears and the whole parameter vector is subject to change under the alternative hypothesis. In the case of the tests of partial structural change, the parameter δ_0 appears and is taken to be constant under the null hypothesis and the alternative (Andrews 1993). This implies that one could test the null hypothesis that the parameters do not change against the alternative hypothesis that a particular sub-set of the parameters does change. Andrews and Ploberger (1994) use a weighted average of the power criterion function and derive the asymptotically optimal tests (exponential and average LM and F tests) for the null hypothesis. The structural break parameter, $\pi \in \Pi \subset (0, 1)$, appears only under the alternative and not under the null hypothesis.

The sub-sample interval used to perform grid-search for the break-point is bounded between the trimming parameters (π_0 and π_1) expressed as a fraction of the total sample period, T . The sub-sample end-points (π_0 and π_1) should not be too close to the beginning and end of the sample space for a good large-sample approximation to the distribution of the test statistic. The $\sup_{\pi \in \Pi} W_T(\pi)$, $\sup_{\pi \in \Pi} LM_T(\pi)$ and $\sup_{\pi \in \Pi} LR_T(\pi)$ test statistics diverge to infinity in probability when $\Pi = (0, 1)$, but these statistics converge in distribution when the closure of Π is bounded away from zero and one (Andrews and Ploberger 1994). It follows that there needs to be a sufficient number of observations on either side of the potential break-point to estimate the regressions before and after the break-point. Andrews (1993) suggests using the restricted interval of $\Pi = \{0.15, 0.85\}$ for the grid-search for the break-point. The study follows Andrews (1993) and sets $\pi_0 = 0.15 \times T$ and $\pi_1 = 0.85 \times T$ to trim the sample symmetrically from the beginning and end of the time space. The Andrews-Quandt (Quandt 1960; Andrews 1993, 2003) and Andrews-Ploberger (Andrews and Ploberger, 1994) tests are then performed to identify a one-time and discrete structural break, endogenously from the data at an unknown point, in the parameters (α , β and σ_ε^2) of model [1].

The Andrews-Quandt (AQ) and Andrews-Ploberger (AP) tests used in the study are based on the Lagrange Multiplier tests for the null hypothesis of no structural break against the alternative of a one-time unknown break in the parameters of the linear regression. The AQ test uses the supremum (maximum) of the LM statistics as the test statistic, while the AP test uses the geometric mean. A series of LM statistics are computed for each of the possible break-point and the grid-search is performed over the trimmed region of the sample space to locate the

break-point, $\pi \in \{\pi_0, 1 - \pi_0\} = \{\pi_0, \pi_1\} = \{0.15, 0.85\} = \{0.15 \times T, 0.85 \times T\}$, in the parameter vector. The asymptotic (large sample) p-values for the AQ and AP test statistics are computed using the approximation procedure suggested by Hansen (1997). Both AQ and AP tests consistently suggest the presence of structural breaks in both intercept, α , and slope, β , parameters of the long-run model (Table 8).

Table 8: Andrews-Quandt and Andrews-Ploberger tests for one structural break.

Break Parameter	Test statistics		Break Year
	Andrews-Quandt	Andrews-Ploberger	
α	9.32** (0.04)	3.02** (0.02)	1976
β	9.10** (0.04)	2.91** (0.02)	1976
All Coefficients	9.34 (0.12)	3.06*** (0.06)	1976
σ^2_ε	1.23 (0.97)	-0.03 (1.00)	1974

Notes: (1) The figures in round parentheses are the p-values; (2) ** and *** indicate the statistical significance at 5 % and 10 % levels, respectively.

3.4.2 Test for Cointegration with One Structural Break

The OLS-based estimator of Gregory and Hansen (OLSGH) (1996) is one of the most commonly used estimators to detect structural breaks in the cointegrating vector. The OLSGH is the direct extension of the residual-based OLSEG and it allows one-time structural break, via dummy variable, in either intercept or both intercept and slope parameter. The break date is unknown, *a priori*, and is determined endogenously by the model. The first step in OLSGH involves the estimation of a set of static regression models augmented with (i) intercept dummy to account for the level shift (Model I), (ii) intercept dummy and a linear trend to assess the level shift with trend (Model II) and (iii) both intercept and slope dummies (entire coefficient vector) to determine the regime shift (Model III) in the cointegrating vector.

Model I: Constant; Level Shift:

$$y_t = \alpha_0 + \alpha_1 DU_t + \beta x_t + \varepsilon_t \tag{15}$$

Model II: Constant and Trend; Level Shift with trend:

$$y_t = \alpha_0 + \alpha_1 DU_t + \phi t + \beta x_t + \varepsilon_t \tag{16}$$

Model III: Constant and Slope; Regime Shift:

$$y_t = \alpha_0 + \alpha_1 DU_t + \beta x_t + \xi DU_t x_t + \varepsilon_t \tag{17}$$

$$DU_t = \begin{cases} 0; & \text{If } t \leq \{\tau \ T\} \\ 1; & \text{If } t > \{\tau \ T\} \end{cases}; \quad t \in \{1, ..., T\}$$

The DU denotes the dummy variable that takes value 0 if it is below and value 1 if it is above the unknown break-point, and $\{\cdot\}$ is the integer part. The unknown regime shift parameter $\tau \in \{0, 1\}$ shows the (relative) timing of the change point in terms of a fraction of the sample space, T. The structural change is reflected in the changes in intercept and/or slope. The second step involves the use of ADF unit root tests on ε_t to test $H_0 : \varepsilon_t \sim (1)$ (no cointegration among I(1) variables) against $H_1 : \varepsilon_t \sim (0)$ (cointegration among I(1) variables) with a single unknown structural break. The observations are trimmed at both beginning and end of the sample space. The ADF(τ) statistics [denoted as GH-ADF*] are computed and the grid-search is performed over the trimmed interval to endogenously determine the break-point $\tau \in \{0.15 \times T, 0.85 \times T\}$. The smallest value (highest absolute value) of GH-ADF* is used to reject the null hypothesis and locate the break-point. The minimized GH-ADF* statistics reject the null hypothesis of no cointegration at 5% level in the model with intercept dummy (Model I), but not in the model with intercept dummy and trend (Model II) and that with intercept and slope dummies (Model III) (Table 9, Figure 4); the horizontal grids in Figure 4 represent the 5% critical levels. The break-point corresponds to 1996 in Model I and Model III each and to 1957 in Model II.

Table 9: OLSGH tests for cointegration with one structural break.

Model	Minimized GH-ADF*	Break Year	Critical Values	
			0.01	0.05
Model I: C	-4.69**	1996	-5.13	-4.61
Model II: C/ T	-4.39	1957	-5.45	-4.99
Model III: C/ S	-4.77	1996	-5.47	-4.95

Notes: (1) C denotes the model estimated with a constant, C/T the model with constant and trend, and C/S the model with constant and slope; (2) The approximate asymptotic critical values for $p = 1$ number of regressors, based on the response surface, are taken from Gregory and Hansen (1996), Table 1, p. 109; (3) ** indicates the statistical significance and implied rejection of the null hypothesis at 5% level.

The FH model [1] is now augmented with the intercept and interaction slope dummies, and is re-estimated to examine the shifts in the intercept and slope parameters.

$$[I/Y]_t = \alpha + \beta[S/Y]_t + \delta_1 DU_t + \delta_2 DU_t \times [S/Y]_t + \nu_t \tag{18}$$

$$DU_t = \begin{cases} 0; & \forall t \leq \lambda \\ 1; & \forall t > \lambda \end{cases}$$

Figure 4: OLSGH tests for cointegration with one structural break [temporal trajectories of the GH-ADF* statistics].

The dummy-augmented FH model [18] transforms to the standard bi-variate model, $[I/Y]_t = \alpha + \beta[S/Y]_t + u_t$, when $DU_t = 0$, and to $[I/Y]_t = (\alpha + \delta_1) + (\beta + \delta_2)[S/Y]_t + u_t$ when $DU_t = 1$. The residual term, $u_t \sim \text{iid}(0, \sigma_u^2)$, in model [18] follows the usual Gaussian iid properties. The sample-split dummy variables approach to modelling structural breaks in the relationship among variables assumes that the structure of the model residuals is the same across different regimes. The estimation of the dummy variables model is similar to the estimation of separate regressions for different regimes, except that the residual processes across sub-samples in the model with binary variables are assumed to be identical. Model [18] is estimated using the break location set at $\lambda = 1996$, as suggested by the OLSGH test. The estimation is carried out using all the OLS, GMM, DOLS, FMOLS and NLLS estimators so as to draw a comparison with the corresponding estimates of the standard FH model [1] without structural break. The standard errors of the parameters in OLS, DOLS and NLLS estimations are adjusted using the HAC estimator of Newey and West (1987).

The standard OLS and optimal DOLS and FMOLS estimates of the dummy-augmented model [18] point towards the upward shift in the intercept and the downward shift in the slope parameter on saving (Table 10). The magnitude of the slope parameter on saving, $\hat{\beta}$, adjusted for the parameter of the interaction dummy, $\hat{\delta}_2$, is consistently low across OLS, DOLS and FMOLS estimates of the dummy-augmented model, as compared to the corresponding slope parameter on saving estimated in the standard FH model without a structural break (see Table 3 vis-a-vis Table 10). The slope parameter is (i) higher in the NLLS and (ii) virtually unchanged in the GMM estimates, as compared to the corresponding slope parameter in the model estimated without a structural break. The lower magnitude of the slope parameter on saving, adjusted for the parameter of the interaction slope dummy, $(\hat{\beta} + \hat{\delta}_2)$, across OLS, DOLS and FMOLS estimates of model [18] suggests the increase in the mobility of capital in the period post mid-1990s.

3.4.3 Tests for Multiple Structural Breaks

The standard tests for model instability preclude the possibilities of multiple breaks in the model parameters. Bai and Perron (BP) (1998, 2003) consider the linear model and use the dynamic programming algorithm to determine m number of unknown breaks and implied $m+1$ number of regimes. The BP statistics are the generalization of the single-break test statistics of Andrews (1993, 2003) and are robust to the serial-correlation and heterogeneity of residuals under the null hypothesis. Kejriwal and Perron (KP) (2008, 2010) allow $I(1)$ as well as $I(0)$ regressors in the cointegrating model, and derive the limiting

Table 10: Single-equation estimates of the long-run model with one structural break.

Regressor	Dependent variable: $ I/Y _t$				
	OLS		DOLS		NLLS
	GMM1	GMM2	$k\{-4, 0, +4\}$	$k\{-5, 0, +5\}$	$k\{-1, 0, +1\}$
Constant	10.24* (8.58)	11.71* (6.01)	13.56* (18.20)	14.57* (21.42)	11.19* (5.30)
$ S/Y _t$	0.52* (8.65)	0.44* (4.48)	0.35* (8.81)	0.30* (8.41)	0.47* (4.49)
DU_t	3.92** (2.44)	3.05 (1.28)	2.48** (2.03)	2.83** (2.11)	1.50 (1.22)
$DU_t \times S/Y _t$	-0.18** (-2.01)	-0.13 (-1.04)	-0.16** (-2.11)	-0.20** (-2.22)	-0.07 (-1.00)
	$J=2.78$ [0.43]	$J=4.45$ [0.22]			$\varphi = 0.66^*$ (7.68)
Null Hypothesis					t-ratios
$H_0: \beta = 0$	8.65*	4.48*	8.81*	8.41*	5.81*
$H_0: \beta = 1$	-8.05*	-5.78*	-16.68*	-19.96*	-6.66*
					3.37* -4.12*

(continued)

Table 10: (continued)

Regressor	Dependent variable: $[I/Y]_t$									
	OLS		GMM		DOLS		FMOLS		NLLS	
	GMM1	GMM2	k{-4, 0, +4}	k{-5, 0, +5}	lw = 1	lw = 4	k{-1, 0, +1}	k{-2, 0, +2}		
Dummy value	Shift in Intercept Parameter: $(\hat{\alpha} + \hat{\delta}_1)$									
DU _t = 0	10.24	12.53	11.71	13.56	14.57	11.37	11.24	11.19	11.65	11.65
DU _t = 1	14.16	14.95	14.76	16.04	17.40	15.00	15.06	12.69	13.66	13.66
Dummy value	Shift in Slope Parameter: $(\hat{\beta} + \hat{\delta}_2)$									
DU _t = 0	0.52	0.40	0.44	0.35	0.30	0.46	0.47	0.47	0.45	0.45
DU _t = 1	0.34	0.29	0.31	0.19	0.10	0.29	0.29	0.40	0.35	0.35

Notes: (1) The figures in round parentheses are the t-ratios; (2) The figures in square brackets corresponding to the *J*-statistics are the p-values; (3) * and ** indicate the statistical significance at 1% and 5% levels, respectively; (4) The parameters of the lag, contemporaneous and lead first-differenced dynamic regressors of $k\{-4, 0, +4\}$ and $k\{-5, 0, +5\}$ used in DOLS and of $k\{-1, 0, +1\}$ and $k\{-2, 0, +2\}$ used in NLLS estimations do not carry any economically meaningful interpretation and are, therefore, not reported to conserve space; (5) The ϕ is the coefficient of the lagged level term of model [7] estimated including the intercept and slope dummies; (6) The GMM estimation is carried out using the Bartlett lag window. The instrument set comprises a constant and two lags of regressors in GMM1, and a constant and five lags of regressors in GMM2.

distribution of the Sup-Wald test under the mild conditions on the errors and regressors for a variety of testing problems. Kejriwal and Perron (2008) show that if the coefficients of integrated regressors are allowed to change, then the estimated break fractions are asymptotically dependent so that the confidence intervals need to be constructed jointly. If, however, only the intercept and/or the coefficients of the stationary regressors are allowed to change, then the estimates of break dates are asymptotically independent as in the stationary case analyzed by Bai and Perron (1998, 2003). The structural breaks can take place in the form of the changes in either intercept or slope of the cointegrating vector. Kejriwal and Perron (2008, 2010) suggest the use of the linear DOLS estimator of Saikkonen (1991) and Stock and Watson (1993) to resolve the problem of endogeneity of regressors and serial-correlation of residuals. The KP results are valid, under very weak conditions, when the potential endogeneity of non-stationary regressors is accounted for via an increasing sequence of lags and leads of the first-differenced dynamic regressors in DOLS. They show that the limiting distributions of the tests based on DOLS are the same as those obtained with the static regression under strict exogeneity.

Both BP and KP suggest three tests for testing multiple breaks. The first test is the Sup-Wald test for the null hypothesis of no structural break ($m = 0$) against the alternative of $m = L$ number of arbitrarily fixed breaks. The second test is the double maximum (UDmax) test for the null hypothesis of no structural break ($m = 0$) against the alternative of an unknown number of breaks between 1 and some upper bound M , such that $1 \leq m \leq M$. The UDmax statistic weighted with the marginal p-values across breaks becomes the WDmax statistic. The third test is the sequential $SEQ_T(L+1)/L$ test, and it sequentially tests the null hypothesis of L against the alternative of $L + 1$ number of breaks. The Sup-F(1|0) test is first used to test the null hypothesis of zero versus one break; if the rejection occurs, then the Sup-F(2|1) is used to test the null of one versus two breaks; if the rejection again occurs, then the Sup-F(3|2) is used to test the null of two versus three breaks, and so on until the non-rejection occurs. The number of breaks is estimated as the number of rejections of the null hypothesis. The model with L breaks is obtained by the global minimization of the residual sum of squares. An alternative to using sequential $SEQ_T(L+1)/L$ test is to use the Bayesian information criterion (BIC) of Yao (1988) or the modified Schwarz information criterion (LWZ) of Liu, Wu, and Zidek (1997) to determine the optimal number of breaks. The sequential procedure, however, performs better as compared to BIC and LWZ in that the sequential procedure can easily allow and take into account the effects of possible serial-correlation in errors (Bai and Perron 1998, 2003).

The study estimates the DOLS model [6] using the lags-leads structure of $k = \{-4, 0, +4\}$ for the first-differenced $I(0)$ regressors. Both intercept and slope

parameters are allowed to change across regimes. The coefficients of the lagged, contemporaneous and lead $I(0)$ regressors are not allowed to break and, thus, are considered fixed and invariant over time. The inclusion of $I(0)$ regressors whose coefficients are not allowed to change does not alter the limit distribution. The DOLS estimation is also carried out using one lower, $k = \{-3, 0, +3\}$, and one higher, $k = \{-5, 0, +5\}$, lags and leads structures of the $I(0)$ regressors so as to assess the robustness of results. The results obtained from the alternative model structures were generally consistent in terms of the number and locations of the break-points.⁸ The results obtained from the multiple structural break tests performed on the model with $k = \{-4, 0, +4\}$ suggest that the F test rejects the null hypothesis of no structural break ($m = 0$) against the alternative of $m = L$ number of breaks for all the dates (Table 11). The Sup-F(m) statistics are significant with L running between 1 and 5. This suggests that at least one break could be present in the relationship. The UDmax statistics are highly significant at 1% level, reinforcing the presence of at least one break in the model (see Panel I, Table 11). The sequential F test is finally used to test the null hypothesis of L against the alternative of $L + 1$ breaks, and determine the optimal number of break-points. The $SEQ_T(L + 1)/L$ statistics are significant at 1% level (see Panel II, Table 11). The $SEQ_T(L + 1)/L$ test rejects the null hypothesis of $L = 4$ breaks and suggests the presence of five breaks and implied six number of regimes (see Panel III, Table 11). The evidence in terms of the number of structural breaks remains consistent across sequential test, minimised residual sum of squares test, and the BIC and LWZ criteria (see Panel II, Table 11). All the tests consistently suggest the presence of five structural breaks.

3.4.4 Test for Cointegration with Multiple Structural Breaks

The break years (1965, 1970, 1975, 1982, 1993) suggested by the multiple structural break tests are now used to set the exogenous break dummies in the VAR model. The ML estimator of Johansen, Mosconi, and Nielsen (2000) is used to estimate the VAR model augmented with such exogenous break dummies, and test the null hypothesis of no cointegration in the presence of multiple structural breaks. The ML estimator is useful to determine the number of cointegrating vectors in the presence of breaks at the known points in time. The estimation is carried out sequentially in that the model is first estimated with one structural break in level corresponding to 1965 (Model I) followed by the model with two

⁸ The results from the DOLS estimations carried out using the alternative model structures of $k = \{-3, 0, +3\}$ and $k = \{-5, 0, +5\}$ in the multiple structural break tests are available from the author on request.

Table 11: Supremum F and $SEQ_T(L+1)/L$ tests for multiple structural breaks.

Panel I: Sup-F test for zero versus an unknown number of structural breaks						
	Sup-F(m) Statistics; $H_0: m = 0; H_1: m = L$					
	Sup-F(1 0)	Sup-F(2 0)	Sup-F(3 0)	Sup-F(4 0)	Sup-F(5 0)	UDmax(L)
Test statistics	19.98*	15.03*	14.87*	30.33*	34.6*	34.6* (5)
Significance level	Critical values					
1 %	17.67	14.73	12.21	10.77	8.82	17.67
5 %	14.30	12.11	10.41	9.19	7.64	14.47
10 %	12.36	11.01	9.60	8.45	6.96	12.64
Panel II: Sequential $SEQ_T(L+1)/L$ statistics Test for L versus (L + 1) Number of Breaks, and the Minimized BIC and LWZ Statistics						
	$SEQ_T(L+1)/L; H_0: L \text{ breaks}; H_1: L+1 \text{ breaks}$					
	Sup-F(1 0)	Sup-F(2 1)	Sup-F(3 2)	Sup-F(4 3)	Sup-F(5 4)	
Test statistics	19.98*	30.06*	44.61*	121.33*	173.01*	
Significance level	Critical values					
1 %	19.04	19.35	19.90	19.99	20.01	
5 %	15.65	16.61	17.12	17.66	17.85	
10 %	14.26	15.02	15.64	16.02	16.51	
Number of breaks = 5 (based on Sup-F statistics); Minimised BIC(L) = -3.33 (5); Minimised LWZ(L) = -1.34 (5); Minimised residual sum of squares = 0.10 (5).						
Panel III: Break-Points and the 95 % Lower and Upper Confidence Bands						
	m = 1	m = 2	m = 3	m = 4	m = 5	
Break year	1965	1970	1975	1982	1993	
95% confidence Band	[1964–1966]	[1969–1971]	[1974–1976]	[1981–1983]	[1992–1994]	

Notes: (1) * indicates the statistical significance at 1 % level; (2) The critical values for the Sup-F test in Panel I and $SEQ_T(L+1)/L$ test in Panel II are taken from Kejriwal and Perron (2010); (3) The figures in round parentheses associated with the (i) minimized values of the residual sum of squares and (ii) BIC and LWZ statistics, are the L number of structural breaks.

(1965, 1970; Model II), three (1965, 1970, 1975; Model III), four (1965, 1970, 1975, 1982; Model IV) and five (1965, 1970, 1975, 1982, 1993; Model V) structural breaks in level (Table 12). Such sequential analysis is intended to discern the possible sensitivity of results to the inclusion of an additional break. The results are sensitive to the use of lag structures and the inclusion of exogenous breaks in

Table 12: Maximum-likelihood system estimates of the long-run model with multiple structural breaks [VAR lag $k=2$].

Model	Eigenvalues		λ -trace Test		λ -trace Test@	
	H0: $r=0$	H0: $r \leq 1$	H0: $r=0$	H0: $r \leq 1$	H0: $r=0$	H0: $r \leq 1$
Model I	0.263	0.088	23.06	5.34	22.18	5.11
Model II	0.269	0.087	23.50	5.29	22.60	5.06
Model III	0.294	0.132	28.45**	8.22**	27.38**	7.83**
Model IV	0.380	0.230	42.85**	15.17**	41.21**	14.48
Model V	0.418	0.255	48.52**	17.10**	46.71**	16.36

Model		Long-run parameters of the first cointegrating vector normalized on I/Y					
	I/Y	S/Y	Constant (1965)	Constant (1970)	Constant (1975)	Constant (1982)	Constant (1993)
Model I	1	-0.18 [1.07] (0.30)	0.78 [1.44] (0.23)				
Model II	1	-0.22 [1.50] (0.22)	0.66 [0.62] (0.43)	-0.09 [0.01] (0.92)			
Model III	1	-0.35*** [3.26] (0.07)	0.54 [0.56] (0.45)	-0.50 [0.32] (0.57)	-0.09 [0.01] (0.91)		
Model IV	1	0.04 [0.01] (0.91)	0.91 [1.19] (0.28)	-0.33 [0.10] (0.76)	-1.19 [1.47] (0.24)	2.64* [6.02] (0.01)	
Model V	1	0.13 [0.13] (0.71)	0.90 [1.38] (0.24)	-0.13 [0.02] (0.90)	-1.17 [1.67] (0.20)	2.51* [7.59] (0.01)	0.41 [0.33] (0.56)

Notes: (1) The r denotes the number of cointegrating vectors; (2) @ λ -trace statistics corrected for small sample; (3) The figures in square brackets are the likelihood ratio test statistics for the exclusion restrictions on the associated variables, and the figures in round parentheses are the p-values; (4) *, ** and *** indicate the statistical significance and implied rejection of the null hypothesis at 1%, 5% and 10% levels, respectively. Some of the p-values are on the border line of critical region and, thus, strictly do not reject the null hypothesis at the indicated level of significance.

the VAR model.⁹ Both asymptotic λ -trace and λ -trace adjusted for small-sample consistently do not reject the null hypothesis of no cointegration in the models estimated with one (Model I) and two (Model II) structural breaks in level, but

⁹ The results for the VAR model with structural breaks estimated (i) using both lower ($k=1$) and higher ($k=3, 4, 5$) lag structures as well as (ii) using the break in trend are available from the author on request.

reject the null hypothesis in the models estimated with three (Model III), four (Model IV) and five (Model V) structural breaks in level (Table 12). The slope parameter on saving is consistently low across all the models, reinforcing the high mobility of capital.

3.4.5 New Tests for Cointegration Breakdowns over the Short Time Periods

The standard structural break estimators rely on the assumption that the post-breakdown periods are relatively long and on the asymptotics in which the length goes to infinity with the sample size. The power of the standard structural break estimators may tend to decline as the break-point moves towards the end of the sample space. These estimators could be inadequate to take an efficient account of structural breaks that may occur over the short time period and at the end of the sample. The possibilities of these short and end-of-sample breaks in the cointegrating vector become particularly pronounced for the models examining the current account imbalances and the associated SI correlations and capital flows. Apart from economic fundamentals, the capital flows are conditioned by the speculative (systematic or stochastic) expectations (rational or irrational) of international investors. Andrews and Kim (AK) (2006) develop the new cointegration breakdown tests that are efficient in the presence of short and end-of-sample breaks in the cointegrating vector. These tests are asymptotically valid when the length, m , of post-breakdown period is fixed, as the total sample size, $T + m$, goes to infinity. The AK tests build on the estimation of the model represented by

$$y_t = \begin{cases} x'_t \beta_0 + u_t; & t \in \{1, \dots, T\} \\ x'_t \beta_t + u_t; & t \in \{T+1, \dots, T+m\} \end{cases} \quad [19]$$

The regressors for all time periods, $x_t : t \in \{1, \dots, T+m\}$, are linear combinations of $I(1)$ random, stationary random and deterministic variables, such as a constant and a linear time trend. The errors for first T periods, $u_t : t \in \{1, \dots, T\}$, are mean-zero, stationary and ergodic. Under the null hypothesis, the model is a well-specified cointegrating regression for all $t \in \{1, \dots, T+m\}$.

$$H_0 : \begin{cases} \beta_t = \beta_0 & \text{for all } t = T+1, \dots, T+m \text{ and} \\ \{u_t : t = 1, \dots, T+m\} & \text{are stationary and ergodic} \end{cases}$$

Under the alternative hypothesis, the model is a well-specified cointegrating regression for all $t \in \{1, \dots, T\}$, but the cointegration breaks down for $t \in \{T+1, \dots, T+m\}$ (Andrews and Kim 2006; Carstensen 2006). The breakdown in cointegration could arise from shift in the (i) cointegrating vector from β_0 to β_t ,

(ii) distribution of u_t from being stationary to being a unit root random variable, (iii) distribution of $\{u_{T+1}, \dots, u_{T+m}\}$ from that of $\{u_1, \dots, u_m\}$, or (iv) some combination of these shifts.

$$H_1: \begin{cases} \beta_t \neq \beta_0 \text{ for some } t \in \{T+1, \dots, T+m\} \text{ and/or the distribution of} \\ \{u_{T+1}, \dots, u_{T+m}\} \text{ differs from the distribution of } \{u_1, \dots, u_m\} \end{cases}$$

The $P \in \{P_a, P_b, P_c\}$ and $R \in \{R_a, R_b, R_c\}$ tests are performed to test H_0 against H_1 . In P tests, the estimates for $t \in \{1, \dots, T\}$ are used to construct the prediction errors, $\hat{u}_t = y_t - x'_t \hat{\beta}_{1-T} : t \in \{T+1, \dots, T+m\}$, and compute $P_a = \sum_{t=T+1}^{T+m} \hat{u}_t^2$. The P_b and P_c tests are based on $\hat{\beta}_{1-[T+(m/2)]}$ and $\hat{\beta}_{1-[T+m]}$; where $\{m/2\}$ is the smallest integer greater than or equal to $\{m/2\}$. In R tests, $R_a = \sum_{i=T+1}^{T+m} \sum_{j=T+1}^{T+m} \min\{i-T, j-T\} \hat{u}_i \hat{u}_j = \sum_{i=T+1}^{T+m} \left[\sum_{j=i}^{T+m} \hat{u}_j \right]^2$; where $\hat{u}_i; i \in \{T+1, \dots, T+m\}$ are the prediction errors. The R_b and R_c are computed, analogous to P_b and P_c , using $\hat{\beta}_{1-[T+(m/2)]}$ and $\hat{\beta}_{1-[T+m]}$, respectively. The R tests draw on the locally best invariant (LBI) test for the presence of unit root disturbances in the second sub-sample $t \in \{T+1, \dots, T+m\}$. The choice of the best test among the six tests is not unambiguously clear in that the P_a and R_a tests are inferior to others in terms of size, while the remaining four tests are not as easy to distinguish (Andrews and Kim 2006). The P_b and R_b tests tend to reject too often under the null, as compared to the P_c and R_c tests. The P_c and R_c appear to be the best tests. Of these, P_c has somewhat better size properties as compared to R_c , while R_c has power that is less variable across different distributions as compared to P_c . On balance, AK prefer P_c , because of its somewhat better size properties compared to R_c .

The study performs $P \in \{P_a, P_b, P_c\}$ and $R \in \{R_a, R_b, R_c\}$ tests on OLS, FMOLS and full-information maximum-likelihood (FIML) estimates of the model so as to assess the robustness of results across estimators. The null hypothesis that the cointegration prevails from 1948 to 2007 is tested against several alternative hypotheses of cointegration breakdowns. The p-values for the $P \in \{P_a, P_b, P_c\}$ and $R \in \{R_a, R_b, R_c\}$ tests are computed using the parametric sub-sampling method suggested by Andrews and Kim (2006). The results suggest that the cointegration prevails and the implied intertemporal budget constraint holds for the U.S. Both P_c and R_c statistics consistently do not reject the null hypothesis of cointegration against the alternative hypotheses of cointegration breakdowns during 1982–2007, 1985–2007, 1990–2007, 1995–2007, 2000–2007, 2001–2007, 2002–2007, 2003–2007, 2004–2007 and 2005–2007 (Table 13). The evidence is predominantly consistent across all $P \in \{P_a, P_b, P_c\}$ and

Table 13: Tests for cointegration breakdowns over the short time periods, and the estimates of the slope parameter on saving.

Estimator	H0: Cointegration Prevails for the Full Sample From 1948 To 2007						
	$\hat{\beta}_{1-T}$	$\hat{\beta}_{1-T+(m/2)}$	Pa	Pb	Pc	Ra	Rb
	1948–1981	1948–1994				H1: Cointegration Breaks Down During: 1982–2007; m = 26	
OLS	0.72	0.52	94.78* (0.00)	34.37 (0.11)	23.07 (0.33)	20342.80* (0.00)	4020.62 (0.33)
FMOLS	0.58	0.46	51.48 (0.56)	27.99 (1.00)	22.97 (0.44)	8720.78 (0.44)	2127.02 (0.78)
FIML	−0.77	0.36	654.12* (0.00)	23.19 (1.00)	24.63 (0.67)	152179.42* (0.00)	387.52 (1.00)
							565.31 (0.78)
							199.72 (1.00)
							277.05 (1.00)
	H1: Cointegration Breaks Down During: 1985–2007; m = 23						
	$\hat{\beta}_{1-T}$	$\hat{\beta}_{1-T+(m/2)}$	Pa	Pb	Pc	Ra	Rb
	1948–1984	1948–1995				H1: Cointegration Breaks Down During: 1990–2007; m = 18	
OLS	0.65	0.52	64.26* (0.00)	29.95 (0.13)	19.00 (0.13)	10036.99* (0.00)	2956.23 (0.40)
FMOLS	0.59	0.47	46.34 (0.33)	24.60 (0.60)	18.73 (0.27)	6374.16 (0.33)	1779.75 (0.60)
FIML	−0.47	0.39	331.50 (0.33)	19.80 (1.00)	20.22 (1.00)	56778.74* (0.00)	604.54 (1.00)
							261.46 (0.83)
	H1: Cointegration Breaks Down During: 1990–2007; m = 18						
	$\hat{\beta}_{1-T}$	$\hat{\beta}_{1-T+(m/2)}$	Pa	Pb	Pc	Ra	Rb
	1948–1989	1948–1998				H1: Cointegration Breaks Down During: 1990–2007; m = 18	
OLS	0.44	0.51	15.56 (0.60)	20.49 (0.16)	14.33 (0.24)	836.48 (0.52)	1810.63 (0.12)
FMOLS	0.29	0.46	17.85 (0.40)	16.84 (0.56)	14.83 (0.48)	137.50 (0.76)	1130.52 (0.44)
FIML	0.01	0.35	65.43** (0.05)	14.42 (0.73)	16.95 (0.64)	3732.28* (0.00)	260.28 (0.55)
							112.39 (0.77)

(continued)

Table 13: (continued)

	1948–1994	1948–2000	H ₁ : Cointegration Breaks Down During: 1995–2007; m = 13					
OLS	0.52	0.50	18.55 (0.26)	15.01 (0.29)	7.03 (0.69)	1252.04*** (0.09)	980.94 (0.14)	338.33 (0.17)
FMOLS	0.46	0.44	12.54 (0.34)	10.24 (0.60)	5.02 (0.89)	788.71 (0.17)	605.37 (0.26)	143.79 (0.63)
FIML	0.36	0.31	6.16 (0.81)	4.80 (0.94)	4.32 (0.78)	254.15 (0.41)	115.10 (0.78)	39.02 (0.91)
	1948–1999	1948–2003	H ₁ : Cointegration Breaks Down During: 2000–2007; m = 8					
OLS	0.50	0.46	14.70 (0.13)	10.61 (0.20)	6.11 (0.38)	386.47* (0.00)	266.28*** (0.07)	129.98 (0.16)
FMOLS	0.45	0.43	10.05 (0.38)	8.22 (0.42)	3.88 (0.73)	248.08 (0.11)	193.58 (0.18)	55.75 (0.44)
FIML	0.32	0.33	3.98 (0.67)	4.12 (0.64)	2.88 (0.64)	56.89 (0.57)	62.50 (0.55)	16.03 (0.76)
	1948–2000	1948–2003	H ₁ : Cointegration Breaks Down During: 2001–2007; m = 7					
OLS	0.50	0.46	12.54*** (0.09)	9.53 (0.19)	5.29 (0.43)	267.69* (0.00)	198.86*** (0.06)	98.36 (0.11)
FMOLS	0.44	0.43	8.16 (0.38)	7.23 (0.45)	3.15 (0.74)	167.01 (0.13)	145.09 (0.17)	42.92 (0.43)
FIML	0.31	0.33	2.85 (0.68)	3.33 (0.64)	2.24 (0.84)	33.93 (0.57)	47.77 (0.52)	13.11 (0.75)

	1948–2001	1948–2004	H ₁ : Cointegration Breaks Down During: 2002–2007; m = 6					
OLS	0.50	0.44	12.08*** (0.06)	7.70 (0.16)	5.28 (0.39)	189.70** (0.02)	117.56*** (0.08)	76.13*** (0.08)
FMOLS	0.43	0.39	7.68 (0.29)	5.42 (0.47)	3.10 (0.65)	117.20 (0.12)	78.32 (0.20)	35.49 (0.43)
FIML	0.33	0.31	3.20 (0.54)	2.62 (0.61)	2.09 (0.70)	37.18 (0.39)	25.23 (0.54)	12.28 (0.72)
	1948–2002	1948–2004	H ₁ : Cointegration Breaks Down During: 2003–2007; m = 5					
OLS	0.48	0.44	10.77** (0.04)	7.62*** (0.10)	5.28 (0.25)	114.74** (0.02)	79.74*** (0.06)	53.30*** (0.06)
FMOLS	0.44	0.39	7.84 (0.16)	5.41 (0.33)	3.04 (0.55)	82.25 (0.10)	54.78 (0.18)	26.75 (0.27)
FIML	0.33	0.31	3.10 (0.50)	2.49 (0.52)	1.80 (0.67)	27.40 (0.31)	19.81 (0.44)	10.60 (0.56)
	1948–2003	1948–2005	H ₁ : Cointegration Breaks Down During: 2004–2007; m = 4					
OLS	0.46	0.42	8.53** (0.04)	6.04 (0.19)	5.08 (0.23)	55.54** (0.04)	37.86 (0.11)	31.01 (0.11)
FMOLS	0.43	0.36	6.72 (0.13)	3.91 (0.40)	3.03 (0.42)	42.67*** (0.09)	22.71 (0.23)	16.45 (0.28)
FIML	0.33	0.28	3.23 (0.38)	1.87 (0.48)	1.74 (0.54)	17.87 (0.28)	8.17 (0.52)	7.26 (0.48)
	(continued)							

(continued)

Table 13: (continued)

	1948–2004	1948–2005	H ₁ : Cointegration Breaks Down During: 2005–2007; <i>m</i> = 3					
OLS	0.44	0.42	5.12 (0.16)	4.39 (0.20)	3.73 (0.25)	18.95 (0.13)	15.72 (0.16)	12.78 (0.20)
FMOLS	0.39	0.36	3.83 (0.29)	2.95 (0.36)	2.35 (0.36)	13.19 (0.18)	9.30 (0.27)	6.68 (0.38)
FIML	0.31	0.28	1.99 (0.37)	1.56 (0.44)	1.47 (0.44)	5.09 (0.38)	3.28 (0.48)	2.91 (0.50)

Notes: (1) The estimates of the intercept term are not reported to conserve space, but are available from the author on request; (2) The figures in round parentheses are the p-values; (3) *, ** and *** indicate the statistical significance and implied rejection of the null hypothesis at 1 %, 5 % and 10 % levels, respectively. Some of the p-values are on the border line of critical region and, thus, strictly do not reject the null hypothesis at the indicated level of significance.

$R \in \{R_a, R_b, R_c\}$ tests. The results, thus, support the cointegrating relationship between the model variables even in the presence of the short period and end-of-sample breaks.

The stylized evidence provides dominant support for the presence of high mobility of capital in the U.S. Such support is consistent with the observed dynamics of current account and the implied financing of domestic investment through foreign saving. The support for low SI correlations and high mobility of capital resonates with the findings of the studies by Schmidt (2003) and Hoffmann (2004) for the OECD countries including the U.S. The support for cointegration between saving and investment found in the study is also consistent with the studies finding support for cointegration (Levy 2000; De Vita and Abbott 2002; Nell and Santos 2008), but inconsistent with the studies providing no (Gulley 1992; Byrne, Fazio, and Fiess 2009) or mixed (Miller 1988; Moreno 1997) support for cointegration between saving and investment. A number of factors seem catalytic to the U.S. current account deficits and implied reliance of domestic investment on foreign saving. First, the level of domestic saving remains inadequate to finance the high levels of investment and such inadequacy induces the need for borrowing from the world financial markets. Second, the current account surpluses in the rest of the world are commensurately reflected in the current account deficits in the U.S., given the reserve-currency characteristic of the U.S. dollar. Third, the international investors seem to speculate low exchange rate risks and prefer the higher holdings of the U.S. financial assets in their asset portfolios. Obstfeld (2010) observes that some recent theories of the global imbalances stress the U.S. as a source of high quality assets that the rest of the world's savers crave. Fourth, the high-valued U.S. currency provides incentive for borrowings from the international financial markets.

4 Conclusions

This study has examined the relationship between domestic saving and investment and measured the international mobility of capital in the United States. The long-run model, “with” and “without” structural breaks, is estimated using several single-equation and system estimators to assess the robustness of results and take an exhaustive account of the methodological and measurement issues. The results provide dominant support for the long-run relationship between domestic saving and investment. The estimates of the slope parameter on saving above zero and the dominant support for cointegration between saving and investment across estimators vindicate the validity of intertemporal budget

constraint and suggest the sustainability of current account deficits. The numerical magnitude of the slope parameter on saving is consistently low across estimators. The estimates of the model with structural breaks reinforce the dominant support for the long-run relationship between domestic saving and investment. The inclusion of these structural breaks in the model generally reduces the numerical magnitude of the slope parameter on saving and suggests the high mobility of capital. The results showing the low slope parameter on saving resonate with the observed high mobility of capital and reflect the globalization of financial markets. The numerically low magnitude of the slope parameter on saving in the wake of observed high mobility of capital is consistent with the theoretical predictions of the model.

The internal need for borrowing from the world financial markets arising from the domestic resource gap (saving minus investment) in the U.S. seems equally-whelmed by the external supply of funds by the international investors to purchase the U.S. assets. The international investors seem to speculate low exchange rate risks and predict the higher exchange-rate-adjusted rates of returns and, as such, prefer the higher holdings of the U.S. assets in their asset portfolios. The reserve-currency characteristic of the U.S. dollar provides an added dimension to the demand for the U.S. currency. The mutually-reinforcing internal demand for and the external supply of loanable funds appear to have played a catalytic role in conditioning the mobility of capital into the U.S. While the capital inflows relinquish the domestic saving and binding financing constraints on domestic investment, these inflows lead to the appreciation of exchange rate, which, in turn, reduces the competitiveness of exports and accentuates the current account deficits. The gains of financial openness remain surrounded by several risks arising from the sudden stops and stochastic reversals of particularly the high-resolution and speculative capital inflows. Such sudden stops and stochastic reversals of the short-term and speculative capital inflows tend to induce financial instability and lead to the spiral of financial and economic calamities in the domestic as well as global economy. This underlines the need to stimulate domestic saving to finance the higher levels of domestic investment and reduce the magnitudes of current account deficits and external debt. The domestic saving could be accelerated through the reduction in budget deficits and the provision of saving incentives to the household and private corporate business sectors. The depreciation of the domestic currency (the U.S. dollar) against the currencies of particularly the major trading partners and/or international lenders would be useful to stimulate the net exports (exports minus imports) as well as to reduce the effective magnitude of the external debt denominated in the U.S. currency.

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Appendix

Annexure 1: Model structures and the sensitivity of optimal single-equation estimates.

Model Structure	Dependent Variable: $[I/Y]_t$		
	Constant	$[S/Y]_t$	φ
k	DOLS Estimates		
$k\{-1, 0, +1\}$	13.43* (10.42)	0.36* (5.45)	
$k\{-2, 0, +2\}$	13.10* (12.08)	0.37* (6.67)	
$k\{-3, 0, +3\}$	13.02* (15.03)	0.37* (8.21)	
lw	FMOLS Estimates		
$lw = 2$	13.82* (11.77)	0.34* (5.42)	
$lw = 3$	13.88* (11.11)	0.34* (5.04)	
$lw = 5$	13.82* (10.71)	0.34* (4.92)	
$lw = 8$	13.94* (11.03)	0.33* (4.93)	
k	NLLS Estimates		
$k\{-3, 0, +3\}$	14.17* (6.61)	0.32* (2.93)	0.18* (3.88)
$k\{-4, 0, +4\}$	12.89* (8.68)	0.38* (4.94)	0.06 (1.45)
$k\{-5, 0, +5\}$	12.79* (12.19)	0.38* (6.85)	-0.006 (-0.15)

Notes: (1) The standard errors of all the models are adjusted using the HAC estimator; (2) The figures in round parentheses are the t-ratios; (3) * indicates the statistical significance at 1% level. The lw denotes the lag window.

Annexure 2: Model structures and the sensitivity of the over-parameterized level-VAR estimates [F-statistics].

Regressor	Maximal Order of Integration (dmax) of the Model Series						Dependent Variable
	dmax = 0		dmax = 1		dmax = 2		
	$ I/Y _t$	$ S/Y _t$	$ I/Y _t$	$ S/Y _t$	$ I/Y _t$	$ S/Y _t$	
$ I/Y _t$ $ S/Y _t$	VAR Lags: $q = [k + dmax] = [4 + 0] = 4$; Zero-Restrictions for first $k = 4$ Lags						VAR Lags: $q = [k + dmax] = [4 + 2] = 6$; Zero-Restrictions for first $k = 4$ Lags
	4.69* (0.00) 2.00 (0.11)	0.97 (0.43) 27.82* (0.00)	3.70* (0.01) 0.70 (0.59)	0.55 (0.70) 13.70* (0.00)	4.69* (0.00) 1.13 (0.35)	0.82 (0.52) 12.95* (0.00)	
$ I/Y _t$ $ S/Y _t$	VAR Lags: $q = [k + dmax] = [5 + 0] = 5$; Zero-Restrictions for first $k = 5$ Lags						VAR Lags: $q = [k + dmax] = [5 + 2] = 7$; Zero-Restrictions for first $k = 5$ Lags
	3.20** (0.02) 1.44 (0.23)	0.68 (0.64) 20.54* (0.00)	3.84* (0.01) 1.41 (0.24)	0.67 (0.65) 12.42* (0.00)	3.81* (0.01) 1.54 (0.20)	0.83 (0.54) 10.50* (0.00)	

Notes: (1) The figures in round parentheses are the p-values; (2) * and ** indicate the statistical significance at 1 % and 5 % levels, respectively. Some of the p-values are on the border line of critical region and, thus, strictly do not reject the null hypothesis at the indicated level of significance.

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