Supplementary Materials:
Error Correction Methods with Political Time Series

February 22, 2015

Contents

Appendix A Additional Details on the Derivation of ECM Models

In this section we provide more information on the origins of the ECM model that DeBoef and Keele (2008) adapt from the econometrics literature.

Kremers, Ericsson, and Dolado (1992) were the first to derive the asymptotic distribution of a conditional ECM t-test with a pre-specified cointegrating vector. Importantly, they found that the distribution of the ECM was dynamic. Assuming an $I(1)$ dependent variable, it would shift based upon the properties of the covariate. The authors also noted the relationship between the ECM and Engle-Granger procedures, which we briefly discuss below.

If we assume a general ECM given as:

$$\Delta y_t = \gamma_0' \Delta z_t + \gamma_1 (y - \delta' z)_{t-1} + \upsilon_{1t} \tag{1}$$

$$\Delta z_t = \epsilon_t \tag{2}$$

where $y - \delta' z$ is the potential cointegrating relationship, then we can establish the relationship between the ECM and the Engle Granger cointegration test. By subtracting $\delta' \Delta z_t$ from both sides of (1) we get:

$$\Delta (y - \delta' z)_t = \gamma_1 (y - \delta' z)_{t-1} + \{(\gamma_o' - \delta') \Delta z_t + \upsilon_{1t}\} \tag{3}$$

Next, redefine the Engle-Granger residual, $(y - \delta' z_t)$ as ω_t. From this point, (3) can be rewritten as

$$\Delta \omega_t = \gamma_1 \omega_{t-1} + e_t \tag{4}$$

where $e_t = (\gamma_0' - \delta') \Delta z_t + \upsilon_{1t}$.

Rewritten in this way, the t-test on γ_1 in (4) is equivalent to the test statistic of the Engle-Granger cointegration test. It is the Dickey-Fuller (DF) test of ω_t, determining whether the cointegrating relationship of y and z indicates cointegration (i.e., stationarity).

Note in (4) however that the Dickey-Fuller test imposes a common factor restriction – ($\gamma_0 = \delta$) – the short and long run elasticities must be the same. In their work on the general ECM Kremers, Ericsson, and Dolado (1992) argue that, more often than not, such a restriction is invalid. In such instances the ECM t-test will be more powerful than the Engle-Granger because it does not impose the same restrictions.

Kremers et al. (1992) derived the distribution of the ECM test under the null hypothesis of no cointegration and found the distribution to be dynamic – it is influenced by the covariate. They found that when the covariate was both (1) stationary and (2) a strong predictor of the dependent variable, the ECM distribution approached the standard normal. The extent to which the distribution would shift away from the Dickey-Fuller distribution was dictated by a nuisance parameter, which they referred to as the "signal-to-noise" ratio. This parameter, specified as q, captured the similarity of the error variances in ($e_t = (\gamma_0 - \delta)\Delta z_t + \upsilon_{1t}$). The larger the value of γ_0, the smaller the effect of e_t and the closer the distribution will be to that of the Dickey-Fuller. Conversely, the more influential the stationary covariate, the larger the value of e_t and the ECM distribution would approximate a normal distribution.

Kremers et al. (1992) gave their signal-to-noise ratio as:

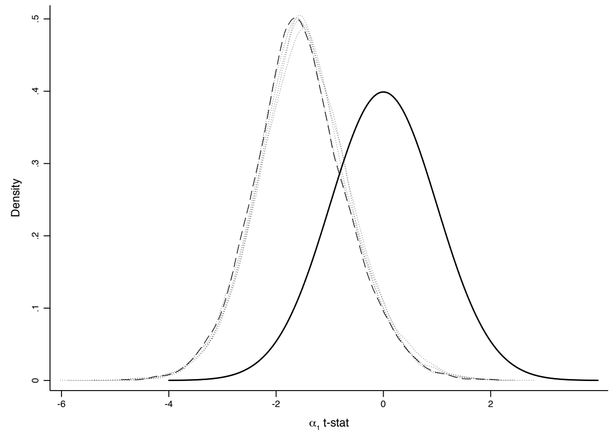
$$q = -(\gamma_0 - \delta)s \tag{5}$$

where s is the ratio $\sigma_\epsilon / \sigma_\upsilon$.

Building off of this work, Hansen (1995) developed the Covariate Augmented Dickey-Fuller (cADF) test which accounted for the information provided by additional stationary covariates. By dropping the common factor restrictions of the standard DF test and instead allowing the use of additional information, Hansen demonstrated a univariate unit-root test with better precision in the estimates, shorter confidence intervals, and increased power of the test statistic, sometimes substantially.[1] With Monte Carlo simulations, Hansen demon-

[1] Caporale and Pittis (1999) investigate the power gains of the cADF and find that the nature of the

Figure A.1: Densities of ECM t-statistic With Valid Common Factor Restrictions



Note: Dashed line is the density of the Dickey-Fuller t-statistic of the DV. Tight dots are the densities of the ECMs' t-statistics with up to 4 IVs included in the model. With $I(0)$ IVs in which ΔX_t =0, the distributions follows that of the DF. Solid line is the standard normal distribution. Each regression model contains a constant. DV is $I(1)$. $T = 60$

strated that under the null hypothesis of a unit-root, $\delta = 0$, the asymptotic distribution of the cADF test statistic $t(\widehat{\delta}) = \widehat{\delta}/s(\widehat{\delta})$ is a weighted combination of the standard normal and DF distributions, weighted by the included covariate's contribution to the long-run correlation in the error term. The covariate contribution is modeled as a nuisance parameter, ρ^2:

$$t(\widehat{\delta}) = \rho(DF) + (1 - \rho^2)^{1/2}N(0, 1) \tag{6}$$

which takes on values in the unit interval such that when when $\rho = 1$, the covariates are uncorrelated and the cADF is equivalent to the Dickey Fuller; as $\rho \Rightarrow 0$ the distribution approximates the standard normal. With the nuisance parameter set on a specific interval, Hansen was able to calculate specific critical values for hypothesis testing.

The asymptotic distribution and critical values of Hansen's cADF rely upon a very strong assumption of stationarity, however, and it will not hold if the assumption is violated. With an $I(1)$ dependent variable and a non-stationary ΔX_t that is not cointegrated, Hansen finds

correlation between error terms of the series being tested and the covariates is determinant. Not only will the addition of a covariate increase the precision of standard errors, but under certain circumstances the coefficient on Y_{t-1} increases in absolute value.

the distribution is biased away from the normal, approximating the distribution estimated by Phillips and Ouliaris (1990) for the Engle-Granger cointegration test. This distribution is even more biased away from the normal than the Dickey-Fuller distribution. The consequences of violating these stationarity assumptions extend to under-differenced data as well. If a covariate is $I(d)$ where $d > 1$, differencing will not account for all of the auto-correlation and the distribution will be biased away from the normal as a result.

The distribution derived by Hansen dealt with testing for univariate unit-roots, but it was a generalization of Kremers, Ericsson, and Dolado (1992). Whereas the nuisance parameter defined by Kremers et al. could take on any positive value making it difficult to use, Hansen's nuisance parameter was placed on a specific interval. In fact, Zivot (2000) derived the asymptotic distribution of Kremers, Ericsson, and Dolado's (1992) conditional ECM t-test for pre-specified cointegrating vectors under more general conditions and found the asymptotic distribution of Hansen's cADF for a unit-root was identical to the asymptotic distribution of the conditional ECM t-test.

A.1 Limitations to Estimating the ECM Distribution

The past research of Kremers, Ericsson, and Dolado (1992), Hansen (1995), and Zivot (2000) determined the distributional properties of the ECM statistic in situations in which the cointegrating coefficients were known, but importantly, these properties only hold under situations of prior knowledge and proper pre-specification.

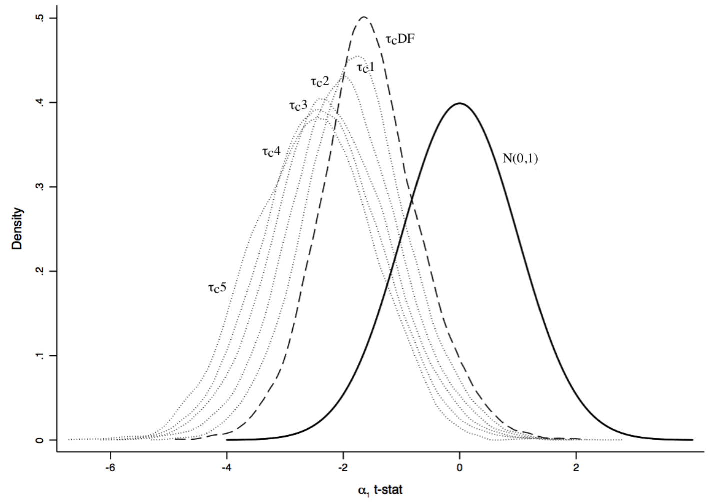
When the ECM model is used in applied research however, we often have no *a priori* knowledge of the cointegrating vector. We cannot pre-specify the nuisance parameter, dictate our covariate's level of influence, or set the direction of correlation, and these limitations have real consequences as to what assumptions we can make about the ECM t-statistic.

For instance, despite Kremers et al. (1992) proving the ECM distribution approximated the normal under certain circumstances, they include a footnote in their paper urging caution when using the ECM test in applied settings. Footnote 5 states that when a researcher has no prior information of the influence of ΔX_t that it is advisable to use the DF test statistics because they were substantively larger. In other words, meeting the assumption of stationarity was not enough. Unable to specify the signal-to-noise ratio in real life, a researcher cannot guarantee that the ECM's distribution approaches the normal. As a result, relying on the normal distribution for hypothesis testing potentially results in Type I errors. Caution behooves the researcher to use the more conservative distribution.

This distinction between the ability to pre-specify the cointegrating vector and having to estimate the cointegration coefficent is worth considering in greater depth because it has real consequences on how the ECM is used within the field of political science. With imperfect knowledge we are left to test for cointegration by estimation, and in order for our hypothesis tests to be valid we need a reliable set of test statistics. But from the work of multiple lines of research we know that the distribution of the ECM t-statistic is non-standard and is not dimension invariant. Kremers, Ericsson, and Dolado (1992) and Hansen (1995) established that when influential, stationary covariates are added, the distribution will shift towards the normal - however, in practice the extent of that shift is generally unknown. Hansen also found that when non-stationary covariates that did not cointegrate were added, the distribution was biased in the negative direction. Banerjee, Dolado, and Mestre (1998) and Ericsson and MacKinnon (2002) used Monte Carlo simulations to compute critical values for the ECM distribution and found that the distribution would shift in the negative with every additional $I(1)$ regressor. The MacKinnon values were computed for the widest number of situations and are widely used today for hypothesis testing for the ECM cointegration test.

But the MacKinnon critical values are only meaningful if we can also guarantee that all series in the model are $I(1)$. *Thus, if we include a mix of stationary and $I(1)$ regressors, our ECM statistic will no longer fit the distribution, our critical values will be incorrect, and we won't know in which direction our test statistic is biased.* As the examination of Caporale and Pittis (1999) found, the reduction (and potential inflation) of standard errors as well as the possibility of inflated test-statistics depend on a mix of factors, including the direction of Granger causality as well as the contemporaneous correlation of the error terms.

Figure A.2: Densities of ECM t-statistic by Number of Covariates



Note: Density plots of the ECM t-statistic for up to 5 IVs included. Each additional IV shifts the distribution further away from the normal. DV and IVs all $I(1)$. $T = 60$

Alternatively, if we use an IV that is $I(d) > 1$, we can expect that the ECM statistic will be biased in the negative direction away from the MacKinnon critical values. The stationarity assumptions of Hansen (1995) are valid, and failing to take them into account will cause serious inferential problems.

We demonstrate this with a simple bivariate regression using an independent variable from Ura and Ellis (2012). We use their variable, *Defense Spending*, which captures all federal defense spending in 2008 dollars. Estimates of its order of integration using Stata's ML estimator are: $d = 1.36$ (s.e.=0.11).

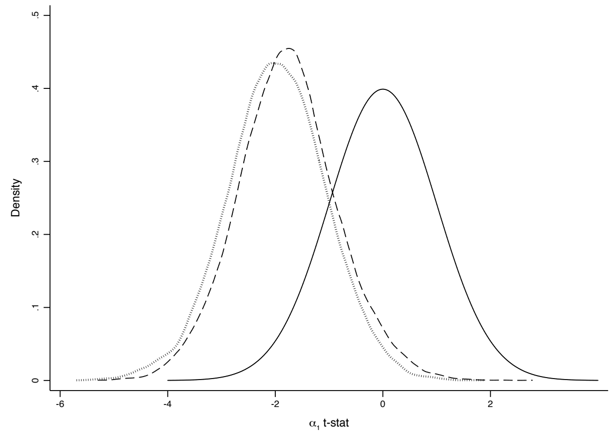
In its most commonly used form, the Bårdsen transformation, the ECM is given as:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_0 \Delta X_t + \beta_1 X_{t-1} + \epsilon_t \tag{7}$$

Recalling the stationarity concerns of Hansen - independent variables must be stationary, and if in differenced form they should not be under-differenced - it is clear that by including *Defense Spending* in the above model, we are going to bias our ECM t-statistic twice. The order of integration of *Defense Spending*$_{\text{t-1}}$, $I(d)$, is much larger than $I(1)$, and Δ*Defense*

$Spending_t$ will therefore be under-differenced. We should expect that the distribution of the ECM t-statistic is biased away from the normal.

Figure A.3: Densities of ECM t-statistic with IV d > 1



Note: Dashed line is density of ECM t-statistic of $I(1)$ bivariate regression. Mean t-statistic = -1.78. Tight dot is t-statistic of random $I(1)$ DV regressed on *Defense Spending*. Mean t-statistic of α_1 = -1.99. Normal density included for comparison. $T = 36$

Figure A.3 presents the density plot of the ECM t-statistic after 10,000 simulations of this model. The density plot of the ideal $I(1)$ bivariate regression is included for comparison, and the bias is clearly evident. And while this bias may appear minimal, were we to use MacKinnon critical values we would reject the null of no cointegration in 7.1% of simulations, compared to the 4.7% rejection rate of the ideal regression. This is just one of the many ways the distribution of the test statistic is moved around.

A.2 Testing the Null of No Cointegration

Research has previously investigated the strength of the ECM as a cointegration test. Crucially, these studies all evaluate the distributional properties of the ECM statistic when the cointegrating vectors *are already known* (De Boef and Granato 1999; De Boef 2001; Hansen 1995; Kremers, Ericsson, and Dolado 1992; Zivot 2000). Assuming that the known cointegrating vector is properly specified, such conditional ECM t-tests testing the null of no-cointegration are often far more powerful than cointegration tests in which the cointegrating vector must be estimated (Zivot 2000).

In the political science literature, studies that examines the ECM test under the null of no cointegration also pre-specifiy the cointegrating vectors (De Boef and Granato 1999; De Boef 2001). When the data do not contain a cointegrating relationship, the ECM test consistently performs as expected, even with near-integrated data. Similarly, under the alternative hypothesis of a cointegrating relationship, the ECM test performs admirably as the amount of available information increases. Under circumstances such as those tested by DeBoef and Granato, when the cointegrating vector is specifically set either to 0 (no cointegration) or -0.05 (cointegration), the ECM test does not suffer from either Type I or II errors. These findings are consistent with previous research (Kremers, Ericsson, and Dolado 1992; Zivot 2000).

But in actual practice, the cointegrating vector is unknown ahead of time and must be estimated. What is the power of the ECM test under these less than ideal circumstances? Were researchers simply using $I(1)$ data series, the work of Banerjee, Dolado, and Mestre (1998) and Ericsson and MacKinnon (2002) would be sufficient to show that the ECM model performs as it should. But in actual practice we have seen a proliferation of studies using the ECM model with series of all orders of integration, and these unbalanced models have led to all sorts of inferential problems. Additionally, little thought has been paid to the interpretations and conclusions when estimating an ECM equation using a stationary series as the dependent variable. And the models often have other complications that make interpretation even more difficult – e.g. interactions are sometimes included and the ECMs of small T series have been estimated with up to 10 independent variables. And this has all occurred while using the standard one-tail t-statistic of -1.645 as the hypothesis test for error correction.

Given the large number of combinations of data series varying by length and order of integration, we set out to broadly simulate data common to political science. Such series tend to be short in duration and are rarely $I(1)$. Based on the work of De Boef and Granato (1999) and De Boef (2001) we also tested the ECM with near-integrated data under the null of no cointegration. When the series were comprised solely of $I(1)$ series, the ECM statistic performs as expected. As we deviate from $I(1)$ series, the power of the ECM model deteriorates rapidly. Type I errors abound and spurious regressions are the norm.

Appendix B Generating Series

All simulations were run in RATS 8.0 although almost all replications were also estimated in Stata to allow readers to more easily replicate our findings.[2] Series were generated to fit a specified order of integration or level of autoregression.

For all simulations we relied on the RATS random number generator and set a specific seed value for replication. The starting value for each series was 0. For $I(1)$ series, the present values were computed as the series' value in the previous period, plus a random error term drawn from the normal distribution with mean of zero and a variance equal to 1:

$$Y_t = Y_{t-1} + \epsilon_t. \tag{8}$$

$I(0)$ series were generated simply as a white noise disturbance from a normal distribution with a mean of zero and variance equal to 1:

$$Y_t = \epsilon_t. \tag{9}$$

Stationary autoregressive series were generated with a value of ρ that varied by increments of 0.01 between 0.90 and 0.99:

$$Y_t = \rho Y_{t-1} + \epsilon_t. \tag{10}$$

Fractionally differenced series were generated using the ARFSIM package in RATS, which generates $(0, d, 0)$ series where one can specify d in the range $-1 < d < 1.5$. To ensure that each series was generated properly, we used Robinson's semi-parametric estimator (RGSE package) to estimate each series' order of d. If the mean d estimate of 10,000 simulations was within 1% of our target integration level, we used the results of the simulation. We provide annotated code for the creation of fractionally differenced series in Appendix I of

[2] All code and replication data can be found in Section I of this supplement.

these Supplementary Materials.[3]

B.1 Related vs. Unrelated Series

Just a brief note on related versus unrelated series. When related series are modeled, the researcher is specifying that the two series share a common stochastic trend such that when the two series are cointegrated, their linear combination is stationary.

For example, in a bivariate system, let $\mathbf{Y}_t = (y_{1t}, y_{2t})' \sim I(1)$ and $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t})' \sim I(0)$ in which $\mathbf{Y}_t$ is cointegrated with cointegrating vector $\boldsymbol{\beta} = (1, -\beta)'$. The cointegration relationship can be represented by the following:

$$y_{1t} = \beta\mu_{1t} + \epsilon_{1t}$$

$$y_{2t} = \mu_{2t} + \epsilon_{2t}$$

In this case, if the linear combination of these two series is to be an $I(0)$ process, then it must be the case that the two series share a common stochastic trend: $\mu_{2t} = \beta\mu_{1t}$. Despite the fact that both series are independently unit roots, the cointegrating relationship annihilates the common trend and the equilibrium error term is stationary:

$$\boldsymbol{\beta}'\mathbf{Y}_t = \beta\mu_t + \epsilon_{1t} - \beta(\mu_t + \epsilon_{2t}) = \epsilon_{1t} - \beta\epsilon_{2t} \sim I(0)$$

It is fairly simple to simulate cointegrated systems. Using Phillips (1991) triangular representation we can specify the relationship between y_{1t} and y_{2t} as:

$$y_{1t} = \beta y_{2t} + u_t \text{ where } u_t \sim I(0)$$

$$y_{2t} = y_{2t-1} + \upsilon_t \text{ where } \upsilon_t \sim I(0)$$

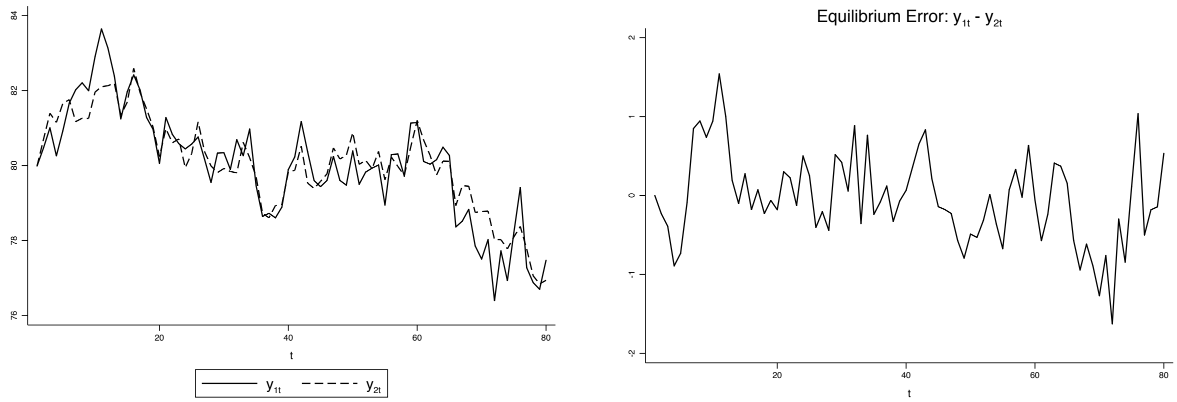
In this representation, y_{1t} captures the long-run equilibrium relationship and y_{2t} describes the common stochastic trend.

For example, Figure B.1 presents the plots of the series for y_{1t} and y_{2t} in which $u_t = .50 * u_{t-1} + \epsilon_t$, $\epsilon_t \sim$ iid $N(0, 1)$. As expected, y_{1t} and y_{2t} follow each other closely and the

[3] RATS packages, as well as examples and supporting documentation can be downloaded from the Estima website http://www.estima.com/procs_perl/mainproclistwrapper.shtml. The ARFSIM package has been updated so that its usage is more intuitive, however we found that it was creating a fatal error when combined with the RGSE package. As a result, we used an earlier version of the ARFSIM package, and our code is based on the old version. It is very easy to adapt our code to the new version of ARFSIM, however it may not be possible to simultaneously estimate the d value of the series.

plot of the cointegrating residual is clearly stationary.

Figure B.1: Two Related, Pre-Specified Series



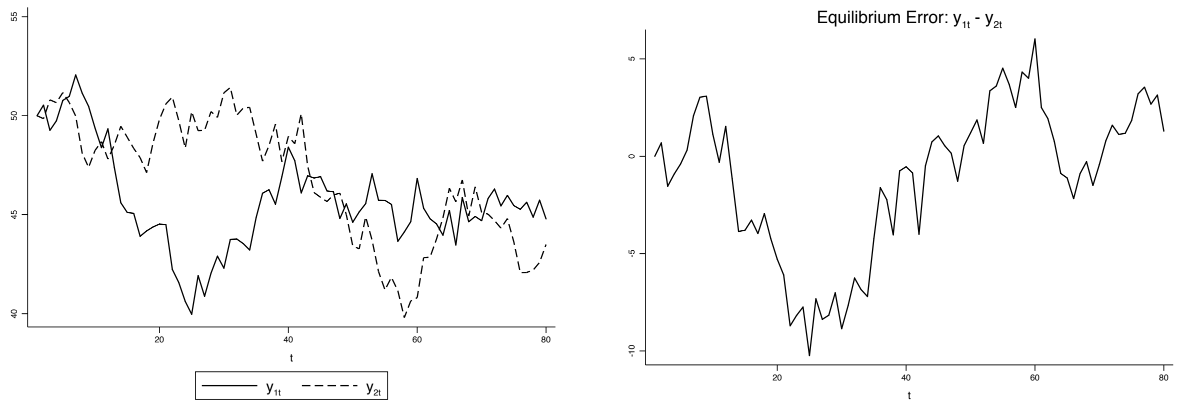
Note: Left plot is of two series in level form. Plot on the right is of the cointegrating residual of the two series. Note that the residual series is stationary.

As we note in the main text, previous research has found that the GECM model adequately detects cointegration when the cointegrating vector has been pre-specified. That is, when two series have been created such that they share a common stochastic trend the GECM model has sufficient power.

On the other hand, this paper focuses on the Type I errors that come from *estimating* the cointegrating vector with the GECM model. In order to evaluate the model's performance, we randomly generate our data such that each series' error term is uncorrelated with all other series within the model. For example, if we simulate y_{1t} and y_{2t} as randomly generated unit-root processes and plot them together, we could get two series that look like those presented in Figure B.2.

In this case, y_{1t} and y_{2t} could potentially be related and an estimation of the GECM model between these two series, with y_{1t} as the dependent variable, yields what appears to be a significant ECM parameter ($t = -2.34$). Such a conclusion would be in error however. As can be seen in the right hand plot of Figure B.2, the residuals of the level form regression of y_{1t} on y_{2t} is clearly not stationary. The two series do not share a common trend and there is no cointegration.

Figure B.2: Two Randomly Generated, Unrelated Series



Note: Left plot is of two series in level form. Plot on the right is of the cointegrating residual of the two series. Note that the residual series is not stationary.

For further information on power of the GECM when the cointegrating vector is pre-specified, see Kremers, Ericsson, and Dolado (1992), De Boef and Granato (1999), and Zivot (2000). For further information on the power of other cointegration tests when the series are pre-specified as fractionally cointegrated, see Gil-Alana (2003) and Caporale and Gil-Alana (2004).

B.2 Generating Bounded Series

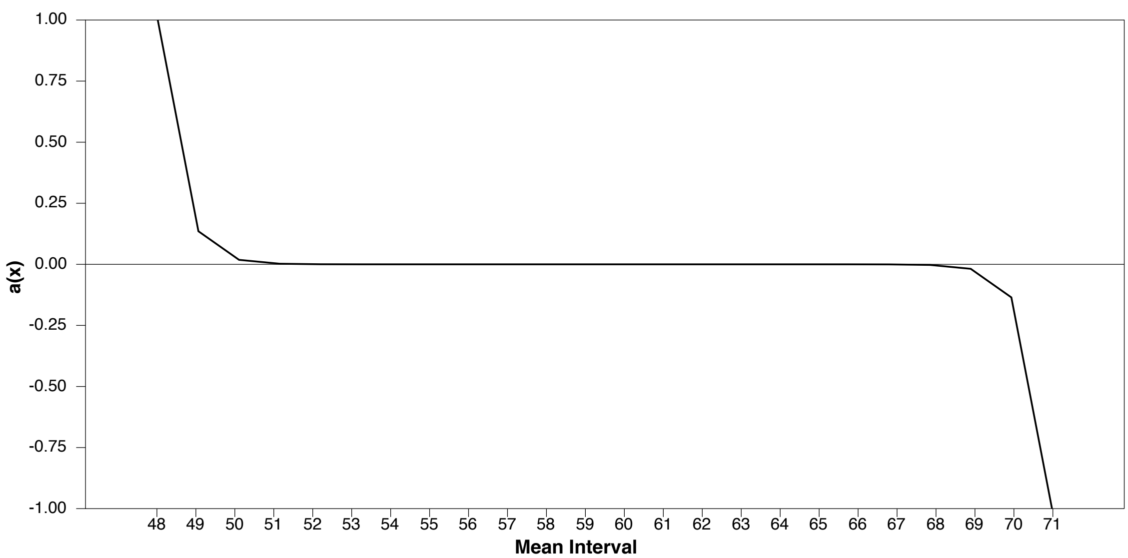
We rely on the work of Nicolau (2002) and the author's discrete-time process to generate the bounded unit roots. The generated series approximate unit-roots when its values fall within a specified interval. However, as the series nears its upper and lower thresholds it tends towards mean reversion. The process is generated by:

$$X_{\mathrm{t}} = X_{\text{t-1}} + e^{k}(e^{-\alpha_1(X_{\text{t-1}}-\tau)} - e^{\alpha_2(X_{\text{t-1}}-\tau)}) + \epsilon_{\mathrm{t}} \tag{11}$$

where $\alpha_1 \geq 0$; $\alpha_2 \geq 0$; $k < 0$; and ϵ_{t} is assumed to be *i.i.d.* with a mean of 0 and variance of 1.

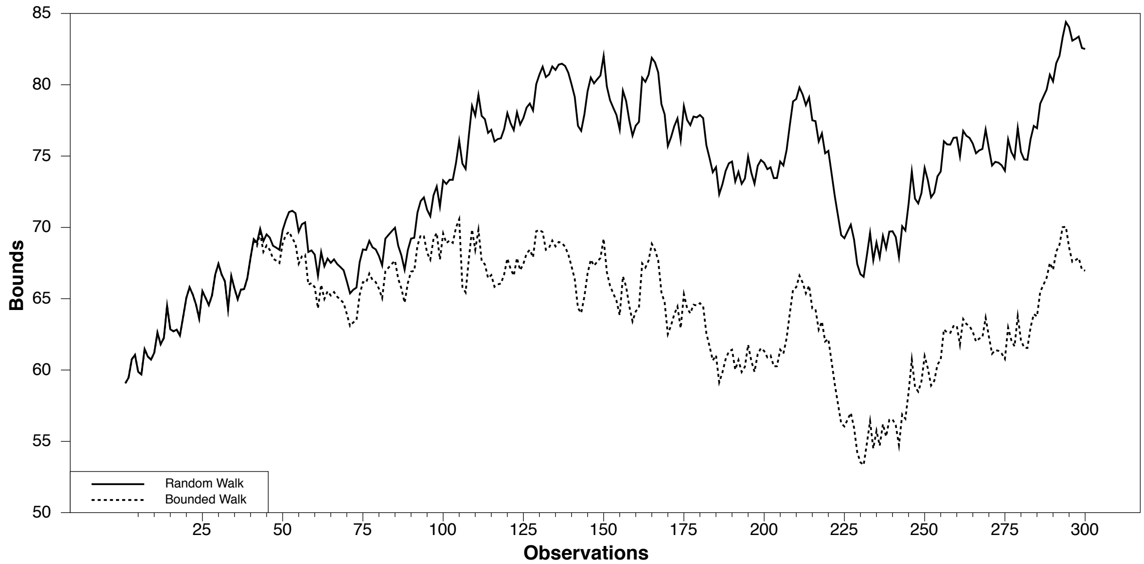
Equation (11) adds an additional function to the basic unit-root. The function $a(x) = e^{k}(e^{-\alpha_1(X_{\text{t-1}}-\tau)} - e^{\alpha_2(X_{\text{t-1}}-\tau)})$ captures the mean reversion of the process. The range of the process under which $a(x)$ behaves as a unit-root is controlled by the k parameter; as $|k|$ increases, so too does the interval over which the series will behave as an $I(1)$ process. The τ parameter is the central tendency of the process. The final parameters, α_1 and α_2, measure the reversion effect of the process as it approaches or exceeds the specified interval. The larger the value of α the stronger the reversion towards the mean. When $\alpha_1 = \alpha_2$, the parameter τ is the mean of the series and the interval is symmetric.

Figure B.3: Value of *a(x)* Over Interval



When $X_{t-1} = \tau$, then $a(x) = 0$ and the generated process will behave as a unit-root. However we can widen the range over which the process varies by selecting the parameters α_1, α_2, and k, such that $a(x) \approx 0$ over a specific range of values surrounding τ. In our case, we chose to create a series that approximates the range of Stimson's (1991) "Mood," a commonly used variable within political science. *Mood* is not strictly bounded, however as with many variables in the field, it has a rather limited range in practice. From 1952 to 2006 the low of *Mood* was 49 and its high was 69. Choosing parameter values of $\alpha_1 = \alpha_2 = 1.5$; $|k| = 16.5$; and $\tau = 59$, we created a variable of similar range. Figure B.3 plots the values of the function $a(x)$. When the series falls within the interval (49,70), the function $a(x)$ is near 0, but as the series shifts either above or below the interval, the strength of the mean reverting process increases.

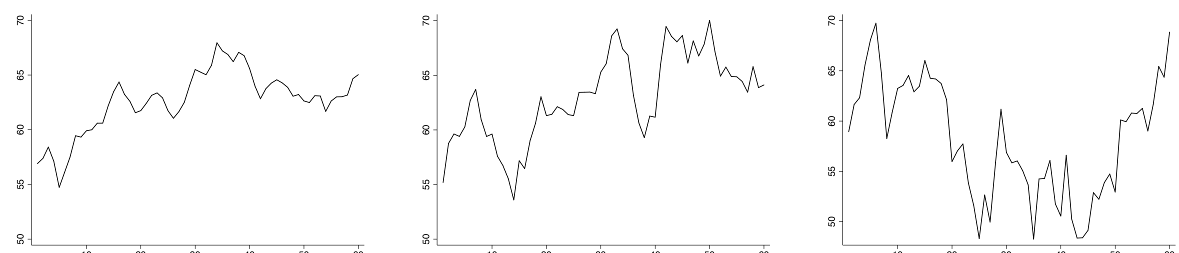
Figure B.4: Bounded Unit-Root Compared to a Unit-Root



An example of this process is shown in Figure B.4. We created two identical unit-root series, however the bounded series has been constrained by our chosen interval. As the two series reach the interval, either above or below the mean, the value of $a(x)$ increases and the bounded series is pushed back towards its mean. The two series are equal for the first 50 or so time points, but as they approach the upper threshold, the bounded unit-root is pushed back while the original unit-root continues to meander without bounds. The two series have diverged, however because their disturbance terms are equal, they still track each other over the range of observations.

Table 3 in the main text provides results of Monte Carlo simulations with a bounded dependent variable with various variances (σ =1, 2, 3). To visualize what such series may look like, Figure B.3 shows plots of individual series with a T of 60 and a specific value of σ.

Figure B.5: Series Plots as Variance Changes



(a) $\sigma_t \sim N(0,1)$ (b) $\sigma_t \sim N(0,2)$ (c) $\sigma_t \sim N(0,3)$

Appendix C Additional Materials: Replication of Casillas, Enns, and Wohlfarth (2011)

We replicate Casillas, Enns, and Wohlfarth's (2011) Tables 1 and 2 in Table C.1. All results are comparable, with the exception of the standard error of the LRM for *Social Forces* in the *Salient Review* model.[4] We find the standard error is somewhat lower, but this has no effect on the substantive findings of the model.

C.1 Full Paper Replication

Table C.1: Replication of Casillas et al. (2011)

	All Reviews	Non-Salient Reviews	Salient Reviews
Long Run Multiplier			
Public Mood	1.05⋆	1.15⋆	
	(0.51)	(0.56)	
Court Ideology	11.67⋆	10.90⋆	13.31⋆
	(2.82)	(3.11)	(4.22)
Social Forces			7.28⋆
			(3.83)
Long Run Effects			
Public Mood$_{t-1}$	0.87⋆	0.88⋆	0.71
	(0.42)	(2.15)	(0.96)
Court Ideology$_{t-1}$	9.68⋆	8.37⋆	16.90⋆
	(3.10)	(3.09)	(5.73)
Social Forces (IV)$_{t-1}$	0.98	-0.01	9.20⋆
	(2.14)	(2.15)	(5.09)
Short Run Effects			
ΔPublic Mood	1.59⋆	1.68⋆	1.24
	(0.78)	(0.79)	(1.81)
ΔCourt Ideology	12.48⋆	11.37⋆	10.47
	(4.29)	(4.41)	(10.03)
ΔSocial Forces (IV)	2.78	2.56	7.49
	(3.00)	(2.98)	(8.03)
Error Correction and Constant			
Percent Liberal$_{t-1}$	-0.83⋆	-0.77⋆	-1.27⋆
	(0.15)	(0.15)	(0.15)
Constant	-6.03	-11.05	31.02
	(25.14)	(25.42)	(58.32)
Fit and Diagnostics			
Centered R^2	0.53	0.49	0.64
Sargan (χ^2)	0.38	0.67	0.21
N	45	45	45

Note: Entries are two-stage least squares coefficients (standard errors in parentheses). ECM significance one-tail t-test. Coefficient significance (*p≤ 0.05, one-tail test).

[4] The long-run multiplier (LRM) is calculated as the ratio of coefficients: β_1/α_1. The formula for the standard errors of the LRM is: $((1/b^2)\text{Var}(a) + (a^2/b^4)\text{Var}(b) - 2(a/b^3)\text{Cov}(a,b))^{1/2}$ See De Boef and Keele (2008, pp.191-192).

C.2 Replication of CEW - First Stage Results

Table C.2 presents the results of the first stage regressions in which Martin-Quinn scores were regressed on the "social forces" that predict the public mood. CEW note that these social forces are substantial predictors of the public mood, therefore when used as instruments for Martin-Quinn scores, they will capture that portion of justice ideology influenced by the same social forces that influence public mood.

Because the table is so large, the social forces which significantly predict our variables to be instrumented are bolded. Fit diagnostics are provided. The null hypothesis of each diagnostic is that the instrument is poor – thus we want to reject the null to show our instruments are valid and that the second stage estimates are reliable. With weak instruments, results of 2SLS are biased towards the results of OLS. This bias only gets worse as more weak instruments are added. With instruments as weak as CEW's, any inferences drawn from the model should be taken with extreme caution.

Note: The weak identification test does not provide a p-value, but instead the Stock-Yogo critical value to determine bias from weak identification of the instruments, the 5% critical value is 19.40. With values of 1.52, 1.59, and 0.97, respectively, the three models fail to reject the null of the Stock-Yogo. The instruments are not useful and the second stage is nearly identical to the OLS estimates. If endogeneity is indeed a problem with this data-set, it doesn't appear that the specified model provides an adequate solution.

Table C.2: First Stage Results from 2SLS

	All Reviews		Non-Salient		Salient	
1st Stage Variables	ΔMQ	MQ_{t-1}	ΔMQ	MQ_{t-1}	ΔMQ	MQ_{t-1}
$Reviews_{t-1}$	**0.04***	-0.00	**0.04***	-0.01	0.01	0.00
	(0.01)	(0.04)	(0.01)	(0.02)	(0.01)	(0.01)
$\Delta Mood_{t}$	**0.25***	**-0.24***	**0.25***	**-0.25***	**0.20***	**-0.24***
	(0.07)	(0.10)	(0.07)	(0.09)	(0.08)	(0.09)
$Mood_{t-1}$	0.13	-0.13	0.13	-0.13	0.15	-0.14
	(0.07)	(0.09)	(0.07)	(0.09)	0.08	(0.09)
ΔSegal-$Cover_{t}$	0.65	0.95	0.65	0.94	0.66	0.96
	(0.48)	(0.65)	(0.47)	(0.65)	(0.54)	(0.65)
Segal-$Cover_{t-1}$	-0.52	1.48	-0.58	1.51	-0.22	1.47
	(0.57)	(0.77)	(0.56)	(0.77)	0.63	(0.75)
"Social Forces" Excluded in 2nd Stage						
Δ% Change $Inflation_{t}$	6.41	0.60	4.49	1.15	10.95	0.55
	(8.46)	(11.44)	(8.41)	(11.56)	(9.46)	(11.36)
% Change $Inflation_{t-1}$	13.67	12.16	13.47	12.28	14.73	12.10
	(11.77)	(15.91)	(11.56)	(15.89)	(13.24)	(15.90)
$\Delta Unemployment_{t}$	-0.18	0.07	-0.16	0.09	-0.03	0.06
	(0.18)	(0.25)	(0.18)	(0.24)	(0.20)	(0.24)
$Unemployment_{t-1}$	0.21	0.19	0.20	0.19	0.23	0.19
	(0.17)	(0.23)	(0.16)	(0.23)	(0.19)	(0.23)
ΔDefense $Budget_{t}$	**-0.15***	0.09	**-0.16***	0.10	-0.08	0.08
	(0.06)	(0.08)	(0.06)	(0.08)	(0.06)	(0.07)
Defense $Budget_{t-1}$	-0.08	-0.04	-0.08	-0.04	-0.05	-0.04
	(0.05)	(0.07)	(0.05)	(0.07)	(0.06)	(0.07)
ΔPolicy $Liberalism_{t}$	-0.07	**0.14***	-0.06	**0.14***	-0.07	**0.13***
	(0.04)	(0.05)	(0.04)	(0.37)	(0.05)	(0.06)
Policy $Liberalism_{t-1}$	0.02	-0.03	0.02	-0.03	0.03	-0.03
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
ΔHomicide $Rate_{t}$	0.18	0.14	0.18	0.12	0.04	0.16
	(0.30)	(0.41)	(0.30)	(0.41)	(0.34)	(0.41)
Homicide $Rate_{t-1}$	-0.31	-0.02	-0.34	-0.03	-0.39	-0.01
	(0.24)	(0.33)	(0.24)	(0.33)	(0.28)	(0.33)
$\Delta Gini_{t}$	-27.94	-3.91	-34.11	-2.28	-15.22	-4.01
	(17.73)	(23.97)	(17.85)	(24.53)	(19.74)	(23.71)
$Gini_{t-1}$	-8.21	3.39	-10.83	4.49	1.20	2.91
	(16.76)	(22.65)	(16.60)	(22.81)	(18.51)	(22.23)
Constant	-4.08	6.59	-2.65	6.13	6.68	31.02
	(9.72)	(13.13)	(9.60)	(13.19)	(13.05)	(58.32)
Fit and Diagnostics						
Underidentification Test‡	0.08		0.07		0.26	
Weak Identification Test†	1.52		1.59		0.97	
Anderson-Rubin Weak Instrument‡	0.71		0.57		0.38	
Stock-Wright Weak Instrument‡	0.53		0.88		0.24	

Note: First stage regressions results of Casillas, Enns, and Wohlfarth (2011). †5% Maximal IV relative bias = 19.40; 30% Maximal IV relative bias = 4.59. ‡p-value (*p$\leq$ 0.05, two-tail test)

C.3 Replications with OLS

In replicating with our series, we chose to adhere to Casillas, Enns, and Wohlfarth's (2011) estimation methods of 2SLS. Their use of 2SLS was intended to control for the effects of social forces on contemporaneous Justice ideology. As noted, we did not have concerns of the endogeneity of beef consumption with the ideological direction of the Court's decision making, however we wanted our estimations to be comparable. Despite CEW's concerns of potential endogeneity, their first stage instruments are so weak that their results are very strongly biased towards the results of OLS.

We also replicate their models, as well as ours, using OLS. With some very minor differences - for instance, the long term effect of Martin-Quinn justice ideology is significant in the *All Review* model, and *Mood* has a substantively larger effect - the results of the 2SLS and OLS replications of Casillas et al. are equivalent. As expected, so too are the results from our nonsense regression series.

Table C.3: Replication of Casillas et al. (2011) with OLS

	All Reviews	Non-Salient Reviews	Salient Reviews
Long Run Effects			
Public Mood_{t-1}	1.08*	1.13*	0.55
	(0.41)	(0.42)	(0.95)
Court Ideology_{t-1}	8.07*	6.00*	18.16*
	(2.97)	(2.84)	(5.43)
$\text{Martin-Quinn}_{t-1}$	3.01*	2.27	7.24*
	(1.57)	(1.56)	(3.73)
Short Run Effects			
ΔPublic Mood	2.04*	2.25*	0.89
	(0.74)	(0.74)	(1.71)
ΔCourt Ideology	10.91*	9.53*	12.33
	(4.39)	(4.44)	(10.06)
ΔMartin-Quinn	2.59	1.67	6.88
	(3.00)	(2.16)	(4.95)
Error Correction and Constant			
Percent Liberal_{t-1}	-0.84*	-0.75*	-1.25*
	(0.15)	(0.15)	(0.16)
Constant	-17.78	-26.69	39.23
	(24.65)	(24.63)	(57.84)
Fit and Diagnostics			
Adjusted R^2	0.47	0.44	0.57
Breusch-Pagan Test (χ^2)	2.22	3.13	7.02*
Breusch-Godfrey LM Test (χ^2)	0.16	1.50	0.04
N	45	45	45

Note: Entries are OLS regression coefficients (standard errors in parentheses). ECM significance one-tail *t*-test. Coefficient significance (*p≤ 0.05, one-tail test).

Table C.4: What Else Affects the Court's Liberal Reversal Rate (Re-estimation of Casillas et al. (2011)) Using OLS

	All Reviews	**Non-Salient Reviews**	**Salient Reviews**
Long Run Effects			
Shark Attacks$_{t-1}$	0.30*	0.30*	0.48*
	(0.12)	(0.12)	(0.21)
Tornado Fatalities$_{t-1}$	0.02	0.01	0.06
	(0.03)	(0.03)	(0.06)
Beef Consumption (IV)$_{t-1}$	-0.88*	-0.91*	-1.81*
	(0.29)	(0.29)	(0.44)
Short Run Effects			
ΔShark Attacks	0.20*	0.18*	0.37
	(0.11)	(0.10)	(0.22)
ΔTornado Fatalities	0.04*	0.03	0.09*
	(0.02)	(0.02)	(0.04)
ΔBeef Consumption (IV)	-0.80	-1.81	4.49
	(1.49)	(1.49)	(3.21)
Error Correction and Constant			
Percent Liberal$_{t-1}$	-0.52*	-0.56*	-0.96*
	(0.14)	(0.15)	(0.16)
Constant	56.62*	60.37*	110.90*
	(27.56)	(17.75)	23.95
Fit and Diagnostics			
Adjusted R^2	0.31	0.27	0.53
Breusch-Pagan Test (χ^2)	0.01	0.01	3.89*
Breusch-Godfrey LM Test (χ^2)	2.98	7.13*	1.46
N	45	45	45

Note: Entries are OLS regression coefficients (standard errors in parentheses). ECM significance one-tail t-test. Coefficient significance (*p≤ 0.05, one-tail test).

As for the ECMs, the estimates of Casillas, Enns, and Wohlfarth (2011) are nearly identical with OLS and their *Salient Review* model still has an estimated ECM of -1.25. The results of our nonsense data series are also similar, however our *Salient Review* ECM has shrunk to -0.96.

C.4 Estimating Fractional Order of Integration

Table 11 of the main text provides the results of each fractionally differenced regression. Table C.5 presents the initial step in the process: investigating the order of integration of each constituent series.[5] Recall that in order to estimate a three-step FECM the order of

[5] All estimates of d were estimated using Stata's exact ML estimator. The exact ML estimator is consistent and asymptotically normal for series -0.5 $< d <$ 0.5, which generally requires first differencing a series and then estimating d. The RATS Local Whittle estimator of Robinson (1995) is in general agreement with the estimates of the Stata program: *All Reviews* (d = 0.62); *Non-Salient Reviews* (d = 0.63); *Salient Reviews* (d = 0.36); *Public Mood* (d = 1.14); *Segal-Cover Scores* (d = 1.15); *Martin-Quinn Score* (d = 1.09). The asymptotic standard error of the Local Whittle estimator is based on m, the bandwidth, or number of Fourier frequencies used by the estimator. For all Local Whittle estimates, m is calculated as $T^{4/5}$ and the asymptotic standard errors are calculated as $(1/\sqrt{4 * m})$: (s.e.=0.11).

integration between a DV and IV must be equivalent. Absent this equivalence, the two (or more) series cannot share a common stochastic trend, and therefore cannot be fractionally cointegrated.

Table C.5: Fractional Order of Integration, Casillas et al (2011)

	Individual Series d	**95% Confidence Interval** d
All Reviews	0.62 (0.11)	[0.404, 0.836]
Non-Salient Reviews	0.62 (0.12)	[0.385, 0.858]
Salient Reviews	0.36 (0.08)	[0.200, 0.529]
Public Mood	1.09 (0.13)	[0.835, 1.345]
Segal-Cover Score	1.07 (0.14)	[0.796, 1.344]
Martin-Quinn Score	1.00 (0.15)	[0.706, 1.294]

† *Note*: Entries are estimates of the order of integration of all series used by Casillas, Enns, and Wohlfarth (2011). Standard errors in parentheses. Estimates conducted in Stata using the exact ML estimator.

Our estimates of d are consistent and reaffirm our decision to not fit an FECM with the data. The three DVs are fractionally integrated, which means that despite the fact that Dickey-Fuller tests cannot reject the null of a unit root for either *All Reviews* or *Non-Salient Reviews*, the two series are not integrated $I(1)$. Shocks are not permanent, but decrease at a hyperbolic rate. It is tempting to conclude that the DV *Salient Reviews* is long-memoried, but stationary ($d < 0.5$), however without more observations this can't be established with 95% confidence. While our results indicate the DVs are not pure unit roots, the confidence intervals on the estimates of the three IVs all overlap 1.0, meaning we cannot reject the null that the three IVs are all integrated.

We also provide the estimates of fractional integration of our nonsense data: *Beef Consumption*: $d = 1.14$ (s.e.= 0.15); *Shark Attacks*: $d = 0.56$ (s.e.= 0.13); and *Tornado Fatalities*: $d = 0.05$ (s.e.= 0.12). In the interests of completeness, we then estimate this data in both fractionally differenced regression models as well as (potentially misspecified) FECMs. As Tables C.6 C.7 demonstrate, when using fractional methods on our Beef-Shark-Tornado data we find only null results – a good sign for the method.

Table C.6: FI Model of Nonsense Data and Supreme Court Reversals

Review Type	**All**	**Non-Salient**	**Salient**
Short Run Effects			
Δ^d Shark Attacks	0.18	0.16	0.28
	(0.11)	(0.11)	(0.24)
Δ^d Tornado Fatalities	0.03	0.02	0.07
	(0.02)	(0.02)	(0.04)
Δ^d Beef Consumption	-1.01	-1.96	4.37
	(1.49)	(1.46)	(3.19)
Constant	-2.10	-2.04	-12.42*
	(1.69)	(1.66)	(3.62)
Fit and Diagnostics			
Adjusted R^2	0.04	0.03	0.09
Durbin-Watson	2.13	2.17	2.35
Breusch-Pagan Test (χ^2)	3.69	4.63	0.38
Breusch-Godfrey LM Test (χ^2)	0.32	0.62	1.65

Note: Entries are OLS coefficients (standard errors in parentheses). All variables have been fractionally differenced by their estimate of *d*. Coefficient significance (*p≤ 0.05, two-tail test).

Table C.7: FECM Model of Nonsense Data and Supreme Court Reversals

Review Type	**All**	**All**	**All**	**Non-Salient**	**Non-Salient**	**Non-Salient**	**Salient**
Short Run Effects							
Δ^d Shark Attacks	0.16	0.17	0.16	0.15	0.15	0.14	0.28
	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)	(0.24)
Δ^d Tornado Fatalities	0.02	0.03	0.02	0.02	0.02	0.01	0.07
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)
Δ^d Beef Consumption	-0.66	-0.72	-0.65	-1.58	-1.62	-1.56	4.37
	(1.55)	(1.55)	(1.55)	(1.53)	(1.53)	(1.52)	(3.19)
Error Correction and Constant							
$FECM_{Sharks}$	-0.10			-0.10			
	(0.15)			(0.15)			
$FECM_{Tornados}$		-0.07			-0.09		
		(0.16)			(0.16)		
$FECM_{Beef}$			-0.14			-0.14	
			(0.16)			(0.16)	
Constant	-2.55	-2.34	-2.34	-2.45	-2.35	-2.28	-12.42*
	(1.89)	(1.87)	(1.75)	(1.86)	(1.83)	(1.73)	(3.62)
Fit and Diagnostics							
Adjusted R^2	0.10	0.09	0.11	0.09	0.08	0.09	0.09
Durbin-Watson	1.97	2.02	1.93	2.03	2.04	1.98	2.35
Breusch-Pagan Test (χ^2)	6.69	5.84	7.15	7.86	9.27	8.57	0.38
Breusch-Godfrey LM Test (χ^2)	1.26	0.01	0.99	0.07	0.09	0.53	1.65

Note: Entries are OLS coefficients (s.e. in parentheses). All variables have been fractionally differenced by their estimate of *d*. FECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, two-tail test).

Appendix D Additional Materials: Replication of Ura and Ellis (2012)

D.1 Full Paper Replication

Below is the complete replication of Table 2 from Ura and Ellis (2012). Because the authors used a Seemingly Unrelated Regression, all replications and Monte Carlo simulations were conducted in Stata so that we could exactly replicate their findings.

Table D.1: Replication of Ura and Ellis - Table 2†

	Republican	Democrat	|Difference|
Long Run Multipliers			
Domestic Spending $10B	-0.28⋆ (0.08)	-0.11⋆ (0.05)	0.16⋆
Defense Spending $10B	0.52⋆ (0.15)	0.29⋆ (0.05)	0.23
Inflation	-0.57⋆ (0.28)	-0.47⋆ (0.19)	0.10
Unemployment	-0.17 (0.83)	0.49 (0.37)	0.66
Top 1% Income Share	2.45⋆ (0.94)	1.54⋆ (0.27)	0.91
Long Run Effects			
Domestic Spending $10B$_{t-1}$	-0.11⋆ (0.02)	-0.07⋆ (0.02)	0.04
Defense Spending $10B$_{t-1}$	0.21⋆ (0.05)	0.20⋆ (0.06)	0.01
Inflation$_{t-1}$	-0.23⋆ (0.12)	-0.33⋆ (0.16)	0.10
Unemployment$_{t-1}$	-0.07 (0.33)	0.34 (0.24)	0.41
Top 1% Income Share$_{t-1}$	0.99⋆ (0.35)	1.07⋆ (0.29)	0.08
Short Run Effects			
ΔDomestic Spending $10B$_t$	-0.04 (0.03)	-0.07⋆ (0.04)	0.03
ΔDefense Spending $10B$_t$	0.43⋆ (0.09)	0.14⋆ (0.07)	0.29⋆
ΔInflation$_t$	-0.12 (0.20)	-0.03 (0.14)	0.09
ΔUnemployment$_t$	0.12 (0.29)	0.68⋆ (0.41)	0.56
ΔTop 1% Income Share$_t$	1.03⋆ (0.23)	0.76⋆ (0.23)	0.27
Error Correction and Constant			
Partisan Mood$_{t-1}$	-0.40⋆ (0.09)	-0.69⋆ (0.17)	0.29
Constant	16.80⋆ (6.65)	33.93⋆ (9.50)	17.13
Fit and Diagnostics			
Adjusted R^2	0.39	0.39	
Breusch-Pagan Test (χ^2)	0.01	0.40	
Breusch-Godfrey LM Test (χ^2)	1.42	0.70	

† *Note*: Entries are seemingly unrelated regression coefficients (standard errors in parentheses). The Dickey-Fuller Test statistic was not included as we couldn't replicate their estimates. N=35

D.2 Full Monte Carlo Results

The result of 10,000 Monte Carlo simulations is presented in Table D.2. We have simulated $I(1)$ dependent variables and regressed them on the IVs used by Ura and Ellis (2012). In keeping with the methodological choice of Ura and Ellis, each iteration was estimated as a SUR, however because the set of independent variables is the same in the two equations, the results of the simulations are essentially equal for both models. This does not affect the conclusions that we draw from the results - the independent variables, two of which have estimated orders of fractional integration significantly greater than $I(1)$, are biasing the ECM $t-$distribution well away from that used to derive the MacKinnon critical values. The result is a finding that approximately 20% of all error correction parameters as significant. The rate of cointegration is overstated.

Table D.2: Summary Statistics Monte Carlo Simulation of Ura and Ellis (2012)

	Random DV 1	Random DV 2
% ECM Significant – one tail t-distribution	86.4	86.5
% ECM Significant – MacKinnon Values	22.4	22.5
Mean of α_1	-0.40	-0.40
% ΔX_t Significant	57.2	57.5
% $\geq 1X_{t-1}$ Significant	69.4	68.4
% ECM and $\geq 1\Delta X_t$ Significant	50.0	50.1
% ECM and $\geq 1\Delta X_t$ Significant*	15.4	14.9
% ECM and $\geq 1X_{t-1}$ Significant	62.3	61.9
% ECM and $\geq 1X_{t-1}$ Significant*	19.9	19.8

Note: Entries provide are the summary results of 10,000 simulations of a seemingly unrelated regression in which randomly generated $I(1)$ series are regressed upon the independent variables from Ura and Ellis (2012).
ΔX_t and X_{t-1} significance (*p$\leq$ 0.05, two-tail test).
MacKinnon Value: -4.268

D.3 Estimating FECM of Ura and Ellis (2012)

Because Ura and Ellis (2012) do not specify which of their variables they believe to be in an equilibrium relationship with the dependent variable we estimate a three-step fractional ECM for each independent variable in each model. After each bivariate regression we then estimated the order of integration of the residuals for comparison with the component series. Even if the parent series are $I(1)$, fractional cointegration may still exist if the fractional integration of the regression residuals are less than $I(1)$, but greater than $I(0)$. The results of these estimates, as well as estimates of the component series, can be found in Table D.3. Only the residuals from the regression of *Partisan Mood* on *Inflation* indicate any decrease in order of integration, however the reduction is marginal.

The estimates in Table D.3 argue strongly against any finding of fractional cointegration. To be sure, we estimate each individual FECM and present the results in Tables D.4 and

Table D.3: FECM Order of Integration

	Individual Series d	Residuals Rep Mood & IV d	Residuals Dem Mood & IV d
Republican Mood	1.05 (0.16)		
Democrat Mood	1.15 (0.16)		
Domestic Spending $10B	1.44 (0.08)	1.04 (0.16)	1.14 (0.16)
Defense Spending $10B	1.32 (0.11)	1.03 (0.16)	1.09 (0.16)
Inflation	1.02 (0.24)	0.91 (0.18)	0.76 (0.21)
Unemployment	0.94 (0.21)	1.08 (0.17)	0.99 (0.18)
Top 1% Income Share	0.89 (0.19)	1.06 (0.16)	1.01 (0.16)

† *Note*: Entries are estimates of the order of integration of each individual series as well as estimates of the residuals of bivariate regressions. Estimates based on results of the Stata exact ML estimator.

D.5 for *Republican Mood* and *Democratic Mood*, respectively.

Table D.4: Three-Step FECM Results - Republican Mood

	(1)	(2)	(3)	(4)
Short Run Effects				
Δ^dDomestic Spending $\$10B_t$	0.02	0.03	0.03	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
Δ^dDefense Spending $\$10B_t$	0.31*	0.31*	0.30*	0.30*
	(0.13)	(0.13)	(0.13)	(0.13)
Δ^dInflation$_t$	-0.31	-0.31	-0.33	-0.29
	(0.20)	(0.21)	(0.20)	(0.21)
Δ^dUnemployment$_t$	-0.47	-0.47	-0.51	-0.47
	(0.37)	(0.37)	(0.38)	(0.37)
Δ^dTop 1% Income Share$_t$	1.21*	1.21*	1.19*	1.22*
	(0.42)	(0.42)	(0.42)	(0.42)
Error Correction and Constant				
Partisan Mood$_{t-1}$†	0.11	0.09	0.06	0.13
	(0.16)	(0.16)	(0.15)	(0.17)
Constant	-1.30	-1.31	-1.34	-1.30
	(0.68)	(0.68)	(0.68)	(0.68)
Fit and Diagnostics				
R^2	0.38	0.38	0.37	0.38
Durbin-Watson	2.22	2.18	2.09	2.23
Breusch-Pagan Test (χ^2)	1.57	1.46	1.17	1.60
Breusch-Godfrey LM Test (χ^2)	1.27	0.93	0.20	1.38

Note: Entries are OLS coefficients. FECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, two-tail test).
† Model (1) - FECM of Mood & Domestic Spending; Model (2) - FECM of Mood & Defense Spending; Model (3) - FECM of Mood & Inflation; Model (4) - FECM of Mood & Unemployment

Comparing the results from the FECM models we see that *Republican Mood* is affected by both increases in *Defense Spending* and in the *Top 1% Income Share*. As each increases, *Republican Mood* shifts in the liberal direction. These results hold across all models. Despite the IVs' significance, we don't find any evidence of an equilibrium relationship between the DV and any of the covariates. For the *Democrat Mood* model, no variables achieve significance. These results are drastically different from those reported by Ura and Ellis with the single equation GECM.

Table D.5: Three-Step FECM Results - Democrat Mood

	(1)	(2)	(3)	(4)
Short Run Effects				
Δ^dDomestic Spending \$10B$_t$	0.00	0.00	0.00	0.00
	(0.04)	(0.04)	(0.04)	(0.04)
Δ^dDefense Spending \$10B$_t$	0.09	0.10	0.10	0.10
	(0.12)	(0.11)	(0.11)	(0.12)
Δ^dInflation$_t$	-0.04	-0.05	-0.01	-0.07
	(0.18)	(0.18)	(0.17)	(0.21)
Δ^dUnemployment$_t$	-0.05	-0.07	0.13	-0.05
	(0.33)	(0.33)	(0.32)	(0.32)
Δ^dTop 1% Income Share$_t$	0.51	0.55	0.62	0.51
	(0.37)	(0.38)	(0.36)	(0.37)
Error Correction and Constant				
Partisan Mood$_{t-1}$†	-0.06	-0.13	-0.19	-0.08
	(0.19)	(0.20)	(0.13)	(0.17)
Constant	-0.13	-0.16	-0.19	-0.12
	(0.61)	(0.60)	(0.57)	(0.59)
Fit and Diagnostics				
R^2	0.08	0.10	0.15	0.09
Durbin-Watson	2.15	2.08	1.99	2.14
Breusch-Pagan Test (χ^2)	0.05	0.04	0.88	0.18
Breusch-Godfrey LM Test (χ^2)	1.83	0.52	0.00	0.44

Note: Entries are OLS coefficients. FECM significance (*p$\leq$ 0.05, one-tail test). Coefficient significance (*p$\leq$ 0.05, two-tail test).
† Model (1) - FECM of Mood & Domestic Spending; Model (2) - FECM of Mood & Defense Spending; Model (3) - FECM of Mood & Inflation; Model (4) - FECM of Mood & Unemployment

We also estimate three-step fractional ECMs for each independent variable in our nonsense model, beginning with onion acreage. The ECM results, presented in Tables D.6 - D.8, are null across all model specifications.

Table D.6: Three-Step FECM Results - Partisan Mood & Onion Acreage

	Republican Mood		Democrat Mood	
Short Run Effects				
Δ^d Onion Acreage	0.02	(0.05)	0.02	(0.04)
Δ^d Coal Emissions	0.02	(0.03)	-0.00	(0.02)
Δ^d Beef Consumption	0.58	(0.40)	-0.23	(0.31)
Δ^d Shark Attacks	0.02	(0.03)	0.00	(0.02)
Δ^d Tornado Fatalities	0.02	(0.01)	0.00	(0.00)
Error Correction and Constant				
FECM†	-0.02	(0.19)	0.09	(0.20)
Constant	-1.25	(1.34)	0.22	(1.02)
Fit and Diagnostics				
Adjusted R^2	0.02		-0.13	
Durbin-Watson	2.04		2.08	
Breusch-Pagan Test (χ^2)	0.18		0.46	
Breusch-Godfrey LM Test (χ^2)	0.13		0.63	

Note: Entries are OLS coefficients (s.e. in parentheses). All variables have been fractionally differenced by their estimate of d.
† FECM of Mood & Onion Acreage; FECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, two-tail test).

Table D.7: Three-Step FECM Nonsense Results - Republican Mood

	(1)	(2)	(3)	(4)
Short Run Effects				
Δ^dOnion Acreage	0.02	0.02	0.02	0.02
	(0.05)	(0.05)	(0.05)	(0.05)
Δ^dCoal Emissions	0.02	0.02	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Δ^dBeef Consumption	0.58	0.58	0.58	0.62
	(0.39)	(0.39)	(0.39)	(0.39)
Δ^dShark Attacks	0.02	0.02	0.02	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Δ^dTornado Fatalities	0.02	0.02	0.02	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Error Correction and Constant				
FECM†	-0.04	-0.02	-0.03	-0.11
	(0.18)	(0.18)	(0.18)	(0.19)
Constant	-1.24	-1.25	-1.24	-1.18
	(1.32)	(1.32)	(1.33)	(1.32)
Fit and Diagnostics				
Adjusted R^2	0.03	0.02	0.03	0.04
Durbin-Watson	2.00	2.03	2.01	1.82
Breusch-Pagan Test (χ^2)	0.15	0.16	0.16	0.04
Breusch-Godfrey LM Test (χ^2)	0.02	0.09	0.03	1.99

Note: Entries are OLS coefficients. FECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, two-tail test).
† Model (1) - FECM of Mood & Coal Emissions; Model (2) - FECM of Mood & Beef Consumption; Model (3) - FECM of Mood & Shark Attacks; Model (4) - FECM of Mood & Tornado Fatalities

Table D.8: Three-Step FECM Nonsense Results - Democrat Mood

	(1)	(2)	(3)	(4)
Short Run Effects				
Δ^dOnion Acreage	0.03	0.03	0.03	0.03
	(0.04)	(0.04)	(0.04)	(0.04)
Δ^dCoal Emissions	-0.00	-0.00	-0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Δ^dBeef Consumption	-0.19	-0.18	-0.19	-0.19
	(0.32)	(0.31)	(0.31)	(0.31)
Δ^dShark Attacks	0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Δ^dTornado Fatalities	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Error Correction and Constant				
FECM†	-0.00	-0.05	-0.02	-0.02
	(0.20)	(0.18)	(0.20)	(0.20)
Constant	0.20	0.15	0.19	0.19
	(1.04)	(1.04)	(1.03)	(0.20)
Fit and Diagnostics				
Adjusted R^2	-0.14	-0.13	-0.14	-0.14
Durbin-Watson	1.91	1.80	1.88	1.87
Breusch-Pagan Test (χ^2)	0.75	0.65	0.72	0.69
Breusch-Godfrey LM Test (χ^2)	0.30	1.05	0.91	1.06

Note: Entries are OLS coefficients. FECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, two-tail test).
† Model (1) - FECM of Mood & Coal Emissions; Model (2) - FECM of Mood & Beef Consumption; Model (3) - FECM of Mood & Shark Attacks; Model (4) - FECM of Mood & Tornado Fatalities

D.4 An Iterative Example of the ECM - Data from Ura and Ellis (2012)

We have previously discussed the fact that the ECM t-ratio is not dimension invariant, its distribution shifts with the number of regressors (Kremers, Ericsson, and Dolado 1992; Banerjee, Dolado, and Mestre 1998; Ericsson and MacKinnon 2002). In addition to the t-ratio however, the size of the α_1 coefficient generally increases as covariates are added to the ECM equation. Monte Carlo simulations with randomly generated $I(1)$ data indicate that moving from a bivariate to a multivariate (5IV) model will double the ECM coefficient.[6] As we have noted, this bias is especially problematic because conclusions as to the strength of the equilibrium relationship are based in part on the size of the ECM coefficient.

To demonstrate this effect with real data, we use the *Democrat Mood* model from Ura and Ellis (2012) and present the results of an iterated ECM model. Adding one IV at a time helps to clarify the potential for inferential problems faced by researchers when using the ECM model. For purposes of this discussion, we treat ECM significance as defined by the standard t-test, which has been the common practice in political science.

Column (1) is the result of a standard Dickey-Fuller test. *Democrat Mood* is not stationary and in fact has a very long memory. *Unemployment* is insignificant across both models of Ura and Ellis (2012) and column (2) finds it insignificant as well when included in a bivariate model. By adding *Domestic Spending* in (3), we find our first significant long run variable, and we see that our ECM has now increased (in absolute terms) by 0.11, however it would still be considered insignificant were we using a standard t-test. Column (4) adds *Inflation* to our model, which is now completely insignificant. With the inclusion of *Inflation* our adjusted R^2 has decreased - we have been punished for its addition - yet our ECM has actually increased by an additional 0.09. We next add *Top 1% Income* and with its inclusion our model boasts one significant short-term IV. But the inclusion of a fourth IV has also increased the size of our ECM by yet another 0.09. The ECM coefficient has now increased by over 600% from the bivariate regression despite a lack of any significant long

[6] See Table 2 of the main paper, or Appendices G&H of the Supplement for simulation results.

Table D.9: Iterative Estimation - Democrat Mood (Ura and Ellis 2012)

	(1)	(2)	(3)	(4)	(5)	(6)
Long Run Effects						
Unemployment$_{t-1}$		0.12	0.30	0.29	0.65	0.34
		(0.22)	(0.23)	(0.30)	(0.43)	(0.37)
Domestic Spending \$10B$_{t-1}$			0.01*	0.01	-0.01	-0.07*
			(0.01)	(0.01)	(0.02)	(0.02)
Inflation$_{t-1}$				-0.20	-0.16	-0.32*
				(0.17)	(0.17)	(0.15)
Top 1% Income Share$_{t-1}$					0.48	1.07*
					(0.40)	(0.38)
Defense Spending \$10B$_{t-1}$						0.20*
						(0.06)
Short Term Effects						
Δ Unemployment$_t$		-0.16	-0.05	0.21	0.53	0.68
		(0.29)	(0.29)	(0.43)	(0.47)	(0.39)
Δ Domestic Spending \$10B$_t$			-0.01	-0.01	-0.01	-0.07
			(0.04)	(0.04)	(0.04)	(0.04)
Δ Inflation$_t$				-0.05	0.03	-0.03
				(0.18)	(0.20)	(0.17)
Δ Top 1% Income Share$_t$					0.78*	0.76*
					(0.38)	(0.32)
Δ Defense Spending \$10B$_t$						0.14
						(0.11)
Error Correction and Constant						
DemMood$_{t-1}$	-0.05	-0.03	-0.14	-0.23	-0.32*	-0.69*
	(0.06)	(0.08)	(0.09)	(0.13)	(0.14)	(0.15)
Constant	-3.26	1.12	6.36	13.62	12.59	33.93*
	(4.23)	(1.31)	(6.20)	(6.40)	(9.12)	(9.86)
Fit and Diagnostics						
Adjusted R^2	-0.01	-0.04	0.04	0.02	0.10	0.39
Breusch-Pagan Test (χ^2)		7.03*	0.20	0.73	2.76	0.40
Breusch-Godfrey LM Test (χ^2)		1.28	1.04	2.49	0.41	0.70

Note: Dependent Variable is the change in *Democrat Mood*. Entries are OLS coefficients (standard errors in parentheses). ECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, two-tail test). N=35

run variables. Finally, in column (6) the inclusion of *Defense Spending* has completely blown apart the consistency of our model. We now have 4 significant long run IVs - of the three that were previously insignificant in (5), their coefficients have more than doubled - and our adjusted R^2 has jumped substantially. More importantly, our ECM has also doubled in size and now sits at an impressive -0.69.

What conclusions should we draw from this exercise? First, we see why the ECM's t-distribution shifts with each added regressor. The absolute value of the coefficient increases - substantially with influential variables - but the standard errors increase much more slowly. Considering that the ECM is simply the dependent variable at $t-1$ predicting changes in itself at time t, such small increases in its standard errors should not come as a surprise.

Second, the ECM's role as an identifier of a close, equilibrating relationship between an IV and DV has been rendered meaningless. The difference between columns (5) and (6) is the inclusion of one influential variable. Were we to stop at (5) we would draw the conclusion that our model was null. Only short-term changes in income inequality significantly affect Democrat mood. But with the inclusion of *Defense Spending* we gain 4 significant long-run variables, each of which supposedly share a close relationship with the dependent variable. Notably, the equilibrium relationship that *every significant regressor* supposedly shares with the DV has massively increased in strength. The inclusion of one influential variable has increased the absolute value of the ECM coefficient by 0.37.[7]

[7]Were we to first test and confirm that all variables in the model were $I(1)$, in practice we would then use the MacKinnon critical values in order to determine if cointegration was present. In this specific case, application of those values would lead to a finding that the ECM was insignificant. Without evidence of cointegration the model is misspecified and it would have to be run first-differences. The use of the model in this way would be just as Hendry, Srba, and Yeo (1978) proposed. Running the regression in first differences would yield null results for the Democrat Mood model.

Appendix E Additional Replications

E.1 Example 1: Sanchez Urribarri, Schorpp, Randazzo, and Songer (*The Journal of Politics, 2011)*, Rights Litigation

We next replicate a recent article by Sanchez Urribarri, Schorpp, Randazzo, and Songer (2011) in which the authors attempt to model the causes behind an increased propensity of the high courts of Canada, UK, and US to place "rights cases" on their dockets. We are agnostic as to causation, however we choose to replicate this article because it very clearly demonstrates the potential for inferential problems when using the ECM with a stationary, or short-memoried, dependent variable. The article has three models, for which the ECMs and their respective standard errors are: Canada ($\alpha_1 = -0.88$, s.e. $= 0.18$), UK ($\alpha_1 = -1.13$, s.e. $= 0.17$), and US ($\alpha_1 = -1.17$, s.e. $= 0.14$). These values draw our attention because it should be impossible to have an error correction rate that is greater than 100%. Our Monte Carlo simulations demonstrate how such results occur.[8]

To begin, we replicate the full results from Sanchez Urribarri et al. (2011) below. As seen in the results, a number of significant long-run effects are significant, but each model also has at least one significant short-run effect as well. Interestingly, the models that are fit by Sanchez Urribarri et al. include only one continuous independent variable, *Judicial Ideology*. The rest are coded either as ordinal (*Support Structure*), or as permanent interventions.

The stationarity of the dependent variables is of interest and Table E.2 provides the Dickey-Fuller test results for each of the three dependent variables used by the authors. From the results, it's clear that we have three different types of DV - *Canada* cannot reject the null of a unit-root and appears strongly autoregressive, the *UK* is very stationary, and the *US* is stationary, however it also indicates some level of autoregression.

We next regress the dependent variables from each model on randomly generated series of

[8] At 60 observations, the U.S. model is longer than our beef-shark-tornado data set. Rather than present an incomplete re-estimation of only the Canadian and UK series, we limit the replication to Monte Carlo simulations and FI estimations.

Table E.1: Replication of Table 1 - Sanchez Urribarri et al. (2011)[†]

Model[‡]	Canada	UK	US
Long Run Effects			
Support Structure$_{t-1}$	-0.00 (0.01)	0.01 (0.01)	0.00 (0.00)
Judicial Ideology$_{t-1}$	-0.17 (0.18)	-0.23* (0.12)	.22* (0.09)
Docket Control$_{t-1}$	0.17* (0.06)		
Charter$_{t-1}$	0.21* (0.07)		
Human Rights Act$_{t-1}$		0.05 (0.04)	
Brown$_{t-1}$			0.03 (0.03)
Mapp$_{t-1}$			0.10* (0.05)
Civil Rights Act$_{t-1}$			0.10* (.05)
Short Run Effects			
Δ Support Structure	0.02 (0.03)	-0.04 (0.03)	0.01 (0.02)
Δ Judicial Ideology	-0.21 (0.14)	-0.15* (.07)	0.20* (0.08)
Δ Docket Control	-0.04 (0.10)		
Δ Charter	0.16* (0.09)		
Δ Human Rights Act		-0.09 (0.08)	
Δ *Brown*			-0.06 (0.06)
Δ *Mapp*			-0.05 (0.06)
Δ Civil Rights Act			-0.05 (0.07)
Error Correction and Constant			
Rights Agenda$_{t-1}$	-0.88* (0.18)	-1.13* (0.17)	-1.17* (0.14)
Constant	0.20* (0.06)	0.40* (0.08)	0.26* (0.05)
Fit and Diagnostics			
Adjusted R^2	0.43	0.55	0.54
Breusch-Pagan Test (χ^2)	1.70	0.20	1.94
Breusch-Godfrey Test (χ^2)	2.78	0.46	0.16
N	35	36	60

[†] *Note*: Dependent variable Δ*Rights Agenda* represents changes to the rights agenda on high court dockets. Significance of ECM and coeffcients ($^\star p < .10$, two-tail test)

white noise independent variables. Recall from Appendix A that regressing the DV on non-influential independent variables is equivalent to imposing the common factor restrictions of the Dickey-Fuller test (Kremers, Ericsson, and Dolado 1992). The Canada DV is regressed on four white noise series, the UK DV on three, and the US DV on five. The results are found in Table E.3

This exercise raises several points worth discussing. First, note the similarities between the α_1 coefficient in Table E.3 and the Dickey-Fuller coefficient results in Table E.2. With stationary series, the baseline for the α_1 parameter is its DF coefficient - the more stationary the DV, the larger the absolute size of error correction found. Second, our two stationary series are guaranteed a significant ECM when applying a one-tail test, and even a non-stationary series such as the Canada model finds over half of all ECM's as significant when applying a standard one-tail test. Do note the work that the MacKinnon values are doing

Table E.2: Dickey-Fuller Results of Three DVs†

Model	Canada	UK	U.S.
Dickey-Fuller coefficient	-0.18	-0.86	-0.34
Dickey-Fuller t-statistic	-1.99	-5.07*	-3.68*
MacKinnon DF Critical Value	-2.97	-2.97	-2.92
Estimated d Value	0.53 (0.13)	0.13 (0.13)	0.45 (0.05)

† *Note*: Dickey-Fuller critical values are from MacKinnon (1994). d values estimated by Stata's exact ML estimator.

Table E.3: Monte Carlo Results with I(0) IVs and DVs of Sanchez Urribarri et al. (2011)†

Model‡	Canada	UK	US
% ECM Significant - one tail t-distribution	55.9	100	100
% ECM Significant - MacKinnon Values	0	95.4	0.02
Mean of α_1	-0.18	-0.84	-0.34
Mean t-statistic of α_1	-1.71	-4.63	-3.39
% ECM & $\geq 1\Delta X_t$ Significant	10.3	15.2	23.4
% ECM & $\geq 1X_{t-1}$ Significant	4.8	14.4	13.3

† *Note*: Results based on 10,000 simulations of each model. ‡ All IVs are level stationary (integrated at $I(0)$). MacKinnon Values are the ECM critical values from Ericsson and MacKinnon (2002) - for Canada (4 IVs, T=35 CV=-4.082); for UK (3IVs, T=36 CV=-3.867); for US (5IVs, T=60 CV=-4.229)

however. With $I(0)$ covariates we should not expect to find evidence of cointegration, and in both the Canada and US models, the MacKinnon values properly exclude that possibility. On the other hand, because of the stationary properties of the dependent variable in the UK model, the DV is automatically in equilibrium - the model is simply capturing its tendency toward mean reversion. Third, even though we simulate white-noise independent variables, the UK and US models suffer from spurious regressions - approximately 13 percent of all models produce at least one significant long-run covariate along with significant error correction. These rates are much too high for randomly generated data, and certainly too high for data generated as white noise processes.

These results arise from the simplest models including only white-noise independent variables. The use of unit-root independent variables complicates matters further, and the results are found in Table E.4. As before, we replace the IVs used by Sanchez Urribarri et al. (2011), this time with series generated as $I(1)$.

The results from Table E.4 indicate the inferential risks from the GECM, even with

Table E.4: Monte Carlo Results with I(1) IVs and DVs of Sanchez Urribarri et al. (2011)†

Model‡	Canada	UK	US
% ECM Significant - one tail t-distribution	97.9	100	100
% ECM Significant - MacKinnon Values	38.9	99.7	92.6
Mean of α_1	-0.71	-1.01	-0.81
Mean t-statistic of α_1	-3.82	-5.50	-5.78
% ECM & $\geq 1\Delta X_t$ Significant	32.3	17.4	34.6
% ECM & $\geq 1X_{t-1}$ Significant	68.4	31.7	82.1

† *Note*: Results based on 10,000 simulations of each model.
‡ All IVs are unit-roots (integrated at $I(1)$). MacKinnon Values are the ECM critical values from Ericsson and MacKinnon (2002) - for Canada (4 IVs, T=35 CV=-4.082); for UK (3IVs, T=36 CV=-3.867); for US (5IVs, T=60 CV=-4.229)

MacKinnon values. First, both the UK and US models are unbalanced - each DV is stationary, and the inclusion of unit-root IVs has compromised the results. The α_1 parameter for the UK model is below the theoretical limit of -1.00 and the US model is approaching it. But according to our Dickey-Fuller test results, the DV in the Canada model is a unit-root. This means that were we to apply a dichotomous $I(1)/I(0)$ value to our DV, the results in the first column would be considered as coming from a balanced model. Despite this fact, the model performs terribly. First, were we to assume that a one-tail test was appropriate, we'd be almost guaranteed a significant ECM, and a high rate of spurious regressions means at least one long-run variable is significant in over 68% of our models. But even were we to use MacKinnon values, a significance rate north of 35% for the ECM parameter means the critical values offer little assistance. It appears that the Canada DV is confounding the model despite the Dickey-Fuller test results leading us to consider it a unit-root.

Tables E.3 and E.4 represent two extremes in that our IVs are generated as either $I(0)$ or $I(1)$ series. To what extent are these results being driven by the models being unbalanced?[9] To find out, we next simulate stationary series to act as our IVs - the DGP is a simple autoregressive process, $X_t = \rho X_{t-1} + \epsilon_t$ with ρ set to 0.75. The results are in Table E.5.

Table E.5, columns 2 and 3, indicates that regression balance may help somewhat, but our issues are not completely solved. Because the US and UK DVs are both stationary, we

[9] Recall that according to the DF results the Canada model in Table E.4 is balanced however.

Table E.5: Monte Carlo Results with Stationary IVs and DVs of Sanchez Urribarri et al. (2011)[†]

Model[‡]	Canada	UK	US
% ECM Significant - one tail t-distribution	78.8	100	100
% ECM Significant - MacKinnon Values	0.3	99.0	33.1
Mean of α_1	-0.29	-0.94	-0.47
Mean t-statistic of α_1	-2.06	-5.15	-4.04
% ECM & $\geq 1\Delta X_t$ Significant	16.8	16.4	26.6
% ECM & $\geq 1X_{t-1}$ Significant	10.8	26.0	35.8

[†] *Note*: Results based on 10,000 simulations of each model.
‡ All IVs are stationary AR processes with $\rho = 0.75$. MacKinnon Values are the ECM critical values from Ericsson and MacKinnon (2002) - for Canada (4 IVs, T=35 CV=-4.082); for UK (3IVs, T=36 CV=-3.867); for US (5IVs, T=60 CV=-4.229)

apply the standard one-tail t-test and each model finds that 100% of ECMs are significant. As noted in the main text, this is to be expected with stationary dependent variables, but spurious regressions are still an issue. At least one long-run IV significant in 25-35% of the models.

As a final test in our replication, we re-estimate the three models after accounting for the fractional integration of the data. The orders of fractional integration of the dependent variables can be found in Table E.2. The estimated order of fractional integration of *Judicial Ideology* is as follows: Canada ($d = 0.32$, s.e.$= 0.11$), UK ($d = -0.13$, s.e.$= 0.16$), US ($d = 0.62$, s.e.$= 0.12$).

Table E.6: FI Model Results - Sanchez Urribarri et al. (2011)[†]

Model[‡]	Canada	UK	US
Δ^d Judicial Ideology	-0.22 (0.15)	-0.14* (.068)	0.05 (0.08)
Δ Support Structure	0.05 (0.04)	-0.04 (0.03)	0.01 (0.02)
Δ Docket Control	-0.14 (0.09)		
Δ Charter	0.13 (0.08)		
ΔHuman Rights Act		-0.10 (0.07)	
Δ*Brown*			-0.10 (0.07)
Δ*Mapp*			-0.04 (0.07)
Δ Civil Rights Act			-0.00 (0.07)
Constant	0.05 (0.02)	0.09 (0.02)	0.04 (0.07)
Fit and Diagnostics			
Adjusted R^2	0.17	0.21	0.05
Breusch-Godfrey Test (χ^2)	2.69	0.74	1.27
Breusch-Pagan Test (χ^2)	6.02	7.40	3.19
N	35	36	59

[†] *Note*: Entries are OLS coefficients (standard errors in parentheses). DV is Δ^d*Rights Agenda*. All variables have been fractionally differenced by their estimate of d. Coefficient significance (*p$\leq$ 0.05, two-tail test).

The results of the fractionally differenced models are drastically different from the original ECM models. Of the three re-estimated models only one IV - *Judicial Ideology* in the United Kingdom model - is significant. Its coefficient size is equivalent to that found in the ECM model. Because the dependent variable in the UK model has an estimated order of fractional integration of $d = 0.13$ and the estimate of *Judicial Ideology* is $d = -0.13$, neither of which are statistically different from $I(0)$, the two series are not candidates for fractional cointegration.

E.2 Example 2: Kelly and Enns (*American Journal of Political Science*, 2010), Inequality and Mood

This replication concerns the article by Kelly and Enns (2010), which uses the indicator *Public Mood* to argue that economic inequality is self-reinforcing. Kelly and Enns (KE) use the GECM model to estimate the effects of economic inequality on public mood while controlling for both policy liberalism as well as a few objective economic indicators. In terms of mass preferences, there is a negative response to shifts in economic inequality. The public becomes less supportive of government intervention when income inequality rises.

Replication of their findings are found in Tables E.7 and E.8 below. The results from their Table 1 (our E.7) indicate consistently significant effects of both *Policy Liberalism* and *Income Inequality*. The ECM for *Liberal Mood* is consistently estimated with a value of -0.25, and the ECM of their DV, *Welfare Support*, indicates a very strong connection between the IVs.

Replication of their second table (our E.8) provides the most interesting results of the paper. KE disaggregate public mood by income group and find that regardless of the level of income, the population responds in similar fashion to shifts in economic inequality. As income inequality rises, the public - whether rich or poor - responds in a conservative style. As they note, these findings contradict the theoretical predictions of both Benabou (2000) and Meltzer and Richard (1981).

Before we begin our replication, we first check the order of integration of the dependent variables. From their Table 1, we have *Public Mood* and *Welfare Support*. From their Table 2, we test *Low Income Mood* and *High Income Mood*. None of the four reject the null hypothesis of a unit-root, although Mood is edging up to the 10% level of significance.

We next simulate our own independent variables in order to test the Type I error rates generated by the GECM models with the dependent variables used by KE. With randomly generated $I(1)$ series, we should find a 5% rejection rate on the significance of the error correction parameter. The results in Table E.10 indicate higher than expected rejection

Table E.7: Replication of Kelly & Enns - Table 1

Independent Variables	(1) Δ Liberal Mood	(2) Δ Liberal Mood	(3) Δ Liberal Mood	(4) Δ Support Welfare
Long Run Effects				
Policy Liberalism$_{t-1}$	-0.07*	-0.09*	-0.07*	-0.65*
	(0.04)	(0.02)	(0.03)	(0.22)
Income Inequality$_{t-1}$		-16.22*	-18.00*	-152.17*
		(8.92)	(9.44)	(65.71)
Unemployment$_{t-1}$	0.04		0.10	
	(0.25)		(0.26)	
Inflation$_{t-1}$	-0.08		-0.13	
	(0.18)		(0.17)	
Short Run Effects				
Δ Policy Liberalism$_t$	0.16	0.10	0.10	-0.24
	(0.11)	(0.10)	(0.11)	(0.42)
Δ Income Inequality$_t$		27.07	-29.56	-175.70
		(34.61)	(37.59)	(122.56)
Δ Unemployment$_t$	-0.00		0.01	
	(-0.38)		(0.38)	
Δ Inflation$_t$	-0.12		-0.13	
	(0.19)		(0.19)	
Error Correction and Constant				
Liberal Mood$_{t-1}$	-0.25*	-0.25*	-0.26*	
	(0.07)	(0.07)	(0.07)	
Support Welfare$_{t-1}$				-0.55*
				(0.16)
Constant	15.41*	21.70*	22.99*	80.03*
	(4.54)	(5.57)	(6.31)	(29.92)
Fit and Diagnostics				
Adjusted R^2	0.20	0.28	0.24	0.26
Breusch-Godfrey LM Test (χ^2)	0.88	0.71	0.60	0.24
Breusch-Pagan Test (χ^2)	0.75	0.49	0.30	3.44
N	54	54	54	33

Note: Entries are OLS regression coefficients (standard errors in parentheses). Two-tailed significance levels: *p<.10)

rates however. First, we clearly see the dangers of failing to account for (α_1) t-statistic's non-standard distribution. Use of a one-tail test practically guarantees a significant ECM in all four models of Table 1. Fortunately, applying the MacKinnon values cuts down on the Type I errors, however with *Liberal Mood* as the DV, the model still tends towards significance - approximately 10% of all models claim an ECM as significant. On the other hand, Model 4, and its DV of *Welfare Support*, appears to understate the significance of the ECM when MacKinnon critical values are applied.

In Table E.10 the coefficient of the ECM is fairly consistent in Models 1 through 3 which is not unsurprising considering that the only variance between each model is the number of unrelated, simulated regressors. Model 4 sees a fairly substantial jump in coefficient

Table E.8: Replication of Kelly & Enns - Table 2

	Δ Liberal Mood			
Independent Variables	**Low Income**	**High Income**	**Low Income**	**High Income**
Long Run Effects				
Policy Liberalism$_{t-1}$	-0.28⋆	-0.24⋆	-0.26⋆	-0.23⋆
	(0.08)	(0.07)	(0.08)	(0.07)
Income Inequality$_{t-1}$	-48.65⋆	-44.26⋆	-64.57⋆	-61.98⋆
	(22.23)	(21.09)	(25.97)	(24.38)
Unemployment$_{t-1}$			-0.33	-0.45
			(0.47)	(0.46)
Inflation$_{t-1}$			-0.39	-0.33
			(0.34)	(0.31)
Short Run Effects				
Δ Policy Liberalism$_t$	-0.16	0.07	-0.22	0.01
	(0.15)	(0.13)	(0.17)	(0.15)
Δ Income Inequality$_t$	19.43	-46.76	-22.56	-41.01
	(53.05)	(42.99)	(55.18)	(44.14)
Δ Unemployment$_t$			0.14	-0.13
			(0.63)	(0.53)
Δ Inflation$_t$			-0.46	-0.19
			(0.32)	(0.28)
Error Correction and Constant				
Liberal Mood$_{t-1}$	-0.48⋆	-0.46⋆	-0.58⋆	-0.57⋆
	(0.12)	(0.11)	(0.14)	(0.13)
Constant	50.25⋆	44.18	66.00	61.54
	(14.91)	(12.93)	(19.56)	(17.03)
Fit and Diagnostics				
Adjusted R^2	0.20	0.25	0.18	.023
rho	0.19	0.32	0.17	0.33
N	50	50	50	50

Note: Entries are Prais-Winsten regression coefficients (standard errors in parentheses). Two-tailed significance levels: ⋆p<.10)

size however. This is consistent with our simulations of an $I(d)$ model when $d = .9$.[10] Additional downward bias in Model 4's (α_1) parameter is likely due to the limited number of observations. Finally, the ECM model suffers from substantial spurious regression problems. In Models 1-3, over half of all simulated models find both a significant error correction parameter and long-run regressor.

But as we have seen, the independent variables also affect the ECM estimates. Of particular interest in this case is any potential bias of the (α_1) t-statistic when the independent variables' order of fractional integration, d, exceeds 1. With *Policy Liberalism* estimated at $d = 1.35$ (s.e.= 0.10), the significance of error correction in these simulations is expected to be inflated. In Table E.11 we simulate our dependent variables and regress them on the IVs of Kelly and Enns. To better approximate a series such as *Mood* we use the bounded DGP

[10] See Section H.3 for simulation results based on varying orders of fractional integration.

Table E.9: Dickey-Fuller Results of K&E DVs†

Model	Liberal Mood	Welfare Support	Low Income Mood	High Income Mood
Dickey-Fuller Coefficient	-0.18	-0.22	-0.11	-0.09
Dickey-Fuller T-statistic	-2.56	-1.88	-2.02	-1.60
MacKinnon DF Critical Value	-2.93	-2.98	-2.93	2.93
Estimated d Value	1.09 (0.11)	0.88 (0.18)	0.98 (0.13)	1.04 (0.13)

† *Note*: Dickey-Fuller critical values are from MacKinnon (1994). d values estimated by Stata's exact ML estimator. Standard errors in parentheses.

Table E.10: Monte Carlo Results - K&E Table 1 - DVs on I(1) IVs†

Model	(1) Δ Liberal Mood	(2) Δ Liberal Mood	(3) Δ Liberal Mood	(4) Δ Support Welfare
% ECM Significant - one tail t-distribution	94.9	96.9	92.9	85.3
% ECM Significant - MacKinnon Values	10.6	11.7	9.2	1.3
Mean of α_1	-0.19	-0.18	-0.21	-0.29
% ECM & $\geq 1\Delta X_t$ Significant	18.8	13.4	24.3	11.1
% ECM & $\geq 1X_{t-1}$ Significant	57.1	49.0	59.4	17.8

† *Note*: Entries provide the summary results of 10,000 simulations of an OLS regression in which the *Liberal Mood* and *Welfare Support* are regressed on randomly generated $I(1)$ series. Number of IVs match those of K&E. Models 1-3 regress *Mood* on IVs ($T = 54$). Model 4 DV is *Welfare Support* ($T = 35$). Significance of IVs based on two-tail test. MacKinnon CV Model 1: -3.822; Model 2: -3.57; Model 3: -4.040; Model 4: -3.621

of Nicolau (2002) to generate one DV and use it in Models 1 through 3. Because *Welfare Support* is less well defined in its boundaries, the DGP for the Model 4 dependent variable is left as a unit-root process.

Table E.11: Monte Carlo Results - K&E Table 1 - BI(1) DVs on IVs†

Model	(1) BI(1) DV1	(2) BI(1) DV1	(3) BI(1) DV1	(4) I(1) DV2
% ECM Significant - one tail t-distribution	65.6	86.8	89.4	75.8
% ECM Significant - MacKinnon Values	6.9	17.1	10.7	8.2
Mean of α_1	-0.20	-0.27	-0.32	-0.32
% ECM & $\geq 1\Delta X_t$ Significant	13.5	13.2	23.7	12.3
% ECM & $\geq 1X_{t-1}$ Significant	21.0	43.8	54.0	31.9

† *Note*: Entries provide the summary results of 10,000 simulations of an OLS regression in which randomly generated $I(1)$ DVs are regressed on the IVs from Table 1 of Kelly and Enns (2010). Significance of IVs based on two-tail test. MacKinnon CV Model 1: -3.822; Model 2: -3.57; Model 3: -4.040; Model 4: -3.621

The results in Table E.11 are as expected. Even when applying the MacKinnon values each model rejects the null of a significant ECM at a rate exceeding 5%. The potential for outsized influence of a particular IV is also on display. Compare the results of Models 2 and 3 to Model 1. Despite the same randomly generated DV across all three models, the inclusion of *Income Inequality* in Models 2 and 3 substantially increases the number of Type I errors and inflates the ECM coefficient of each model as well.

Replicating Table 2 of KE's paper, we chose to randomly generate two $I(1)$ variables for use as dependent variables and to run our MC simulation with the Prais-Winsten estimator.[11] The effect size due to estimator choice is striking. While not directly comparable, the number of significant ECMs using the Prais-Winsten estimator in Table E.12 is twice the size of those when using OLS.

Table E.12: Monte Carlo Results - K&E Table 2 - I(1) DVs on IVs†

	Model 1 & 2	**Model 3 & 4**
% ECM Significant – one tail t-distribution	86.1	84.7
% ECM Significant – MacKinnon Values	31.1	21.8
Mean of α_1	-0.37	-0.37
% ECM & $\geq \Delta X_t$ Significant	18.2	28.8
% $\geq 1X_{t-1}$ Significant	51.4	59.2

Note: Entries provide are the summary results of 10,000 simulations of a Prais-Winsten regression in which randomly generated $I(1)$ series are regressed upon the independent variables from Table 2 of Kelly and Enns (2010). Coefficient significance (*p$\leq$ 0.05, two-tail test). MacKinnon CV Models 1&2: -3.578; Models 3&4: -4.047.

To put the ECM model's susceptibility to Type I errors into context, we use our nonsense data sets from the main paper in place of the IVs in the model. Unfortunately, because of the length of the series, we are unable to use our *Shark Attack* series. Regardless, as with all other replications, we find a high rate of significance. Fortunately, we finally find a model in which *Beef Consumption* is not a significant predictor. In Model 4, our two nonsense series do not predict *Welfare Support*, but note that had we been following standard practice in political science and using the normal t-test, we would conclude there was significant ECM despite no significant covariates.

For completeness, we also employ the same nonsense series with KE's dependent variables from their Table 2. Based on our past replications and simulations we expect spurious regressions, and that is what we find.

[11] According to Engle and Granger (1987, p.264), the use of "serial correlation correction" such as a Cochrane Orcutt or Prais-Winsten estimator in the cointegrating regression will produce inconsistent estimates. Kelly and Enns use the Prais-Winsten estimator despite Breusch-Godfrey test $p > \chi^2$ values of .1748,

Table E.13: What Else Moves Mood? (Re-estimation of Table 1)

Independent Variables	(1) Δ Liberal Mood	(2) Δ Liberal Mood	(3) Δ Liberal Mood	(4) Δ Support Welfare
Long Run Effects				
Beef Consumption$_{t-1}$	-0.10*	-0.19*	-0.36*	-0.94
	(0.04)	(0.07)	0.09	0.80
Coal Emissions$_{t-1}$		0.01*	0.04*	0.06
		(0.01)	0.01	(0.04)
Tornado Fatalities$_{t-1}$	-0.00		-0.01	
	(0.00)		0.00	
Onion Acreage$_{t-1}$	0.17		-0.78*	
	(0.15)		0.32	
Short Run Effects				
Δ Beef Consumption$_t$	0.29	0.20	0.10	0.05
	(0.30)	(0.30)	0.29	1.01
Δ Coal Emissions$_t$		0.01	0.01	-0.08
		0.01	(0.02)	(0.08)
Δ Tornado Fatalities$_t$	0.00		0.00	
	(0.00)		0.00	
Δ Onion Acreage$_t$	0.28		-0.12	
	(0.39)		(0.38)	
Error Correction and Constant				
Liberal Mood$_{t-1}$	-0.18*	-0.17*	-0.20*	
	(0.06)	(0.06)	(0.05)	
Support Welfare$_{t-1}$				-0.28*
				(0.13)
Constant	12.99*	12.66*	20.91*	25.56
	(4.49)	(3.87)	(4.77)	(20.37)
Fit and Diagnostics				
Adjusted R^2	0.26	0.21	0.38	0.12
Breusch-Pagan Test (χ^2)	0.74	0.15	1.07	3.40
Breusch-Godfrey LM Test (χ^2)	1.25	0.00	0.27	0.11

Note: Entries are OLS regression coefficients (standard errors in parentheses). ECM significance (*p$\leq$ 0.05, one-tail test). Coefficient significance: two-tailed: *p<.10).

Finally, we test the Kelly and Enns model for fractional cointegration and fractional error correction. As with all other replications, we first provide the order of integration of the IVs as well as the residuals of the static regressions in Table E.15. We do find some reduction in the residual's order of fractional integration, however a calculation of the confidence intervals surrounding these estimates indicates overlap between the residual estimates and the estimates of each constituent series.

In Tables E.16 and E.17 we report the results of the fractional ECM models. If two IVs were significant in a model, we included them both in the cointegrating equation. Whether we estimated the cointegration individually, or with both *Policy Liberalism* and *Income*

.0634, .1828, and .1032 for OLS estimation of Table 2, Models 1-4 respectively.

Table E.14: What Else Moves Mood? (Re-estimation of Table 2)

Variables	(1) Δ Low Income Mood	(2) Δ High Income Mood	(3) Δ Low Income Mood	(4) Δ High Income Mood
Long Run Effects				
Beef $Consumption_{t-1}$	-0.51⋆	-0.46⋆	-0.53⋆	-0.70⋆
	(0.24)	(0.18)	0.31	0.24
Coal $Emissions_{t-1}$	0.04⋆	0.04⋆	0.05	0.07⋆
	(0.02)	(0.01)	(0.03)	(0.03)
Tornado $Fatalities_{t-1}$			-0.00	-0.00
			0.01	(0.01)
Onion $Acreage_{t-1}$			-0.49	-0.87
			(0.58)	(0.53)
Short Run Effects				
Δ Beef $Consumption_t$	-0.75	-0.34	-0.76	-0.49
	(0.46)	(0.41)	0.50	(0.45)
Δ Coal $Emissions_t$	-0.02	0.01	-0.02	0.02
	(0.04)	0.03	(0.04)	(0.03)
Δ Tornado $Fatalities_t$			0.01	0.00
			(0.01)	(0.00)
Δ Onion $Acreage_t$			-1.01	-0.36
			(0.70)	(0.64)
Error Correction and Constant				
Liberal $Mood_{t-1}$	-0.31⋆	-0.25⋆	-0.30⋆	-0.30⋆
	(0.11)	(0.09)	(0.12)	(0.10)
Constant	27.10⋆	20.83⋆	28.82⋆	30.82⋆
	(10.18)	(7.85)	(13.19)	(10.54)
Fit and Diagnostics				
Adjusted R^2	0.15	0.21	0.16	0.09
Breusch-Pagan Test (χ^2)	0.03	0.51	0.09	0.37
Breusch-Godfrey LM Test (χ^2)	0.83	0.92	0.96	0.28

Note: Entries are OLS regression coefficients (standard errors in parentheses). ECM significance (*p≤ 0.05, one-tail test). Coefficient significance: two-tailed: ⋆p<.10).

Inequality as a part of the cointegrating vector, the results are the same. We fail to find any evidence of fractional cointegration in any model, and we also fail to find any significant independent variables.

Table E.15: FECM Order of Integration - Kelly and Enns (2010)

	Individual Series *d*	**Residuals Liberal Mood** *d*	**Residuals Welfare** *d*	**Residuals Low Inc. Mood** *d*	**Residuals High Inc. Mood** *d*
Liberal Mood	1.08 (0.11)				
Welfare Support	0.88 (0.18)				
Low Income Mood	0.98 (0.13)				
High Income Mood	1.04 (0.13)				
Policy Liberalism	1.35 (0.09)	1.06 (0.11)	0.74 (0.19)	0.65 (0.18)	0.80 (0.16)
Income Inequality	0.80 (0.10)	1.09 (0.11)	0.89 (0.18)	1.00 (0.13)	1.06 (0.13)
Unemployment	0.83 (0.14)				
Inflation	0.95 (0.16)				
Policy & Inequality		1.04 (0.11)	0.66 (0.20)	0.67 (0.18)	0.79 (0.15)

† *Note*: Entries are estimates of the order of integration of all significant long-run variables from Kelly and Enns (2010) as well as estimates of the residuals of static bivariate regressions of the DV and each significant variable. Estimates generated by Stata's exact ML estimator. Standard errors in parentheses

Table E.16: Three-Step FECM Results - Kelly and Enns (2010)†

Table 1 Models	**Liberal Mood**	**Liberal Mood**	**Liberal Mood**	**Welfare Support**
Short Run Effects				
Δ^d Policy Liberalism	0.09	0.09	0.09	0.10
	(0.11)	(0.11)	(0.11)	0.14
Δ^d Income Inequality		-29.58	-33.91	-58.80
		(38.99)	(39.97)	(43.63)
Δ^d Unemployment	-0.01		-0.01	
	(0.29)		(0.29)	
Δ^d Inflation	-0.11		-0.14	
	(0.17)		(0.18)	
Error Correction and Constant				
FECM - Policy Liberalism$_{t\text{-}1}$	-0.14			
	(0.13)			
FECM - Policy Liberalism & Inequality$_{t\text{-}1}$		-0.15	-0.16	-0.01
		(0.13)	(0.13)	0.06
Constant	0.02	0.05	0.07	0.25
	(0.28)	(0.28)	(0.29)	(0.35)
Fit and Diagnostics				
Adjusted R^2	-0.03	0.01	-0.02	-0.03
Durbin-Watson	1.78	1.72	1.76	1.77
Breusch-Pagan Test (χ^2)	1.01	0.93	1.74	0.89
Breusch-Godfrey LM Test (χ^2)	0.83	2.16	1.37	0.40

† *Note*: Entries are OLS coefficients. Standard errors in parentheses. Models 1-3: DV is Δ^d Liberal Mood. Model 4: DV is Δ^d Welfare Support. FECM captures equilibrium relationship between *Policy Liberalism* and/or *Income Inequality* with DV. FECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, one-tail test).

Table E.17: Three-Step FECM Results - Kelly and Enns (2010)†

Table 2 Models	Low Income Mood	High Income Mood	Low Income Mood	High Income Mood
Short Run Effects				
Δ^d Policy Liberalism	-0.10	0.10	-0.09	0.11
	(0.17)	(0.15)	(0.17)	0.15
Δ^d Income Inequality	31.82	-24.84	17.70	-31.04
	(67.45)	(59.74)	(67.62)	(59.98)
Δ^d Unemployment			-0.02	-0.24
			(0.51)	(0.44)
Δ^d Inflation			-0.44	-0.23
			(0.29)	(0.25)
Error Correction and Constant				
FECM - Policy Liberalism & Inequality$_{t\text{-}1}$	-0.14	-0.14	-0.17	-0.14
	(0.14)	(0.13)	(0.15)	0.14
Constant	-0.32	-0.03	-0.28	0.00
	(0.49)	(0.42)	(0.49)	(0.42)
Fit and Diagnostics				
Adjusted R^2	-0.03	-0.02	-0.02	-0.04
Durbin-Watson	1.79	1.72	1.86	1.77
Breusch-Pagan Test (χ^2)	6.27	3.57	8.38	4.36
Breusch-Godfrey LM Test (χ^2)	2.29	3.36	1.38	3.47

† *Note*: Entries are OLS coefficients. Standard errors in parentheses. Models 1& 3: DV is Δ^d Low Income Mood. Model 2 & 4: DV is Δ^d High Income Mood. FECM captures equilibrium relationship between *Policy Liberalism* and *Income Inequality* with DV. FECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, one-tail test).

E.3 Example 3: Volscho & Kelly (*American Sociological Review*, 2012) Top 1% Income Share

What accounts for the rise of the super-rich? This is the question that Volscho and Kelly (2012) set out to answer in their recent paper, and they do so using the GECM model. We take note of this paper due to the sheer number of independent variables used in their models. Model 4 has 17 estimated IVs with a T of 60. In all of these models, VK rely on the standard t-statistic distribution and use a two-tail test of significance for their ECMs. Also, VK note in their Footnote 15 that they estimated the same models using a fractional ECM and received results that were largely similar. The FECM models were included in their supplement.

The ECM follows its own distribution, so the standard two-tail test is inappropriate for use with the ECM models. Additionally, the ECM distribution is biased by the inclusion of covariates that are not $I(1)$. As VK note, their data is a mix of data types (stationary and integrated), so any hypothesis tests will be based on unbalanced equations.

A main point of interest for this replication was the fractional ECM model that VK estimated. If, as they claim, a fractional model gives results very similar to the GECM then our arguments are significantly weakened. But VK's use of fractional methods is incorrect – they do not remove auto-correlation from each variable and from the ECM. Instead, what they do is fractionally difference their IVs, and then include them in the general ECM model with the level-form lags of all IVs and the lag of the dependent variable. With an $I(1)$ dependent variable, including non-stationary variables on the right hand side biases the model estimates and defeats the purpose of fractional differencing. Just as spurious regressions are prevalent in a static regression of non-stationary variables, the inclusion of some differenced - or fractionally differenced - independent variables does not provide a solution. Volscho and Kelly misapply fractional methods and should not be claiming to find corroboration in them.

We re-estimate their models with a proper fractional ECM model and find drastically different results from what they report. We initially estimate the order of fractional integration of all variables. As VK report, their variables are a mix of data types.

Table E.18: FECM Order of Integration, Volscho and Kelly (2012)

	Individual Series d	**Residuals Model 1** d	**Residuals Model 2** d	**Residuals Model 3** d	**Residuals Model 4**	**Residuals Model 5**
Top 1% Share	0.93					
% Congressional Democrat	0.87					
% Union Membership	1.33					
Top Marginal Tax Rate	1.14					
Cap. Gains Tax Rate	1.26					
3 Month Treasury Bill Rate	1.00					
Trade Openness	1.02				0.92	0.92
Unemployment Rate	0.95					
Log Real GDP	0.96					
Real S&P Composite Index	1.37				0.97	0.97
Shiller Home Price Index	1.58					

† *Note*: Entries are estimates of the order of integration of all significant long-run variables from Volscho and Kelly (2012) as well as estimates of the residuals of bivariate regressions of the DV and each significant variable. *Dem President* and *Divided Government* are dichotomous variables and are used in first differences. Estimates conducted in RATS using Robinson's (1995) semi-parametric estimator. Because d was estimated using the Local Whittle, the asymptotic standard errors are provided - using the following formula $(1/\sqrt{4 * m})$ with $m = T^{4/5}$. (s.e. = 0.10).

Note that we only estimate the residuals of two variables from Models 4 and 5. This is because these are the only two variables to achieve significance for which a fractional ECM could be estimated. With two significant variables, we included them in the same cointegrating regression. In this case the ECM captures the long-term equilibrium relationship of both *Trade Openness* and *Real S&P Composite Index* with the *Top 1% Income Share*. We find a significant ECM in Models 4 and 5.

With the exception of *Dem President* in Model 1, all other variables are insignificant and failed to approach significance. The results of the fractionally differenced models are provided below. Contrary to Volscho and Kelly's supplement, when the data is run through a proper fractional ECM model, the significance of the results are far different. Re-estimating their power resources model (Model 1), policy model (Model 2) and their politics and policy model (Model 3), we find no support for either politics or policy having significant effects on the concentration of income among the Top 1%. Furthermore, a look at the R^2 of these models indicate a rather poor fit. It is not until Models 4 and 5, which account for economic indicators, that we see an improvement. Within these fully specified models, we again fail to find any significant effects of either politics or policy. Our re-estimation of their data finds that the only significant influences on the income share of the top 1% are market factors, specifically levels of trade openness and the valuation of the stock market.

Table E.19: Three-Step FECM Results - Volscho and Kelly (2012)†

	Model 1	Model 2	Model 3	Model 4	Model 5
Short Run Effects					
Δ^d Democrat President	**1.30**⋆				
	(0.55)				
Δ^d % Congressional Democrat	-0.02		-0.02	-0.00	-0.01
	(0.04)		(0.04)	(0.04)	(0.04)
Δ^d Divided Government	0.70		0.03	0.13	0.15
	(0.48)		(0.42)	(0.36)	(0.36)
Δ^d % Union Membership	-0.05		0.01	-0.12	-0.06
	(0.30)		(0.32)	(0.29)	(0.26)
Δ^d Top Marginal Tax Rate		-0.02	-0.02	-0.02	-0.02
		(0.04)	(0.04)	(0.03)	(0.03)
Δ^d Cap. Gains Tax Rate		-0.07	-0.06	-0.08	-0.07
		(0.06)	(0.06)	(0.05)	(0.05)
Δ^d 3 Month Treasury Bill Rate		0.12	0.11	-0.15	-0.13
		(0.11)	(0.12)	(0.15)	(0.14)
Δ^d Trade Openness				**0.36**⋆	**0.38**⋆
				(0.20)	(0.19)
Δ^d Unemployment Rate				-0.15	
				(0.33)	
Δ^d Log Real GDP				-1.67	3.45
				(13.39)	(6.89)
Δ^d Real S&P Composite Index				**0.07**⋆	**0.07**⋆
				(0.01)	(0.01)
Δ^d Shiller Home Price Index				0.32	0.32
				(0.27)	(0.27)
Error Correction and Constant					
$\text{FECM}_{\text{t-1}}$				**-0.38**⋆	**-0.35**⋆
				(0.15)	(0.14)
Constant	0.18	0.15	0.15	0.10	0.01
	(0.15)	(0.15)	(0.16)	(0.26)	(0.18)
Fit and Diagnostics					
Adjusted R^2	0.03	0.00	-0.06	0.35	0.36
Durbin-Watson	2.09	2.11	2.12	1.92	1.89
Breusch-Pagan Test (χ^2)	2.85	8.33⋆	11.18	14.53	13.81
Breusch-Godfrey LM Test (χ^2)	0.37	0.27	0.40	1.71	0.97

† *Note*: Entries are OLS coefficients.Standard errors in parentheses. DV is Δ^d Top 1% Share. FECM captures equilibrium relationship between *Trade Openness* and *S&P Index* with DV. FECM significance (*p≤ 0.05, one-tail test). Coefficient significance (*p≤ 0.05, one-tail test).

Appendix F Additional Materials - Common Misinterpretation of De Boef and Keele (2008)

As we note in the main text, while De Boef and Keele are discussing the use of the GECM under the specific condition of stationarity, common practice is to assume that the model can be used under any circumstances. Most papers do not check the stationarity properties of their data and the reason for this oversight stems directly from a widespread belief that any and all types of data are appropriate for use in the model. Below we highlight a sample of this misunderstanding in practice.

- Volscho and Kelly (ASR 2012): "In summary, the ECM is a very general model that is easy to implement and estimate, does not impose assumptions about cointegration, and can be applied to both stationary and nonstationary data (Banerjee et a. 1993, DeBoef and Keele 2008)."
- Buthe and Milner (WP 2014): "These powerful dynamic models, which are equivalent to autoregressive distributed lag (ADL) models after a straightforward mathematical transformation (fn to D&K), also provide a safeguard against spurious correlation that might arise in time series analysis when variables are trending together."
- Casillas, Enns, Wohlfarth (AJPS 2011): "The ECM provides a conservative empirical test of our argument and a general model that is appropriate with both stationary and nonstationary data (De Boef and Keele 2008)."
- Enns (AJPS 2014): "Finally, because the ECM estimates the change in the dependent variable, we overcome the concern of estimating a spurious relationship among nonstationary time series (De Boef and Granato 1997, De Boef and Keele 2008)."
- Faricy (JOP 2011): "ECMs are appropriate when using both stationary and nonstationary data and offer a conservative test of the theory (DeBoef and Keele 2008)."
- Jennings and John (AJPS 2009): "While error-correction models tend to be isomorphic with the concept of cointegration for political scientists (see DeBoef and Keele 2008), this framework is appropriate for modeling feedback and equilibrium relationships in stationary as well as nonstationary data (Banerjee, Dolado, Galbraith 1993, Davidson and MacKinnon, DeBoef and Keele 2008)."
- Kayser (AJPS 2009): "I err on the side of caution and assume nonstationarity bearing in mind that many ECMs offer the same benefits of capturing long- and short-term dynamics in stationary data as in nonstationary but cointegrated data (DeBoef and Keele 2008)."

- Kelly and Enns (AJPS 2010): "While the use of an ECM is often motivated by the presence of a nonstationary time-series as a dependent variable, our application of this model is based on the fact that it is among the most general time-series models that imposes the fewest restrictions. (DeBoef and Keele 2008)."

- Kono (JOP 2008): "I employ an error-correction model both to guard against integration problems....Because the error-correction model thus imposes fewer restrictive assumptions than other time series models (DeBoef and Keele 2008), it is the most general and conservative one I can estimate."

- Rickard (JOP 2012): "Differencing the series also minimizes the potential for a spurious correlation between two series exhibiting a time trend (DeBoef and Keele 2008)."

- Sanchez-Urribari (JOP 2011): "Following the suggestion of DeBoef and Keele, we estimate an error correction model (ECM) to specifically control for the dynamic effect of the covariates."

- Ura (AJPS 2014): "Though ECMs were originally developed for investigating cointegrated time series, DeBoef and Keele (2008) note that they may also be applied in a variety of time-series contexts in the absence of cointegration with either stationary or nonstationary data."

- Ura and Ellis (JOP 2012): "The error-correction model is often used with integrated series, but is also appropriate for use with nonintegrated series as well (DeBoef and Keele 2008)."

- Ura and Wohlfarth (JOP 2010): "Though the model specification was originally developed for investigating cointegrated time series, DeBoef and Keele (2008) note that it may also be applied in a variety of time series contexts in the absence of cointegration with either stationary or nonstationary data."

Appendix G Additional Materials: Near-Integrated Data

G.1 Tables - Varying AR - Monte Carlo Results

The results in the following tables are meant to provide as much information as possible in as little space as possible. Therefore, we have tried to include a wide a range of models. The top row of each table contains models run in which the level of autoregression in the DV varies, but the IV(s) all have unit roots. The middle row contain results of models in which all series within each model share the same level of autoregression. These equations are balanced. The bottom row also allows the DV to vary by levels of autoregression, but the IV(s) are all generated as $I(0)$ - the IV(s) contain very little, if any, information.

Table G.1: Summary Statistics of Bivariate ECM Model by DV and IV (T=60)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	8662	8408	8143	7872	7598	7031	7048	6780	6464	6132	5675
ECM Significant*	1281	1147	1062	955	862	789	708	669	605	564	533
Mean of α_1	-0.21	-0.20	-0.19	-0.18	-0.17	-0.16	-0.16	-0.15	-0.14	-0.13	-0.12
$\geq 1\Delta X_t$ Significant	592	585	587	587	594	605	600	605	603	607	610
$\geq 1X_{t-1}$ Significant	1369	1409	1478	1548	1597	1668	1714	1778	1765	1756	1716
ECM and $\geq 1\Delta X_t$ Significant	514	493	478	474	473	459	471	455	429	416	384
ECM and $\geq 1\Delta X_t$ Significant*	105	92	86	80	71	69	65	65	55	47	49
ECM and $\geq 1X_{t-1}$ Significant	1320	1343	1395	1443	1457	1498	1513	1554	1515	1467	1410
ECM and $\geq 1X_{t-1}$ Significant*	519	491	477	452	415	395	373	380	355	330	310
Model 2**											
ECM Significant	8295	8042	7764	7455	7176	6954	6731	6479	6257	6005	
ECM Significant*	1050	952	874	799	748	694	622	581	569	551	
Mean of α_1	-0.19	-0.19	-0.18	-0.17	-0.16	-0.16	-0.15	-0.14	-0.13	-0.13	
$\geq 1\Delta X_t$ Significant	585	597	607	608	606	619	620	619	622	611	
$\geq 1X_{t-1}$ Significant	1136	1185	1242	1292	1331	1381	1467	1508	1563	1635	
ECM and $\geq 1\Delta X_t$ Significant	501	504	500	483	472	473	466	449	434	416	
ECM and $\geq 1\Delta X_t$ Significant*	93	89	83	72	68	68	65	59	57	55	
ECM and $\geq 1X_{t-1}$ Significant	1082	1118	1159	1190	1210	1227	1277	1297	1336	1367	
ECM and $\geq 1X_{t-1}$ Significant*	363	353	346	334	330	313	303	303	302	307	
Model 3***											
ECM Significant	7906	7552	7181	6799	6422	6075	5745	5422	5160	4909	4482
ECM Significant*	597	529	469	416	375	312	276	251	242	240	219
Mean of α_1	-0.17	-0.17	-0.16	-0.15	-0.14	-0.13	-0.13	-0.12	-0.11	-0.10	-0.09
$\geq 1\Delta X_t$ Significant	561	560	562	563	557	561	566	560	548	551	542
$\geq 1X_{t-1}$ Significant	595	601	601	599	601	601	597	606	606	602	593
ECM and $\geq 1\Delta X_t$ Significant	449	436	427	414	388	372	361	338	317	308	257
ECM and $\geq 1\Delta X_t$ Significant*	66	59	53	44	38	34	35	30	27	25	21
ECM and $\geq 1X_{t-1}$ Significant	497	485	475	449	428	405	390	384	364	345	308
ECM and $\geq 1X_{t-1}$ Significant*	89	81	74	64	57	52	42	39	38	36	33

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.27.

$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

$\star\star$ Model 2: Both IV and DV data generating process based on same level of ρ.

$\star\star\star$ Model 3: IV is integrated $I(0)$ and DV varies by level of ρ specified.

Table G.2: Summary Statistics of Multivariate (2 IVs) ECM Model by DV and IV (T=60)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	8925	8744	8562	8353	8140	7905	7673	7432	7177	6926	6488
ECM Significant*	1133	1053	970	896	842	781	718	677	632	593	552
Mean of α_1	-0.24	-0.23	-0.22	-0.22	-0.20	-0.19	-0.19	-0.18	-0.17	-0.16	-0.15
$\geq 1\Delta X_t$ Significant	1213	1214	1227	1228	1223	1228	1225	1217	1208	1212	1227
$\geq 1X_{t-1}$ Significant	2541	2592	2664	2716	2580	2849	2933	2947	3019	3002	2945
ECM and $\geq 1\Delta X_t$ Significant	1109	1099	1092	1058	1032	1014	985	963	914	895	862
ECM and $\geq 1\Delta X_t$ Significant*	216	204	185	174	161	154	148	137	125	116	110
ECM and $\geq 1X_{t-1}$ Significant	2463	2491	2538	2563	2580	2619	2669	2643	2643	2594	2497
ECM and $\geq 1X_{t-1}$ Significant*	731	699	658	614	584	552	513	491	477	451	430
Model 2**											
ECM Significant	8459	8278	8056	7856	7645	7456	7250	7101	6946	6769	
ECM Significant*	871	816	761	718	667	632	652	579	553	547	
Mean of α_1	-0.22	-0.21	-0.20	-0.20	-0.19	-0.18	-0.17	-0.17	-0.16	-0.15	
$\geq 1\Delta X_t$ Significant	1193	1197	1210	1206	1205	1214	1228	1243	1235	1241	
$\geq 1X_{t-1}$ Significant	2159	2227	2304	2380	2470	2574	2657	2718	2801	2864	
ECM and $\geq 1\Delta X_t$ Significant	1049	1042	1034	1004	984	969	950	950	931	912	
ECM and $\geq 1\Delta X_t$ Significant*	154	144	136	131	124	123	114	111	106	109	
ECM and $\geq 1X_{t-1}$ Significant	2037	2081	2137	2184	2229	2284	2328	2350	2379	2438	
ECM and $\geq 1X_{t-1}$ Significant*	526	505	491	474	448	436	428	415	403	412	
Model 3***											
ECM Significant	7661	7321	6964	6633	6257	5895	5581	5296	4974	4760	4340
ECM Significant*	260	229	213	177	157	139	127	115	98	88	94
Mean of α_1	-0.17	-0.16	-0.16	-0.15	-0.14	-0.13	-0.12	-0.12	-0.11	-0.10	-0.09
$\geq 1\Delta X_t$ Significant	1092	1092	1096	1096	1101	1105	1103	1030	1101	1110	1099
$\geq 1X_{t-1}$ Significant	1216	1216	1207	1212	1214	1212	1226	1222	1224	1215	1195
ECM and $\geq 1\Delta X_t$ Significant	878	845	800	774	739	715	665	645	617	602	546
ECM and $\geq 1\Delta X_t$ Significant*	45	41	36	28	23	22	21	17	15	13	20
ECM and $\geq 1X_{t-1}$ Significant	990	960	915	885	855	822	794	763	733	703	634
ECM and $\geq 1X_{t-1}$ Significant*	78	69	63	48	42	39	33	27	23	20	22

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.565.

$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

$\star\star$ Model 2: Both IVs and DV data generating process based on same level of ρ.

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV varies by level of ρ specified.

Table G.3: Summary Statistics of Multivariate (3 IVs) ECM Model by DV and IV (T=60)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	9127	8986	8834	8675	8503	8320	8150	7954	7731	7489	7197
ECM Significant*	1071	990	923	852	809	761	712	647	636	593	527
Mean of α_1	-0.27	-0.26	-0.25	-0.24	-0.23	-0.23	-0.22	-0.21	-0.20	-0.19	-0.18
$\geq 1\Delta X_t$ Significant	1707	1712	1706	1710	1710	1712	1715	1735	1738	1762	1733
$\geq 1X_{t-1}$ Significant	3496	3554	3641	3705	3770	3814	3858	3892	3909	3921	3897
ECM and $\geq 1\Delta X_t$ Significant	1585	1566	1544	1525	1501	1488	1461	1455	1420	1404	1329
ECM and $\geq 1\Delta X_t$ Significant*	266	253	246	223	216	205	191	158	178	170	152
ECM and $\geq 1X_{t-1}$ Significant	3387	3422	3476	3506	3539	3541	3538	3544	3521	3488	3415
ECM and $\geq 1X_{t-1}$ Significant*	802	761	726	679	650	615	586	542	525	507	452
Model 2**											
ECM Significant	8600	8453	8286	8108	7954	7815	7685	7544	7419	7321	
ECM Significant*	785	730	685	642	620	606	595	578	557	541	
Mean of α_1	-0.24	-0.23	-0.23	-0.22	-0.21	-0.21	-0.20	-0.20	-0.19	-0.18	
$\geq 1\Delta X_t$ Significant	1737	1746	1776	1789	1803	1820	1824	1827	1809	1776	
$\geq 1X_{t-1}$ Significant	3159	3230	3356	3429	3532	3636	3685	3726	3783	3846	
ECM and $\geq 1\Delta X_t$ Significant	1532	1517	1521	1510	1503	1504	1487	1465	1433	1388	
ECM and $\geq 1\Delta X_t$ Significant*	214	199	196	188	191	186	189	183	171	162	
ECM and $\geq 1X_{t-1}$ Significant	3003	3042	3117	3179	3243	3296	3308	3325	3349	3394	
ECM and $\geq 1X_{t-1}$ Significant*	589	556	537	511	504	498	497	479	460	463	
Model 3***											
ECM Significant	7330	6990	6640	6294	5933	5615	5313	5053	4801	4544	4206
ECM Significant*	137	115	102	87	80	66	67	57	523	49	53
Mean of α_1	-0.17	-0.16	-0.16	-0.15	-0.14	-0.13	-0.13	-0.12	-0.11	-0.10	-0.09
$\geq 1\Delta X_t$ Significant	1513	1512	1521	1515	1508	1500	1501	1506	1504	1495	1530
$\geq 1X_{t-1}$ Significant	1715	1717	1713	1714	1710	1722	1705	1695	1691	1700	1683
ECM and $\geq 1\Delta X_t$ Significant	1133	1089	1040	998	944	896	846	818	772	730	701
ECM and $\geq 1\Delta X_t$ Significant*	35	30	27	23	25	22	21	15	16	19	21
ECM and $\geq 1X_{t-1}$ Significant	1341	1304	1245	1197	1139	1099	1031	990	955	900	846
ECM and $\geq 1X_{t-1}$ Significant*	71	58	53	47	40	32	29	26	22	19	25

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.816.
$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.
$\star\star$ Model 2: Both IVs and DV data generating process based on same level of ρ.
$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV varies by level of ρ specified.

Table G.4: Summary Statistics of Multivariate (4 IVs) ECM Model by DV and IV (T=60)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	9270	9187	9069	8964	8827	8693	8553	8354	8165	7954	7666
ECM Significant*	1054	989	911	840	785	734	693	665	605	555	496
Mean of α_1	-0.30	-0.29	-0.28	-0.27	-0.27	-0.26	-0.25	-0.24	-0.23	-0.22	-0.21
$\geq 1\Delta X_{\mathrm{t}}$ Significant	2301	2304	2307	2300	2298	2308	2302	2295	2300	2300	2292
$\geq 1X_{\mathrm{t-1}}$ Significant	4261	4329	4382	4447	4518	4559	4604	4599	4617	4624	4599
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant	2174	2159	2138	2113	2094	2065	2033	1986	1954	1914	1838
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant*	349	334	314	295	281	269	255	244	227	227	200
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant	4135	4184	4208	4243	4275	4282	4302	4252	4226	4189	4108
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant*	869	826	769	713	677	640	605	585	535	505	447
Model 2**											
ECM Significant	8733	8621	8476	8370	8242	8125	8053	7950	7846	7760	
ECM Significant*	699	667	640	628	595	579	563	538	526	506	
Mean of α_1	-0.27	-0.26	-0.25	-0.25	-0.24	-0.24	-0.23	-0.23	-0.22	-0.22	
$\geq 1\Delta X_{\mathrm{t}}$ Significant	2301	2309	2318	2325	2326	2335	2347	2350	2342	2318	
$\geq 1X_{\mathrm{t-1}}$ Significant	3898	3974	4060	4171	4268	4337	4421	4510	4545	4589	
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant	2041	2027	2010	1999	1982	1973	1983	1962	1930	1886	
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant*	254	243	241	242	240	241	238	229	223	214	
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant	3692	3739	3791	3859	3925	3969	4020	4067	4090	4121	
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant*	580	562	542	544	522	512	501	481	476	465	
Model 3***											
ECM Significant	7168	6883	6499	6140	5799	5489	5149	4900	4658	4339	3998
ECM Significant*	72	65	55	46	40	31	23	19	21	19	16
Mean of α_1	-0.17	-0.16	-0.16	-0.15	-0.14	-0.13	-0.12	-0.12	-0.11	-0.10	-0.09
$\geq 1\Delta X_{\mathrm{t}}$ Significant	2006	1997	1980	1978	1976	1992	1978	1989	1999	2014	2012
$\geq 1X_{\mathrm{t-1}}$ Significant	2204	2209	2219	2219	2223	2222	2224	2206	2203	2216	2201
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant	1466	1400	1339	1276	1204	1138	1075	1033	1016	959	881
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant*	25	24	20	16	15	12	8	9	10	8	9
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant	1684	1630	1560	1487	1415	1343	1294	1221	1174	1124	1055
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant*	45	40	30	24	21	18	15	13	13	13	8

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -4.035.

$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

$\star\star$ Model 2: Both IVs and DV data generating process based on same level of ρ.

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV varies by level of ρ specified.

Table G.5: Summary Statistics of Multivariate (5 IVs) ECM Model by DV and IV (T=60)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	9318	9237	9137	9047	8921	8785	8668	8544	8422	8271	8024
ECM Significant*	992	937	883	828	788	728	686	641	597	569	514
Mean of α_1	-0.33	-0.32	-0.31	-0.31	-0.30	-0.29	-0.28	-0.27	-0.26	-0.25	-0.24
$\geq 1\Delta X_t$ Significant	2844	2848	2839	2850	2851	2855	2869	2892	2886	2900	2875
$\geq 1X_{t\text{-}1}$ Significant	4967	5044	5083	5113	5146	5148	5198	5210	5218	5217	5228
ECM and $\geq 1\Delta X_t$ Significant	2688	2675	2642	2631	2607	2579	2572	2565	2533	2511	2428
ECM and $\geq 1\Delta X_t$ Significant*	408	383	362	344	337	318	306	288	272	260	250
ECM and $\geq 1X_{t\text{-}1}$ Significant	4806	4857	4868	4878	4883	4833	4851	4821	4795	4761	4710
ECM and $\geq 1X_{t\text{-}1}$ Significant*	860	824	778	728	696	642	611	576	539	519	481
Model 2**											
ECM Significant	8801	8718	8636	8559	8483	8373	8284	8214	8153	8076	
ECM Significant*	646	626	610	604	597	586	568	555	557	540	
Mean of α_1	-0.29	-0.29	-0.28	-0.28	-0.27	-0.27	-0.26	-0.26	-0.25	-0.25	
$\geq 1\Delta X_t$ Significant	2819	2832	2853	2862	2868	2885	2892	2897	2893	2892	
$\geq 1X_{t\text{-}1}$ Significant	4583	4683	4770	4833	4918	4994	5038	5087	5127	5192	
ECM and $\geq 1\Delta X_t$ Significant	2553	2552	2544	2535	2514	2507	2501	2494	2468	2451	
ECM and $\geq 1\Delta X_t$ Significant*	276	268	259	259	259	255	252	254	263	259	
ECM and $\geq 1X_{t\text{-}1}$ Significant	4328	4408	4466	4509	4559	4604	4617	4650	4665	4688	
ECM and $\geq 1X_{t\text{-}1}$ Significant*	564	558	548	540	538	528	519	510	514	501	
Model 3***											
ECM Significant	6895	6590	6290	5982	5629	5318	5050	4769	4537	4298	3959
ECM Significant*	36	32	30	26	25	21	16	18	12	14	12
Mean of α_1	-0.17	-0.16	-0.16	-0.15	-0.14	-0.13	-0.12	-0.12	-0.11	-0.10	-0.09
$\geq 1\Delta X_t$ Significant	2480	2477	2479	2477	2480	2479	2474	2464	2449	2452	2467
$\geq 1X_{t\text{-}1}$ Significant	2647	2657	2660	2663	2663	2659	2652	2653	2646	2645	2633
ECM and $\geq 1\Delta X_t$ Significant	1767	1702	1642	1559	1484	1424	1366	1288	1210	1149	1057
ECM and $\geq 1\Delta X_t$ Significant*	12	13	13	9	7	8	7	10	6	8	6
ECM and $\geq 1X_{t\text{-}1}$ Significant	1976	1915	1836	1766	1682	1607	1536	1476	1406	1351	1251
ECM and $\geq 1X_{t\text{-}1}$ Significant*	22	23	22	17	18	15	11	12	8	9	7

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -4.229.

$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

$\star\star$ Model 2: Both IVs and DV data generating process based on same level of ρ.

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV varies by level of ρ specified.

Table G.6: Summary Statistics of Bivariate ECM Model by DV and IV (T=150)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	9971	9941	9877	9755	9559	9261	8791	8141	7427	6708	5769
ECM Significant*	4768	3973	3263	2677	2133	1686	1318	1014	790	662	501
Mean of α_1	-0.14	-0.13	-0.12	-0.11	-0.10	-0.09	-0.08	-0.08	-0.07	-0.06	-0.05
$\geq 1\Delta X_{\text{t}}$ Significant	550	550	550	555	554	553	554	558	562	559	562
$\geq 1X_{\text{t-1}}$ Significant	943	973	1044	1109	1164	1264	1391	1492	1635	1774	1639
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	550	548	545	545	531	510	487	457	414	386	338
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	275	227	186	156	127	104	82	68	46	41	36
ECM and $\geq 1X_{\text{t-1}}$ Significant	942	972	1043	1108	1156	1247	1348	1424	1492	1526	1343
ECM and $\geq 1X_{\text{t-1}}$ Significant*	809	761	737	685	618	580	513	442	381	342	270
Model 2**											
ECM Significant	9944	9894	9816	9672	9402	9011	8454	7759	7056	6473	
ECM Significant*	4286	3478	2820	2231	1741	1366	1074	844	685	598	
Mean of α_1	-0.13	-0.13	-0.12	-0.11	-0.10	-0.09	-0.08	-0.07	-0.06	-0.06	
$\geq 1\Delta X_{\text{t}}$ Significant	549	552	559	560	570	579	574	578	581	560	
$\geq 1X_{\text{t-1}}$ Significant	733	755	795	832	900	972	1077	1191	1335	1489	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	547	547	549	543	542	519	487	454	424	378	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	234	206	155	124	101	81	70	52	48	35	
ECM and $\geq 1X_{\text{t-1}}$ Significant	732	751	790	826	891	942	1022	1098	1178	1247	
ECM and $\geq 1X_{\text{t-1}}$ Significant*	542	506	469	422	392	363	330	314	298	280	
Model 3***											
ECM Significant	9954	9910	9836	9639	9350	8837	8128	7207	6243	5452	4542
ECM Significant*	3604	2856	2206	1667	1234	906	631	461	332	274	216
Mean of α_1	-0.13	-0.12	-0.11	-0.10	-0.09	-0.08	-0.07	-0.06	-0.05	-0.05	-0.04
$\geq 1\Delta X_{\text{t}}$ Significant	548	550	547	554	552	554	550	546	541	534	536
$\geq 1X_{\text{t-1}}$ Significant	559	560	563	563	563	563	564	564	566	571	561
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	546	547	539	535	520	489	447	398	340	299	270
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	206	170	134	101	77	53	37	27	19	12	13
ECM and $\geq 1X_{\text{t-1}}$ Significant	556	555	552	541	522	489	453	404	353	333	294
ECM and $\geq 1X_{\text{t-1}}$ Significant*	231	195	154	117	89	73	53	40	27	17	14

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.236.

$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

$\star\star$ Model 2: Both IV and DV data generating process based on same level of ρ.

$\star\star\star$ Model 3: IV is integrated $I(0)$ and DV varies by level of ρ specified.

Table G.7: Summary Statistics of Multivariate (2 IVs) ECM Model by DV and IV (T=150)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	9963	9935	9884	9788	9632	9382	9027	8588	8096	7511	6695
ECM Significant*	3861	3277	2724	2216	1789	1429	1111	900	741	618	467
Mean of α_1	-0.15	-0.14	-0.13	-0.12	-0.12	-0.11	-0.10	-0.09	-0.08	-0.07	-0.06
$\geq 1\Delta X_t$ Significant	1036	1035	1038	1036	1034	1034	1032	1033	1031	1060	1047
$\geq 1X_{t-1}$ Significant	1936	2010	2085	2189	2293	2442	2584	2750	2929	3070	2958
ECM and $\geq 1\Delta X_t$ Significant	1032	1027	1028	1012	993	968	929	897	857	823	728
ECM and $\geq 1\Delta X_t$ Significant*	446	386	326	254	206	155	128	108	100	91	59
ECM and $\geq 1X_{t-1}$ Significant	1936	2009	2080	2176	2269	2395	2505	2622	2716	2727	2525
ECM and $\geq 1X_{t-1}$ Significant*	1347	1257	1150	1049	920	807	685	604	526	470	365
Model 2**											
ECM Significant	9936	9870	9780	9618	9375	9053	8625	8113	7603	7154	
ECM Significant*	3047	2497	2040	1642	1342	1064	850	693	585	549	
Mean of α_1	-0.14	-0.13	-0.12	-0.11	-0.11	-0.10	-0.09	-0.08	-0.07	-0.07	
$\geq 1\Delta X_t$ Significant	1015	1010	1016	1012	1024	1028	1030	1029	1037	1046	
$\geq 1X_{t-1}$ Significant	1536	1589	1669	1754	1865	1972	2154	2330	2547	2808	
ECM and $\geq 1\Delta X_t$ Significant	1008	996	994	962	956	930	894	854	815	787	
ECM and $\geq 1\Delta X_t$ Significant*	351	280	229	183	147	117	93	78	68	65	
ECM and $\geq 1X_{t-1}$ Significant	1533	1580	1653	1731	1819	1904	2042	2153	2297	2456	
ECM and $\geq 1X_{t-1}$ Significant*	886	817	757	676	616	531	473	419	386	362	
Model 3***											
ECM Significant	9932	9864	9747	9525	9197	8674	7964	7067	6114	5333	4475
ECM Significant*	1944	1470	1058	760	542	385	271	186	134	112	85
Mean of α_1	-0.13	-0.12	-0.11	-0.10	-0.09	-0.08	-0.07	-0.06	-0.05	-0.05	-0.04
$\geq 1\Delta X_t$ Significant	994	992	984	988	985	977	980	985	973	966	969
$\geq 1X_{t-1}$ Significant	1034	1034	1035	1039	1037	1044	1051	1052	1048	1049	1018
ECM and $\geq 1\Delta X_t$ Significant	988	980	962	944	906	846	784	714	619	541	447
ECM and $\geq 1\Delta X_t$ Significant*	214	162	120	89	64	44	28	16	11	9	7
ECM and $\geq 1X_{t-1}$ Significant	1029	1022	1008	989	958	909	862	782	672	607	492
ECM and $\geq 1X_{t-1}$ Significant*	249	193	157	114	88	58	40	29	19	25	14

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.528.

$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

$\star\star$ Model 2: Both IVs and DV data generating process based on same level of ρ.

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV varies by level of ρ specified.

Table G.8: Summary Statistics of Multivariate (3 IVs) ECM Model by DV and IV (T=150)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	9970	9947	9913	9846	9712	9553	9300	8977	8556	8111	7348
ECM Significant*	3405	2878	2411	2012	1657	1381	1115	916	754	612	479
Mean of α_1	-0.17	-0.16	-0.15	-0.14	-0.13	-0.12	-0.11	-0.10	-0.09	-0.08	-0.07
$\geq 1\Delta X_{\text{t}}$ Significant	1514	1527	1526	1525	1535	1534	1549	1558	1565	1563	1559
$\geq 1X_{\text{t-1}}$ Significant	2898	2878	3088	3218	3339	3494	3646	3751	3871	3966	3903
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	1508	1519	1508	1497	1495	1470	1449	1426	1360	1296	1184
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	562	494	425	351	290	246	201	175	145	116	92
ECM and $\geq 1X_{\text{t-1}}$ Significant	2894	2983	3079	3204	3310	3438	3532	3577	3603	3609	3428
ECM and $\geq 1X_{\text{t-1}}$ Significant*	1705	1570	1405	1278	1113	988	843	712	603	500	396
Model 2**											
ECM Significant	9934	9885	9808	9667	9472	9190	8888	8481	8091	7707	
ECM Significant*	2381	1983	1650	1355	1094	909	753	664	592	521	
Mean of α_1	-0.15	-0.14	-0.13	-0.12	-0.12	-0.11	-0.10	-0.09	-0.09	-0.08	
$\geq 1\Delta X_{\text{t}}$ Significant	1518	1518	1526	1538	1541	1552	1569	1562	1573	1568	
$\geq 1X_{\text{t-1}}$ Significant	2359	2445	2569	2660	2790	2937	3137	3342	3557	3827	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	1504	1499	1500	1492	1463	1437	1414	1355	1301	1241	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	379	330	265	234	195	162	138	117	109	92	
ECM and $\geq 1X_{\text{t-1}}$ Significant	2353	2436	2548	2626	2731	2852	2992	3115	3255	3416	
ECM and $\geq 1X_{\text{t-1}}$ Significant*	1093	984	886	770	681	607	538	494	465	426	
Model 3***											
ECM Significant	9933	9855	9727	9508	9146	8591	7856	6979	6080	5286	4420
ECM Significant*	1067	792	573	403	269	190	128	92	64	45	32
Mean of α_1	-0.13	-0.12	-0.11	-0.10	-0.09	-0.08	-0.07	-0.06	-0.05	-0.05	-0.04
$\geq 1\Delta X_{\text{t}}$ Significant	1469	1466	1472	1474	1473	1478	1477	1472	1474	1467	1467
$\geq 1X_{\text{t-1}}$ Significant	1540	1550	1557	1558	1551	1556	1562	1559	1569	1599	1581
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	1457	1439	1423	1391	1340	1266	1147	1029	908	794	659
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	162	122	94	70	47	32	21	20	10	10	9
ECM and $\geq 1X_{\text{t-1}}$ Significant	1531	1529	1515	1478	1424	1351	1258	1136	996	912	746
ECM and $\geq 1X_{\text{t-1}}$ Significant*	242	187	141	103	66	37	24	22	18	8	6

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.78.

$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

$\star\star$ Model 2: Both IVs and DV data generating process based on same level of ρ.

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV varies by level of ρ specified.

Table G.9: Summary Statistics of Multivariate (4 IVs) ECM Model by DV and IV (T=150)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	9963	9937	9901	9838	9745	9630	9442	9189	8897	8521	7931
ECM Significant*	2960	2507	2145	1820	1509	1264	1058	875	741	620	503
Mean of α_1	-0.18	-0.17	-0.16	-0.15	-0.14	-0.13	-0.12	-0.12	-0.11	-0.10	-0.09
$\geq 1\Delta X_{\text{t}}$ Significant	2020	2027	2032	2040	2053	2059	2034	2032	2034	2057	2066
$\geq 1X_{\text{t-1}}$ Significant	3562	3665	3789	3921	4053	4193	4347	4492	4625	4708	4678
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	2014	2015	2015	2008	2003	1983	1911	1853	1801	1773	1659
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	689	603	506	442	387	325	277	223	177	152	129
ECM and $\geq 1X_{\text{t-1}}$ Significant	3557	3656	3775	3898	4020	4142	4265	4361	4418	4404	4258
ECM and $\geq 1X_{\text{t-1}}$ Significant*	1776	1597	1463	1303	1141	995	865	739	643	540	449
Model 2**											
ECM Significant	9937	9891	9825	9701	9503	9300	9014	8731	8449	8201	
ECM Significant*	1983	1642	1403	1206	1015	861	737	663	590	545	
Mean of α_1	-0.16	-0.15	-0.14	-0.13	-0.13	-0.12	-0.11	-0.10	-0.10	-0.09	
$\geq 1\Delta X_{\text{t}}$ Significant	2010	2017	2021	2032	2052	2051	2061	2061	2077	2045	
$\geq 1X_{\text{t-1}}$ Significant	3101	3191	3324	3461	3623	3771	3973	4183	4379	4573	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	1994	1994	1985	1970	1944	1898	1850	1800	1773	1704	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	446	377	310	274	232	199	189	169	150	141	
ECM and $\geq 1X_{\text{t-1}}$ Significant	3093	3179	3305	3425	3552	3667	3818	3957	4081	4194	
ECM and $\geq 1X_{\text{t-1}}$ Significant*	1181	1039	934	844	750	667	588	559	510	480	
Model 3***											
ECM Significant	9912	9831	9664	9422	9030	8478	7771	6887	5998	5171	4371
ECM Significant*	592	422	288	203	126	80	52	36	28	18	15
Mean of α_1	-0.13	-0.12	-0.11	-0.10	-0.09	-0.08	-0.07	-0.06	-0.05	-0.05	-0.04
$\geq 1\Delta X_{\text{t}}$ Significant	1922	1912	1914	1912	1914	1922	1935	1936	1932	1929	1917
$\geq 1X_{\text{t-1}}$ Significant	2032	2034	2033	2037	2042	2040	2030	2035	2020	2009	2018
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	1900	1873	1831	1785	1712	1619	1474	1306	1154	990	865
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	140	103	76	58	37	22	15	9	6	7	5
ECM and $\geq 1X_{\text{t-1}}$ Significant	2008	1996	1964	1913	1846	1743	1607	1436	1268	1094	961
ECM and $\geq 1X_{\text{t-1}}$ Significant*	195	141	98	58	42	27	19	14	10	7	7

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -4.003.

$\star$ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

$\star\star$ Model 2: Both IVs and DV data generating process based on same level of ρ.

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV varies by level of ρ specified.

Table G.10: Summary Statistics of Multivariate (5 IVs) ECM Model by DV and IV (T=150)

ρ	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00
Model 1*											
ECM Significant	9982	9971	9947	9899	9830	9733	9560	9367	9148	8891	8414
ECM Significant*	2812	2419	2092	1779	1494	1276	1082	896	741	626	505
Mean of α_1	-0.19	-0.18	-0.17	-0.16	-0.16	-0.15	-0.14	-0.13	-0.12	-0.11	-0.10
$\geq 1\Delta X_t$ Significant	2479	2489	2499	2505	2502	2528	2535	2542	2549	2537	2541
$\geq 1X_{t-1}$ Significant	4474	4586	4697	4825	4959	5044	5159	5266	5386	5448	5427
ECM and $\geq 1\Delta X_t$ Significant	2477	2484	2487	2483	2460	2460	2421	2382	2342	2273	2171
ECM and $\geq 1\Delta X_t$ Significant*	797	703	615	524	440	392	339	282	246	206	173
ECM and $\geq 1X_{t-1}$ Significant	4471	4580	4687	4806	4925	4987	5059	5116	5171	5161	5008
ECM and $\geq 1X_{t-1}$ Significant*	1963	1764	1592	1403	1213	1057	929	801	668	573	470
Model 2**											
ECM Significant	9925	9873	9809	9705	9559	9390	9177	8976	8770	8567	
ECM Significant*	1648	1422	1189	1014	886	773	677	592	541	510	
Mean of α_1	-0.17	-0.16	-0.15	-0.14	-0.14	-0.13	-0.12	-0.12	-0.11	-0.10	
$\geq 1\Delta X_t$ Significant	2402	2421	2432	2452	2456	2467	2492	2513	2543	2543	
$\geq 1X_{t-1}$ Significant	3772	3895	4023	4176	4356	4552	4763	4976	5182	5321	
ECM and $\geq 1\Delta X_t$ Significant	2386	2392	2382	2378	2349	2325	2297	2274	2252	2213	
ECM and $\geq 1\Delta X_t$ Significant*	478	422	356	300	274	250	224	196	183	174	
ECM and $\geq 1X_{t-1}$ Significant	3759	3877	3995	4132	4284	4445	4601	4749	4893	4960	
ECM and $\geq 1X_{t-1}$ Significant*	1115	1008	887	784	699	636	576	512	481	463	
Model 3***											
ECM Significant	9879	9784	9638	9388	9001	8465	7709	6808	5920	5143	4342
ECM Significant*	359	266	181	127	75	48	30	22	19	9	14
Mean of α_1	-0.13	-0.12	-0.11	-0.10	-0.09	-0.08	-0.07	-0.06	-0.05	-0.05	-0.04
$\geq 1\Delta X_t$ Significant	2303	2310	2313	2308	2304	2310	2310	2319	2324	2318	2313
$\geq 1X_{t-1}$ Significant	2438	2433	2435	2438	2444	2452	2462	2484	2466	2460	2418
ECM and $\geq 1\Delta X_t$ Significant	2270	2257	2228	2162	2064	1941	1769	1581	1379	1216	1043
ECM and $\geq 1\Delta X_t$ Significant*	108	76	58	44	26	19	13	8	7	3	5
ECM and $\geq 1X_{t-1}$ Significant	2407	2383	2351	2291	2221	2107	1953	1770	1549	1355	1136
ECM and $\geq 1X_{t-1}$ Significant*	150	107	79	53	33	22	16	12	9	5	6

Note: Cell entries are the result of 10,000 simulations for each model at each specified level of ρ. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -4.205.

⋆ Model 1: IV is integrated $I(1)$ and DV varies by ρ.

⋆⋆ Model 2: Both IVs and DV data generating process based on same level of ρ.

⋆⋆⋆ Model 3: IVs are integrated $I(0)$ and DV varies by level of ρ specified.

Appendix H Additional Materials: Fractionally Integrated Series

H.1 Addressing Concerns as to Estimation of Long Memory

When estimating the long-memory of a series, semiparametric estimators such as Robinson's Local Whittle are appealing for a number of reasons. First, they are agnostic as to the short-run dynamics of the process, and are therefore robust to misspecification. The practitioner does not need to know the true DGP of the process to consistently estimate the long-memory parameter. Additionally, the estimators are generally robust in the presence of short-run dynamics. Semiparametric estimators require the practitioner to choose the bandwidth of the estimator, a decision which involves a trade-off between minimization of bias and variance. With a (0,d,0) series, increasing the number of frequencies (increasing the bandwidth) reduces the variance of the estimate at the expense of a slight increase in bias. This increase in bias is generally negligible with pure fractional processes. Should it become apparent that short-run dynamics are present however, the practitioner can simply reduce the number of frequencies, and focus more specifically on the low frequency components of the periodogram.

While this is generally true, semiparametric estimators are not perfect. In the presence of significant short-run dynamics the low frequencies are contaminated by the higher frequencies of the spectral density. Significant ARMA coefficients, especially positive AR noise, will bias estimates, sometimes substantially so. Baillie and Kapetanios (2007) investigates the bias of semiparametric estimators under these circumstances and find that the bias increases as the short-run noise becomes more persistent. Thus, in the presence of short-run dynamics, a practitioner is better served by reducing the bandwidth of the estimator, however the extent of the reduction in bias is dependent upon the degree of AR persistence.

Short-run dynamics will also bias the estimates of the exact ML (EML) estimator (Nielsen and Frederiksen 2005).[12] This bias occurs even though the EML can simultaneously estimate the short-run dynamics and the long-memory of a series. When ARMA dynamics are present,

[12]The EML is the standard estimator in Stata's ARFIMA package.

the EML estimates are negatively biased, the variance of the estimates balloon, and the estimator is generally unreliable. With persistent AR noise in the range of 0.40, the EML actually performs worse than most semiparametric estimators even when the DGP is properly specified. The problems associated with the EML are alleviated somewhat with longer time series, but not to the point that using the EML in the presence of AR dynamics is recommended.

The possibility of finite sample bias of semiparametric estimators and the outright failure of the EML estimator when AR noise is present does not mean that long-memory can't be reliably estimated. First, in terms of estimators, the problems highlighted above are not encountered with the approximate frequency domain ML (FML) estimator. Nielsen and Frederiksen (2005) compares the performance of the FML in larger samples and finds that the estimator is unbiased, robust to AR and MA noise, and doesn't suffer from bias when the true DGP is overfit. Grant (n.d.) compares the FML to various semiparametric and parametric estimators in small samples and finds the FML dominates all other estimators in terms of bias and RMSE, even when AR and MA noise is present. Thus, reliable estimates are possible even when a series exhibits significant short-run dynamics.

Another important consideration when it comes to estimating the long-memory of a series is whether we should expect political time series to exhibit significant short-run dynamics. In other words, do we routinely estimate political time series as higher-order processes? Byers, Davidson, and Peel (2000) estimates the long-memory of a number of political opinion series and finds that a large majority of the series were best approximated by (0,d,0) models. Of those series for which the information criteria chose a higher-order model, the gains were often minimal. This is expected to be the case for most political time series, which are generally shorter in duration and the product of an aggregation of heterogeneous autoregressive processes (Granger and Joyeux 1980).[13] To demonstrate that most series are fractional noise

[13]Previous work on fractional integration of political time series has reported higher-order models after relying on information criteria (see, e.g., Box-Steffensmeier and Tomlinson 2000). This is most certainly due to an error in the formula used by Ox at the time. Re-estimating these series with both the EML and FML estimators using Schwartz Information Criteria indicates that (0,d,0) models are preferred.

- they are uncorrelated after differencing by only the d parameter - and that long-memory estimates can be consistent, we provide Tables H.1 and H.2. Table H.1 shows the BIC values after our fitting multiple (p, d, q) models - the BIC values are from the Stata EML estimator.[14] Table H.2 presents long-memory estimates of each series from three different estimators - the semiparametric Local Whittle of Robinson (1995), the EML estimator used in Stata's ARFIMA package, and the FML estimator, which is estimated using the TSM add-on of Davidson (2014) to Ox (Doornik 2014). A fourth column also reports the results of the Box-Pierce test of the residuals of each series after fractional differencing. The results are consistent across all three estimator types.

Table H.1: Exact Maximum-Likelihood Estimation - BIC Values

	(0,d,0)	(1,d,0)	(0,d,1)	(1,d,1)
CEW				
All Reviews	334.19*	335.44	335.17	338.41
Non-Salient Reviews	332.48*	334.57	334.42	338.01
Salient Reviews	419.34*	420.89	421.54	424.71
UE				
Democrat Mood	129.98*	136.59	146.85	140.01
Republican Mood	151.57*	156.15	155.04	158.00
SSRS				
Canada Rights	-65.85*	-65.76	-65.80	-65.68
UK Rights	-79.11*	-75.51	-75.50	***
US Rights	-141.89*	-138.59	-138.39	-134.52
KE				
Liberal Mood	245.23*	257.14	247.51	250.86
Welfare Mood	215.18*	221.72	217.21	215.99
Low Income Mood	266.57*	269.10	268.78	272.69
High Income Mood	253.14*	260.67	255.88	264.00
VK				
Top 1% Income	344.99*	348.41	348.26	352.80

Note: * Marks the minimum value in each row. *** indicates the model did not converge in Stata.

As seen in Table H.1 of the thirteen dependent variables estimated, the BIC chose a (0,d,0) model for each. This is not to say that we will never encounter a higher-order process, but quite often the simple model that estimates only the long memory will be sufficient. Further, absent the presence of significant short-memory dynamics many of the estimation problems discussed above are not at issue with our estimates. The estimates do not suffer from bias nor is the variance of our estimators inflated. In fact, our estimates are remarkably consistent

[14] Because the series are generally short, we only go so far as to estimate (1,d,1) models.

across the three different estimators and the Box-Pierce residual test is insignificant for the residuals of each series. Fractionally differencing our series with its estimate of d is sufficient to address any autocorrelation in the series. Additionally, note that the 95% confidence intervals of many of the series would overlap with 1, indicating a unit-root. Considering the low power of many unit-root tests, the ability to estimate the order of fractional integration provides an additional tool when a variable's order of integration is in question. This can be seen in the disparity in results for *All Reviews* and *Non-Salient Reviews*, both of which failed to reject the null of the Dickey-Fuller, but which all three of our estimators found to be fractionally integrated.

Table H.2: Various Estimates of Long Memory - (0,d,0) Models

	LW	EML	FML	Box-Pierce (12 lags)
CEW				
All Reviews	0.63 (0.11)	0.62 (0.11)	0.63 (0.11)	18.51
Non-Salient Reviews	0.65 (0.11)	0.62 (0.11)	0.65 (0.13)	15.32
Salient Reviews	0.30 (0.11)	0.36 (0.08)	0.31 (0.12)	11.24
UE				
Democrat Mood	1.28 (0.12)	1.15 (0.15)	1.27 (0.18)	5.18
Republican Mood	1.17 (0.12)	1.04 (0.16)	1.17 (0.18)	6.34
SSRS				
Canada Rights	0.62 (0.10)	0.52 (0.12)	0.57 (0.13)	9.38
UK Rights	0.08 (0.12)	0.13 (0.13)	0.08 (0.17)	4.98
US Rights	0.40 (0.10)	0.45 (0.05)	0.41 (0.10)	11.79
KE				
Liberal Mood	1.12 (0.10)	1.08 (0.11)	1.14 (0.11)	12.92
Welfare Mood	1.01 (0.13)	0.88 (0.18)	1.00 (0.21)	8.09
Low Income Mood	1.03 (0.11)	0.98 (0.13)	1.05 (0.14)	11.33
High Income Mood	1.11 (0.11)	1.04 (0.13)	1.15 (0.14)	5.15
VK				
Top 1% Income	0.93 (0.10)	0.95 (0.09)	0.91 (0.11)	7.30

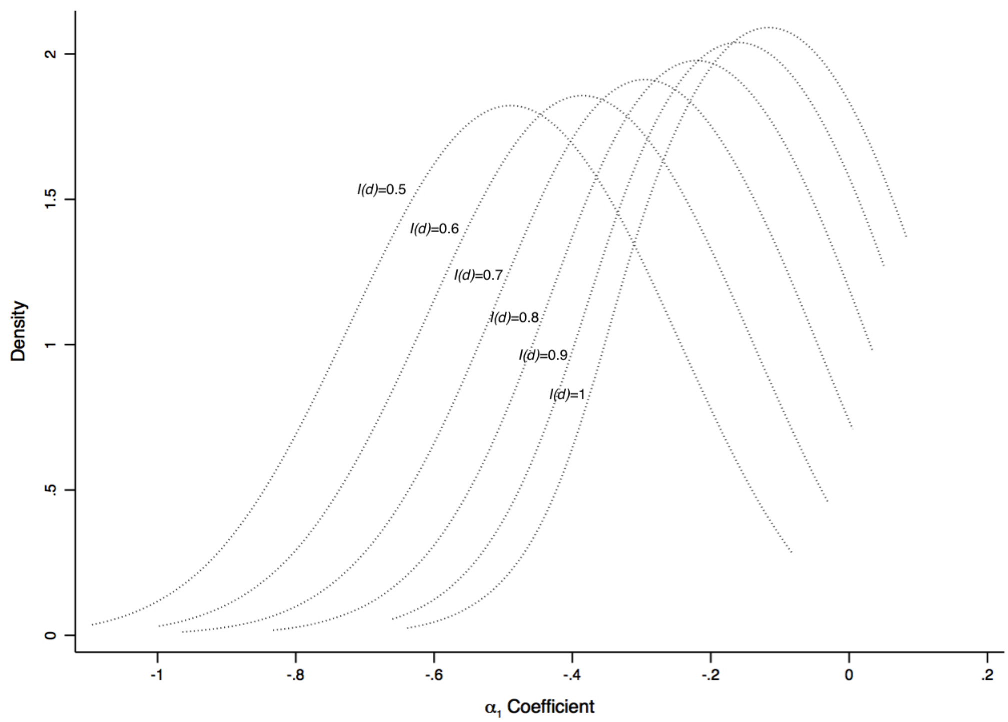
Note: LW: semiparametric Local Whittle; EML: exact maximum likelihood; FML: frequency maximum likelihood. All estimates based on the first-differenced series and then adding 1 back to the estimate. Standard errors in parentheses. Standard errors for the LW are computed as $(1/sqrt4 * m)$ with the bandwidth m calculated as $T^{4/5}$. Box-Pierce test is of the residuals following fractional differencing with the FML estimator.

H.2 Shifting ECM Coefficient

Any deviation from strictly $I(1)$ series will lead to substantial issues for the interpretation of the ECM coefficient and its t-statistic. Figures 3 and 4 in the main paper depict both the increasing significance of the ECM as well as the increasing (absolute) size of the coefficient as the fractional integration of the dependent variable moves further below 1. Figure H.1

presents another look at the size of the ECM coefficient. The bias in the ECM coefficient is troubling. If our DV series is fractionally integrated, we are likely to overstate the strength of whatever equilibrium relationship is being studied. Further, because the Long Run Multipliers are are calculated as a ratio in which the denominator is the α_1 coefficient, our estimation and interpretation of the Long Run Multipliers will also be subject to this bias.

Figure H.1: Mean ECM Coefficient by Order of Fractional Integration



Note: Density plots from 10,000 Monte Carlo simulations of bivariate ECM model. DV and IV both fractionally integrated of order $I(d)$. $T = 60$

H.3 Tables - I(d) - Monte Carlo Simulations

The results in the following tables are meant to provide as much information as possible in as little space as possible. Therefore, we have tried to include a wide a range of models. The top row of each table contains models run in which the order of fractional integration in the DV varies, but the IV(s) all have unit roots. The middle row contain results of models in which all series within each model share the same order of fractional integration. These equations are balanced. The bottom row also allows the DV to vary by its order of fractional integration, but the IV(s) are all generated as $I(0)$ - the IV(s) contain very little, if any, information.

Table H.3: Summary Statistics of Bivariate ECM Model by Fractionally Integrated DV and IV (T=60)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	9998	9959	9686	8853	7356	5675
ECM Significant*	10000	10000	10000	9997	9862	9099	7233	4627	2425	1070	533
Mean of α_1	-1.03	-1.03	-0.93	-0.79	-0.64	-0.53	-0.42	-0.32	-0.24	-0.17	-0.12
$\geq 1\Delta X_t$ Significant	574	588	596	609	640	670	661	659	643	624	610
$\geq 1X_{t-1}$ Significant	603	579	932	1371	1744	1922	1954	1888	1763	1630	1716
ECM and $\geq 1\Delta X_t$ Significant	574	588	596	609	640	670	660	642	590	491	384
ECM and $\geq 1\Delta X_t$ Significant*	574	588	596	609	634	620	516	338	188	82	49
ECM and $\geq 1X_{t-1}$ Significant	603	579	932	1371	1744	1922	1954	1886	1744	1541	1410
ECM and $\geq 1X_{t-1}$ Significant*	603	579	932	1371	1744	1900	1808	1446	924	499	310
Model 2**											
ECM Significant		10000	10000	10000	10000	9998	9931	9607	8651	7160	
ECM Significant*		10000	10000	9990	9752	8685	6548	4042	2092	1014	
Mean of α_1		-1.02	-0.91	-0.76	-0.61	-0.50	-0.40	-0.30	-0.22	-0.16	
$\geq 1\Delta X_t$ Significant		569	582	610	667	687	685	677	646	610	
$\geq 1X_{t-1}$ Significant		540	570	711	879	1005	1152	1234	1328	1471	
ECM and $\geq 1\Delta X_t$ Significant		569	582	610	667	687	679	644	561	458	
ECM and $\geq 1\Delta X_t$ Significant*		569	582	609	652	599	452	299	172	91	
ECM and $\geq 1X_{t-1}$ Significant		540	570	711	879	1004	1150	1230	1303	1367	
ECM and $\geq 1X_{t-1}$ Significant*		540	570	710	876	978	1041	904	678	484	
Model 3***											
ECM Significant	10000	10000	10000	10000	10000	9996	9909	9390	8107	6140	4482
ECM Significant*	10000	10000	10000	9989	9692	8353	5804	3096	1364	501	219
Mean of α_1	-1.01	-1.02	-0.91	-0.76	-0.59	-0.48	-0.37	-0.27	-0.19	-0.13	-0.09
$\geq 1\Delta X_t$ Significant	560	578	581	564	562	579	576	580	607	592	542
$\geq 1X_{t-1}$ Significant	541	559	567	537	512	510	503	500	519	557	593
ECM and $\geq 1\Delta X_t$ Significant	560	578	581	564	562	579	572	535	477	369	257
ECM and $\geq 1\Delta X_t$ Significant*	560	578	581	563	543	329	363	177	88	29	21
ECM and $\geq 1X_{t-1}$ Significant	541	559	567	537	512	510	501	481	450	386	308
ECM and $\geq 1X_{t-1}$ Significant*	541	559	567	537	506	472	369	226	132	59	33

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.27.
$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified
$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified
$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.4: Summary Statistics of Multivariate (2IVs) ECM Model by Fractionally Integrated DV and IV (T=60)

	$I(0)$	$d = .1$	$d = .2$	$d = .3$	$d = .4$	$d = .5$	$d = .6$	$d = .7$	$d = .8$	$d = .9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	9997	9984	9837	9261	8079	6488
ECM Significant*	10000	10000	9998	9989	9723	8802	6834	4368	2379	1129	552
Mean of α_1	-1.05	-1.05	-0.95	-0.82	-0.68	-0.57	-0.47	-0.37	-0.28	-0.21	-0.15
$\geq 1\Delta X_t$ Significant	1163	1033	1078	1131	1189	1158	1187	1175	1172	1187	1227
$\geq 1X_{t-1}$ Significant	1112	1067	1586	2226	2725	3098	3177	3133	3020	2955	2945
ECM and $\geq 1\Delta X_t$ Significant	1163	1033	1078	1131	1189	1157	1186	1161	1115	1013	862
ECM and $\geq 1\Delta X_t$ Significant*	1163	1033	1078	1130	1158	1058	888	627	384	206	110
ECM and $\geq 1X_{t-1}$ Significant	1112	1067	1586	2226	2725	3098	3176	3132	2993	2797	2497
ECM and $\geq 1X_{t-1}$ Significant*	1112	1067	1586	2226	2715	3007	2813	2150	1380	762	430
Model 2**											
ECM Significant		10000	10000	10000	9999	9992	9931	9650	8930	7824	
ECM Significant*		10000	9998	9951	9366	7940	5552	3369	1783	933	
Mean of α_1		-1.02	-0.91	-0.77	-0.62	-0.52	-0.42	-0.33	-0.26	-0.20	
$\geq 1\Delta X_t$ Significant		1013	1044	1103	1179	1208	1221	1236	1208	1181	
$\geq 1X_{t-1}$ Significant		1064	1137	1329	1594	1787	1999	2156	2304	2511	
ECM and $\geq 1\Delta X_t$ Significant		1013	1044	1103	1179	1208	1218	1203	1114	975	
ECM and $\geq 1\Delta X_t$ Significant*		1013	1043	1097	1107	1006	728	495	296	168	
ECM and $\geq 1X_{t-1}$ Significant		1064	1137	1329	1594	1787	1998	2145	2259	2369	
ECM and $\geq 1X_{t-1}$ Significant*		1064	1137	1328	1571	1676	1593	1309	936	600	
Model 3***											
ECM Significant	10000	10000	10000	10000	10000	9995	9873	9329	7976	6033	4340
ECM Significant*	10000	10000	9998	9947	9100	7005	4209	1988	755	245	94
Mean of α_1	-1.02	-1.02	-0.90	-0.75	-0.59	-0.48	-0.37	-0.27	-0.19	-0.13	-0.09
$\geq 1\Delta X_t$ Significant	1124	1050	1059	1066	1065	1045	1027	1032	1021	1030	1099
$\geq 1X_{t-1}$ Significant	1088	1116	1123	1124	1053	950	946	962	980	1072	1195
ECM and $\geq 1\Delta X_t$ Significant	1124	1050	1059	1066	1065	1043	1004	963	826	650	546
ECM and $\geq 1\Delta X_t$ Significant*	1124	1050	1059	1059	960	728	472	273	126	51	20
ECM and $\geq 1X_{t-1}$ Significant	1088	1116	1123	1124	1053	950	938	911	830	707	634
ECM and $\geq 1X_{t-1}$ Significant*	1088	1116	1123	1121	1010	807	583	348	162	64	22

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.565.

$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified

$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.5: Summary Statistics of Multivariate (3IVs) ECM Model by Fractionally Integrated DV and IV (T=60)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	10000	9988	9882	9467	8586	7197
ECM Significant*	10000	10000	10000	9972	9556	8552	6548	4234	2275	1067	527
Mean of α_1	-1.07	-1.07	-0.97	-0.85	-0.72	-0.61	-0.51	-0.42	-0.32	-0.25	-0.18
$\geq 1\Delta X_{\text{t}}$ Significant	1542	1540	1572	1646	1714	1723	1733	1763	1754	1762	1733
$\geq 1X_{\text{t-1}}$ Significant	1563	1561	2163	2883	3509	3828	4004	3979	3904	3864	3897
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	1542	1540	1572	1646	1714	1723	1730	1738	1675	1563	1329
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	1542	1540	1572	1642	1653	1536	1266	885	542	303	152
ECM and $\geq 1X_{\text{t-1}}$ Significant	1563	1561	2163	2883	3509	3828	4004	3974	3873	3712	3415
ECM and $\geq 1X_{\text{t-1}}$ Significant*	1563	1561	2163	2883	3490	3646	3304	2480	1566	835	452
Model 2**											
ECM Significant		10000	10000	10000	9999	9994	9941	9724	9161	8268	
ECM Significant*		9999	9993	9870	8801	7070	4790	2912	1586	874	
Mean of α_1		-1.02	-0.91	-0.78	-0.64	-0.54	-0.44	-0.36	-0.28	-0.23	
$\geq 1\Delta X_{\text{t}}$ Significant		1589	1620	1680	1801	1836	1847	1828	1797	1781	
$\geq 1X_{\text{t-1}}$ Significant		1499	1611	1861	2240	2488	2764	2997	3256	3501	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant		1589	1620	1680	1800	1833	1838	1778	1680	1539	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*		1589	1619	1651	1588	1331	965	632	408	255	
ECM and $\geq 1X_{\text{t-1}}$ Significant		1499	1611	1861	2240	2487	2762	2980	3195	3306	
ECM and $\geq 1X_{\text{t-1}}$ Significant*		1499	1611	1861	2167	2201	1988	1550	1069	693	
Model 3***											
ECM Significant	10000	10000	10000	10000	10000	9991	9853	9201	7776	5880	4206
ECM Significant*	10000	10000	9995	9830	8194	5586	2937	1207	415	125	53
Mean of α_1	-1.02	-1.02	-0.91	-0.76	-0.59	-0.48	-0.37	-0.27	-0.19	-0.13	-0.09
$\geq 1\Delta X_{\text{t}}$ Significant	1500	1515	1503	1507	1504	1545	1535	1532	1531	1514	1530
$\geq 1X_{\text{t-1}}$ Significant	1546	1515	1526	1478	1424	1408	1371	1369	1403	1501	1683
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	1500	1515	1503	1507	1504	1541	1501	1390	1196	925	701
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	1500	1515	1503	1468	1218	909	515	238	97	40	21
ECM and $\geq 1X_{\text{t-1}}$ Significant	1546	1515	1526	1478	1424	1407	1352	1298	1170	1007	846
ECM and $\geq 1X_{\text{t-1}}$ Significant*	1546	1515	1526	1466	1299	1033	641	329	132	50	25

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance (p$\leq$ 0.05, one-tail test). Coefficient significance (p$\leq$ 0.05, two-tail test) *ECM significance (*p$\leq$ 0.05, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.816.

$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified

$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.6: Summary Statistics of Multivariate (4IVs) ECM Model by Fractionally Integrated DV and IV (T=60)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	9999	9991	9927	9640	8926	7666
ECM Significant*	10000	9999	9998	9934	9407	8238	6201	3997	2127	1030	496
Mean of α_1	-1.09	-1.09	-1.00	-0.88	-0.75	-0.65	-0.56	-0.46	-0.37	-0.29	-0.21
$\geq 1\Delta X_{t}$ Significant	2073	2016	2057	2161	2243	2242	2284	2312	2282	2314	2292
$\geq 1X_{t\text{-}1}$ Significant	2069	2074	2738	3445	4047	4324	4509	4585	4575	4534	4599
ECM and $\geq 1\Delta X_{t}$ Significant	2073	2016	2057	2161	2243	2242	2282	2296	2214	2102	1838
ECM and $\geq 1\Delta X_{t}$ Significant*	2073	2015	2053	2146	2151	1916	1549	1105	639	334	200
ECM and $\geq 1X_{t\text{-}1}$ Significant	2069	2074	2738	3445	4047	4324	4508	4577	4530	4369	4108
ECM and $\geq 1X_{t\text{-}1}$ Significant*	2069	2074	2737	3440	3983	4005	3524	2654	1593	870	447
Model 2**											
ECM Significant		10000	10000	10000	10000	9995	9948	9774	9297	8553	
ECM Significant*		9998	9978	9659	8210	6183	4158	2482	1425	802	
Mean of α_1		-1.02	-0.92	-0.79	-0.65	-0.56	-0.47	-0.39	-0.32	-0.26	
$\geq 1\Delta X_{t}$ Significant		1987	2041	2125	2247	2246	2281	2265	2264	2282	
$\geq 1X_{t\text{-}1}$ Significant		1918	2045	2354	2846	3104	3394	3654	3917	4286	
ECM and $\geq 1\Delta X_{t}$ Significant		1987	2041	2125	2247	2245	2268	2215	2141	2026	
ECM and $\geq 1\Delta X_{t}$ Significant*		1985	2035	2044	1891	1514	1084	719	438	284	
ECM and $\geq 1X_{t\text{-}1}$ Significant		1918	2045	2354	2846	3104	3390	3632	3844	4067	
ECM and $\geq 1X_{t\text{-}1}$ Significant*		1918	2045	2333	2657	2505	2161	1568	1031	672	
Model 3***											
ECM Significant	10000	10000	10000	10000	9998	9977	9789	9008	7544	5682	3998
ECM Significant*	9996	9995	9970	9497	7150	4376	2023	742	246	66	16
Mean of α_1	-1.02	-1.02	-0.91	-0.76	-0.60	-0.48	-0.37	-0.27	-0.20	-0.13	-0.09
$\geq 1\Delta X_{t}$ Significant	1982	2028	2048	2055	2038	1984	2007	2000	1979	1979	2012
$\geq 1X_{t\text{-}1}$ Significant	2007	2086	2088	2028	1928	1839	1762	1799	1872	2038	2201
ECM and $\geq 1\Delta X_{t}$ Significant	1982	2028	2048	2055	2038	1975	1938	1777	1490	1159	881
ECM and $\geq 1\Delta X_{t}$ Significant*	1980	2027	2039	1942	1485	902	435	155	63	23	9
ECM and $\geq 1X_{t\text{-}1}$ Significant	2007	2086	2088	2028	1928	1834	1739	1667	1517	1159	1055
ECM and $\geq 1X_{t\text{-}1}$ Significant*	2005	2085	2087	1984	1638	1114	588	248	115	23	8

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -4.035.
$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified
$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified
$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.7: Summary Statistics of Multivariate (5IVs) ECM Model by Fractionally Integrated DV and IV (T=60)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	9998	9992	9947	9726	9108	8024
ECM Significant*	9998	9998	9978	9847	9192	7913	5979	3813	2143	1078	514
Mean of α_1	-1.10	-1.10	-1.02	-0.91	-0.79	-0.69	-0.60	-0.50	-0.41	-0.32	-0.24
$\geq 1\Delta X_t$ Significant	2454	2517	2598	2700	2802	2766	2801	2822	2851	2867	2875
$\geq 1X_{t-1}$ Significant	2492	2534	3129	3837	4436	4842	5042	5156	5166	5180	5228
ECM and $\geq 1\Delta X_t$ Significant	2454	2517	2598	2700	2802	2766	2799	2812	2793	2672	2428
ECM and $\geq 1\Delta X_t$ Significant*	2453	2517	2597	2679	2642	2323	1881	1315	868	476	250
ECM and $\geq 1X_{t-1}$ Significant	2492	2534	3129	3837	4436	4842	5041	5149	5129	5011	4710
ECM and $\geq 1X_{t-1}$ Significant*	2492	2534	3128	3823	4311	4352	3808	2798	1727	942	481
Model 2**											
ECM Significant		10000	10000	10000	9999	9990	9932	9757	9405	8809	
ECM Significant*		9982	9908	9322	7451	5417	3556	2137	1303	756	
Mean of α_1		-1.02	-0.92	-0.79	-0.66	-0.57	-0.49	-0.41	-0.35	-0.29	
$\geq 1\Delta X_t$ Significant		2409	2419	2511	2655	2689	2711	2765	2779	2818	
$\geq 1X_{t-1}$ Significant		2359	2414	2772	3222	3573	3915	4195	4493	4833	
ECM and $\geq 1\Delta X_t$ Significant		2409	2419	2511	2654	2684	2686	2696	2633	2563	
ECM and $\geq 1\Delta X_t$ Significant*		2401	2391	2338	2044	1609	1144	755	522	337	
ECM and $\geq 1X_{t-1}$ Significant		2359	2414	2772	3221	3571	3911	4171	4413	4598	
ECM and $\geq 1X_{t-1}$ Significant*		2358	2406	2709	2883	2637	2189	1563	1065	676	
Model 3***											
ECM Significant	10000	10000	10000	10000	9998	9976	9751	8945	7396	5425	3959
ECM Significant*	9986	9989	9883	8970	5928	3178	1308	440	147	37	12
Mean of α_1	-1.02	-1.02	-0.91	-0.76	-0.60	-0.48	-0.37	-0.28	-0.20	-0.13	-0.09
$\geq 1\Delta X_t$ Significant	2466	2451	2468	2498	2486	2361	2389	2422	2411	2425	2467
$\geq 1X_{t-1}$ Significant	2406	2434	2438	2367	2260	2161	2124	2126	2254	2396	2633
ECM and $\geq 1\Delta X_t$ Significant	2466	2451	2468	2498	2486	2354	2323	2155	1803	1361	1057
ECM and $\geq 1\Delta X_t$ Significant*	2460	2447	2431	2251	1577	787	357	133	52	17	6
ECM and $\geq 1X_{t-1}$ Significant	2406	2434	2438	2367	2259	2157	2093	1965	1804	1481	1251
ECM and $\geq 1X_{t-1}$ Significant*	2403	2433	2432	2264	1736	1023	497	198	81	21	7

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -4.229.
$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified
$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified
$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.8: Summary Statistics of Bivariate ECM Model by Fractionally Integrated DV and IV (T=150)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1[⋆]											
ECM Significant	10000	10000	10000	10000	10000	10000	10000	9980	9604	8091	5769
ECM Significant*	10000	10000	10000	10000	10000	9998	9770	8056	4497	1624	501
Mean of α_1	-1.01	-1.01	-0.89	-0.73	-0.55	-0.42	-0.30	-0.21	-0.13	-0.08	-0.05
$\geq 1\Delta X_t$ Significant	536	514	530	539	564	527	529	522	515	524	562
$\geq 1X_{t-1}$ Significant	530	535	1173	2057	2709	2925	2846	2565	2092	1721	1639
ECM and $\geq 1\Delta X_t$ Significant	536	514	530	539	564	527	529	522	491	438	338
ECM and $\geq 1\Delta X_t$ Significant*	536	514	530	539	564	527	517	425	240	83	36
ECM and $\geq 1X_{t-1}$ Significant	530	535	1173	2057	2709	2925	2846	2565	2090	1671	1343
ECM and $\geq 1X_{t-1}$ Significant*	530	535	1173	2057	2709	2925	2843	2438	1551	717	270
Model 2[⋆⋆]											
ECM Significant		10000	10000	10000	10000	10000	9999	9959	8476	7938	
ECM Significant*		10000	10000	10000	10000	9990	9615	7492	4009	1466	
Mean of α_1		-1.01	-0.89	-0.72	-0.53	-0.40	-0.29	-0.19	-0.12	-0.08	
$\geq 1\Delta X_t$ Significant		508	522	567	639	700	689	641	602	539	
$\geq 1X_{t-1}$ Significant		516	554	717	1036	1296	1490	1544	1515	1511	
ECM and $\geq 1\Delta X_t$ Significant		508	522	567	639	700	688	637	565	425	
ECM and $\geq 1\Delta X_t$ Significant*		508	522	567	639	699	660	487	270	92	
ECM and $\geq 1X_{t-1}$ Significant		516	554	717	1036	1296	1490	1544	1511	1449	
ECM and $\geq 1X_{t-1}$ Significant*		516	554	717	1036	1296	1484	1448	1090	613	
Model 3[⋆⋆⋆]											
ECM Significant	10000	10000	10000	10000	10000	10000	10000	9941	9187	7045	4542
ECM Significant*	10000	10000	10000	10000	10000	9991	9448	6710	2901	802	216
Mean of α_1	-1.01	-1.01	-0.88	-0.71	-0.52	-0.39	-0.27	-0.18	-0.11	-0.06	-0.04
$\geq 1\Delta X_t$ Significant	532	498	491	490	516	477	473	491	494	493	536
$\geq 1X_{t-1}$ Significant	530	521	525	501	443	393	363	339	385	444	561
ECM and $\geq 1\Delta X_t$ Significant	532	498	491	490	516	477	473	489	453	342	270
ECM and $\geq 1\Delta X_t$ Significant*	532	498	491	490	516	477	446	327	136	43	13
ECM and $\geq 1X_{t-1}$ Significant	530	521	525	501	443	393	363	338	354	337	294
ECM and $\geq 1X_{t-1}$ Significant*	530	521	525	501	443	393	350	257	141	47	14

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.236.

⋆ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified

⋆⋆ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified

⋆⋆⋆ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.9: Summary Statistics of Multivariate (2IVs) ECM Model by Fractionally Integrated DV and IV (T=150)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	10000	10000	9991	9794	8721	6695
ECM Significant*	10000	10000	10000	10000	10000	9998	9777	8086	4480	1667	467
Mean of α_1	-1.02	-1.02	-0.91	-0.75	-0.58	-0.45	-0.34	-0.24	-0.16	-0.10	-0.06
$\geq 1\Delta X_{\text{t}}$ Significant	994	1005	1045	1079	1109	1094	1113	1103	1073	1071	1047
$\geq 1X_{\text{t-1}}$ Significant	1027	998	1954	3189	4053	4380	4365	4047	3553	3119	2958
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	994	1005	1045	1079	1109	1094	1113	1100	1054	937	728
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	994	1005	1045	1079	1109	1094	1081	905	526	208	59
ECM and $\geq 1X_{\text{t-1}}$ Significant	1027	998	1954	3189	4053	4380	4365	4047	3552	3051	2525
ECM and $\geq 1X_{\text{t-1}}$ Significant*	1027	998	1954	3189	4053	4380	4351	3782	2459	1064	365
Model 2**											
ECM Significant		10000	10000	10000	10000	10000	9999	9972	9669	8481	
ECM Significant*		10000	10000	10000	10000	9972	9443	7013	3629	1321	
Mean of α_1		-1.01	-0.89	-0.72	-0.54	-0.41	-0.30	-0.21	-0.14	-0.09	
$\geq 1\Delta X_{\text{t}}$ Significant		1033	1036	1159	1320	1332	1330	1246	1143	1088	
$\geq 1X_{\text{t-1}}$ Significant		1024	1071	1395	1876	2275	2562	2664	2640	2660	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant		1033	1036	1159	1320	1332	1329	1243	1106	919	
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*		1033	1036	1159	1320	1330	1259	864	454	166	
ECM and $\geq 1X_{\text{t-1}}$ Significant		1024	1071	1395	1876	2275	2562	2664	2637	2567	
ECM and $\geq 1X_{\text{t-1}}$ Significant*		1024	1071	1395	1876	2275	2542	2372	1651	809	
Model 3***											
ECM Significant	10000	10000	10000	10000	10000	10000	9999	9940	9208	7002	4475
ECM Significant*	10000	10000	10000	10000	10000	9944	8967	5379	1830	404	85
Mean of α_1	-1.00	-1.00	-0.88	-0.71	-0.52	-0.39	-0.27	-0.18	-0.11	-0.06	-0.04
$\geq 1\Delta X_{\text{t}}$ Significant	984	995	1016	990	1011	1012	1011	1006	997	982	969
$\geq 1X_{\text{t-1}}$ Significant	984	998	967	891	832	819	761	750	798	888	1018
ECM and $\geq 1\Delta X_{\text{t}}$ Significant	984	995	1016	990	1011	1012	1011	1002	925	697	447
ECM and $\geq 1\Delta X_{\text{t}}$ Significant*	984	998	1016	990	1011	1008	906	569	199	49	7
ECM and $\geq 1X_{\text{t-1}}$ Significant	984	998	967	891	832	819	761	748	739	660	492
ECM and $\geq 1X_{\text{t-1}}$ Significant*	984	998	967	891	832	816	701	455	205	66	14

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p\leq 0.05$, one-tail test). Coefficient significance ($p\leq 0.05$, two-tail test) *ECM significance (*$p\leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.528.
$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified
$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified
$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.10: Summary Statistics of Multivariate (3IVs) ECM Model by Fractionally Integrated DV and IV (T=150)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	10000	10000	9994	9891	9174	7348
ECM Significant*	10000	10000	10000	10000	10000	9994	9777	8042	4496	1653	479
Mean of α_1	-1.03	-1.02	-0.92	-0.77	-0.60	-0.48	-0.36	-0.26	-0.18	-0.12	-0.07
$\geq 1\Delta X_{\mathrm{t}}$ Significant	1451	1424	1470	1535	1580	1564	1591	1564	1546	1523	1559
$\geq 1X_{\mathrm{t-1}}$ Significant	1454	1388	2454	3902	4877	5165	5230	4962	4541	4078	3903
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant	1451	1424	1470	1535	1580	1564	1591	1564	1529	1406	1184
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant*	1451	1424	1470	1535	1580	1564	1560	1276	730	306	92
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant	1454	1388	2454	3902	4877	5165	5230	4962	4538	4012	3428
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant*	1454	1388	2454	3902	4877	5165	5201	4540	2919	1270	396
Model 2**											
ECM Significant		10000	10000	10000	10000	10000	10000	9979	9757	8897	
ECM Significant*		10000	10000	10000	10000	10000	9222	6749	3466	1318	
Mean of α_1		-1.01	-0.89	-0.73	-0.55	-0.43	-0.32	-0.23	-0.16	-0.11	
$\geq 1\Delta X_{\mathrm{t}}$ Significant		1516	1578	1731	1905	1984	1936	1840	1725	1627	
$\geq 1X_{\mathrm{t-1}}$ Significant		1495	1574	1989	2673	3222	3572	3694	3673	3666	
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant		1516	1578	1731	1905	1984	1936	1837	1685	1460	
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant*		1516	1578	1731	1905	1973	1796	1260	605	227	
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant		1495	1574	1989	2673	3222	3572	3694	3668	3572	
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant*		1495	1574	1989	2673	3220	3508	3164	2025	962	
Model 3***											
ECM Significant	10000	10000	10000	10000	10000	10000	9999	9931	9086	6874	4420
ECM Significant*	10000	10000	10000	10000	10000	9877	8177	4171	1177	208	32
Mean of α_1	-1.01	-1.01	-0.88	-0.71	-0.53	-0.39	-0.27	-0.18	-0.11	-0.06	-0.04
$\geq 1\Delta X_{\mathrm{t}}$ Significant	1452	1441	1445	1456	1458	1437	1444	1441	1458	1455	1467
$\geq 1X_{\mathrm{t-1}}$ Significant	1480	1414	1417	1322	1198	1076	1006	1049	1114	1256	1581
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant	1452	1441	1445	1456	1458	1437	1444	1425	1304	1019	659
ECM and $\geq 1\Delta X_{\mathrm{t}}$ Significant*	1452	1441	1445	1456	1458	1413	1172	618	189	42	9
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant	1480	1414	1417	1322	1198	1076	1006	1040	1020	902	746
ECM and $\geq 1X_{\mathrm{t-1}}$ Significant*	1480	1414	1417	1322	1198	1068	890	539	178	51	6

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -3.78.
$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified
$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified
$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.11: Summary Statistics of Multivariate (4IVs) ECM Model by Fractionally Integrated DV and IV (T=150)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	10000	10000	9996	9930	9412	7931
ECM Significant*	10000	10000	10000	10000	10000	9988	9731	8029	4497	1722	503
Mean of α_1	-1.03	-1.03	-0.93	-0.78	-0.62	-0.50	-0.39	-0.29	-0.20	-0.14	-0.09
$\geq 1\Delta X_t$ Significant	1910	1998	2024	2055	2101	2144	2163	2135	2152	2148	2066
$\geq 1X_{t-1}$ Significant	1751	1779	2860	4233	5292	5724	5795	5597	5240	4840	4678
ECM and $\geq 1\Delta X_t$ Significant	1910	1998	2055	2101	2144	2163	2134	2134	2137	2035	1659
ECM and $\geq 1\Delta X_t$ Significant*	1910	1998	2055	2101	2144	2119	1781	1781	1062	429	129
ECM and $\geq 1X_{t-1}$ Significant	1751	1779	2860	4233	5292	5724	5795	5597	5239	4779	4258
ECM and $\geq 1X_{t-1}$ Significant*	1751	1779	2860	4233	5292	5724	5754	5095	3287	1438	449
Model 2**											
ECM Significant		10000	10000	10000	10000	10000	10000	9987	9819	9198	
ECM Significant*		10000	10000	10000	9998	9917	8976	6400	3304	1346	
Mean of α_1		-1.00	-0.89	-0.73	-0.56	-0.44	-0.33	-0.24	-0.18	-0.12	
$\geq 1\Delta X_t$ Significant		1930	2003	2176	2396	2505	2441	2326	2206	2093	
$\geq 1X_{t-1}$ Significant		1882	1981	2465	3291	3866	4268	4385	4361	4421	
ECM and $\geq 1\Delta X_t$ Significant		1930	2003	2176	2396	2505	2441	2322	2167	1935	
ECM and $\geq 1\Delta X_t$ Significant*		1930	2003	2176	2395	2483	2213	1537	762	325	
ECM and $\geq 1X_{t-1}$ Significant		1882	1981	2465	3291	3866	4268	4385	4352	4325	
ECM and $\geq 1X_{t-1}$ Significant*		1882	1981	2465	3291	3861	4129	3549	2194	1065	
Model 3***											
ECM Significant	10000	10000	10000	10000	10000	10000	10000	9925	9035	6806	4371
ECM Significant*	10000	10000	10000	10000	9996	9694	7287	3234	771	135	15
Mean of α_1	-1.01	-1.01	-0.89	-0.71	-0.52	-0.39	-0.27	-0.18	-0.11	-0.06	-0.04
$\geq 1\Delta X_t$ Significant	1946	1964	1955	1929	1895	1888	1906	1934	1924	1955	1917
$\geq 1X_{t-1}$ Significant	1956	1894	1862	1754	1592	1492	1445	1446	1527	1678	2018
ECM and $\geq 1\Delta X_t$ Significant	1946	1964	1955	1929	1895	1888	1906	1918	1729	1351	865
ECM and $\geq 1\Delta X_t$ Significant*	1946	1964	1955	1929	1895	1827	1397	657	174	34	5
ECM and $\geq 1X_{t-1}$ Significant	1956	1894	1862	1754	1592	1492	1445	1437	1405	1211	961
ECM and $\geq 1X_{t-1}$ Significant*	1956	1894	1862	1754	1592	1469	1187	612	172	41	7

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -4.003.
$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified
$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified
$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Table H.12: Summary Statistics of Multivariate (5IVs) ECM Model by Fractionally Integrated DV and IV (T=150)

	$I(0)$	$d=.1$	$d=.2$	$d=.3$	$d=.4$	$d=.5$	$d=.6$	$d=.7$	$d=.8$	$d=.9$	$I(1)$
Model 1*											
ECM Significant	10000	10000	10000	10000	10000	10000	10000	10000	9965	9630	8414
ECM Significant*	10000	10000	10000	10000	10000	9993	9767	8077	4502	1696	505
Mean of α_1	-1.04	-1.04	-0.94	-0.80	-0.64	-0.52	-0.41	-0.31	-0.22	-0.15	-0.10
$\geq 1\Delta X_t$ Significant	2361	2342	2371	2474	2495	2599	2603	2563	2537	2515	2541
$\geq 1X_{t-1}$ Significant	2246	2239	3388	4771	5787	6204	6322	6186	5868	5517	5427
ECM and $\geq 1\Delta X_t$ Significant	2361	2342	2371	2474	2495	2599	2603	2563	2529	2433	2171
ECM and $\geq 1\Delta X_t$ Significant*	2361	2342	2371	2474	2495	2596	2539	2142	1226	458	173
ECM and $\geq 1X_{t-1}$ Significant	2246	2239	3388	4771	5787	6204	6322	6186	5865	5467	5008
ECM and $\geq 1X_{t-1}$ Significant*	2246	2239	3388	4771	5787	6203	6283	5538	3457	1443	470
Model 2**											
ECM Significant		10000	10000	10000	10000	10000	9999	9988	9868	9387	
ECM Significant*		10000	10000	10000	9999	9867	8817	6042	3079	1276	
Mean of α_1		-1.01	-0.89	-0.73	-0.56	-0.45	-0.34	-0.26	-0.19	-0.14	
$\geq 1\Delta X_t$ Significant		2290	2374	2573	2798	2893	2870	2734	2647	2515	
$\geq 1X_{t-1}$ Significant		2351	2434	2980	3860	4454	4900	5056	5074	5121	
ECM and $\geq 1\Delta X_t$ Significant		2290	2374	2573	2798	2893	2869	2730	2069	2363	
ECM and $\geq 1\Delta X_t$ Significant*		2290	2374	2573	2797	2855	2531	1678	859	382	
ECM and $\geq 1X_{t-1}$ Significant		2351	2434	2980	3860	4454	4900	5056	5067	5056	
ECM and $\geq 1X_{t-1}$ Significant*		2351	2434	2980	3860	4448	4690	3863	2340	1098	
Model 3***											
ECM Significant	10000	10000	10000	10000	10000	10000	9997	9805	9015	6843	4342
ECM Significant*	10000	10000	10000	10000	9992	9486	6483	2479	487	77	14
Mean of α_1	-1.01	-1.01	-0.88	-0.71	-0.52	-0.39	-0.27	-0.18	-0.11	-0.06	-0.04
$\geq 1\Delta X_t$ Significant	2278	2324	2311	2293	2305	2293	2275	2268	2260	2294	2313
$\geq 1X_{t-1}$ Significant	2363	2267	2246	2144	1959	1842	1729	1711	1854	2071	2418
ECM and $\geq 1\Delta X_t$ Significant	2278	2324	2311	2293	2305	2293	2274	2249	2029	1580	1043
ECM and $\geq 1\Delta X_t$ Significant*	2278	2324	2311	2293	2302	2169	1485	578	122	25	5
ECM and $\geq 1X_{t-1}$ Significant	2363	2267	2246	2144	1959	1842	1728	1700	1696	1472	1136
ECM and $\geq 1X_{t-1}$ Significant*	2363	2267	2246	2144	1959	1787	1284	552	157	27	6

Note: Cell entries are the result of 10,000 simulations for each model at each specified order of d. ECM significance ($p \leq 0.05$, one-tail test). Coefficient significance ($p \leq 0.05$, two-tail test) *ECM significance (*$p \leq 0.05$, one-tail test) with MacKinnon CVs: 5% $\leq$ -4.205.

$\star$ Model 1: IVs are integrated $I(1)$ and DV is integrated at $I(d)$ order specified

$\star\star$ Model 2: Both IVs and DV are integrated at the same $I(d)$ order specified

$\star\star\star$ Model 3: IVs are integrated $I(0)$ and DV is integrated at $I(d)$ order specified

Appendix I Replication Code and Data

I.1 Bounded Data

The bounded series used in the Monte Carlo simulations were generated using the process of Nicolau (2002). Because we specified the data generating processes with differing variances for data sets of varying length, and simulated two different sets of bounds, we have a number of specific parameters values that must be used for each replication. The main change which must be made is to the strength of the mean reversion. The volatility in the process that arises with increased variance in the disturbance term can occasionally send the series outside of the boundary for a brief moment, at which point the mean reversion process will over correct. With tighter bounds, if that over correction sends the process too sharply towards the other bound the series will remain permanently outside of the bounds. This problem also highlights the necessity of providing an initial starting value within the boundary.

Table I.1: Parameter Values for Generating Bounded Series

	Parameters		
σ **& Bounds**	$\alpha_1 = \alpha_2$	$\boldsymbol{k}$	τ
σ **= 1**			
(0,100)	1.5	73.5	49
(49,71)	1.5	16.5	59
σ **=2**			
(0,100)	0.5	24.5	49
(49,71)	0.5	5.49998	59
σ **= 3**			
(0,100)	0.3	14.7	49
(49,71)	0.3	3.29864	59

Note:MacKinnon Values with 1 IV: T=60: -3.27; T=100: -3.248;T=150: -3.236
MacKinnon Values with 2 IVs: T=60:-3.565; T=100:-3.54; T=150: -3.528

The simulations of the bounded series were run in RATS 8.0, however we have also attached code to run the bounded simulations in Stata. The results from the Stata simulations are comparable to those from RATS.

I.1.1 Estimating the Bound Parameters - RATS

To change the bounds, one may use the following code to estimate the parameters α_1, α_2, τ and k. This code was written in RATS 8.0, but it can very easily be re-written in Stata. The values in the code below are used for calculating the bounds of a series of (49,71) with a series disturbance $\sim N(0, 1)$.

```
************************************
*** Calculating Bounds (x & y) ***
************************************
* set length of series to play with, this should be +/- 2 on either side of chosen bounds
all 24
* set initial starting value, also a little wider than actual bounds
set x = 48
set x 2 * = x{1} + 1
```

```
* a check to make sure the bounds length is correct
print / x

* set power of mean reversion
set a = 1.5
set b = 1.5
* set initial value for central tendency
set tau = 59

* y is the function a(x) using the specific values above
set y = (exp((-a)*(x{1} - tau)) - (exp((b)*(x{1} - tau))))
print / y x
* results are symmetric values set around the central 0 point.
* in this case, the 0 is at 60, this will be the focal point
* find the boundary values  - they should be symmetric
* in this case they are (14650719.42895, -14650719.42895)
* take natural log of boundary value (value is 14650719.42895)

dis log('boundary value')

* this provides the value of k for the final model
set k = 16.5
```

I.1.2 Bivariate Bounded Data - RATS

Annotated RATS code is below:

```
*****************************************************
***** Simulation of Bounded Bivariate I(1) Model *****
*****************************************************
* 1 X that is I(1)
* MacKinnon Critical Values
* 60=-3.27; 100=-3.248; 150=-3.236
*
seed 5000
all 60
*
* Values for simulations (parameter values change as needed)
*
set a = b = 1.5
set k = 16.5
set tau = 59
*
comp draws = 10000
infobox(action=define, progress, lower=1, upper=draws) 'Simulations Completed'
*
* Model Counters
*
comp bi_ecm5  = 0
comp bi_ecmXD = 0
comp bi_ecmXL = 0
comp bi_XDsig = 0
comp bi_XLsig = 0
comp mv_ecm5 = 0
comp mv_ecmXD = 0
comp mv_ecmXL = 0
comp bi_error = 0

*
* Regression Output
*
set bi_betaECM 1 draws = 0
set bi_tstatECM 1 draws = 0
set bi_seECM 1 draws = 0
set bi_betaXD 1 draws = 0
set bi_tstatXD 1 draws = 0
```

```
set bi_seXD 1 draws = 0
set bi_betaXL 1 draws = 0
set bi_tstatXL 1 draws = 0
set bi_seXL 1 draws = 0
set bi_betaECM2 1 draws = 0
set bi_tstatECM2 1 draws = 0
set bi_seECM2 1 draws = 0
*
* Begin Loop
*
do i = 1,draws
infobox(current=i)
*
* Random Draw (if using the tighter bounds (49,71) initial value should be (50,59)
*
set y = %uniform(50,59)
*set y = %uniform(1,99)
set x = 0
*
* Bounded Random Walk and Differencing (error variance can be either 1,2,3)
*
set y 2 * = y{1} + exp(-k)*(exp((-a)*(y{1} - tau)) - (exp((b)*(y{1} - tau)))) + %ran(1)
diff y 2 * dy
*
set x 2 * = x{1} + %ran(1)
diff x 2 * dx
*
* Bivariate Regression Model
*
lin(noprint) dy ; # constant y{1} dx x{1}
*
* ECM statistics
*
com bi_betaECM(i) = %beta(2)
com bi_seECM(i) = %stderrs(2)
com bi_tstatECM(i) = %tstats(2)
*
* 1/10,000 models may have mean reversion that shoots it out of bounds
* to ensure that estimates of the ECM coefficient aren't biased
*
if bi_betaECM(i).gt.-1.5 ; com bi_betaECM2(i) = %beta(2)
if bi_betaECM(i).gt.-1.5 ; com bi_seECM2(i) = %stderrs(2)
if bi_betaECM(i).gt.-1.5 ; com bi_tstatECM2(i) = %tstats(2)
*
* Xd (diff) statistics
*
com bi_betaXD(i) = %beta(3)
com bi_seXD(i) = %stderrs(3)
com bi_tstatXD(i) = %tstats(3)
*
* XL (lag) statistics
*
com bi_betaXL(i) = %beta(4)
com bi_seXL(i) = %stderrs(4)
com bi_tstatXL(i) = %tstats(4)
*
* Counter for Errors (how many models broke the ECM bound of -1)
*
if bi_betaECM(i).lt.-1 ; comp bi_error = bi_error + 1
*
* Counter for ECMs (w/ MacKinnon CVs)
*
if bi_tstatECM(i) < -3.27.AND.bi_betaECM(i).gt.-1 ; comp mv_ecm5 = mv_ecm5 + 1
if bi_tstatECM(i).lt.-3.27.AND.bi_betaECM(i).gt.-1.AND.(bi_tstatXD(i).lt.-1.96.OR $
.bi_tstatXD(i).gt.1.96) ; comp mv_ecmXD = mv_ecmXD + 1
if bi_tstatECM(i).lt.-3.27.AND.bi_betaECM(i).gt.-1.AND.(bi_tstatXL(i).lt.-1.96.OR $
.bi_tstatXL(i).gt.1.96) ; comp mv_ecmXL = mv_ecmXL + 1
*
```

```
* Counter for ECMs
*
if bi_tstatECM(i) < -1.645.AND.bi_betaECM(i).gt.-1.5 ; comp bi_ecm5 = bi_ecm5 + 1
if bi_tstatECM(i).lt.-1.645.AND.bi_betaECM(i).gt.-1.5.AND.(bi_tstatXD(i).lt.-1.96.OR $
.bi_tstatXD(i).gt.1.96) ; comp bi_ecmXD = bi_ecmXD + 1
if bi_tstatECM(i).lt.-1.645.AND.bi_betaECM(i).gt.-1.5.AND.(bi_tstatXL(i).lt.-1.96.OR $
.bi_tstatXL(i).gt.1.96) ; comp bi_ecmXL = bi_ecmXL + 1
*
* Counter for X variables
*
if bi_tstatXD(i).lt.-1.96.OR.bi_tstatXD(i).gt.1.96 ; comp bi_XDsig = bi_XDsig + 1
if bi_tstatXL(i).lt.-1.96.OR.bi_tstatXL(i).gt.1.96 ; comp bi_XLsig = bi_XLsig + 1
*
end do i
infobox(action=remove)
*
*
** Print Output **
*
dis '**************** Output of FI Models **************** '
dis #
dis ' Number of Significant ECMs   ' #################### bi_ECM5
dis #
dis ' Number of Significant ECMs (MacKinnon) ' #################### mv_ECM5
dis #
dis 'Errors - ECM coefficients less than 1' bi_error
dis '****************************************************** '
*
table / bi_betaECM bi_betaECM2
```

I.1.3 Bivariate Bounded Data - Stata

```
cd "  "

 global nobs = 150
 gen id = _n
 global nmc = 10000
 set seed 5000
 set obs $nobs

 tsset id

 * Set the parameter values
 scalar ecmsig = -1.645
 scalar ecmMCVm1 = -3.27
 scalar up = 1.96
 scalar lp = -1.96
 scalar alpha = .05

 * Set values for bounds
 scalar a = 1.5
 scalar b = 1.5
 scalar tau = 59
 scalar k = 16.5

 * Generating starting values for DV
 gen dv1 = (59-50)*runiform()+50
 *gen dv1 = (99-1)*runiform()+1
 gen iv1 = 0

* generating errors
 gen e = .
 *gen e2 = .
 *gen e3 = .
 gen u = .

 tempname sim
```

```
 postfile `sim' m1a1 m1sea1 m1ta1 m1b0 m1se0 m1tb0 m1b1 m1se1 m1tb1  m1asig m1asigMCV ///
m1dxsig m1xlsig m1dxecm m1dxecmMCV m1lxecm m1lxecmMCV using MCMC_bounded_1IV, replace

 quietly {
 forvalues i = 1/$nmc {
 replace e = rnormal()
 *replace e2 = rnormal(0,2)
 *replace e3 = rnormal(0,3)
 replace u = rnormal()

 replace dv1 = l.dv1 + exp(-k)*(exp((-a)*(l.dv1 - tau)) - (exp((b)*(l.dv1 - tau)))) + e3 in 2/$nobs
 replace iv1 = l.iv1 + u in 2/$nobs

 * Model 1 *
 reg d.dv1 l.dv1 d.iv1 l.iv1

 * coefficient values
 scalar m1a1 = _b[l.dv1]
 scalar m1b0 = _b[d.iv1]
 scalar m1b1 = _b[l.iv1]

 * standard errors
 scalar m1sea1 = _se[l.dv1]
 scalar m1se0 = _se[d.iv1]
 scalar m1se1 = _se[l.iv1]

 * t-statistics
 scalar m1ta1 = m1a1/m1sea1
 scalar m1tb0 = m1b0/m1se0
 scalar m1tb1 = m1b1/m1se1

  * Significance
 scalar m1asig = m1ta1<ecmsig
 scalar m1asigMCV = m1ta1<=ecmMCVm1
 scalar m1dxsig = (m1tb0>up | m1tb0<lp)
 scalar m1xlsig = (m1tb1>up | m1tb1<lp)
 scalar m1dxecm = (m1ta1<ecmsig & (m1tb0>up | m1tb0<lp))
 scalar m1dxecmMCV = (m1ta1<ecmMCVm1 & (m1tb0>up | m1tb0<lp))
 scalar m1lxecm = (m1ta1<ecmsig & (m1tb1>up | m1tb1<lp))
 scalar m1lxecmMCV = (m1ta1<ecmMCVm1 & (m1tb1>up | m1tb1<lp))

 post `sim' (m1a1) (m1sea1) (m1ta1) (m1b0) (m1se0) (m1tb0) (m1b1) (m1se1) (m1tb1) (m1asig) ///
(m1asigMCV) (m1dxsig) (m1xlsig) (m1dxecm) (m1dxecmMCV) (m1lxecm) (m1lxecmMCV)

 }
 }
 postclose `sim'

 use MCMC_bounded_1IV, clear

 sum m1asig m1asigMCV m1a1 m1dxsig m1xlsig m1dxecm m1dxecmMCV m1lxecm m1lxecmMCV if m1a1 >-1
```

I.1.4 Multivariate (2IVs) Bounded Data - RATS

```
*****************************************************
***** Simulation of Bounded Multivariate I(1) Model *****
*****************************************************
* 2 x's that are I(1)
*
* MacKinnon Critical Values
* 60=-3.565; 100=-3.54; 150=-3.528
*
seed 5000
all 600
*
set a = b = 1.5
set k = 16.5
set tau = 59
```

```
*
* Values for simulations
*
comp draws = 10000
infobox(action=define, progress, lower=1, upper=draws) 'Simulations Completed'
*
* Model Counters
*
comp m1rw_ecm5  = 0
comp m1rw_ecmXD = 0
comp m1rw_ecmXL = 0
comp m1rw_ecmX2D = 0
comp m1rw_ecmX2L = 0
comp m1rw_ecmORXD = 0
comp m1rw_ecmORXL = 0
comp m1rw_ecmBOTHX = 0
comp m1rw_ecmBOTHX2 = 0
comp m1rw_ecmBOTHXL = 0
comp m1rw_ecmBOTHXD = 0
comp m1rw_XDsig = 0
comp m1rw_XLsig = 0
comp m1rw_X2Dsig = 0
comp m1rw_X2Lsig = 0
comp m1rw_bothXDsig = 0
comp m1rw_bothXLsig = 0
comp m1rw_ORXDsig = 0
comp m1rw_ORXLsig = 0
comp m1mv_ecm5  = 0
comp m1mv_ecmXD = 0
comp m1mv_ecmXL = 0
comp m1mv_ecmX2D = 0
comp m1mv_ecmX2L = 0
comp m1mv_ecmORXD = 0
comp m1mv_ecmORXL = 0
comp m1mv_ecmBOTHX = 0
comp m1mv_ecmBOTHX2 = 0
comp m1mv_ecmBOTHXL = 0
comp m1mv_ecmBOTHXD = 0
comp m1rw_error = 0

*
* Regression Output
*
set m1rw_betaECM 1 draws = 0
set m1rw_tstatECM 1 draws = 0
set m1rw_seECM 1 draws = 0
set m1rw_betaXD 1 draws = 0
set m1rw_tstatXD 1 draws = 0
set m1rw_seXD 1 draws = 0
set m1rw_betaXL 1 draws = 0
set m1rw_tstatXL 1 draws = 0
set m1rw_seXL 1 draws = 0
set m1rw_betaX2D 1 draws = 0
set m1rw_tstatX2D 1 draws = 0
set m1rw_seX2D 1 draws = 0
set m1rw_betaX2L 1 draws = 0
set m1rw_tstatX2L 1 draws = 0
set m1rw_seX2L 1 draws = 0
set m1rw_betaECM2 1 draws = 0
set m1rw_tstatECM2 1 draws = 0
set m1rw_seECM2 1 draws = 0
*
* Begin Loop
*
do i = 1,draws
infobox(current=i)
*
* Random Draw (if using tighter bounds set random draw at (50,59)
```

```
*
set y = %uniform(50,59)
*set y = %uniform(1,99)
set x = 0
set x2 = 0
set e = %ran(1)
*
* Bounded Random Walk and Differencing
*
set y 2 * = y{1} + exp(-k)*(exp((-a)*(y{1} - tau)) - (exp((b)*(y{1} - tau)))) + %ran(1)
diff y 2 * dy
*
set x 2 * = x{1} + %ran(1)
diff x 2 * dx
*
set x2 2 * = x2{1} + %ran(1)
diff x2 2 * dx2
*
* Multivariate Regression Model
*
lin(noprint) dy ; # constant y{1} dx x{1} dx2 x2{1}
*
* ECM statistics
*
com m1rw_betaECM(i) = %beta(2)
com m1rw_seECM(i) = %stderrs(2)
com m1rw_tstatECM(i) = %tstats(2)
*
* Computing ECM stats excluding any models that exceed ECM bounds
*
if m1rw_betaECM(i).gt.-1 ; com m1rw_betaECM2(i) = %beta(2)
if m1rw_betaECM(i).gt.-1 ; com m1rw_seECM2(i) = %stderrs(2)
if m1rw_betaECM(i).gt.-1 ; com m1rw_tstatECM2(i) = %tstats(2)
*
* Xd (diff) statistics
*
com m1rw_betaXD(i) = %beta(3)
com m1rw_seXD(i) = %stderrs(3)
com m1rw_tstatXD(i) = %tstats(3)
*
* XL (lag) statistics
*
com m1rw_betaXL(i) = %beta(4)
com m1rw_seXL(i) = %stderrs(4)
com m1rw_tstatXL(i) = %tstats(4)
*
* X2d (diff) statistics
*
com m1rw_betaX2D(i) = %beta(5)
com m1rw_seX2D(i) = %stderrs(5)
com m1rw_tstatX2D(i) = %tstats(5)
*
* X2L (lag) statistics
*
com m1rw_betaX2L(i) = %beta(6)
com m1rw_seX2L(i) = %stderrs(6)
com m1rw_tstatX2L(i) = %tstats(6)
*
* Counter for Errors
*
if m1rw_betaECM(i).lt.-1 ; comp m1rw_error = m1rw_error + 1
*
* Counter for ECMs (MacKinnon Critical Values)
*
if m1rw_tstatECM(i) < -3.565.AND.m1rw_betaECM(i).gt.-1 ; comp m1mv_ecm5 = m1mv_ecm5 + 1
if m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1.AND. $(m1rw_tstatXD(i).lt.-1.96 $
.OR.m1rw_tstatXD(i).gt.1.96) ; comp m1mv_ecmXD = m1mv_ecmXD + 1
if m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1.AND. $(m1rw_tstatX2D(i).lt.-1.96 $
```

```
.OR.m1rw_tstatX2D(i).gt.1.96) ; comp m1mv_ecmX2D = m1mv_ecmX2D + 1
if m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1.AND. $(m1rw_tstatXD(i).lt.-1.96 $
.OR.m1rw_tstatXD(i).gt.1.96).OR.m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1. $
AND.(m1rw_tstatX2D(i).lt.-1.96.OR.m1rw_tstatX2D(i).gt.1.96) ; comp m1mv_ecmORXD  $
= m1mv_ecmORXD + 1
if m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatXL(i).lt.-1.96.OR. $
m1rw_tstatXL(i).gt.1.96) ; comp m1mv_ecmXL = m1mv_ecmXL + 1
if m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatX2L(i).lt.-1.96 $
.OR.m1rw_tstatX2L(i).gt.1.96); comp m1mv_ecmX2L = m1mv_ecmX2L + 1
if m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatXL(i).lt.-1.96. $
OR.m1rw_tstatXL(i).gt.1.96).OR.m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1. $
AND.(m1rw_tstatX2L(i).lt.-1.96.OR.m1rw_tstatX2L(i).gt.1.96) $
 ; comp m1mv_ecmORXL = m1mv_ecmORXL + 1
if (m1rw_tstatXD(i).lt.-1.96.OR.m1rw_tstatXD(i).gt.1.96).AND.(m1rw_tstatXL(i).lt.-1.96. $
OR.m1rw_tstatXL(i).gt.1.96).AND.m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1 $
; comp m1mv_ecmBOTHX = m1mv_ecmBOTHX + 1
if (m1rw_tstatX2D(i).lt.-1.96.OR.m1rw_tstatX2D(i).gt.1.96).AND.(m1rw_tstatX2L(i).lt.-1.96 $
.OR.m1rw_tstatX2L(i).gt.1.96).AND.m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1 $
; comp m1mv_ecmBOTHX2 = m1mv_ecmBOTHX2 + 1
if (m1rw_tstatXD(i).lt.-1.96.OR.m1rw_tstatXD(i).gt.1.96).AND.(m1rw_tstatX2D(i).lt.-1.96. $
OR.m1rw_tstatX2D(i).gt.1.96).AND.m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1 $
; comp m1mv_ecmBOTHXD = m1mv_ecmBOTHXD + 1
if (m1rw_tstatXL(i).lt.-1.96.OR.m1rw_tstatXL(i).gt.1.96).AND.(m1rw_tstatX2L(i).lt.-1.96.OR $
.m1rw_tstatX2L(i).gt.1.96).AND.m1rw_tstatECM(i).lt.-3.565.AND.m1rw_betaECM(i).gt.-1 ; $
comp m1mv_ecmBOTHXL = m1mv_ecmBOTHXL + 1
*
* Counter for ECMs
*
if m1rw_tstatECM(i) < -1.645.AND.m1rw_betaECM(i).gt.-1 ; comp m1rw_ecm5 = m1rw_ecm5 + 1
if m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatXD(i).lt.-1.96.OR. $
m1rw_tstatXD(i).gt.1.96) ; comp m1rw_ecmXD = m1rw_ecmXD + 1
if m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatX2D(i).lt.-1.96.OR. $
m1rw_tstatX2D(i).gt.1.96) ; comp m1rw_ecmX2D = m1rw_ecmX2D + 1
if m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatXD(i).lt.-1.96.OR $
.m1rw_tstatXD(i).gt.1.96).OR.m1rw_tstatECM(i).lt.-1.645.AND.(m1rw_tstatX2D(i).lt.-1.96. $
OR.m1rw_tstatX2D(i).gt.1.96) ; comp m1rw_ecmORXD = m1rw_ecmORXD + 1
if m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatXL(i).lt.-1.96.OR. $
m1rw_tstatXL(i).gt.1.96) ; comp m1rw_ecmXL = m1rw_ecmXL + 1
if m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatX2L(i).lt.-1.96.OR. $
m1rw_tstatX2L(i).gt.1.96) ; comp m1rw_ecmX2L = m1rw_ecmX2L + 1
if m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1.AND.(m1rw_tstatXL(i).lt.-1.96.OR $
.m1rw_tstatXL(i).gt.1.96).OR.m1rw_tstatECM(i).lt.-1.645.AND.(m1rw_tstatX2L(i).lt.-1.96. $
OR.m1rw_tstatX2L(i).gt.1.96) ; comp m1rw_ecmORXL = m1rw_ecmORXL + 1
if (m1rw_tstatXD(i).lt.-1.96.OR.m1rw_tstatXD(i).gt.1.96).AND.(m1rw_tstatXL(i).lt.-1.96.OR. $
m1rw_tstatXL(i).gt.1.96).AND.m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1 ; $
comp m1rw_ecmBOTHX = m1rw_ecmBOTHX + 1
if (m1rw_tstatX2D(i).lt.-1.96.OR.m1rw_tstatX2D(i).gt.1.96).AND.(m1rw_tstatX2L(i).lt.-1.96.
OR.m1rw_tstatX2L(i).gt.1.96).AND.m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1 $
; comp m1rw_ecmBOTHX2 = m1rw_ecmBOTHX2 + 1
if (m1rw_tstatXD(i).lt.-1.96.OR.m1rw_tstatXD(i).gt.1.96).AND.(m1rw_tstatX2D(i).lt.-1.96.OR $
.m1rw_tstatX2D(i).gt.1.96).AND.m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1 ; $
comp m1rw_ecmBOTHXD = m1rw_ecmBOTHXD + 1
if (m1rw_tstatXL(i).lt.-1.96.OR.m1rw_tstatXL(i).gt.1.96).AND.(m1rw_tstatX2L(i).lt.-1.96. $
OR.m1rw_tstatX2L(i).gt.1.96).AND.m1rw_tstatECM(i).lt.-1.645.AND.m1rw_betaECM(i).gt.-1 $
; comp m1rw_ecmBOTHXL = m1rw_ecmBOTHXL + 1

*
* Counter for X variables
*
if m1rw_tstatXD(i).lt.-1.96.OR.m1rw_tstatXD(i).gt.1.96 ; comp m1rw_XDsig = m1rw_XDsig + 1
if m1rw_tstatXL(i).lt.-1.96.OR.m1rw_tstatXL(i).gt.1.96 ; comp m1rw_XLsig = m1rw_XLsig + 1
if m1rw_tstatX2D(i).lt.-1.96.OR.m1rw_tstatX2D(i).gt.1.96 ; comp m1rw_X2Dsig = m1rw_X2Dsig + 1
if m1rw_tstatX2L(i).lt.-1.96.OR.m1rw_tstatX2L(i).gt.1.96 ; comp m1rw_X2Lsig = m1rw_X2Lsig + 1
if (m1rw_tstatXD(i).lt.-1.96.OR.m1rw_tstatXD(i).gt.1.96).OR.(m1rw_tstatX2D(i).lt.-1.96.OR $
.m1rw_tstatX2D(i).gt.1.96) ; comp m1rw_ORXDsig = m1rw_ORXDsig + 1
if (m1rw_tstatXD(i).lt.-1.96.OR.m1rw_tstatXD(i).gt.1.96).AND.(m1rw_tstatX2D(i).lt.-1.96.OR. $
m1rw_tstatX2D(i).gt.1.96) ; comp m1rw_bothXDsig = m1rw_bothXDsig + 1
if (m1rw_tstatXL(i).lt.-1.96.OR.m1rw_tstatXL(i).gt.1.96).OR.(m1rw_tstatX2L(i).lt.-1.96.OR. $
```

```
m1rw_tstatX2L(i).gt.1.96) ; comp m1rw_ORXLsig = m1rw_ORXLsig + 1
if (m1rw_tstatXL(i).lt.-1.96.OR.m1rw_tstatXL(i).gt.1.96).AND.(m1rw_tstatX2L(i).lt.-1.96.OR. $
m1rw_tstatX2L(i).gt.1.96) ; comp m1rw_bothXLsig = m1rw_bothXLsig + 1
*

end do i
infobox(action=remove)
*
*
** Print Output **
*
dis '**************** Output of FI Models **************** '
dis #
dis ' Number of Significant ECMs   ' #################### m1rw_ECM5
dis #
dis ' Number of Significant ECMs  (MacKinnon) ' #################### m1mv_ECM5
dis #
dis 'Errors - ECM coefficients less than 1.5' m1rw_error
dis '***************************************************** '
*
table / m1rw_betaECM m1rw_betaECM2
```

I.1.5 Multivariate (2IVs) Bounded Data - Stata

```
cd "  "

 global nobs = 60
 gen id = _n
 global nmc = 10000
 set seed 5000
 set obs $nobs

 tsset id

 * Set the values of the parameters
 scalar ecmsig = -1.645
 scalar ecmMCVm1 = -3.565
 scalar up = 1.96
 scalar lp = -1.96
 scalar alpha = .05

 * Set values for Dem bounds
 scalar a = 1.5
 scalar b = 1.5
 scalar tau = 59
 scalar k = 16.5

 * Generating starting values for DV
 gen dv1 = (59-50)*runiform()+50
 *gen dv1 = (99-1)*runiform()+1
 gen iv1 = 0
 gen iv2 = 0

* generating errors
 gen e = .
 *gen e2 = .
 *gen e3 = .
 gen u = .
 gen v = .

 tempname sim

 postfile `sim' m1a1 m1sea1 m1ta1 m1b0 m1se0 m1tb0 m1b1 m1se1 m1tb1 m1b2 m1se2 m1tb2 ///
m1b3 m1se3 m1tb3 m1asig m1asigMCV m1dxsig m1xlsig m1dxecm m1dxecmMCV m1lxecm ///
m1lxecmMCV using MCMC_bounded_2IV, replace

 quietly {
```

```
forvalues i = 1/$nmc {
replace e = rnormal()
*replace e2 = rnormal(0,2)
*replace e3 = rnormal(0,3)
replace u = rnormal()
replace v = rnormal()

replace dv1 = l.dv1 + exp(-k)*(exp((-a)*(l.dv1 - tau)) - (exp((b)*(l.dv1 - tau)))) + e in 2/$nobs
replace iv1 = l.iv1 + u in 2/$nobs
replace iv2 = l.iv2 + v in 2/$nobs

* Model 1 *
reg d.dv1 l.dv1 d.iv1 l.iv1 d.iv2 l.iv2

* Model 1 coefficient values
scalar m1a1 = _b[l.dv1]
scalar m1b0 = _b[d.iv1]
scalar m1b1 = _b[l.iv1]
scalar m1b2 = _b[d.iv2]
scalar m1b3 = _b[l.iv2]

* Model 1 standard errors
scalar m1sea1 = _se[l.dv1]
scalar m1se0 = _se[d.iv1]
scalar m1se1 = _se[l.iv1]
scalar m1se2 = _se[d.iv2]
scalar m1se3 = _se[l.iv2]

* Model 1 t-statistics
scalar m1ta1 = m1a1/m1sea1
scalar m1tb0 = m1b0/m1se0
scalar m1tb1 = m1b1/m1se1
scalar m1tb2 = m1b2/m1se2
scalar m1tb3 = m1b3/m1se3

 * Calculating significance totals (Model 1)
scalar m1asig = m1ta1<ecmsig
scalar m1asigMCV = m1ta1<=ecmMCVm1
scalar m1dxsig = (m1tb0>up | m1tb0<lp) | (m1tb2>up | m1tb2<lp)
scalar m1xlsig = (m1tb1>up | m1tb1<lp)  | (m1tb3>up | m1tb3<lp)
scalar m1dxecm = (m1ta1<ecmsig & (m1tb0>up | m1tb0<lp)) | (m1ta1<ecmsig & ///
(m1tb2>up | m1tb2<lp))
scalar m1dxecmMCV = (m1ta1<ecmMCVm1 & (m1tb0>up | m1tb0<lp)) | (m1ta1<ecmMCVm1 & ///
(m1tb2>up | m1tb2<lp))
scalar m1lxecm = (m1ta1<ecmsig & (m1tb1>up | m1tb1<lp)) | (m1ta1<ecmsig & ///
(m1tb3>up | m1tb3<lp))
scalar m1lxecmMCV = (m1ta1<ecmMCVm1 & (m1tb1>up | m1tb1<lp)) | (m1ta1<ecmMCVm1 & ///
(m1tb3>up | m1tb3<lp))

post ‘sim’ (m1a1) (m1sea1) (m1ta1) (m1b0) (m1se0) (m1tb0) (m1b1) (m1se1) (m1tb1) (m1b2) ///
(m1se2) (m1tb2) (m1b3) (m1se3) (m1tb3) (m1asig) (m1asigMCV) (m1dxsig) (m1xlsig) ///
(m1dxecm) (m1dxecmMCV) (m1lxecm) (m1lxecmMCV)

}
}
postclose ‘sim’

use MCMC_bounded_2IV, clear

sum m1asig m1asigMCV m1a1 m1dxsig m1xlsig m1dxecm m1dxecmMCV m1lxecm m1lxecmMCV if m1a1 >-1
```

I.2 Casillas, Enns, Wohlfarth

I.2.1 CEW - MC with $I(1)$ IVs

Code for Monte Carlo simulations with $I(1)$ IVs. For $I(0)$, change the generated IVs to white noise.

```
global nobs = 46
global nmc = 10000
set seed 5000
set obs $nobs
tsset term

* Set significance parameter values
scalar ecmsig = -1.645
scalar ecmMCVm1 = -3.838
scalar ecmMCVm2 = -3.838
scalar ecmMCVm3 = -3.838
scalar up = 1.96
scalar lp = -1.96
scalar alpha = .05

* Generating random starting values for DV
gen iv1 = 0
gen iv2 = 0
gen iv3 = 0

* generating errors
gen e = .
gen u = .
gen v = .

tempname sim

postfile `sim'   m1a1 m1sea1 m1ta1 m1b0 m1se0 m1tb0 m1b1 m1se1 m1tb1 m1b2 m1se2 m1tb2 m1b3 m1se3 m1tb3 ///
 m1b4 m1se4 m1tb4 m1b5 m1se5 m1tb5 m1asig m1asigMCV m1dxsig m1xlsig m1dxecm m1dxecmMCV m1lxecm ///
 m1lxecmMCV ///
 m2a1 m2sea1 m2ta1 m2b0 m2se0 m2tb0 m2b1 m2se1 m2tb1 m2b2 m2se2 m2tb2 m2b3 m2se3 m2tb3 m2b4 ///
 m2se4 m2tb4 m2b5 m2se5 m2tb5 m2asig m2asigMCV m2dxsig m2xlsig m2dxecm m2dxecmMCV ///
 m2lxecm m2lxecmMCV ///
    m3a1 m3sea1 m3ta1 m3b0 m3se0 m3tb0 m3b1 m3se1 m3tb1 m3b2 m3se2 m3tb2 m3b3 m3se3 m3tb3 m3b4 ///
    m3se4 m3tb4 m3b5 m3se5 m3tb5 m3asig m3asigMCV m3dxsig m3xlsig m3dxecm m3dxecmMCV m3lxecm ///
    m3lxecmMCV   using casillas_results_mackinnon_m1-m3, replace

quietly {
forvalues i = 1/$nmc {
replace e = rnormal()
replace u = rnormal()
replace v = rnormal()

replace iv1 = l.iv1 + e in 2/$nobs
replace iv2 = l.iv2 + u in 2/$nobs
replace iv3 = l.iv3 + v in 2/$nobs

* Model 1 *
ivregress 2sls d.all_rev l.all_rev d.iv1 l.iv1 d.iv2 l.iv2 (d.iv3 l.iv3 = d.perchcpi d.unem ///
 d.policylib d.def_budg d.homicide d.inequality l.perchcpi l.unem l.policylib ///
 l.def_budg l.homicide l.inequality)

* Model 1 coefficient values
scalar m1a1 = _b[l.all_rev]
scalar m1b0 = _b[d.iv1]
scalar m1b1 = _b[l.iv1]
scalar m1b2 = _b[d.iv2]
scalar m1b3 = _b[l.iv2]
scalar m1b4 = _b[d.iv3]
```

```
scalar m1b5 = _b[l.iv3]
* Model 1 standard errors
scalar m1sea1 = _se[l.all_rev]
scalar m1se0 = _se[d.iv1]
scalar m1se1 = _se[l.iv1]
scalar m1se2 = _se[d.iv2]
scalar m1se3 = _se[l.iv2]
scalar m1se4 = _se[d.iv3]
scalar m1se5 = _se[l.iv3]
* Model 1 t-statistics
scalar m1ta1 = m1a1/m1sea1
scalar m1tb0 = m1b0/m1se0
scalar m1tb1 = m1b1/m1se1
scalar m1tb2 = m1b2/m1se2
scalar m1tb3 = m1b3/m1se3
scalar m1tb4 = m1b4/m1se4
scalar m1tb5 = m1b5/m1se5

* Model 2 *
ivregress 2sls d.sal_rev l.sal_rev d.iv1 l.iv1 d.iv2 l.iv2 (d.iv3 l.iv3 = d.perchcpi d.unem ///
 d.policylib d.def_budg d.homicide d.inequality l.perchcpi l.unem l.policylib l.def_budg ///
  l.homicide l.inequality)

* Model 2 coefficient values
scalar m2a1 = _b[l.sal_rev]
scalar m2b0 = _b[d.iv1]
scalar m2b1 = _b[l.iv1]
scalar m2b2 = _b[d.iv2]
scalar m2b3 = _b[l.iv2]
scalar m2b4 = _b[d.iv3]
scalar m2b5 = _b[l.iv3]
* Model 2 standard errors
scalar m2sea1 = _se[l.sal_rev]
scalar m2se0 = _se[d.iv1]
scalar m2se1 = _se[l.iv1]
scalar m2se2 = _se[d.iv2]
scalar m2se3 = _se[l.iv2]
scalar m2se4 = _se[d.iv3]
scalar m2se5 = _se[l.iv3]
* Model 2 t-statistics
scalar m2ta1 = m2a1/m2sea1
scalar m2tb0 = m2b0/m2se0
scalar m2tb1 = m2b1/m2se1
scalar m2tb2 = m2b2/m2se2
scalar m2tb3 = m2b3/m2se3
scalar m2tb4 = m2b4/m2se4
scalar m2tb5 = m2b5/m2se5

* Model 3 *
ivregress 2sls d.nosal_rev l.nosal_rev d.iv1 l.iv1 d.iv2 l.iv2 (d.iv3 l.iv3 = d.perchcpi d.unem ///
d.policylib d.def_budg d.homicide d.inequalityl.perchcpi l.unem l.policylib l.def_budg ///
l.homicide l.inequality)

* Model 1 coefficient values
scalar m3a1 = _b[l.nosal_rev]
scalar m3b0 = _b[d.iv1]
scalar m3b1 = _b[l.iv1]
scalar m3b2 = _b[d.iv2]
scalar m3b3 = _b[l.iv2]
scalar m3b4 = _b[d.iv3]
scalar m3b5 = _b[l.iv3]
* Model 1 standard errors
scalar m3sea1 = _se[l.nosal_rev]
scalar m3se0 = _se[d.iv1]
scalar m3se1 = _se[l.iv1]
scalar m3se2 = _se[d.iv2]
scalar m3se3 = _se[l.iv2]
scalar m3se4 = _se[d.iv3]
```

```
scalar m3se5 = _se[l.iv3]
* Model 1 t-statistics
scalar m3ta1 = m3a1/m3sea1
scalar m3tb0 = m3b0/m3se0
scalar m3tb1 = m3b1/m3se1
scalar m3tb2 = m3b2/m3se2
scalar m3tb3 = m3b3/m3se3
scalar m3tb4 = m3b4/m3se4
scalar m3tb5 = m3b5/m3se5

* Calculating significance totals (Model 1)
scalar m1asig = m1ta1<ecmsig
scalar m1asigMCV = m1ta1<ecmMCVm1
scalar m1dxsig = (m1tb0>up | m1tb0<lp) | (m1tb2>up | m1tb2<lp) | (m1tb4>up | m1tb4<lp)
scalar m1xlsig = (m1tb1>up | m1tb1<lp) | (m1tb3>up | m1tb3<lp) | (m1tb5>up | m1tb5<lp)
scalar m1dxecm = (m1ta1<ecmsig & (m1tb0>up | m1tb0<lp)) | (m1ta1<ecmsig & (m1tb2>up ///
| m1tb2<lp)) | (m1ta1<ecmsig & (m1tb4>up | m1tb4<lp))
scalar m1dxecmMCV = (m1ta1<ecmMCVm1 & (m1tb0>up | m1tb0<lp)) ///
| (m1ta1<ecmMCVm1 & (m1tb2>up | m1tb2<lp))| (m1ta1<ecmMCVm1 & (m1tb4>up | m1tb4<lp))
scalar m1lxecm = (m1ta1<ecmsig & (m1tb1>up | m1tb1<lp)) | (m1ta1<ecmsig & ///
(m1tb3>up | m1tb3<lp)) | (m1ta1<ecmsig & (m1tb5>up | m1tb5<lp))
scalar m1lxecmMCV = (m1ta1<ecmMCVm1 & (m1tb1>up | m1tb1<lp)) ///
| (m1ta1<ecmMCVm1 & (m1tb3>up | m1tb3<lp)) | (m1ta1<ecmMCVm1 & (m1tb5>up | m1tb5<lp))

* Calculating significance totals (Model 2)
scalar m2asig = m2ta1<ecmsig
scalar m2asigMCV = m2ta1<ecmMCVm2
scalar m2dxsig = (m2tb0>up | m2tb0<lp) | (m2tb2>up | m2tb2<lp) | (m2tb4>up | m2tb4<lp)
scalar m2xlsig = (m2tb1>up | m2tb1<lp) | (m2tb3>up | m2tb3<lp) | (m2tb5>up | m2tb5<lp)
scalar m2dxecm = (m2ta1<ecmsig & (m2tb0>up | m2tb0<lp)) | (m2ta1<ecmsig & ///
  (m2tb2>up | m2tb2<lp)) | (m2ta1<ecmsig & (m2tb4>up | m2tb4<lp))
scalar m2dxecmMCV = (m2ta1<ecmMCVm2 & (m2tb0>up | m2tb0<lp)) | ///
(m2ta1<ecmMCVm2 & (m2tb2>up | m2tb2<lp)) | (m2ta1<ecmMCVm2 & (m2tb4>up | m2tb4<lp))
scalar m2lxecm = (m2ta1<ecmsig & (m2tb1>up | m2tb1<lp)) | (m2ta1<ecmsig & ///
(m2tb3>up | m2tb3<lp)) | (m2ta1<ecmsig & (m2tb5>up | m2tb5<lp))
scalar m2lxecmMCV = (m2ta1<ecmMCVm2 & (m2tb1>up | m2tb1<lp)) | ///
(m2ta1<ecmMCVm2 & (m2tb3>up | m2tb3<lp)) | (m2ta1<ecmMCVm2 & (m2tb5>up | m2tb5<lp))

* Calculating significance totals (Model 3)
scalar m3asig = m3ta1<ecmsig
scalar m3asigMCV = m3ta1<ecmMCVm3
scalar m3dxsig = (m3tb0>up | m3tb0<lp) | (m3tb2>up | m3tb2<lp) | (m3tb4>up | m3tb4<lp)
scalar m3xlsig = (m3tb1>up | m3tb1<lp) | (m3tb3>up | m3tb3<lp) | (m3tb5>up | m3tb5<lp)
scalar m3dxecm = (m3ta1<ecmsig & (m3tb0>up | m3tb0<lp)) | (m3ta1<ecmsig & (m3tb2>up | ///
m3tb2<lp)) | (m3ta1<ecmsig & (m3tb4>up | m3tb4<lp))
scalar m3dxecmMCV = (m3ta1<ecmMCVm3 & (m3tb0>up | m3tb0<lp)) | (m3ta1<ecmMCVm3 &///
 (m3tb2>up | m3tb2<lp)) | (m3ta1<ecmMCVm3 & (m3tb4>up | m3tb4<lp))
scalar m3lxecm = (m3ta1<ecmsig & (m3tb1>up | m3tb1<lp)) | (m3ta1<ecmsig & ///
 (m3tb3>up | m3tb3<lp)) | (m3ta1<ecmsig & (m3tb5>up | m3tb5<lp))
scalar m3lxecmMCV = (m3ta1<ecmMCVm3 & (m3tb1>up | m3tb1<lp)) | ///
(m3ta1<ecmMCVm3 & (m3tb3>up | m3tb3<lp)) | (m3ta1<ecmMCVm3 & (m3tb5>up | m3tb5<lp))

post 'sim' (m1a1) (m1sea1) (m1ta1) (m1b0) (m1se0) (m1tb0) (m1b1) (m1se1) (m1tb1) (m1b2) ///
(m1se2) (m1tb2) (m1b3) (m1se3) (m1tb3) (m1b4) (m1se4) (m1tb4) (m1b5) (m1se5) (m1tb5) ///
(m1asig) (m1asigMCV) (m1dxsig) (m1xlsig) (m1dxecm) (m1dxecmMCV) (m1lxecm) (m1lxecmMCV)  ///
     (m2a1) (m2sea1) (m2ta1) (m2b0) (m2se0) (m2tb0) (m2b1) (m2se1) (m2tb1) (m2b2) (m2se2) ///
 (m2tb2) (m2b3) (m2se3) (m2tb3) (m2b4) (m2se4) (m2tb4) (m2b5) (m2se5) (m2tb5) (m2asig) ///
 (m2asigMCV) (m2dxsig) (m2xlsig) (m2dxecm) (m2dxecmMCV) (m2lxecm) (m2lxecmMCV) ///
     (m3a1) (m3sea1) (m3ta1) (m3b0) (m3se0) (m3tb0) (m3b1) (m3se1) (m3tb1) (m3b2) (m3se2) ///
     (m3tb2) (m3b3) (m3se3) (m3tb3) (m3b4) (m3se4) (m3tb4) (m3b5) (m3se5) (m3tb5) (m3asig) ///
     (m3asigMCV) (m3dxsig) (m3xlsig)  (m3dxecm) (m3dxecmMCV) (m3lxecm) (m3lxecmMCV)
}
}
postclose 'sim'

use casillas_results_mackinnon_m1-m3, clear
```

I.2.2 CEW FECM - RATS

```
** Casillas, Enns, Wohlfarth -- Public Opinion and the Supreme Court **
calendar 1955 1 1
allocate 46
open data po_sc.xls
data(format=xls, org=columns) / term all sal nosal all_rev sal_rev nosal_rev $
  sc_med mq_med zsc_med zmq_med mood mood_ct unem perchcpi def_budg policylib $
  homicide inequality beef_miltons sharks tornadodeath
*
diff sal / sald
diff nosal / nosald
diff all_rev / all_revd
diff sal_rev / sal_revd
diff nosal_rev / nosal_revd
diff sc_med / sc_medd
diff mq_med / mq_medd
diff zsc_med / zsc_medd
diff zmq_med / zmq_medd
diff mood / moodd
diff mood_ct / mood_ctd
diff unem / unemd
diff perchcpi / perchcpid
diff def_budg / def_budgd
diff policylib / policylibd
diff homicide / homicided
diff inequality / inequalityd
diff beef_miltons / beefd
diff sharks / sharksd
diff tornadodeath / tornadod
*
************* Fractionally Differencing Variables
*
@rgse all_revd
diff(fract=-.37) all_revd / all_revdf
*
@rgse nosal_revd
diff(fract=-.35) nosal_revd / nosal_revdf
*
@rgse sal_revd
diff(fract=-.70) sal_revd / sal_revdf
*
@rgse moodd
diff(fract=.14) moodd / mooddf
*
@rgse zsc_medd
diff(fract=.15) zsc_medd / zsc_meddf
*
@rgse zmq_medd
diff(fract=.09) zmq_medd / zmq_meddf
*
***********************************************************************
************** Generating the Residuals (all-reviews)
*
linreg all_rev / ecm
# constant mood
*
linreg all_rev / ecm2
# constant zsc_med
*
************** Fractionally Differencing Residuals (all-reviews)
*
diff ecm / ecmd
diff ecm2 / ecm2d
*
@rgse ecmd
diff(fract=-.37) ecmd / ecmdf
*
```

```
@rgse ecm2d
diff(fract=-.67) ecm2d / ecm2df
*
************ Estimating FECM models (all_reviews)
*
linreg all_revdf / res1 ; # constant mooddf zsc_meddf zmq_meddf ecmdf{1}
*
linreg all_revdf / res1 ; # constant mooddf zsc_meddf zmq_meddf ecm2df{1}
*
************************************************************************
************* Generating the Residuals (non salient-reviews)
*
linreg nosal_rev / noecm
# constant mood
*
linreg nosal_rev / noecm2
# constant zsc_med
*
************* Fractionally Differencing Residuals (non salient-reviews)
*
diff noecm / noecmd
diff noecm2 / noecm2d
*
@rgse noecmd
diff(fract=-.26) noecmd / noecmdf
*
@rgse noecm2d
diff(fract=-.54) noecm2d / noecm2df
*
************* Estimating FECM Models (all_reviews)
*
linreg nosal_revdf / res1 ; # constant mooddf zsc_meddf zmq_meddf noecmdf{1}
*
linreg nosal_revdf / res1 ; # constant mooddf zsc_meddf zmq_meddf noecm2df{1}
*
************************************************************************
************* FI Model for (salient-reviews  all insignificant)
*
* linreg sal_revdf / res1 ; # constant mooddf zsc_meddf zmq_meddf/ secm
*
************************************************************************
************* Testing Nonsense Data for FECM
*
@rgse beefd
diff(fract=.27) beefd / beefdf

@rgse sharksd
diff(fract=-.38) sharksd / sharksdf

@rgse tornadod
diff(fract=-1) tornadod / tornadodf
*
************* FI Model
*
linreg all_revdf / res1 ; # constant beefdf sharksdf tornadodf
*
linreg nosal_revdf / res2 ; # constant beefdf sharksdf tornadodf
*
linreg sal_revdf / res3 ; # constant beefdf sharksdf tornadodf
```

I.3 Ura and Ellis

I.3.1 UE MC - Stata

```
cd " "
use " ", clear
 global nobs = 38
```

```
 global nmc = 10000
 set seed 5000
 set obs $nobs
 tsset year

 * Set the values of the parameters
 scalar ecmsig = -1.645
 scalar ecmMCV = -4.268
 scalar up = 1.96
 scalar lp = -1.96
 scalar alpha = .05

 * Generating random starting values for DV
 gen demy = 0
 gen repy = 0

* generating errors
 gen u =.
 gen e = .

 tempname sim

 postfile `sim' da1 dsea1 dta1 db0 dse0 dtb0 db1 dse1 dtb1 db2 dse2 dtb2 db3 dse3 dtb3 ///
db4 dse4 dtb4 db5 dse5 dtb5 db6 dse6 dtb6 db7 dse7 dtb7 db8 dse8 dtb8 db9 dse9 dtb9 ///
dasig dasigMCV ddxsig dxlsig ddxecm ddxecmMCV dlxecm dlxecmMCV ///
ra1 rsea1 rta1 rb0 rse0 rtb0 rb1 rse1 rtb1 rb2 rse2 rtb2 rb3 rse3 rtb3 rb4 rse4 rtb4 ///
 rb5 rse5 rtb5 rb6 rse6 rtb6 rb7 rse7 rtb7 rb8 rse8 rtb8 rb9 rse9 rtb9 rasig rasigMCV ///
  rdxsig rxlsig rdxecm rdxecmMCV rlxecm rlxecmMCV p1 rej1 p2 rej2 ddw rdw ///
using results_mackinnon, replace

 quietly {
 forvalues i = 1/$nmc {
 replace u = rnormal()
 replace e = rnormal()
 replace demy = l.demy + u in 2/$nobs
 replace repy = l.repy + e in 2/$nobs
 reg d.demy l.demy d.domestic10b l.domestic10b d.defense10b l.defense10b d.top1share ///
l.top1share d.inflation l.inflation d.unemployment l.unemployment
 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p1 = r(p)
 scalar rej1 = (p1[1,1]<alpha)
 estat dwatson
 scalar ddw = r(dw)
 est store dem
 reg d.repy l.repy d.domestic10b l.domestic10b d.defense10b l.defense10b d.top1share ///
l.top1share d.inflation l.inflation d.unemployment l.unemployment
 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p2 = r(p)
 scalar rej2 = (p2[1,1]<alpha)
 estat dwatson
 scalar rdw = r(dw)
 est store rep
 suest dem rep
 * Dem coefficient values
 scalar da1 = _b[dem_mean:l.demy]
 scalar db0 = _b[dem_mean:d.domestic10b]
 scalar db1 = _b[dem_mean:l.domestic10b]
 scalar db2 = _b[dem_mean:d.defense10b]
 scalar db3 = _b[dem_mean:l.defense10b]
 scalar db4 = _b[dem_mean:d.top1share]
 scalar db5 = _b[dem_mean:l.top1share]
 scalar db6 = _b[dem_mean:d.inflation]
 scalar db7 = _b[dem_mean:l.inflation]
 scalar db8 = _b[dem_mean:d.unemployment]
 scalar db9 = _b[dem_mean:l.unemployment]
 * Dem standard errors
```

```
 scalar dsea1 = _se[dem_mean:l.demy]
 scalar dse0 = _se[dem_mean:d.domestic10b]
 scalar dse1 = _se[dem_mean:l.domestic10b]
 scalar dse2 = _se[dem_mean:d.defense10b]
 scalar dse3 = _se[dem_mean:l.defense10b]
 scalar dse4 = _se[dem_mean:d.top1share]
 scalar dse5 = _se[dem_mean:l.top1share]
 scalar dse6 = _se[dem_mean:d.inflation]
 scalar dse7 = _se[dem_mean:l.inflation]
 scalar dse8 = _se[dem_mean:d.unemployment]
 scalar dse9 = _se[dem_mean:l.unemployment]
 * Dem t-statistics
 scalar dta1 = da1/dsea1
 scalar dtb0 = db0/dse0
 scalar dtb1 = db1/dse1
 scalar dtb2 = db2/dse2
 scalar dtb3 = db3/dse3
 scalar dtb4 = db4/dse4
 scalar dtb5 = db5/dse5
 scalar dtb6 = db6/dse6
 scalar dtb7 = db7/dse7
 scalar dtb8 = db8/dse8
 scalar dtb9 = db9/dse9
 * Rep Coefficient values
 scalar ra1 = _b[rep_mean:l.repy]
 scalar rb0 = _b[rep_mean:d.domestic10b]
 scalar rb1 = _b[rep_mean:l.domestic10b]
 scalar rb2 = _b[rep_mean:d.defense10b]
 scalar rb3 = _b[rep_mean:l.defense10b]
 scalar rb4 = _b[rep_mean:d.top1share]
 scalar rb5 = _b[rep_mean:l.top1share]
 scalar rb6 = _b[rep_mean:d.inflation]
 scalar rb7 = _b[rep_mean:l.inflation]
 scalar rb8 = _b[rep_mean:d.unemployment]
 scalar rb9 = _b[rep_mean:l.unemployment]
 * Rep standard errors
 scalar rsea1 = _se[rep_mean:l.repy]
 scalar rse0 = _se[rep_mean:d.domestic10b]
 scalar rse1 = _se[rep_mean:l.domestic10b]
 scalar rse2 = _se[rep_mean:d.defense10b]
 scalar rse3 = _se[rep_mean:l.defense10b]
 scalar rse4 = _se[rep_mean:d.top1share]
 scalar rse5 = _se[rep_mean:l.top1share]
 scalar rse6 = _se[rep_mean:d.inflation]
 scalar rse7 = _se[rep_mean:l.inflation]
 scalar rse8 = _se[rep_mean:d.unemployment]
 scalar rse9 = _se[rep_mean:l.unemployment]
 * Rep t-statistics
 scalar rta1 = ra1/rsea1
 scalar rtb0 = rb0/rse0
 scalar rtb1 = rb1/rse1
 scalar rtb2 = rb2/rse2
 scalar rtb3 = rb3/rse3
 scalar rtb4 = rb4/rse4
 scalar rtb5 = rb5/rse5
 scalar rtb6 = rb6/rse6
 scalar rtb7 = rb7/rse7
 scalar rtb8 = rb8/rse8
 scalar rtb9 = rb9/rse9
 * Calculating significance totals
 scalar dasig = dta1<ecmsig
 scalar dasigMCV = dta1<ecmMCV
 scalar rasig = rta1<ecmsig
 scalar rasigMCV = rta1<ecmMCV
 scalar ddxsig = (dtb0>up | dtb0<lp) | (dtb2>up | dtb2<lp) | (dtb4>up | dtb4<lp) ///
| (dtb6>up | dtb6<lp) | (dtb8>up | dtb8<lp)
 scalar rdxsig = (rtb0>up | rtb0<lp) | (rtb2>up | rtb2<lp) | (rtb4>up | rtb4<lp) ///
| (rtb6>up | rtb6<lp) | (rtb8>up | rtb8<lp)
```

```
 scalar dxlsig = (dtb1>up | dtb1<lp) | (dtb3>up | dtb3<lp) | (dtb5>up | dtb5<lp) ///
| (dtb7>up | dtb7<lp) | (dtb9>up | dtb9<lp)
 scalar rxlsig = (rtb1>up | rtb1<lp) | (rtb3>up | rtb3<lp) | (rtb5>up | rtb5<lp) ///
| (rtb7>up | rtb7<lp) | (rtb9>up | rtb9<lp)
 scalar ddxecm = (dta1<ecmsig & (dtb0>up | dtb0<lp)) | ///
(dta1<ecmsig & (dtb2>up | dtb2<lp)) | (dta1<ecmsig & (dtb4>up | dtb4<lp)) ///
| (dta1<ecmsig & (dtb6>up | dtb6<lp)) | (dta1<ecmsig & (dtb8>up | dtb8<lp))
 scalar ddxecmMCV = (dta1<ecmMCV & (dtb0>up | dtb0<lp)) ///
| (dta1<ecmMCV & (dtb2>up | dtb2<lp)) | (dta1<ecmMCV & (dtb4>up | dtb4<lp))///
 | (dta1<ecmMCV & (dtb6>up | dtb6<lp)) | (dta1<ecmMCV & (dtb8>up | dtb8<lp))
 scalar rdxecm = (rta1<ecmsig & (rtb0>up | rtb0<lp)) ///
| (rta1<ecmsig & (rtb2>up | rtb2<lp)) | (rta1<ecmsig & (rtb4>up | rtb4<lp)) ///
| (rta1<ecmsig & (rtb6>up | rtb6<lp)) | (rta1<ecmsig & (rtb8>up | rtb8<lp))
 scalar rdxecmMCV = (rta1<ecmMCV & (rtb0>up | rtb0<lp)) | (rta1<ecmMCV & ///
(rtb2>up | rtb2<lp)) | (rta1<ecmMCV & (rtb4>up | rtb4<lp)) ///
| (rta1<ecmMCV & (rtb6>up | rtb6<lp)) | (rta1<ecmMCV & (rtb8>up | rtb8<lp))
 scalar dlxecm = (dta1<ecmsig & (dtb1>up | dtb1<lp)) | (dta1<ecmsig & ///
(dtb3>up | dtb3<lp)) | (dta1<ecmsig & (dtb5>up | dtb5<lp)) | ///
(dta1<ecmsig & (dtb7>up | dtb7<lp)) | (dta1<ecmsig & (dtb9>up | dtb9<lp))
 scalar dlxecmMCV = (dta1<ecmMCV & (dtb1>up | dtb1<lp)) | (dta1<ecmMCV & ///
(dtb3>up | dtb3<lp)) | (dta1<ecmMCV & (dtb5>up | dtb5<lp)) | ///
(dta1<ecmMCV & (dtb7>up | dtb7<lp)) | (dta1<ecmMCV & (dtb9>up | dtb9<lp))
 scalar rlxecm = (rta1<ecmsig & (rtb1>up | rtb1<lp)) | (rta1<ecmsig & ///
(rtb3>up | rtb3<lp)) | (rta1<ecmsig & (rtb5>up | rtb5<lp)) | ///
(rta1<ecmsig & (rtb7>up | rtb7<lp)) | (rta1<ecmsig & (rtb9>up | rtb9<lp))
 scalar rlxecmMCV = (rta1<ecmMCV & (rtb1>up | rtb1<lp)) | (rta1<ecmMCV & ///
(rtb3>up | rtb3<lp)) | (rta1<ecmMCV & (rtb5>up | rtb5<lp)) | ///
(rta1<ecmMCV & (rtb7>up | rtb7<lp)) | (rta1<ecmMCV & (rtb9>up | rtb9<lp))


 post ‘sim’ (da1) (dsea1) (dta1) (db0) (dse0) (dtb0) (db1) (dse1) (dtb1) (db2) ///
(dse2) (dtb2) (db3) (dse3) (dtb3) (db4) (dse4) (dtb4) (db5) (dse5) (dtb5) ///
(db6) (dse6) (dtb6) (db7) (dse7) (dtb7) ///
  (db8) (dse8) (dtb8) (db9) (dse9) (dtb9) (dasig) (dasigMCV) (ddxsig) ///
(dxlsig) (ddxecm) (ddxecmMCV) (dlxecm) (dlxecmMCV) ///
  (ra1) (rsea1) (rta1) (rb0) (rse0) (rtb0) (rb1) (rse1) (rtb1) (rb2) (rse2) ///
(rtb2) (rb3) (rse3) (rtb3) (rb4) (rse4) (rtb4) (rb5) (rse5) (rtb5) (rb6) (rse6)///
 (rtb6) (rb7) (rse7) (rtb7) (rb8) (rse8) (rtb8) (rb9) (rse9) (rtb9) ///
(rasig) (rasigMCV) (rdxsig) (rxlsig) (rdxecm) (rdxecmMCV) (rlxecm) ///
(rlxecmMCV) (p1[1,1]) (rej1) (p2[1,1]) (rej2) (ddw) (rdw)

 }
 }
 postclose ‘sim’

 use results_mackinnon, clear
```

I.3.2 UE - FECM - Stata

```
cd " "
use " ", clear

tsset year
*Results reported in Table 1
reg indmood100 l.indmood100 demmood100
reg indmood100 l.indmood100 repmood100
reg indmood100 l.indmood100 demmood100 repmood100
newey d.indmood d.demmood d.repmood, lag(1)
*Results reported in Table 2
reg d.demmood l.demmood d.domestic10b l.domestic10b d.defense10b l.defense10b ///
d.top1share l.top1share d.inflation l.inflation d.unemployment l.unemployment
est store dem
estat bgodfrey, lags(1)
estat hettest
reg d.repmood l.repmood d.domestic10b l.domestic10b d.defense10b l.defense10b d.top1share ///
l.top1share d.inflation l.inflation d.unemployment l.unemployment
est store rep
```

```
estat bgodfrey, lags(1)
estat hettest
suest dem rep

* Recover variance-covariance matrix from SER estimation for computing the
* standard errors of the model's LRMs.

matrix b = e(b)
matrix V = e(V)

* SE of LRM is given by
* Var(a/b) = (1/b^2)Var(a) + (a^2/b^4)Var(b) - 2(a/b^3)Cov(a,b)
* Generic SE equation is square root of variance

*   dis sqrt((1/b1^2)*vara3 + (a3^2/b1^4)*varb1 - 2*(a3/b1^3)*cova3b1)

*So l.variable are 3, 5, 7, 9, 11
*ECM is 1
scalar a3 = b[1,3]
scalar a5 = b[1,5]
scalar a7 = b[1,7]
scalar a9 = b[1,9]
scalar a11 = b[1,11]
scalar b1 = b[1,1]

scalar vara3=V[3,3]
scalar vara5=V[5,5]
scalar vara7=V[7,7]
scalar vara9=V[9,9]
scalar vara11=V[11,11]
scalar varb1=V[1,1]

scalar cova3b1=V[3,1]
scalar cova5b1=V[5,1]
scalar cova7b1=V[7,1]
scalar cova9b1=V[9,1]
scalar cova11b1=V[11,1]

*** Test on whether coefficients are significantly different from each other
* do same for Republicans

dis _b[dem_mean:l.demmood]-_b[rep_mean:l.repmood]
dis _b[dem_mean: d.domestic10b]-_b[rep_mean: d.domestic10b]
dis _b[dem_mean:l.domestic10b]-_b[rep_mean:l.domestic10b]
dis _b[dem_mean:d.defense10b]-_b[rep_mean:d.defense10b]
dis _b[dem_mean:l.defense10b]-_b[rep_mean:l.defense10b]
dis _b[dem_mean:d.top1share]-_b[rep_mean:d.top1share]
dis _b[dem_mean:d.inflation]-_b[rep_mean:d.inflation]
dis _b[dem_mean:l.inflation]-_b[rep_mean:l.inflation]
dis _b[dem_mean:d.unemployment]-_b[rep_mean:d.unemployment]
dis _b[dem_mean:l.unemployment]-_b[rep_mean:l.unemployment]

test _b[dem_mean:l.demmood]=_b[rep_mean:l.repmood]
test _b[dem_mean: d.domestic10b]=_b[rep_mean: d.domestic10b]
test _b[dem_mean:l.domestic10b]=_b[rep_mean:l.domestic10b]
test _b[dem_mean:d.defense10b]=_b[rep_mean:d.defense10b]
test _b[dem_mean:l.defense10b]=_b[rep_mean:l.defense10b]
test _b[dem_mean:d.top1share]=_b[rep_mean:d.top1share]
test _b[dem_mean:d.inflation]=_b[rep_mean:d.inflation]
test _b[dem_mean:l.inflation]=_b[rep_mean:l.inflation]
test _b[dem_mean:d.unemployment]=_b[rep_mean:d.unemployment]
test _b[dem_mean:l.unemployment]=_b[rep_mean:l.unemployment]

*** Creation of Long Run Multipliers
dis _b[dem_mean:l.domestic10b]/_b[dem_mean:l.demmood]
dis _b[dem_mean:l.domestic10b]/_b[dem_mean:l.demmood]
dis _b[dem_mean:l.domestic10b]/_b[dem_mean:l.demmood]
dis _b[dem_mean:l.domestic10b]/_b[dem_mean:l.demmood]
```

```
dis _b[dem_mean:l.domestic10b]/_b[dem_mean:l.demmood]


******************
* Fractional ECM

* Test variables to see if stationary
dfgls or dfuller
* neither are stationary

* regress DV on potential IV
reg demmood domestic10b
* calculate residuasl
predict dres1, r
reg demmood defense10b
predict dres2, r
reg demmood inflation
predict dres3, r
reg demmood unemployment
predict dres4, r
reg demmood top1share
predict dres5, r

* Republicans
reg repmood domestic10b
predict rres1, r
reg repmood defense10b
predict rres2, r
reg repmood inflation
predict rres3, r
reg repmood unemployment
predict rres4, r
reg repmood top1share
predict rres5, r


* 3 step ECM - first fractionally difference (do this for all IVs, DVs, and residuals)
arfima d.demmood
predict dv, fdifference
arfima d.repmood
predict rdv, fdifference
arfima d.domestic
predict iv1, fdiff
arfima d.defense
predict iv2, fdiff
arfima d.inflation
predict iv3, fdiff
arfima d.unemployment
predict iv4, fdiff
arfima d.top1share
predict iv5, fdiff

* Dem residuals
arfima d.dres1
predict dres1f, fdiff
arfima d.dres2
predict dres2f, fdiff
arfima d.dres3
predict dres3f, fdiff
arfima d.dres4
predict dres4f, fdiff
arfima d.dres5
predict dres5f, fdiff

*Rep residuals
arfima d.rres1
predict rres1f, fdiff
arfima d.rres2
```

```
predict rres2f, fdiff
arfima d.rres3
predict rres3f, fdiff
arfima d.rres4
predict rres4f, fdiff
arfima d.rres5
predict rres5f, fdiff

* 3 step ECM (DEM) - lag of fractionally differenced residuals with all other FI var
reg dv iv1 iv2 iv3 iv4 iv5 l.dres1f
reg dv iv1 iv2 iv3 iv4 iv5 l.dres2f
reg dv iv1 iv2 iv3 iv4 iv5 l.dres3f
reg dv iv1 iv2 iv3 iv4 iv5 l.dres4f
reg dv iv1 iv2 iv3 iv4 iv5 l.dres5f
* 3 step ECM (REP) - lag of fractionally differenced residuals with all other FI var
reg rdv iv1 iv2 iv3 iv4 iv5 l.rres1f
reg rdv iv1 iv2 iv3 iv4 iv5 l.rres2f
reg rdv iv1 iv2 iv3 iv4 iv5 l.rres3f
reg rdv iv1 iv2 iv3 iv4 iv5 l.rres4f
reg rdv iv1 iv2 iv3 iv4 iv5 l.rres5f
```

I.4 Sanchez Urribarri, Schorpp, Randazzo, Songer

This code is to replicate each of the three models for randomly generated $I(1)$ series presented in Model 2 of Table E.3. Model 1 can be replicated by setting each variable as $I(0)$.

I.4.1 SSRS - Canada - Stata

```
cd " "
use " ", clear
 global nobs = 38
 global nmc = 10000
 set seed 5000
 set obs $nobs
 tsset year

 * Set the values of the parameters
 scalar ecmsig = -1.645
 scalar ecmMCV = -3.867
 scalar up = 1.96
 scalar lp = -1.96
 scalar alpha = .05

 * Generating random starting values for DV
 gen iv1 = 0
 gen iv2 = 0
 gen iv3 = 0

* generating errors
 gen e = .
 gen u = .
 gen v = .

 tempname sim

 postfile `sim' da1 dsea1 dta1 db0 dse0 dtb0 db1 dse1 dtb1 db2 dse2 dtb2 db3 dse3 dtb3 ///
db4 dse4 dtb4 db5 dse5 dtb5 dasig dasigMCV ddxsig dxlsig ///
  ddxecm ddxecmMCV dlxecm dlxecmMCV  p1 rej1  ddw ///
 using urribarri_results_mackinnon_UKDV_IVwn, replace

 quietly {
 forvalues i = 1/$nmc {
 replace e = rnormal()
 replace u = rnormal()
 replace v = rnormal()

 replace iv1 =  l.iv1 + e in 2/$nobs
 replace iv2 =  l.iv2 + u in 2/$nobs
 replace iv3 =  l.iv3 + v in 2/$nobs

 reg d.rights_agenda l.rights_agenda d.iv1 l.iv1 d.iv2 l.iv2 d.iv3 l.iv3

 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p1 = r(p)
 scalar rej1 = (p1[1,1]<alpha)
 estat dwatson
 scalar ddw = r(dw)

  * coefficient values
 scalar da1 = _b[l.rights_agenda]
 scalar db0 = _b[d.iv1]
 scalar db1 = _b[l.iv1]
 scalar db2 = _b[d.iv2]
 scalar db3 = _b[l.iv2]
 scalar db4 = _b[d.iv3]
 scalar db5 = _b[l.iv3]
 *  standard errors
 scalar dsea1 = _se[l.rights_agenda]
```

```
 scalar dse0 = _se[d.iv1]
 scalar dse1 = _se[l.iv1]
 scalar dse2 = _se[d.iv2]
 scalar dse3 = _se[l.iv2]
 scalar dse4 = _se[d.iv3]
 scalar dse5 = _se[l.iv3]
 * t-statistics
 scalar dta1 = da1/dsea1
 scalar dtb0 = db0/dse0
 scalar dtb1 = db1/dse1
 scalar dtb2 = db2/dse2
 scalar dtb3 = db3/dse3
 scalar dtb4 = db4/dse4
 scalar dtb5 = db5/dse5
  * Calculating significance totals
 scalar dasig = dta1<ecmsig
 scalar dasigMCV = dta1<ecmMCV
 scalar ddxsig = (dtb0>up | dtb0<lp) | (dtb2>up | dtb2<lp) | (dtb4>up | dtb4<lp)
 scalar dxlsig = (dtb1>up | dtb1<lp) | (dtb3>up | dtb3<lp) | (dtb5>up | dtb5<lp)
 scalar ddxecm = (dta1<ecmsig & (dtb0>up | dtb0<lp)) | (dta1<ecmsig & (dtb2>up | dtb2<lp))///
 | (dta1<ecmsig & (dtb4>up | dtb4<lp))
 scalar ddxecmMCV = (dta1<ecmMCV & (dtb0>up | dtb0<lp)) | (dta1<ecmMCV & ///
(dtb2>up | dtb2<lp)) | (dta1<ecmMCV & (dtb4>up | dtb4<lp))
 scalar dlxecm = (dta1<ecmsig & (dtb1>up | dtb1<lp)) | (dta1<ecmsig & ///
(dtb3>up | dtb3<lp)) | (dta1<ecmsig & (dtb5>up | dtb5<lp))
 scalar dlxecmMCV = (dta1<ecmMCV & (dtb1>up | dtb1<lp)) | (dta1<ecmMCV & ///
(dtb3>up | dtb3<lp)) | (dta1<ecmMCV & (dtb5>up | dtb5<lp))


 post ‘sim’ (da1) (dsea1) (dta1) (db0) (dse0) (dtb0) (db1) (dse1) (dtb1) (db2) (dse2) ///
(dtb2) (db3) (dse3) (dtb3) (db4) (dse4) (dtb4) (db5) (dse5) (dtb5) (dasig) (dasigMCV) ///
(ddxsig) (dxlsig) (ddxecm) (ddxecmMCV) (dlxecm) (dlxecmMCV) (p1[1,1]) (rej1) (ddw)

 }
 }
 postclose ‘sim’

 use urribarri_results_mackinnon_UKDV_IVwn, clear
```

I.4.2 SSRS - UK - Stata

```
cd " "
use " ", clear
 global nobs = 38
 global nmc = 10000
 set seed 5000
 set obs $nobs
 tsset year

 * Set the values of the parameters
 scalar ecmsig = -1.645
 scalar ecmMCV = -3.867
 scalar up = 1.96
 scalar lp = -1.96
 scalar alpha = .05

 * Generating random starting values for DV
 gen iv1 = 0
 gen iv2 = 0
 gen iv3 = 0

* generating errors
 gen e = .
 gen u = .
 gen v = .

 tempname sim
```

```
 postfile ‘sim’ da1 dsea1 dta1 db0 dse0 dtb0 db1 dse1 dtb1 db2 dse2 dtb2 db3 dse3 dtb3 ///
db4 dse4 dtb4 db5 dse5 dtb5 dasig dasigMCV ddxsig dxlsig ddxecm ddxecmMCV dlxecm ///
dlxecmMCV  p1 rej1  ddw  using urribarri_results_mackinnon_UKDV_IVwn, replace

 quietly {
 forvalues i = 1/$nmc {
 replace e = rnormal()
 replace u = rnormal()
 replace v = rnormal()

 replace iv1 =  l.iv1 + e in 2/$nobs
 replace iv2 =  l.iv2 + u in 2/$nobs
 replace iv3 =  l.iv3 + v in 2/$nobs

 reg d.rights_agenda l.rights_agenda d.iv1 l.iv1 d.iv2 l.iv2 d.iv3 l.iv3

 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p1 = r(p)
 scalar rej1 = (p1[1,1]<alpha)
 estat dwatson
 scalar ddw = r(dw)
  * Coefficient values
 scalar da1 = _b[l.rights_agenda]
 scalar db0 = _b[d.iv1]
 scalar db1 = _b[l.iv1]
 scalar db2 = _b[d.iv2]
 scalar db3 = _b[l.iv2]
 scalar db4 = _b[d.iv3]
 scalar db5 = _b[l.iv3]
 * Standard errors
 scalar dsea1 = _se[l.rights_agenda]
 scalar dse0 = _se[d.iv1]
 scalar dse1 = _se[l.iv1]
 scalar dse2 = _se[d.iv2]
 scalar dse3 = _se[l.iv2]
 scalar dse4 = _se[d.iv3]
 scalar dse5 = _se[l.iv3]
 * t-statistics
 scalar dta1 = da1/dsea1
 scalar dtb0 = db0/dse0
 scalar dtb1 = db1/dse1
 scalar dtb2 = db2/dse2
 scalar dtb3 = db3/dse3
 scalar dtb4 = db4/dse4
 scalar dtb5 = db5/dse5
  * Paramters
 scalar dasig = dta1<ecmsig
 scalar dasigMCV = dta1<ecmMCV
 scalar ddxsig = (dtb0>up | dtb0<lp) | (dtb2>up | dtb2<lp) | (dtb4>up | dtb4<lp)
 scalar dxlsig = (dtb1>up | dtb1<lp) | (dtb3>up | dtb3<lp) | (dtb5>up | dtb5<lp)
 scalar ddxecm = (dta1<ecmsig & (dtb0>up | dtb0<lp)) | (dta1<ecmsig & ///
(dtb2>up | dtb2<lp)) | (dta1<ecmsig & (dtb4>up | dtb4<lp))
 scalar ddxecmMCV = (dta1<ecmMCV & (dtb0>up | dtb0<lp)) | (dta1<ecmMCV & ///
(dtb2>up | dtb2<lp)) | (dta1<ecmMCV & (dtb4>up | dtb4<lp))
 scalar dlxecm = (dta1<ecmsig & (dtb1>up | dtb1<lp)) | (dta1<ecmsig & ///
(dtb3>up | dtb3<lp)) | (dta1<ecmsig & (dtb5>up | dtb5<lp))
 scalar dlxecmMCV = (dta1<ecmMCV & (dtb1>up | dtb1<lp)) | (dta1<ecmMCV & ///
(dtb3>up | dtb3<lp)) | (dta1<ecmMCV & (dtb5>up | dtb5<lp))


 post ‘sim’ (da1) (dsea1) (dta1) (db0) (dse0) (dtb0) (db1) (dse1) (dtb1) (db2) (dse2)///
 (dtb2) (db3) (dse3) (dtb3) (db4) (dse4) (dtb4) (db5) (dse5) (dtb5) ///
   (dasig) (dasigMCV) (ddxsig) (dxlsig) (ddxecm) (ddxecmMCV) (dlxecm) ///
 (dlxecmMCV) (p1[1,1]) (rej1) (ddw)

 }
 }
```

```
 postclose ‘sim’

 use urribarri_results_mackinnon_UKDV_IVwn, clear
```

I.4.3 SSRS - US- Stata

```
cd " "
use " ", clear
 global nobs = 61
 global nmc = 10000
 set seed 5000
 set obs $nobs
 tsset year

 * Set the values of the parameters
 scalar ecmsig = -1.645
 scalar ecmMCV = -4.229
 scalar up = 1.96
 scalar lp = -1.96
 scalar alpha = .05

 * Generating random starting values for DV
 gen iv1 = 0
 gen iv2 = 0
 gen iv3 = 0
 gen iv4 = 0
 gen iv5 = 0

* generating errors
 gen e = .
 gen u = .
 gen v = .
 gen w = .
 gen o = .

 tempname sim

 postfile ‘sim’ da1 dsea1 dta1 db0 dse0 dtb0 db1 dse1 dtb1 db2 dse2 dtb2 db3 dse3 ///
dtb3 db4 dse4 dtb4 db5 dse5 dtb5 db6 dse6 dtb6 db7 dse7 dtb7 db8 dse8 dtb8 db9 ///
dse9 dtb9 dasig dasigMCV ddxsig dxlsig ///
  ddxecm ddxecmMCV dlxecm dlxecmMCV  p1 rej1  ddw ///
 using urribarri_results_mackinnon_USDV, replace

 quietly {
 forvalues i = 1/$nmc {
 replace e = rnormal()
 replace u = rnormal()
 replace v = rnormal()
 replace w = rnormal()
 replace o = rnormal()

 replace iv1 = l.iv1 + e in 2/$nobs
 replace iv2 = l.iv2 + u in 2/$nobs
 replace iv3 = l.iv3 + v in 2/$nobs
 replace iv4 = l.iv4 + w in 2/$nobs
 replace iv5 = l.iv5 + o in 2/$nobs

 reg d.rights_agenda l.rights_agenda d.iv1 l.iv1 d.iv2 l.iv2 d.iv3 l.iv3 d.iv4 l.iv4 d.iv5 l.iv5

* Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p1 = r(p)
 scalar rej1 = (p1[1,1]<alpha)
 estat dwatson
 scalar ddw = r(dw)

  *  coefficient values
 scalar da1 = _b[l.rights_agenda]
```

```
 scalar db0 = _b[d.iv1]
 scalar db1 = _b[l.iv1]
 scalar db2 = _b[d.iv2]
 scalar db3 = _b[l.iv2]
 scalar db4 = _b[d.iv3]
 scalar db5 = _b[l.iv3]
 scalar db6 = _b[d.iv4]
 scalar db7 = _b[l.iv4]
 scalar db8 = _b[d.iv5]
 scalar db9 = _b[l.iv5]
 * standard errors
 scalar dsea1 = _se[l.rights_agenda]
 scalar dse0 = _se[d.iv1]
 scalar dse1 = _se[l.iv1]
 scalar dse2 = _se[d.iv2]
 scalar dse3 = _se[l.iv2]
 scalar dse4 = _se[d.iv3]
 scalar dse5 = _se[l.iv3]
 scalar dse6 = _se[d.iv4]
 scalar dse7 = _se[l.iv4]
 scalar dse8 = _se[d.iv5]
 scalar dse9 = _se[l.iv5]
 *t-statistics
 scalar dta1 = da1/dsea1
 scalar dtb0 = db0/dse0
 scalar dtb1 = db1/dse1
 scalar dtb2 = db2/dse2
 scalar dtb3 = db3/dse3
 scalar dtb4 = db4/dse4
 scalar dtb5 = db5/dse5
 scalar dtb6 = db6/dse6
 scalar dtb7 = db7/dse7
 scalar dtb8 = db8/dse8
 scalar dtb9 = db9/dse9
  * Calculating significance totals
 scalar dasig = dta1<ecmsig
 scalar dasigMCV = dta1<ecmMCV
 scalar ddxsig = (dtb0>up | dtb0<lp) | (dtb2>up | dtb2<lp) | (dtb4>up | dtb4<lp)///
 | (dtb6>up | dtb6<lp) | (dtb8>up | dtb8<lp)
 scalar dxlsig = (dtb1>up | dtb1<lp) | (dtb3>up | dtb3<lp) | (dtb5>up | dtb5<lp) ///
| (dtb7>up | dtb7<lp) | (dtb9>up | dtb9<lp)
 scalar ddxecm = (dta1<ecmsig & (dtb0>up | dtb0<lp)) | (dta1<ecmsig & ///
(dtb2>up | dtb2<lp)) | (dta1<ecmsig & (dtb4>up | dtb4<lp)) | (dta1<ecmsig & ///
 (dtb6>up | dtb6<lp)) | (dta1<ecmsig & (dtb8>up | dtb8<lp))
 scalar ddxecmMCV = (dta1<ecmMCV & (dtb0>up | dtb0<lp)) | (dta1<ecmMCV & ///
(dtb2>up | dtb2<lp)) | (dta1<ecmMCV & (dtb4>up | dtb4<lp)) | ///
(dta1<ecmMCV & (dtb6>up | dtb6<lp)) | (dta1<ecmMCV & (dtb8>up | dtb8<lp))
 scalar dlxecm = (dta1<ecmsig & (dtb1>up | dtb1<lp)) | (dta1<ecmsig & ///
(dtb3>up | dtb3<lp)) | (dta1<ecmsig & (dtb5>up | dtb5<lp)) | (dta1<ecmsig & ///
(dtb7>up | dtb7<lp)) | (dta1<ecmsig & (dtb9>up | dtb9<lp))
 scalar dlxecmMCV = (dta1<ecmMCV & (dtb1>up | dtb1<lp)) | (dta1<ecmMCV & ///
(dtb3>up | dtb3<lp)) | (dta1<ecmMCV & (dtb5>up | dtb5<lp)) | (dta1<ecmsig & ///
(dtb7>up | dtb7<lp)) | (dta1<ecmsig & (dtb9>up | dtb9<lp))


 post ‘sim’ (da1) (dsea1) (dta1) (db0) (dse0) (dtb0) (db1) (dse1) (dtb1) (db2) ///
(dse2) (dtb2) (db3) (dse3) (dtb3) (db4) (dse4) (dtb4) (db5) (dse5) (dtb5) ///
 (db6) (dse6) (dtb6) (db7) (dse7) (dtb7) ///
  (db8) (dse8) (dtb8) (db9) (dse9) (dtb9) (dasig) (dasigMCV) (ddxsig) ///
(dxlsig) (ddxecm) (ddxecmMCV) (dlxecm) (dlxecmMCV) (p1[1,1]) (rej1) (ddw)

 }
 }
 postclose ‘sim’

 use urribarri_results_mackinnon_USDV, clear
```

I.5 Kelly and Enns

For any MC simulations of Table 2, change the DV names, and or limit the data by the proper year.

I.5.1 KE - MC with $I(1)$ IVs

```
cd " "
use " ", clear
 global nobs = 55
 global nmc = 10000
 set seed 5000
 set obs $nobs
 tsset year

 * Set the values of the parameters
 scalar ecmsig = -1.645
 scalar ecmMCVm1 = -3.822
 scalar ecmMCVm2 = -3.570
 scalar ecmMCVm3 = -4.040
 scalar ecmMCVm4 = -3.621
 scalar up = 1.96
 scalar lp = -1.96
 scalar alpha = .05

 * Generating random starting values for DV
 gen iv1 = 0
 gen iv2 = 0
 gen iv3 = 0
 gen iv4 = 0

* generating errors
 gen e = .
 gen u = .
 gen w = .
 gen o = .

 tempname sim

 postfile `sim' m1a1 m1sea1 m1ta1 m1b0 m1se0 m1tb0 m1b1 m1se1 m1tb1 m1b2 m1se2 ///
  m1tb2 m1b3 m1se3 m1tb3 m1b4 m1se4 m1tb4 m1b5 m1se5 m1tb5 m1asig m1asigMCV ///
m1dxsig m1xlsig m1dxecm m1dxecmMCV m1lxecm m1lxecmMCV  p1 rej1  m1dw   ///
 m2a1 m2sea1 m2ta1 m2b0 m2se0 m2tb0 m2b1 m2se1 m2tb1 m2b2 m2se2 m2tb2 m2b3 ///
m2se3 m2tb3 m2asig m2asigMCV m2dxsig m2xlsig m2dxecm m2dxecmMCV m2lxecm ///
m2lxecmMCV  p2 rej2  m2dw m3a1 m3sea1 m3ta1 m3b0 m3se0 m3tb0 m3b1 m3se1 m3tb1 m3b2 ///
m3se2 m3tb2 m3b3 m3se3 m3tb3 m3b4 m3se4 m3tb4 m3b5 m3se5 m3tb5 ///
  m3b6 m3se6 m3tb6 m3b7 m3se7 m3tb7 m3asig m3asigMCV m3dxsig m3xlsig ///
m3dxecm m3dxecmMCV m3lxecm m3lxecmMCV  p3 rej3  m3dw  ///
  m4a1 m4sea1 m4ta1 m4b0 m4se0 m4tb0 m4b1 m4se1 m4tb1 m4b2 m4se2 m4tb2 m4b3 ///
m4se3 m4tb3 m4asig m4asigMCV m4dxsig m4xlsig m4dxecm m4dxecmMCV m4lxecm ///
m4lxecmMCV  p4 rej4  m4dw  using kelly_enns_results_mackinnon_IV, replace

 quietly {
 forvalues i = 1/$nmc {
 replace e = rnormal()
 replace u = rnormal()
 replace w = rnormal()
 replace o = rnormal()

 replace iv1 = l.iv1 + e in 2/$nobs
 replace iv2 = l.iv2 + u in 2/$nobs
 replace iv3 = l.iv3 + w in 2/$nobs
 replace iv4 = l.iv4 + o in 2/$nobs
 * Model 1 *
 reg d.mood l.mood d.iv1 l.iv1 d.iv3 l.iv3 d.iv4 l.iv4
 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p1 = r(p)
```

```
scalar rej1 = (p1[1,1]<alpha)
estat dwatson
scalar m1dw = r(dw)
 * Model 1 coefficient values
scalar m1a1 = _b[l.mood]
scalar m1b0 = _b[d.iv1]
scalar m1b1 = _b[l.iv1]
scalar m1b2 = _b[d.iv3]
scalar m1b3 = _b[l.iv3]
scalar m1b4 = _b[d.iv4]
scalar m1b5 = _b[l.iv4]
* Model 1 standard errors
scalar m1sea1 = _se[l.mood]
scalar m1se0 = _se[d.iv1]
scalar m1se1 = _se[l.iv1]
scalar m1se2 = _se[d.iv3]
scalar m1se3 = _se[l.iv3]
scalar m1se4 = _se[d.iv4]
scalar m1se5 = _se[l.iv4]
* Model 1 t-statistics
scalar m1ta1 = m1a1/m1sea1
scalar m1tb0 = m1b0/m1se0
scalar m1tb1 = m1b1/m1se1
scalar m1tb2 = m1b2/m1se2
scalar m1tb3 = m1b3/m1se3
scalar m1tb4 = m1b4/m1se4
scalar m1tb5 = m1b5/m1se5

* Model 2 *
reg d.mood l.mood d.iv1 l.iv1 d.iv2 l.iv2
* Breusch Godfrey test
estat bgodfrey, lags(1)
matrix p2 = r(p)
scalar rej2 = (p2[1,1]<alpha)
estat dwatson
scalar m2dw = r(dw)
* Model 2 coefficient values
scalar m2a1 = _b[l.mood]
scalar m2b0 = _b[d.iv1]
scalar m2b1 = _b[l.iv1]
scalar m2b2 = _b[d.iv2]
scalar m2b3 = _b[l.iv2]
* Model 2 standard errors
scalar m2sea1 = _se[l.mood]
scalar m2se0 = _se[d.iv1]
scalar m2se1 = _se[l.iv1]
scalar m2se2 = _se[d.iv2]
scalar m2se3 = _se[l.iv2]
* Model 2 t-statistics
scalar m2ta1 = m2a1/m2sea1
scalar m2tb0 = m2b0/m2se0
scalar m2tb1 = m2b1/m2se1
scalar m2tb2 = m2b2/m2se2
scalar m2tb3 = m2b3/m2se3

* Model 3 *
reg d.mood l.mood d.iv1 l.iv1 d.iv2 l.iv2 d.iv3 l.iv3 d.iv4 l.iv4
* Breusch Godfrey test
estat bgodfrey, lags(1)
matrix p3 = r(p)
scalar rej3 = (p3[1,1]<alpha)
estat dwatson
scalar m3dw = r(dw)
 * Model 3 coefficient values
scalar m3a1 = _b[l.mood]
scalar m3b0 = _b[d.iv1]
scalar m3b1 = _b[l.iv1]
scalar m3b2 = _b[d.iv2]
```

```
 scalar m3b3 = _b[l.iv2]
 scalar m3b4 = _b[d.iv3]
 scalar m3b5 = _b[l.iv3]
 scalar m3b6 = _b[d.iv4]
 scalar m3b7 = _b[l.iv4]
 * Model 3 standard errors
 scalar m3sea1 = _se[l.mood]
 scalar m3se0 = _se[d.iv1]
 scalar m3se1 = _se[l.iv1]
 scalar m3se2 = _se[d.iv2]
 scalar m3se3 = _se[l.iv2]
 scalar m3se4 = _se[d.iv3]
 scalar m3se5 = _se[l.iv3]
 scalar m3se6 = _se[d.iv4]
 scalar m3se7 = _se[l.iv4]
 * Model 3 t-statistics
 scalar m3ta1 = m3a1/m3sea1
 scalar m3tb0 = m3b0/m3se0
 scalar m3tb1 = m3b1/m3se1
 scalar m3tb2 = m3b2/m3se2
 scalar m3tb3 = m3b3/m3se3
 scalar m3tb4 = m3b4/m3se4
 scalar m3tb5 = m3b5/m3se5
 scalar m3tb6 = m3b6/m3se6
 scalar m3tb7 = m3b7/m3se7

 * Model 4 *
 reg d.welfare l.welfare d.iv1 l.iv1 d.iv2 l.iv2
 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p4 = r(p)
 scalar rej4 = (p4[1,1]<alpha)
 estat dwatson
 scalar m4dw = r(dw)
 * Model 2 coefficient values
 scalar m4a1 = _b[l.welfare]
 scalar m4b0 = _b[d.iv1]
 scalar m4b1 = _b[l.iv1]
 scalar m4b2 = _b[d.iv2]
 scalar m4b3 = _b[l.iv2]
 * Model 2 standard errors
 scalar m4sea1 = _se[l.welfare]
 scalar m4se0 = _se[d.iv1]
 scalar m4se1 = _se[l.iv1]
 scalar m4se2 = _se[d.iv2]
 scalar m4se3 = _se[l.iv2]
 * Model 2 t-statistics
 scalar m4ta1 = m4a1/m4sea1
 scalar m4tb0 = m4b0/m4se0
 scalar m4tb1 = m4b1/m4se1
 scalar m4tb2 = m4b2/m4se2
 scalar m4tb3 = m4b3/m4se3


  * Calculating significance totals (Model 1)
 scalar m1asig = m1ta1<ecmsig
 scalar m1asigMCV = m1ta1<ecmMCVm1
 scalar m1dxsig = (m1tb0>up | m1tb0<lp) | (m1tb2>up | m1tb2<lp) | ///
 (m1tb4>up | m1tb4<lp)
 scalar m1xlsig = (m1tb1>up | m1tb1<lp) | (m1tb3>up | m1tb3<lp) | ///
(m1tb5>up | m1tb5<lp)
 scalar m1dxecm = (m1ta1<ecmsig & (m1tb0>up | m1tb0<lp)) | ///
(m1ta1<ecmsig & (m1tb2>up | m1tb2<lp)) | (m1ta1<ecmsig & (m1tb4>up | m1tb4<lp))
 scalar m1dxecmMCV = (m1ta1<ecmMCVm1 & (m1tb0>up | m1tb0<lp)) | (m1ta1<ecmMCVm1 & ///
(m1tb2>up | m1tb2<lp)) | (m1ta1<ecmMCVm1 & (m1tb4>up | m1tb4<lp))
 scalar m1lxecm = (m1ta1<ecmsig & (m1tb1>up | m1tb1<lp)) | (m1ta1<ecmsig & ///
(m1tb3>up | m1tb3<lp)) | (m1ta1<ecmsig & (m1tb5>up | m1tb5<lp))
 scalar m1lxecmMCV = (m1ta1<ecmMCVm1 & (m1tb1>up | m1tb1<lp)) | (m1ta1<ecmMCVm1 & ///
```

```
(m1tb3>up | m1tb3<lp)) | (m1ta1<ecmMCVm1 & (m1tb5>up | m1tb5<lp))

 * Calculating significance totals (Model 2)
 scalar m2asig = m2ta1<ecmsig
 scalar m2asigMCV = m2ta1<ecmMCVm2
 scalar m2dxsig = (m2tb0>up | m2tb0<lp) | (m2tb2>up | m2tb2<lp)
 scalar m2xlsig = (m2tb1>up | m2tb1<lp) | (m2tb3>up | m2tb3<lp)
 scalar m2dxecm = (m2ta1<ecmsig & (m2tb0>up | m2tb0<lp)) | (m2ta1<ecmsig & ///
(m2tb2>up | m2tb2<lp))
 scalar m2dxecmMCV = (m2ta1<ecmMCVm2 & (m2tb0>up | m2tb0<lp)) | ///
(m2ta1<ecmMCVm2 & (m2tb2>up | m2tb2<lp))
 scalar m2lxecm = (m2ta1<ecmsig & (m2tb1>up | m2tb1<lp)) | ///
(m2ta1<ecmsig & (m2tb3>up | m2tb3<lp))
 scalar m2lxecmMCV = (m2ta1<ecmMCVm2 & (m2tb1>up | m2tb1<lp)) | ///
(m2ta1<ecmMCVm2 & (m2tb3>up | m2tb3<lp))

 * Calculating significance totals (Model 3)
 scalar m3asig = m3ta1<ecmsig
 scalar m3asigMCV = m3ta1<ecmMCVm3
 scalar m3dxsig = (m3tb0>up | m3tb0<lp) | (m3tb2>up | m3tb2<lp) | ///
(m3tb4>up | m3tb4<lp) | (m3tb6>up | m3tb6<lp)
 scalar m3xlsig = (m3tb1>up | m3tb1<lp) | (m3tb3>up | m3tb3<lp) | ///
(m3tb5>up | m3tb5<lp) | (m3tb7>up | m3tb7<lp)
 scalar m3dxecm = (m3ta1<ecmsig & (m3tb0>up | m3tb0<lp)) | ///
(m3ta1<ecmsig & (m3tb2>up | m3tb2<lp)) | (m3ta1<ecmsig & (///
m3tb4>up | m3tb4<lp)) | (m3ta1<ecmsig & (m3tb6>up | m3tb6<lp))
 scalar m3dxecmMCV = (m3ta1<ecmMCVm3 & (m3tb0>up | m3tb0<lp)) | ///
(m3ta1<ecmMCVm3 & (m3tb2>up | m3tb2<lp)) | (m3ta1<ecmMCVm3 & (m3tb4>up | m3tb4<lp)) ///
 | (m3ta1<ecmMCVm3 & (m3tb6>up | m3tb6<lp))
 scalar m3lxecm = (m3ta1<ecmsig & (m3tb1>up | m3tb1<lp)) | (m3ta1<ecmsig & ///
(m3tb3>up | m3tb3<lp)) | (m3ta1<ecmsig & (m3tb5>up | m3tb5<lp)) | ///
(m3ta1<ecmsig & (m3tb7>up | m3tb7<lp))
 scalar m3lxecmMCV = (m3ta1<ecmMCVm3 & (m3tb1>up | m3tb1<lp)) | ///
(m3ta1<ecmMCVm3 & (m3tb3>up | m3tb3<lp)) | (m3ta1<ecmMCVm3 & ///
(m3tb5>up | m3tb5<lp)) | (m3ta1<ecmMCVm3 & (m3tb7>up | m3tb7<lp))

 * Calculating significance totals (Model 4)
 scalar m4asig = m4ta1<ecmsig
 scalar m4asigMCV = m4ta1<ecmMCVm4
 scalar m4dxsig = (m4tb0>up | m4tb0<lp) | (m4tb2>up | m4tb2<lp)
 scalar m4xlsig = (m4tb1>up | m4tb1<lp) | (m4tb3>up | m4tb3<lp)
 scalar m4dxecm = (m4ta1<ecmsig & (m4tb0>up | m4tb0<lp)) | (m4ta1<ecmsig & ///
(m4tb2>up | m4tb2<lp))
 scalar m4dxecmMCV = (m4ta1<ecmMCVm4 & (m4tb0>up | m4tb0<lp)) | (m4ta1<ecmMCVm4 & ///
(m4tb2>up | m4tb2<lp))
 scalar m4lxecm = (m4ta1<ecmsig & (m4tb1>up | m4tb1<lp)) | (m4ta1<ecmsig & ///
(m4tb3>up | m4tb3<lp))
 scalar m4lxecmMCV = (m4ta1<ecmMCVm4 & (m4tb1>up | m4tb1<lp)) | (m4ta1<ecmMCVm4 & ///
(m4tb3>up | m4tb3<lp))

 post `sim' (m1a1) (m1sea1) (m1ta1) (m1b0) (m1se0) (m1tb0) (m1b1) (m1se1) (m1tb1) (m1b2) ///
 (m1se2) (m1tb2) (m1b3) (m1se3) (m1tb3) (m1b4) (m1se4) (m1tb4) (m1b5) (m1se5) (m1tb5) ///
  (m1asig) (m1asigMCV) (m1dxsig) (m1xlsig) (m1dxecm) (m1dxecmMCV) (m1lxecm) (m1lxecmMCV) ///
 (p1[1,1]) (rej1) (m1dw) ///
   (m2a1) (m2sea1) (m2ta1) (m2b0) (m2se0) (m2tb0) (m2b1) (m2se1) (m2tb1) (m2b2) (m2se2)///
 (m2tb2) (m2b3) (m2se3) (m2tb3) (m2asig) (m2asigMCV) (m2dxsig) (m2xlsig) ///
    (m2dxecm) (m2dxecmMCV) (m2lxecm) (m2lxecmMCV) (p2[1,1]) (rej2) (m2dw) ///
      (m3a1) (m3sea1) (m3ta1) (m3b0) (m3se0) (m3tb0) (m3b1) (m3se1) (m3tb1) (m3b2) (m3se2) ///
(m3tb2) (m3b3) (m3se3) (m3tb3) (m3b4) (m3se4) (m3tb4) (m3b5) (m3se5) (m3tb5) ///
  (m3b6) (m3se6) (m3tb6) (m3b7) (m3se7) (m3tb7) (m3asig) (m3asigMCV) (m3dxsig) ///
(m3xlsig) (m3dxecm) (m3dxecmMCV) (m3lxecm) (m3lxecmMCV) (p3[1,1]) (rej3) (m3dw) ///
  (m4a1) (m4sea1) (m4ta1) (m4b0) (m4se0) (m4tb0) (m4b1) (m4se1) (m4tb1) (m4b2) (m4se2) ///
(m4tb2) (m4b3) (m4se3) (m4tb3) (m4asig) (m4asigMCV) (m4dxsig) (m4xlsig) ///
    (m4dxecm) (m4dxecmMCV) (m4lxecm) (m4lxecmMCV) (p2[1,1]) (rej2) (m4dw)
 }
 }
 postclose `sim'
```

```
use kelly_enns_results_mackinnon_IV, clear
```

I.5.2 KE - MC with Bounded DVs

```
cd "  "
use "  ", clear
 global nobs = 55
 global nmc = 10000
 set seed 5000
 set obs $nobs
 tsset year

 * Set the values of the parameters
 scalar ecmsig = -1.645
 scalar ecmMCVm1 = -3.822
 scalar ecmMCVm2 = -3.570
 scalar ecmMCVm3 = -4.040
 scalar ecmMCVm4 = -3.621
 scalar up = 1.96
 scalar lp = -1.96
 scalar alpha = .05

 *Set values for Dem bounds
 scalar a = 1.5
 scalar b = 1.5
 scalar tau = 59
 scalar k = 16.5

 * Generating starting values for DV
 gen dv1 = (59-50)*runiform()+50
 gen dv2 = (99-1)*runiform()+1

* generating errors
 gen e = .

 tempname sim

 postfile ‘sim’ m1a1 m1sea1 m1ta1 m1b0 m1se0 m1tb0 m1b1 m1se1 m1tb1 m1b2 m1se2 m1tb2 m1b3 ///
 m1se3 m1tb3 m1b4 m1se4 m1tb4 m1b5 m1se5 m1tb5 m1asig m1asigMCV m1dxsig m1xlsig ///
  m1dxecm m1dxecmMCV m1lxecm m1lxecmMCV  p1 rej1  m1dw    m2a1 m2sea1 m2ta1 m2b0 m2se0 ///
 m2tb0 m2b1 m2se1 m2tb1 m2b2 m2se2 m2tb2 m2b3 m2se3 m2tb3 m2asig m2asigMCV m2dxsig m2xlsig ///
  m2dxecm m2dxecmMCV m2lxecm m2lxecmMCV  p2 rej2  m2dw m3a1 m3sea1 m3ta1 m3b0 m3se0 m3tb0 ///
 m3b1 m3se1 m3tb1 m3b2 m3se2 m3tb2 m3b3 m3se3 m3tb3 m3b4 m3se4 m3tb4 m3b5 m3se5 m3tb5 ///
  m3b6 m3se6 m3tb6 m3b7 m3se7 m3tb7 m3asig m3asigMCV m3dxsig m3xlsig m3dxecm m3dxecmMCV ///
m3lxecm m3lxecmMCV  p3 rej3  m3dw  ///
  m4a1 m4sea1 m4ta1 m4b0 m4se0 m4tb0 m4b1 m4se1 m4tb1 m4b2 m4se2 m4tb2 m4b3 m4se3 m4tb3 ///
 m4asig m4asigMCV m4dxsig m4xlsig ///
  m4dxecm m4dxecmMCV m4lxecm m4lxecmMCV  ///
p4 rej4  m4dw using kelly_enns_results_mackinnon_boundedDV2, replace

 quietly {
 forvalues i = 1/$nmc {
 replace e = rnormal()


 replace dv1 = l.dv1 + exp(-k)*(exp((-a)*(l.dv1 - tau)) - ///
(exp((b)*(l.dv1 - tau)))) + e in 2/$nobs
 replace dv2 = l.dv2 + e in 2/$nobs

 * Model 1 *
 reg d.dv1 l.dv1 d.policy l.policy d.unemployment l.unemployment d.inflation l.inflation
 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p1 = r(p)
 scalar rej1 = (p1[1,1]<alpha)
 estat dwatson
 scalar m1dw = r(dw)
  * Model 1 coefficient values
```

```
 scalar m1a1 = _b[l.dv1]
 scalar m1b0 = _b[d.policy]
 scalar m1b1 = _b[l.policy]
 scalar m1b2 = _b[d.unemployment]
 scalar m1b3 = _b[l.unemployment]
 scalar m1b4 = _b[d.inflation]
 scalar m1b5 = _b[l.inflation]
 * Model 1 standard errors
 scalar m1sea1 = _se[l.dv1]
 scalar m1se0 = _se[d.policy]
 scalar m1se1 = _se[l.policy]
 scalar m1se2 = _se[d.unemployment]
 scalar m1se3 = _se[l.unemployment]
 scalar m1se4 = _se[d.inflation]
 scalar m1se5 = _se[l.inflation]
 * Model 1 t-statistics
 scalar m1ta1 = m1a1/m1sea1
 scalar m1tb0 = m1b0/m1se0
 scalar m1tb1 = m1b1/m1se1
 scalar m1tb2 = m1b2/m1se2
 scalar m1tb3 = m1b3/m1se3
 scalar m1tb4 = m1b4/m1se4
 scalar m1tb5 = m1b5/m1se5

 * Model 2 *
 reg d.dv1 l.dv1 d.policy l.policy d.gini l.gini
 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p2 = r(p)
 scalar rej2 = (p2[1,1]<alpha)
 estat dwatson
 scalar m2dw = r(dw)
 * Model 2 coefficient values
 scalar m2a1 = _b[l.dv1]
 scalar m2b0 = _b[d.policy]
 scalar m2b1 = _b[l.policy]
 scalar m2b2 = _b[d.gini]
 scalar m2b3 = _b[l.gini]
 * Model 2 standard errors
 scalar m2sea1 = _se[l.dv1]
 scalar m2se0 = _se[d.policy]
 scalar m2se1 = _se[l.policy]
 scalar m2se2 = _se[d.gini]
 scalar m2se3 = _se[l.gini]
 * Model 2 t-statistics
 scalar m2ta1 = m2a1/m2sea1
 scalar m2tb0 = m2b0/m2se0
 scalar m2tb1 = m2b1/m2se1
 scalar m2tb2 = m2b2/m2se2
 scalar m2tb3 = m2b3/m2se3

 * Model 3 *
 reg d.dv1 l.dv1 d.policy l.policy d.gini l.gini d.unemployment l.unemployment ///
d.inflation l.inflation
 * Breusch Godfrey test
 estat bgodfrey, lags(1)
 matrix p3 = r(p)
 scalar rej3 = (p3[1,1]<alpha)
 estat dwatson
 scalar m3dw = r(dw)
  * Model 3 coefficient values
 scalar m3a1 = _b[l.dv1]
 scalar m3b0 = _b[d.policy]
 scalar m3b1 = _b[l.policy]
 scalar m3b2 = _b[d.gini]
 scalar m3b3 = _b[l.gini]
 scalar m3b4 = _b[d.unemployment]
 scalar m3b5 = _b[l.unemployment]
```

```
scalar m3b6 = _b[d.inflation]
scalar m3b7 = _b[l.inflation]
* Model 3 standard errors
scalar m3sea1 = _se[l.dv1]
scalar m3se0 = _se[d.policy]
scalar m3se1 = _se[l.policy]
scalar m3se2 = _se[d.gini]
scalar m3se3 = _se[l.gini]
scalar m3se4 = _se[d.unemployment]
scalar m3se5 = _se[l.unemployment]
scalar m3se6 = _se[d.inflation]
scalar m3se7 = _se[l.inflation]
* Model 3 t-statistics
scalar m3ta1 = m3a1/m3sea1
scalar m3tb0 = m3b0/m3se0
scalar m3tb1 = m3b1/m3se1
scalar m3tb2 = m3b2/m3se2
scalar m3tb3 = m3b3/m3se3
scalar m3tb4 = m3b4/m3se4
scalar m3tb5 = m3b5/m3se5
scalar m3tb6 = m3b6/m3se6
scalar m3tb7 = m3b7/m3se7

* Model 4 *
reg d.dv2 l.dv2 d.policy l.policy d.gini l.gini if year>1972
* Breusch Godfrey test
estat bgodfrey, lags(1)
matrix p4 = r(p)
scalar rej4 = (p4[1,1]<alpha)
estat dwatson
scalar m4dw = r(dw)
* Model 4 coefficient values
scalar m4a1 = _b[l.dv2]
scalar m4b0 = _b[d.policy]
scalar m4b1 = _b[l.policy]
scalar m4b2 = _b[d.gini]
scalar m4b3 = _b[l.gini]
* Model 4 standard errors
scalar m4sea1 = _se[l.dv2]
scalar m4se0 = _se[d.policy]
scalar m4se1 = _se[l.policy]
scalar m4se2 = _se[d.gini]
scalar m4se3 = _se[l.gini]
* Model 4 t-statistics
scalar m4ta1 = m4a1/m4sea1
scalar m4tb0 = m4b0/m4se0
scalar m4tb1 = m4b1/m4se1
scalar m4tb2 = m4b2/m4se2
scalar m4tb3 = m4b3/m4se3

 * Calculating significance totals (Model 1)
scalar m1asig = m1ta1<ecmsig
scalar m1asigMCV = m1ta1<ecmMCVm1
scalar m1dxsig = (m1tb0>up | m1tb0<lp) | (m1tb2>up | m1tb2<lp) | (m1tb4>up | m1tb4<lp)
scalar m1xlsig = (m1tb1>up | m1tb1<lp) | (m1tb3>up | m1tb3<lp) | (m1tb5>up | m1tb5<lp)
scalar m1dxecm = (m1ta1<ecmsig & (m1tb0>up | m1tb0<lp)) | (m1ta1<ecmsig & ///
(m1tb2>up | m1tb2<lp)) | (m1ta1<ecmsig & (m1tb4>up | m1tb4<lp))
scalar m1dxecmMCV = (m1ta1<ecmMCVm1 & (m1tb0>up | m1tb0<lp)) | (m1ta1<ecmMCVm1 & ///
(m1tb2>up | m1tb2<lp)) | (m1ta1<ecmMCVm1 & (m1tb4>up | m1tb4<lp))
scalar m1lxecm = (m1ta1<ecmsig & (m1tb1>up | m1tb1<lp)) | (m1ta1<ecmsig & ///
(m1tb3>up | m1tb3<lp)) | (m1ta1<ecmsig & (m1tb5>up | m1tb5<lp))
scalar m1lxecmMCV = (m1ta1<ecmMCVm1 & (m1tb1>up | m1tb1<lp)) | (m1ta1<ecmMCVm1 & ///
(m1tb3>up | m1tb3<lp)) | (m1ta1<ecmMCVm1 & (m1tb5>up | m1tb5<lp))

* Calculating significance totals (Model 2)
scalar m2asig = m2ta1<ecmsig
scalar m2asigMCV = m2ta1<ecmMCVm2
scalar m2dxsig = (m2tb0>up | m2tb0<lp) | (m2tb2>up | m2tb2<lp)
```

```
 scalar m2xlsig = (m2tb1>up | m2tb1<lp) | (m2tb3>up | m2tb3<lp)
 scalar m2dxecm = (m2ta1<ecmsig & (m2tb0>up | m2tb0<lp)) | (m2ta1<ecmsig & ///
(m2tb2>up | m2tb2<lp))
 scalar m2dxecmMCV = (m2ta1<ecmMCVm2 & (m2tb0>up | m2tb0<lp)) | ///
(m2ta1<ecmMCVm2 & (m2tb2>up | m2tb2<lp))
 scalar m2lxecm = (m2ta1<ecmsig & (m2tb1>up | m2tb1<lp)) | ///
(m2ta1<ecmsig & (m2tb3>up | m2tb3<lp))
 scalar m2lxecmMCV = (m2ta1<ecmMCVm2 & (m2tb1>up | m2tb1<lp)) | ///
(m2ta1<ecmMCVm2 & (m2tb3>up | m2tb3<lp))

 * Calculating significance totals (Model 3)
 scalar m3asig = m3ta1<ecmsig
 scalar m3asigMCV = m3ta1<ecmMCVm3
 scalar m3dxsig = (m3tb0>up | m3tb0<lp) | (m3tb2>up | m3tb2<lp) | (m3tb4>up | m3tb4<lp) ///
 | (m3tb6>up | m3tb6<lp)
 scalar m3xlsig = (m3tb1>up | m3tb1<lp) | (m3tb3>up | m3tb3<lp) | (m3tb5>up | m3tb5<lp) ///
| (m3tb7>up | m3tb7<lp)
 scalar m3dxecm = (m3ta1<ecmsig & (m3tb0>up | m3tb0<lp)) | (m3ta1<ecmsig & (m3tb2>up | m3tb2<lp)) ///
| (m3ta1<ecmsig & (m3tb4>up | m3tb4<lp)) | (m3ta1<ecmsig & (m3tb6>up | m3tb6<lp))
 scalar m3dxecmMCV = (m3ta1<ecmMCVm3 & (m3tb0>up | m3tb0<lp)) | (m3ta1<ecmMCVm3 & ///
 (m3tb2>up | m3tb2<lp)) | (m3ta1<ecmMCVm3 & (m3tb4>up | m3tb4<lp)) | (m3ta1<ecmMCVm3 & ///
 (m3tb6>up | m3tb6<lp))
 scalar m3lxecm = (m3ta1<ecmsig & (m3tb1>up | m3tb1<lp)) | (m3ta1<ecmsig & (m3tb3>up | m3tb3<lp)) ///
| (m3ta1<ecmsig & (m3tb5>up | m3tb5<lp)) | (m3ta1<ecmsig & (m3tb7>up | m3tb7<lp))
 scalar m3lxecmMCV = (m3ta1<ecmMCVm3 & (m3tb1>up | m3tb1<lp)) | (m3ta1<ecmMCVm3 & ///
(m3tb3>up | m3tb3<lp)) | (m3ta1<ecmMCVm3 & (m3tb5>up | m3tb5<lp)) | (m3ta1<ecmMCVm3 & ///
 (m3tb7>up | m3tb7<lp))

 * Calculating significance totals (Model 2)
 scalar m4asig = m4ta1<ecmsig
 scalar m4asigMCV = m4ta1<ecmMCVm4
 scalar m4dxsig = (m4tb0>up | m4tb0<lp) | (m4tb2>up | m4tb2<lp)
 scalar m4xlsig = (m4tb1>up | m4tb1<lp) | (m4tb3>up | m4tb3<lp)
 scalar m4dxecm = (m4ta1<ecmsig & (m4tb0>up | m4tb0<lp)) | (m4ta1<ecmsig & ///
(m4tb2>up | m4tb2<lp))
 scalar m4dxecmMCV = (m4ta1<ecmMCVm4 & (m4tb0>up | m4tb0<lp)) | ///
(m4ta1<ecmMCVm4 & (m4tb2>up | m4tb2<lp))
 scalar m4lxecm = (m4ta1<ecmsig & (m4tb1>up | m4tb1<lp)) |  ///
(m4ta1<ecmsig & (m4tb3>up | m4tb3<lp))
 scalar m4lxecmMCV = (m4ta1<ecmMCVm4 & (m4tb1>up | m4tb1<lp)) | ///
(m4ta1<ecmMCVm4 & (m4tb3>up | m4tb3<lp))

 post ‘sim’ (m1a1) (m1sea1) (m1ta1) (m1b0) (m1se0) (m1tb0) (m1b1) (m1se1) (m1tb1) ///
(m1b2) (m1se2) (m1tb2) (m1b3) (m1se3) (m1tb3) (m1b4) (m1se4) (m1tb4) (m1b5) ///
(m1se5) (m1tb5) (m1asig) (m1asigMCV) (m1dxsig) (m1xlsig) (m1dxecm) (m1dxecmMCV) ///
(m1lxecm) (m1lxecmMCV) (p1[1,1]) (rej1) (m1dw) ///
   (m2a1) (m2sea1) (m2ta1) (m2b0) (m2se0) (m2tb0) (m2b1) (m2se1) (m2tb1) (m2b2) ///
(m2se2) (m2tb2) (m2b3) (m2se3) (m2tb3) (m2asig) (m2asigMCV) (m2dxsig) (m2xlsig) ///
    (m2dxecm) (m2dxecmMCV) (m2lxecm) (m2lxecmMCV) (p2[1,1]) (rej2) (m2dw) ///
      (m3a1) (m3sea1) (m3ta1) (m3b0) (m3se0) (m3tb0) (m3b1) (m3se1) (m3tb1) (m3b2) (m3se2) ///
 (m3tb2) (m3b3) (m3se3) (m3tb3) (m3b4) (m3se4) (m3tb4) (m3b5) (m3se5) (m3tb5) ///
  (m3b6) (m3se6) (m3tb6) (m3b7) (m3se7) (m3tb7) (m3asig) (m3asigMCV) (m3dxsig) ///
(m3xlsig) (m3dxecm) (m3dxecmMCV) (m3lxecm) (m3lxecmMCV) (p3[1,1]) (rej3) (m3dw) ///
  (m4a1) (m4sea1) (m4ta1) (m4b0) (m4se0) (m4tb0) (m4b1) (m4se1) (m4tb1) (m4b2) (m4se2) ///
 (m4tb2) (m4b3) (m4se3) (m4tb3) (m4asig) (m4asigMCV) (m4dxsig) (m4xlsig) ///
    (m4dxecm) (m4dxecmMCV) (m4lxecm) (m4lxecmMCV) (p4[1,1]) (rej4) (m4dw)
 }
 }
 postclose ‘sim’

 use kelly_enns_results_mackinnon_boundedDV, clear
```

I.5.3 KE - Estimating FECM

```
* Fractional Differencing and FECM

* Create Individual ECMs *
* TABLE 1 *
```

```
reg mood policy
predict res11, r
reg mood gini
predict res12, r
reg welfare policy
predict res13, r
reg welfare gini
predict res14, r

* TABLE 2 *
reg mood_lowinc policy
predict res21, r
reg mood_lowinc gini
predict res22, r
reg mood_highinc policy
predict res23, r
reg mood_highinc gini
predict res24, r

* Create Combination ECMs *
* TABLE 1 *
reg mood policy gini
predict resfull1, r
reg welfare policy gini
predict resfull2, r

* TABLE 2 *
reg mood_lowinc policy gini
predict resfull3, r
reg mood_highinc policy gini
predict resfull4, r

* Fractionally Difference *
arfima d.mood
predict dmoodf, fdiff
arfima d.welfare
predict dwelf, fdiff
arfima d.policy
predict dpolicyf, fdiff
arfima d.gini
predict dginif, fdiff
arfima d.unemployment
predict dunemf, fdiff
arfima d.inflation
predict dinf, fdiff

arfima d.mood_lowinc
predict dmoodlowf, fdiff
arfima d.mood_highinc
predict dmoodhighf, fdiff

arfima d.res11
predict dres11f, fdiff
arfima d.res12
predict dres12f, fdiff
arfima d.res13
predict dres13f, fdiff
arfima d.res14
predict dres14f, fdiff

arfima d.res21
predict dres21f, fdiff
arfima d.res22
predict dres22f, fdiff
arfima d.res23
predict dres23f, fdiff
arfima d.res24
predict dres24f, fdiff
```

```
arfima d.resfull1
predict dresfull1f, fdiff
arfima d.resfull2
predict dresfull2f, fdiff

arfima d.resfull3
predict dresfull3f, fdiff
arfima d.resfull4
predict dresfull4f, fdiff

**** Table 1 - Individual FECMs ****
* Model 1
reg dmoodf dpolicyf dunemf dinf l.dres11f
* Model 2
reg dmoodf dpolicyf dginif l.dres12f
* Model 3
reg dmoodf dpolicyf dginif dunemf dinf l.dres11f
reg dmoodf dpolicyf dginif dunemf dinf l.dres12f
* Model 4
reg dwel dpolicyf dginif l.dres13f
reg dwel dpolicyf dginif l.dres14f

**** Table 1 - Groups FECMs ****
* Model 1
reg dmoodf dpolicyf dunemf dinf l.dres11f
* Model 2
reg dmoodf dpolicyf dginif l.dresfull1f
* Model 3
reg dmoodf dpolicyf dginif dunemf dinf l.dresfull1f
* Model 4
reg dwelf dpolicyf dginif l.dresfull2f

**** Table 2 - FECM ****
* Model 1
reg dmoodlowf dpolicyf dginif l.dres21f
reg dmoodlowf dpolicyf dginif l.dres22f
* Model 2
reg dmoodhighf dpolicyf dginif l.dres23f
reg dmoodhighf dpolicyf dginif l.dres24f
* Model 3
reg dmoodlowf dpolicyf dginif dunemf dinf l.dres21f
reg dmoodlowf dpolicyf dginif dunemf dinf l.dres22f
* Model 4
reg dmoodhighf dpolicyf dginif dunemf dinf l.dres23f
reg dmoodhighf dpolicyf dginif dunemf dinf l.dres24f

**** Table 2 - Groups FECMs ****
* Model 1
reg dmoodlowf dpolicyf dginif l.dresfull3f
* Model 2
reg dmoodhighf dpolicyf dginif l.dresfull4f
* Model 3
reg dmoodlowf dpolicyf dginif dunemf dinf l.dresfull3f
* Model 4
reg dmoodhighf dpolicyf dginif dunemf dinf l.dresfull4f
```

I.6 Voscho Kelly

I.6.1 Estimating FECM - RATS

```
** Recreating Volscho Kelly ASR **
calendar 1948 1 1
allocate 62
open data Volscho Kelly.xls
data(format=xls, org=columns) / year top1_cg dempres cdpercen divided union topmarg $
capgtax tbill_3 openness unemp ln_rgdp05 real_sp shiller_hpi
*
```

```
diff top1_cg / top1_cgd
diff dempres / dempresd
diff cdpercen / cdpercend
diff divided / dividedd
diff union / uniond
diff topmarg / topmargd
diff capgtax / capgtaxd
diff tbill_3 / tbill_3d
diff openness / opennessd
diff unemp / unempd
diff ln_rgdp05 / ln_rgdp05d
diff real_sp / real_spd
diff shiller_hpi / shiller_hpid
*
************* Fractionally Differencing Variables
*
@rgse top1_cgd
diff(fract=-.04) top1_cgd / top1_cgdf
*
@rgse cdpercend
diff(fract=-.09) cdpercend / cdpercendf
*
@rgse uniond
diff(fract=.31) uniond / uniondf
*
@rgse topmargd
diff(fract=0.16) topmargd / topmargdf
*
@rgse capgtaxd
diff(fract=.27) capgtaxd / capgtaxdf
*
@rgse tbill_3d
diff(fract=.01) tbill_3d / tbill_3df
*
@rgse opennessd
diff(fract=.01) opennessd / opennessdf
*
@rgse unempd
diff(fract=-0.23) unempd / unempdf
*
@rgse ln_rgdp05d
diff(fract=-.06) ln_rgdp05d / ln_rgdp05df
*
@rgse real_spd
diff(fract=.53) real_spd / real_spdf
*
@rgse shiller_hpid
diff(fract=.59) shiller_hpid / shiller_hpidf
*
******************************************
************** FI Models *****************
*
* MODEL 1
*
linreg top1_cgdf / res1 ; # constant dempresd cdpercendf dividedd uniondf
*
* Breusch-Godfrey Test
*
linreg res1 ; # constant dempresd cdpercendf dividedd uniondf res1{1}
cdf(title="Breusch-Godfrey SC Test") chisqr %trsq 1
*
* MODEL 2
*
linreg top1_cgdf / res2 ; # constant topmargdf capgtaxdf tbill_3df
*
* Breusch-Godfrey Test
*
linreg res2 ; # constant topmargdf capgtaxdf tbill_3df res2{1}
```

```
cdf(title="Breusch-Godfrey SC Test") chisqr %trsq 1
*
* MODEL 3
*
linreg top1_cgdf / res3 ; # constant cdpercendf dividedd uniondf topmargdf  $
capgtaxdf tbill_3df
*
* Breusch-Godfrey
*
linreg res3 ; # constant cdpercendf dividedd uniondf topmargdf capgtaxdf  $
tbill_3df res3{1}
cdf(title="Breusch-Godfrey SC Test") chisqr %trsq 1
*
* MODEL 4 -
*
linreg top1_cgdf / res4 ; # constant cdpercendf dividedd topmargdf capgtaxdf  $
tbill_3df opennessdf unempdf ln_rgdp05df real_spdf shiller_hpidf
*
* Breusch-Godfrey
*
linreg res4 ; # constant cdpercendf dividedd topmargdf capgtaxdf tbill_3df  $
opennessdf unempdf ln_rgdp05df real_spdf shiller_hpidf res4{1}
cdf(title="Breusch-Godfrey SC Test") chisqr %trsq 1
*
  ar1(method=pw) top1_cgdf / res4b ; # constant cdpercendf dividedd topmargdf $
capgtaxdf tbill_3df opennessdf unempdf ln_rgdp05df real_spdf shiller_hpidf
*
* MODEL 5
*
linreg top1_cgdf / res5 ; # constant cdpercendf dividedd uniondf topmargdf $
capgtaxdf tbill_3df opennessdf ln_rgdp05df real_spdf shiller_hpidf
*
* Breusch-Godfrey
*
linreg res5 ; # constant cdpercendf dividedd uniondf topmargdf capgtaxdf $
 tbill_3df opennessdf ln_rgdp05df real_spdf shiller_hpidf res5{1}
cdf(title="Breusch-Godfrey SC Test") chisqr %trsq 1
*
ar1(method=pw) top1_cgdf / res5b ; # constant cdpercendf dividedd uniondf $
 topmargdf capgtaxdf tbill_3df opennessdf ln_rgdp05df real_spdf shiller_hpidf
******************************************
*
******************************************
************** Generating the Residuals (Model 4)
*
* Estimate dual ECM
*
linreg top1_cg / ecm_34
# constant real_sp openness
*
************** Fractionally Differencing Residuals (Model 4)
*
diff ecm_34 / ecm_34d
*
@rgse ecm_34d
diff(fract=-0.11) ecm_34d / ecm_34df
************ Estimating FECM models (Model 4)
*
* FECM MODEL 4 -
*
linreg top1_cgdf / res4b ; # constant cdpercendf dividedd uniondf topmargdf $
capgtaxdf tbill_3df opennessdf unempdf ln_rgdp05df real_spdf shiller_hpidf ecm_34df{1}
*
* Breusch-Godfrey
*
linreg res4b; # constant cdpercendf dividedd topmargdf capgtaxdf tbill_3df $
opennessdf unempdf ln_rgdp05df real_spdf shiller_hpidf ecm_34df{1} res4b{1}
cdf(title="Breusch-Godfrey SC Test") chisqr %trsq 1
```

```
*
******************************************
************** Generating the Residuals (Model 5)
*
linreg top1_cg / ecm_35
# constant real_sp openness
*
************** Fractionally Differencing Residuals (Model 5)
*
diff ecm_35 / ecm_35d
*
@rgse ecm_35d
diff(fract=-.11) ecm_35d / ecm_35df
*
************ Estimating FECM models (Model 5)
*
* FECM MODEL 5_3
*
linreg top1_cgdf / res5 ; # constant cdpercendf dividedd uniondf topmargdf $
capgtaxdf tbill_3df opennessdf ln_rgdp05df real_spdf shiller_hpidf ecm_35df{1}
*
* Breusch-Godfrey
*
linreg res5; # constant cdpercendf dividedd topmargdf capgtaxdf tbill_3df $
opennessdf unempdf ln_rgdp05df real_spdf shiller_hpidf ecm_35df{1} res5{1}
cdf(title="Breusch-Godfrey SC Test") chisqr %trsq 1
```

I.7 Replication with Nonsense Data

Our replication data is provided below in a format that can hopefully be copy and pasted and opened in a CSV spreadsheet. Cumulative sharks (cumsharks) for the time period of the data was used in the Ura and Ellis data set to approximate the trending IVs *Defense Spending* and *Domestic Spending*. Data from the papers we replicated can be found at the various authors' dataverse pages. Thank you to the authors for making their data and models publicly available, without which we could not have conducted this analysis.

```
year,1952,1953,1954,1955,1956,1957,1958,1959,1960,1961,1962,1963,1964,1965,1966,1967,1968,
1969,1970,1971,1972,1973,1974,1975,1976,1977,1978,1979,1980,1981,1982,1983,1984,1985,1986,
1987,1988,1989,1990,1991,1992,1993,1994,1995,1996,1997,1998,1999,2000,2001,2002,2003,2004,
2005,2006,2007,2008,2009,2010,2011,
beef_miltons,20.5,22.4,23.4,24.3,25.8,26.1,26.1,26.4,25.6,27.7,29.2,30.9,31.3,31.9,33.6,
35.3,37.0,37.9,38.3,38.1,38.5,38.8,41.9,43.7,46.1,46.5,47.0,45.8,45.6,46.0,45.9,47.2,48.5,
49.3,51.0,50.9,51.3,51.6,53.0,53.7,52.8,52.3,53.0,53.8,54.3,55.0,54.9,55.9,56.2,55.2,56.8,
57.4,58.4,59.7,61.8,63.2,63.4,64.0,64.3,62.5,
sharks,,,,21,10,10,10,55,26,26,31,21,28,21,24,13,22,12,19,17,9,11,23,20,13,14,14,12,14,
30,23,24,23,20,13,20,33,33,35,36,48,42,59,69,43,50,52,56,88,77,65,55,65,56,56,70,52,66,80,,
cumsharks,,,,,,,,,,,,,,,,,,,,,9,20,43,63,76,90,104,116,130,160,183,207,230,250,263,283,
316,349,384,420,468,510,569,638,681,731,783,839,927,1004,1069,1124,1189,1245,1301,1371,
1423,1489,,,
tornadodeath,230,515,36,126,83,191,66,58,47,51,28,31,73,296,98,114,131,66,72,156,27,87,
361,60,44,43,53,83,28,24,64,34,122,93,15,59,32,50,53,39,39,33,69,30,25,67,130,94,41,40,
55,54,35,38,67,81,126,21,45,553,
acre10k,11.979,13.545,11.898,11.807,12.703,11.855,11.651,12.133,11.142,9.711,10.272,
9.951,10.582,10.257,10.273,10.896,11.463,10.74,10.663,10.278,9.88,10.827,11.325,10.696,
11.383,11.29,12.9,12.971,11.685,11.446,13.008,12.811,13.293,12.71,12.43,12.982,13.429,
13.783,14.29,14.079,14.87,16.54,17.206,17.177,17.543,17.507,17.837,18.551,17.828,17.3,
17.155,17.286,17.84,17.122,17.528,16.688,16.059,15.731,15.527,,
Coalemission,287,288,247,283,288,274,242,241,250,244,251,264,278,293,307,302,313,313,
309,293,306,329,323,322,345,355,354,385,392,405,391,406,436,447,441,461,484,490,497,
493,497,513,516,522,544,556,563,562,588,
569,571,583,589,595,586,592,583,512,541,512,
```

I.7.1 Casillas, Enns, Wohlfarth

```
* Nonsense - Casillas, Enns, Wohlfarth
```

```
* Model 1
ivreg2 d.all_rev l.all_rev d.tornadod l.tornadod d.sharks l.sharks (d.beef l.beef = ///
d.perchcpi d.unem d.policylib d.def_budg d.homicide d.inequality l.perchcpi ///
l.unem l.policylib l.def_budg l.homicide l.inequality), first

matrix b = e(b)
matrix V = e(V)
* Long Run Multiplier
* Lag of beef
scalar a2 = b[1,2]
* Lag of Sharks
scalar a7 = b[1,7]
* ECM
scalar b1 = b[1,3]
*Variances
scalar vara2 = V[2,2]
scalar vara7 = V[7,7]
scalar varb1 = V[3,3]
* Covariances
scalar cova2b1 = V[2,3]
scalar cova7b1 = V[7,3]

*s.e. for Beef
dis sqrt((1/b1^2)*vara2 + (a2^2/b1^4)*varb1 - 2*(a2/b1^3)*cova2b1)
* s.e. for sharks
dis sqrt((1/b1^2)*vara7 + (a7^2/b1^4)*varb1 - 2*(a7/b1^3)*cova7b1)

* Model 2
ivreg2 d.nosal_rev l.nosal_rev d.tornadod l.tornadod d.sharks l.sharks (d.beef ///
l.beef = d.perchcpi d.unem d.policylib d.def_budg d.homicide d.inequality ///
l.perchcpi l.unem l.policylib l.def_budg l.homicide l.inequality), first

matrix b = e(b)
matrix V = e(V)
* Long Run Multiplier
* Lag of beef
scalar a2 = b[1,2]
* Lag of Sharks
scalar a7 = b[1,7]
* ECM
scalar b1 = b[1,3]
*Variances
scalar vara2 = V[2,2]
scalar vara7 = V[7,7]
scalar varb1 = V[3,3]
* Covariances
scalar cova2b1 = V[2,3]
scalar cova7b1 = V[7,3]

*s.e. for Beef
dis sqrt((1/b1^2)*vara2 + (a2^2/b1^4)*varb1 - 2*(a2/b1^3)*cova2b1)
* s.e. for sharks
dis sqrt((1/b1^2)*vara7 + (a7^2/b1^4)*varb1 - 2*(a7/b1^3)*cova7b1)

* Model 3
ivreg2 d.sal_rev l.sal_rev d.tornadod l.tornadod d.sharks l.sharks (d.beef l.beef ///
 = d.perchcpi d.unem d.policylib d.def_budg d.homicide d.inequality l.perchcpi ///
l.unem l.policylib l.def_budg l.homicide l.inequality), first

matrix b = e(b)
matrix V = e(V)
* Long Run Multiplier
* Lag of beef
scalar a2 = b[1,2]
* Lag of Sharks
scalar a7 = b[1,7]
* ECM
scalar b1 = b[1,3]
```

```
*Variances
scalar vara2 = V[2,2]
scalar vara7 = V[7,7]
scalar varb1 = V[3,3]
* Covariances
scalar cova2b1 = V[2,3]
scalar cova7b1 = V[7,3]

*s.e. for Beef
dis sqrt((1/b1^2)*vara2 + (a2^2/b1^4)*varb1 - 2*(a2/b1^3)*cova2b1)
* s.e. for sharks
dis sqrt((1/b1^2)*vara7 + (a7^2/b1^4)*varb1 - 2*(a7/b1^3)*cova7b1)


* 1st stage results, what do they look like?
reg d.zmq_med d.perchcpi d.unem d.policylib d.def_budg d.homicide d.inequality l.perchcpi ///
l.unem l.policylib l.def_budg l.homicide l.inequality

reg l.zmq_med d.perchcpi d.unem d.policylib d.def_budg d.homicide d.inequality l.perchcpi ///
l.unem l.policylib l.def_budg l.homicide l.inequality
```

I.7.2 Ura and Ellis

```
* keep original DVs and use all nonsense variables
reg d.demmood l.demmood d.onion1000 l.onion1000 d.beef l.beef d.coalemiss  ///
l.coalemiss d.cumsharks l.cumsharks d.tornadodeath l.tornadodeath
estat bgodfrey, lags(1)
estat hettest
est store dem
reg d.repmood l.repmood d.onion1000 l.onion1000  d.beef l.beef d.coalemiss ///
l.coalemiss d.cumsharks l.cumsharks d.tornadodeath l.tornadodeath
estat bgodfrey, lags(1)
estat hettest
est store rep
suest dem rep

*** Test on whether coefficients are significantly different from each other
dis _b[dem_mean:l.demmood]-_b[rep_mean:l.repmood]
dis _b[dem_mean: d.onion1000]-_b[rep_mean: d.onion1000]
dis _b[dem_mean:l.onion1000]-_b[rep_mean:l.onion1000]
dis _b[dem_mean:d.beef]-_b[rep_mean:d.beef]
dis _b[dem_mean:l.beef]-_b[rep_mean:l.beef]
dis _b[dem_mean:d.coalemiss]-_b[rep_mean:d.coalemiss]
dis _b[dem_mean:l.coalemiss]-_b[rep_mean:l.coalemiss]
dis _b[dem_mean:d.cumsharks]-_b[rep_mean:d.cumsharks]
dis _b[dem_mean:l.cumsharks]-_b[rep_mean:l.cumsharks]
dis _b[dem_mean:d.tornadodeath]-_b[rep_mean:d.tornadodeath]
dis _b[dem_mean:l.tornadodeath]-_b[rep_mean:l.tornadodeath]


test _b[dem_mean:l.demmood]=_b[rep_mean:l.repmood]
test _b[dem_mean: d.onion1000]=_b[rep_mean: d.onion1000]
test _b[dem_mean:l.onion1000]=_b[rep_mean:l.onion1000]
test _b[dem_mean:d.beef]=_b[rep_mean:d.beef]
test _b[dem_mean:l.beef]=_b[rep_mean:l.beef]
test _b[dem_mean:d.coalemiss]=_b[rep_mean:d.coalemiss]
test _b[dem_mean:l.coalemiss]=_b[rep_mean:l.coalemiss]
test _b[dem_mean:d.cumsharks]=_b[rep_mean:d.cumsharks]
test _b[dem_mean:l.cumsharks]=_b[rep_mean:l.cumsharks]
test _b[dem_mean:d.tornadodeath]=_b[rep_mean:d.tornadodeath]
test _b[dem_mean:l.tornadodeath]=_b[rep_mean:l.tornadodeath]

*** Creation of Long Run Multipliers
dis _b[dem_mean:l.onion1000]/_b[dem_mean:l.demmood]
dis _b[dem_mean:l.beef]/_b[dem_mean:l.demmood]
dis _b[dem_mean:l.coalemiss]/_b[dem_mean:l.demmood]
dis _b[dem_mean:l.cumsharks]/_b[dem_mean:l.demmood]
```

```
dis _b[dem_mean:l.tornadodeath]/_b[dem_mean:l.demmood]

dis _b[rep_mean:l.onion1000]/_b[rep_mean:l.repmood]
dis _b[rep_mean:l.beef]/_b[rep_mean:l.repmood]
dis _b[rep_mean:l.coalemiss]/_b[rep_mean:l.repmood]
dis _b[rep_mean:l.cumsharks]/_b[rep_mean:l.repmood]
dis _b[rep_mean:l.tornadodeath]/_b[rep_mean:l.repmood]

dis _b[rep_mean:l.onion1000]/_b[rep_mean:l.repmood] - ///
_b[dem_mean:l.onion1000]/_b[dem_mean:l.demmood]
dis _b[rep_mean:l.beef]/_b[rep_mean:l.repmood] - ///
_b[dem_mean:l.beef]/_b[dem_mean:l.demmood]
dis _b[rep_mean:l.coalemiss]/_b[rep_mean:l.repmood] -  ///
_b[dem_mean:l.coalemiss]/_b[dem_mean:l.demmood]
dis _b[rep_mean:l.cumsharks]/_b[rep_mean:l.repmood] - ///
_b[dem_mean:l.cumsharks]/_b[dem_mean:l.demmood]
dis _b[rep_mean:l.tornadodeath]/_b[rep_mean:l.repmood] - ///
_b[dem_mean:l.tornadodeath]/_b[dem_mean:l.demmood]

* SE of LRM is given by
* Var(a/b) = (1/b^2)Var(a) + (a^2/b^4)Var(b) - 2(a/b^3)Cov(a,b)
*So l.variable are 3, 5, 7, 9, 11
*ECM is 1

matrix b = e(b)
matrix V = e(V)
* FOR DEMOCRATS --
scalar a3 = b[1,3]
scalar a5 = b[1,5]
scalar a7 = b[1,7]
scalar a9 = b[1,9]
scalar a11 = b[1,11]
scalar b1 = b[1,1]

scalar vara3=V[3,3]
scalar vara5=V[5,5]
scalar vara7=V[7,7]
scalar vara9=V[9,9]
scalar vara11=V[11,11]
scalar varb1=V[1,1]

scalar cova3b1=V[3,1]
scalar cova5b1=V[5,1]
scalar cova7b1=V[7,1]
scalar cova9b1=V[9,1]
scalar cova11b1=V[11,1]
* generic SE equation is square root of variance
dis sqrt((1/b1^2)*vara3 + (a3^2/b1^4)*varb1 - 2*(a3/b1^3)*cova3b1)

* ------

* FOR REPUBLICANS ----- ECM is b14
scalar b14 = b[1,14]
scalar a16 = b[1,16]
scalar a18 = b[1,18]
scalar a20 = b[1,20]
scalar a22 = b[1,22]
scalar a24 = b[1,24]

scalar varb14 = V[14,14]
scalar vara16 = V[16,16]
scalar vara18 = V[18,18]
scalar vara20 = V[20,20]
scalar vara22 = V[22,22]
scalar vara24 = V[24,24]

scalar cova16b14=V[16,14]
scalar cova18b14=V[18,14]
```

```
scalar cova20b14=V[20,14]
scalar cova22b14=V[22,14]
scalar cova24b14=V[24,14]
* generic SE equation is square root of variance
dis sqrt((1/b14^2)*vara3 + (a3^2/b14^4)*varb14 - 2*(a3/b14^3)*cova3b14)
```

I.7.3 Kelly and Enns

```
**** Kelly and Enns nonsense regression

* Nonsense regression Model 1
 reg d.mood l.mood d.beef l.beef d.coal l.coal d.acre10k l.acre10k

* Nonsense regression Model 2
 reg d.mood l.mood d.beef l.beef d.coal l.coal

* Nonsense regression Model 3
 reg d.mood l.mood d.beef l.beef d.coal l.coal d.acre10k l.acre10k d.tornadodeath l.tornadodeath

* Nonsense regression Model 4
 reg d.welfare l.welfare d.beef l.beef d.coal l.coal

* TABLE 2

* Nonsense regression Model 1
 reg d.mood_lowinc l.mood_lowinc d.beef l.beef d.coal l.coal

* Nonsense regression Model 2
 reg d.mood_highinc l.mood_highinc d.beef l.beef d.coal l.coal

* Nonsense regression Model 3
 reg d.mood_lowinc l.mood_lowinc d.beef l.beef d.coal l.coal d.acre10k l.acre10k ///
      d.tornadodeath l.tornadodeath

* Nonsense regression Model 4
 reg d.mood_highinc l.mood_highinc d.beef l.beef d.coal l.coal d.acre10k l.acre10k ///
     d.tornadodeath l.tornadodeath
```

I.8 AR MC

Set ρ manually by changing the value of r. The code below is for a bivariate regression, but can easily be edited to fit a specific number of variables. Proper MacKinnon values must be set for the ECM counter based upon T and number of IVs.

```
********************************************
***** Simulation of Bivariate I(1) Model *****
********************************************
* 1 X that is I(1)

seed 5000
all 60
*
* Load source files
*
* Values for simulations
*
comp draws = 10000
infobox(action=define, progress, lower=1, upper=draws) 'Simulations Completed'
*
* Model Counters
*
comp rw_ecm5  = 0
comp rw_ecmXD = 0
comp rw_ecmXL = 0
comp rw_XDsig = 0
```

```
comp rw_XLsig = 0
comp mv_ecm5 = 0
comp mv_ecmXD = 0
comp mv_ecmXL = 0

*
* Regression Output
*
set rw_betaECM 1 draws = 0
set rw_tstatECM 1 draws = 0
set rw_seECM 1 draws = 0
set rw_betaXD 1 draws = 0
set rw_tstatXD 1 draws = 0
set rw_seXD 1 draws = 0
set rw_betaXL 1 draws = 0
set rw_tstatXL 1 draws = 0
set rw_seXL 1 draws = 0
set df 1 draws = 0
set dfbeta 1 draws = 0
set dfse 1 draws = 0
set rsq 1 draws = 0
*
* Begin Loop
*
do i = 1,draws
infobox(current=i)
*
* Random Draw
*
set y = 0
set x = 0
set r = .95
*
* Random Walk (with AR) and Differencing
*
set y 2 * = r*y{1} + %ran(1)
diff y 2 * dy
*
@dfunit(noprint) y
com df(i) = %cdstat
*
set x 2 * = x{1} + %ran(1)
diff x 2 * dx
*
* Bivariate Regression Model
*
lin(noprint) dy ; # constant y{1}
com dfbeta(i) = %beta(2)
com dfse(i) = %stderrs(2)

lin(noprint) dy ; # constant y{1} dx x{1}
*
* ECM statistics
*
com rsq(i) = %rsquared
com rw_betaECM(i) = %beta(2)
com rw_seECM(i) = %stderrs(2)
com rw_tstatECM(i) = %tstats(2)
*
* Xd (diff) statistics
*
com rw_betaXD(i) = %beta(3)
com rw_seXD(i) = %stderrs(3)
com rw_tstatXD(i) = %tstats(3)
*
* XL (lag) statistics
*
com rw_betaXL(i) = %beta(4)
```

```
com rw_seXL(i) = %stderrs(4)
com rw_tstatXL(i) = %tstats(4)
*
* Counter for ECMs
*
if rw_tstatECM(i) < -1.645 ; comp rw_ecm5 = rw_ecm5 + 1
if rw_tstatECM(i).lt.-1.645.AND.(rw_tstatXD(i).lt.-1.96.OR.rw_tstatXD(i).gt.1.96) ; comp rw_ecmXD = rw_ecmXD + 1
if rw_tstatECM(i).lt.-1.645.AND.(rw_tstatXL(i).lt.-1.96.OR.rw_tstatXL(i).gt.1.96) ; comp rw_ecmXL = rw_ecmXL + 1
*
* Counter for ECMs (w/ MacKinnon CVs)
*
if rw_tstatECM(i) < -3.27 ; comp mv_ecm5 = mv_ecm5 + 1
if rw_tstatECM(i).lt.-3.27.AND.(rw_tstatXD(i).lt.-1.96.OR.rw_tstatXD(i).gt.1.96) ; comp mv_ecmXD = mv_ecmXD + 1
if rw_tstatECM(i).lt.-3.27.AND.(rw_tstatXL(i).lt.-1.96.OR.rw_tstatXL(i).gt.1.96) ; comp mv_ecmXL = mv_ecmXL + 1
*
* Counter for X variables
*
if rw_tstatXD(i).lt.-1.96.OR.rw_tstatXD(i).gt.1.96 ; comp rw_XDsig = rw_XDsig + 1
if rw_tstatXL(i).lt.-1.96.OR.rw_tstatXL(i).gt.1.96 ; comp rw_XLsig = rw_XLsig + 1
*
end do i
infobox(action=remove)
*
*
** Print Output **
*
dis '**************** Output of FI Models **************** '
dis #
dis ' Number of Significant ECMs   ' #################### rw_ECM5
dis #
dis ' Number of Significant ECMs (MCV) ' #################### mv_ECM5
dis #
dis ' Number of D&K Models with >= 1 Significant DX ' ################ rw_XDsig
dis #
dis ' Number of D&K Models with >= 1 Significant X{1} ' ################ rw_XLsig
dis #
dis ' Number of D&K Models with Sig ECM and >=1 Sig DX ' ################ rw_ecmXD
dis #
dis ' Number of D&K Models with Sig ECM and >=1 Sig DX  (MCV) ' ################ mv_ecmXD
dis #
dis ' Number of D&K Models with Sig ECM and >=1 Sig X{1} ' ################ rw_ecmXL
dis #
dis ' Number of D&K Models with Sig ECM and >=1 Sig X{1} (MCV) ' ################ mv_ecmXL
dis #
dis '**************************************************** '
*
table / rw_betaECM
```

I.9 FI MC

Code uses ARFSIM, XGAMMA, and RGSE packages in RATS 8.0. ARFSIM has been updated and XGAMMA has been packaged within it, however we used an old version to ensure that the FI of our series was correct. If using this code, the allocation must be at least double the n size to be estimated.

```
********************************************
***** Simulation of Bivariate FI Model *****
********************************************
* 1 X that is I(1)
* Critical Values for d --> for .1 use .00001, for .2, use .12, for .3 use .26, all others are as expected
seed 5000
all 120
frequency 1 60
*
* Load source files
*
```

```
source(noecho) xgamma.src
source(noecho) arfsim.src
source(noecho) rgse.src
*
* Values for simulations
*
comp d = .9
comp n = 60
comp draws = 10000
infobox(action=define, progress, lower=1, upper=draws) 'Simulations Completed'
*
* Model Counters
*
comp fibi_ecm5  = 0
comp fibi_ecmXD = 0
comp fibi_ecmXL = 0
comp fibi_XDsig = 0
comp fibi_XLsig = 0
comp mv_ecm5 = 0
comp mv_ecmXD = 0
comp mv_ecmXL = 0

*
* Regression Output
*
set fibi_betaECM 1 draws = 0
set fibi_tstatECM 1 draws = 0
set fibi_seECM 1 draws = 0
set fibi_betaXD 1 draws = 0
set fibi_tstatXD 1 draws = 0
set fibi_seXD 1 draws = 0
set fibi_betaXL 1 draws = 0
set fibi_tstatXL 1 draws = 0
set fibi_seXL 1 draws = 0
set fibi_df 1 draws = 0
set fibi_dfbeta 1 draws = 0
set fibi_dfse 1 draws = 0
set fibi_rsq 1 draws = 0
*
* @rgse Statistics
*
set fibi_rgsedy 1 draws = 0
*
* Begin Loop
*
do i = 1,draws
infobox(current=i)
*
* Draw of FI data for DV
*
@arfsim d n y
*
* Random Draw
*
set x = 0
*
* Random Walk and Differencing
*
diff y 2 * dyf
*
@dfunit(noprint) dyf
com fibi_df(i) = %cdstat
*
set x 2 * = x{1} + %ran(1)
diff x 2 * dx
*
@rgse(noprint) dyf
comp fibi_rgsedy(i) = %%d
```

```
*
* Bivariate Regression Model
*
lin(noprint) dyf ; # constant y{1}
com fibi_dfbeta(i) = %beta(2)
com fibi_dfse(i) = %stderrs(2)

lin(noprint) dyf ; # constant y{1} dx x{1}
*
* ECM statistics
*
com fibi_rsq(i) = %rsquared
com fibi_betaECM(i) = %beta(2)
com fibi_seECM(i) = %stderrs(2)
com fibi_tstatECM(i) = %tstats(2)
*
* Xd (diff) statistics
*
com fibi_betaXD(i) = %beta(3)
com fibi_seXD(i) = %stderrs(3)
com fibi_tstatXD(i) = %tstats(3)
*
* XL (lag) statistics
*
com fibi_betaXL(i) = %beta(4)
com fibi_seXL(i) = %stderrs(4)
com fibi_tstatXL(i) = %tstats(4)
*
* Counter for ECMs
*
if fibi_tstatECM(i) < -1.645 ; comp fibi_ecm5 = fibi_ecm5 + 1
if fibi_tstatECM(i).lt.-1.645.AND.(fibi_tstatXD(i).lt.-1.96.OR.fibi_tstatXD(i).gt.1.96) ; comp fibi_ecmXD = fibi_ecmXD + 1
if fibi_tstatECM(i).lt.-1.645.AND.(fibi_tstatXL(i).lt.-1.96.OR.fibi_tstatXL(i).gt.1.96) ; comp fibi_ecmXL = fibi_ecmXL + 1
*
* Counter for ECMs (w/ MacKinnon CVs) (CV for 60 = -3.27, for 150 = -3.236)
*
if fibi_tstatECM(i) < -3.27 ; comp mv_ecm5 = mv_ecm5 + 1
if fibi_tstatECM(i).lt.-3.27.AND.(fibi_tstatXD(i).lt.-1.96.OR.fibi_tstatXD(i).gt.1.96) ; comp mv_ecmXD = mv_ecmXD + 1
if fibi_tstatECM(i).lt.-3.27.AND.(fibi_tstatXL(i).lt.-1.96.OR.fibi_tstatXL(i).gt.1.96) ; comp mv_ecmXL = mv_ecmXL + 1
*
* Counter for X variables
*
if fibi_tstatXD(i).lt.-1.96.OR.fibi_tstatXD(i).gt.1.96 ; comp fibi_XDsig = fibi_XDsig + 1
if fibi_tstatXL(i).lt.-1.96.OR.fibi_tstatXL(i).gt.1.96 ; comp fibi_XLsig = fibi_XLsig + 1
*
end do i
infobox(action=remove)
*
*
** Print Output **
*
dis '**************** Output of FI Models **************** '
dis #
dis ' Number of Significant ECMs   ' #################### fibi_ECM5
dis #
dis ' Number of Significant ECMs (MCV) ' #################### mv_ECM5
dis #
dis ' Number of D&K Models with >= 1 Significant DX ' ################ fibi_XDsig
dis #
dis ' Number of D&K Models with >= 1 Significant X{1} ' ################ fibi_XLsig
dis #
dis ' Number of D&K Models with Sig ECM and >=1 Sig DX ' ################ fibi_ecmXD
dis #
dis ' Number of D&K Models with Sig ECM and >=1 Sig DX  (MCV) ' ################ mv_ecmXD
dis #
dis ' Number of D&K Models with Sig ECM and >=1 Sig X{1} ' ################ fibi_ecmXL
dis #
dis ' Number of D&K Models with Sig ECM and >=1 Sig X{1} (MCV) ' ################ mv_ecmXL
```

```
dis #
dis '***************************************************** '
*
table / 1 to 15
```

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