

Using cointegrating relationships to capture the
cyclical and long-run dynamics of revenue forecasts:
A simple example from Massachusetts

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Advantages of Using Cointegrating Relationships

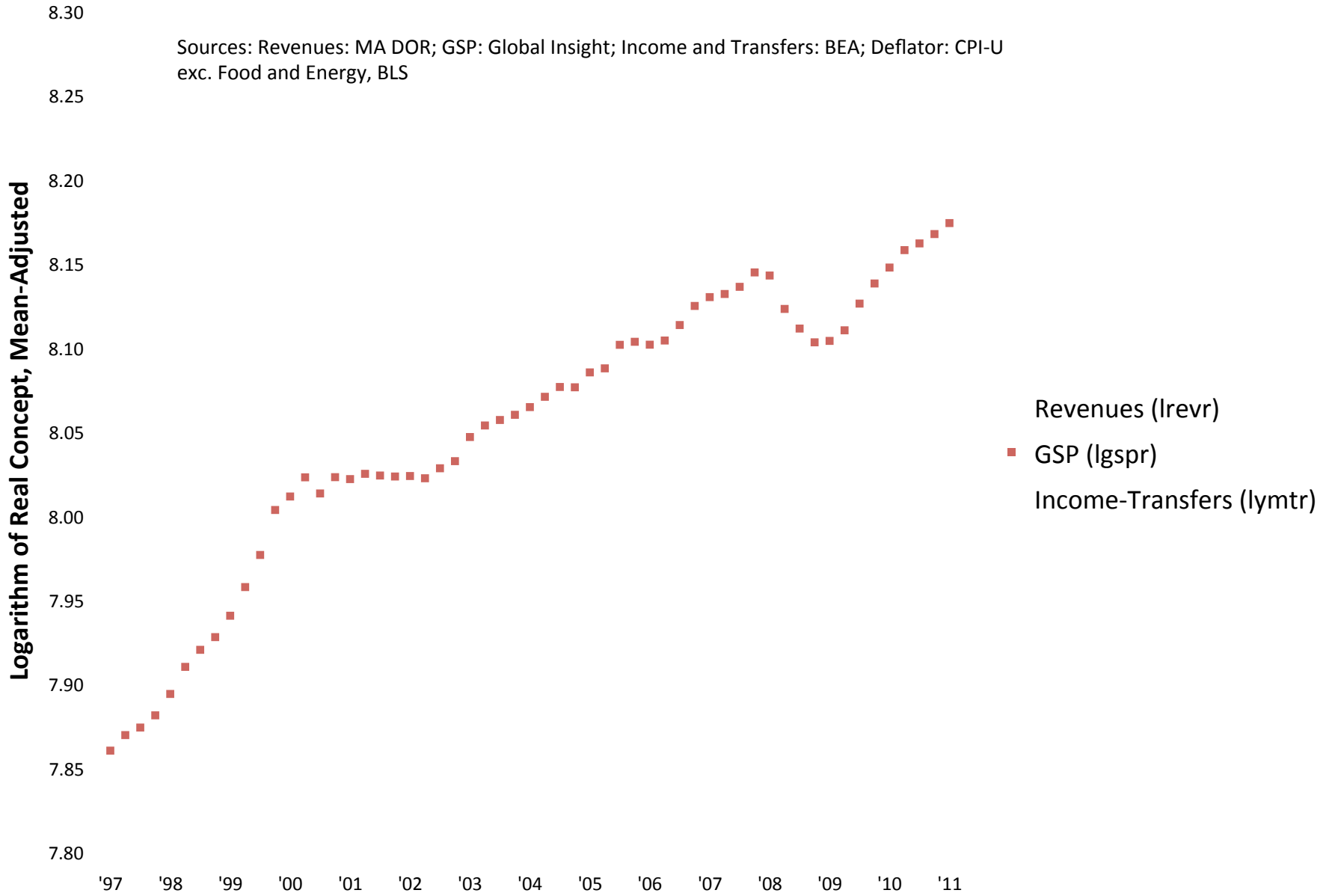
- Makes use of the dynamic adjustments towards a long-run equilibrium. Can capture cyclical dynamics better than a (misspecified) VAR model.
- Avoids the misspecification error of a VAR model in differences (when equilibrium relations exist).
- Can give more reliable (than VAR models in differences) estimates of long-term growth trends.
- The long-term trend can be used to estimate the cyclical deficit via a Beveridge-Nelson trend.
- It's easy to implement.
- Most state revenue systems are closely linked to output and/or incomes, so cointegrating relationships are likely to exist.

Steps in Estimating and Forecasting Cointegrated Models

- Identify the probable cointegrating relationships.
- Test for cointegration: Augmented Dickey-Fuller tests for a unit root and Engle-Granger Augmented Dickey-Fuller tests for stationary linear combinations are simple to do.
- Dynamic OLS (DOLS) estimates of the cointegrating relationships are easy to do and are better than OLS for short periods of history.
- Estimate a Vector Error-Correction (VECM) model – simply a VAR model with error correction terms.
- Use the usual time-series techniques, e.g., AIC and BIC criteria, for finding the best lag structures in the DOLS and VECM models, as well as for the ADF and EG-ADF tests.
- Carry out the forecast.
- Calculate the Beveridge-Nelson trend if it is useful for you.

Revenues, Gross State Product, and Income Minus Transfers

Sources: Revenues: MA DOR; GSP: Global Insight; Income and Transfers: BEA; Deflator: CPI-U exc. Food and Energy, BLS



The Cointegrating Relationships and Error-Correction Terms

$$lrevr_t = \theta_{g0} + \theta_{g1}lgspr_t + \eta_{gt}$$

$$lrevr_t = \theta_{y0} + \theta_{y1}lymtr_t + \eta_{yt}$$

Where: $lrevr$, $lgspr$, and $lymtr$ are I(1), and

η_{gt} , η_{yt} are stationary.

$$ec_g_t = lrevr_t - \hat{\theta}_{g0} - \hat{\theta}_{g1}lgspr_t$$

$$ec_y_t = lrevr_t - \hat{\theta}_{y0} - \hat{\theta}_{y1}lymtr_t$$

Dynamic OLS (DOLS) Estimates of the Cointegrating Coefficients

- $$lrevr_t = \gamma_{g0} + \theta_{g1}lgspr_t + \sum_{i=-p}^p \delta_{gi}\Delta lgspr_{t-i} + e_{gt}$$
$$lrevr_t = \gamma_{y0} + \theta_{y1}lymtr_t + \sum_{i=-q}^q \delta_{yi}\Delta lymtr_{t-i} + e_{yt}$$

Note: use HAC (Newey-West) standard errors for hypothesis tests.

$$\hat{\theta}_{g0} = \text{mean value of: } lrevr_t - \hat{\theta}_{g1}lgspr_t$$

$$\hat{\theta}_{y0} = \text{mean value of: } lrevr_t - \hat{\theta}_{y1}lymtr_t$$

DOLS Estimates of the Cointegration Coefficient on GSP (lgspr)

```

*
* DOLS with newey-west std err : GSP
*
. newey lrevr lgspr L(-4/4).dlgspr, lag(3)

Regression with Newey-West standard errors          Number of obs =          48
maximum lag: 3                                     F( 10, 37) =          11.82
                                                    Prob > F =           0.0000

```

| | Coef. | Newey-West Std. Err. | t | P> t | [95% Conf. Interval] | |
|--------|-----------|-------------------------|-------|-------|----------------------|----------|
| lgspr | .8728016 | .3089833 | 2.82 | 0.008 | .2467419 | 1.498861 |
| dlgspr | | | | | | |
| F4. | -.5481994 | .923495 | -0.59 | 0.556 | -2.419378 | 1.322979 |
| F3. | -1.386603 | 1.336892 | -1.04 | 0.306 | -4.095404 | 1.322198 |
| F2. | -.6752612 | .7453761 | -0.91 | 0.371 | -2.185537 | .8350143 |
| F1. | .4675015 | 1.270931 | 0.37 | 0.715 | -2.107649 | 3.042652 |
| --. | 1.021733 | 1.05158 | 0.97 | 0.338 | -1.108971 | 3.152436 |
| L1. | .8863019 | 1.040486 | 0.85 | 0.400 | -1.221922 | 2.994526 |
| L2. | .5469576 | 1.595779 | 0.34 | 0.734 | -2.686398 | 3.780313 |
| L3. | 1.94619 | 1.232476 | 1.58 | 0.123 | -.5510433 | 4.443424 |
| L4. | 3.798816 | 1.210382 | 3.14 | 0.003 | 1.346349 | 6.251282 |
| _cons | 3.658146 | 2.502795 | 1.46 | 0.152 | -1.412999 | 8.729291 |

DOLS Estimates of the Cointegration Coefficient on Income-Transfers (lymtr)

```

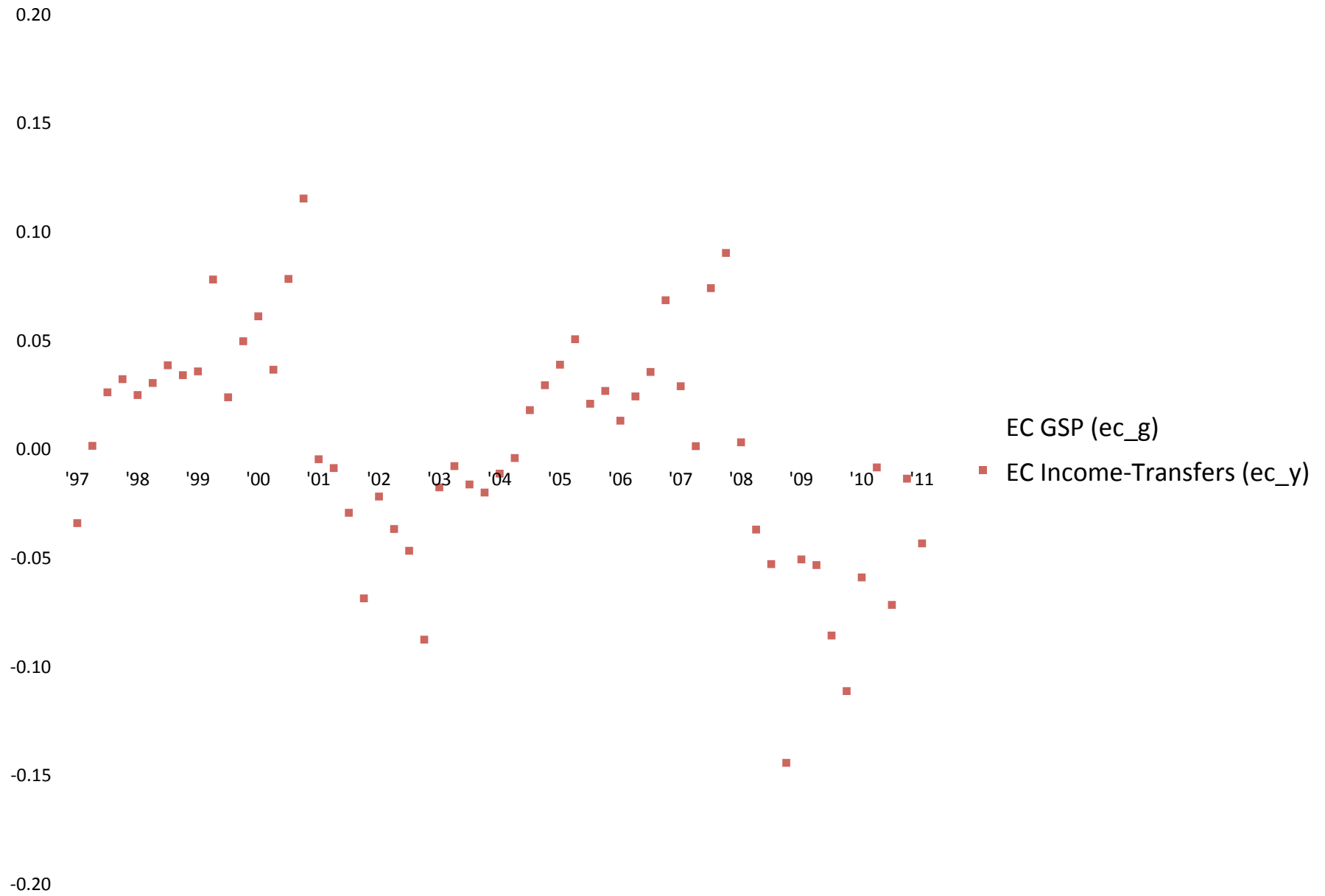
. *
. * DOLS with newey-west std err: Income-transfers
. *
. newey lrevr lymtr L(-4/4).dlymtr, lag(3)

Regression with Newey-West standard errors          Number of obs =          48
maximum lag: 3                                     F( 10, 37) =          53.24
                                                    Prob > F =          0.0000

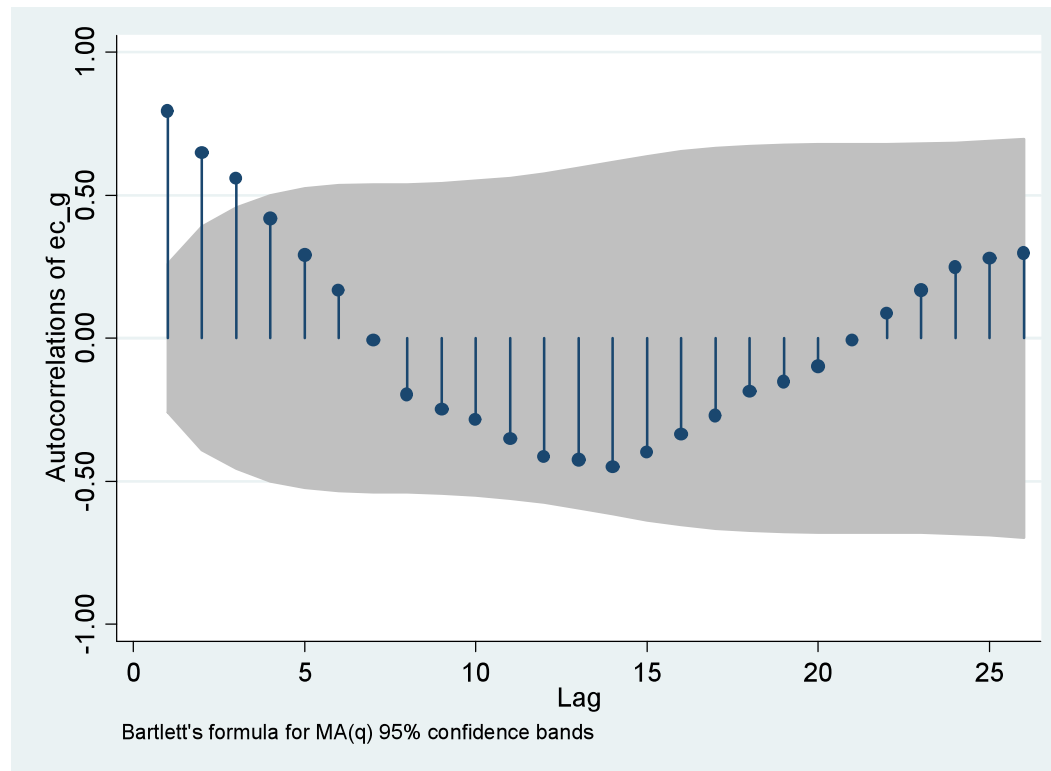
```

| | Coef. | Newey-West Std. Err. | t | P> t | [95% Conf. Interval] | |
|--------|-----------|-------------------------|-------|-------|----------------------|----------|
| lrevr | | | | | | |
| lymtr | .8541221 | .0929745 | 9.19 | 0.000 | .6657378 | 1.042506 |
| dlymtr | | | | | | |
| F4. | -.3384281 | .3536237 | -0.96 | 0.345 | -1.054938 | .3780816 |
| F3. | -.5674194 | .4812396 | -1.18 | 0.246 | -1.542503 | .4076647 |
| F2. | .1285599 | .412168 | 0.31 | 0.757 | -.7065717 | .9636916 |
| F1. | .4563609 | .5019408 | 0.91 | 0.369 | -.5606678 | 1.47339 |
| --. | .113619 | .4269499 | 0.27 | 0.792 | -.7514637 | .9787016 |
| L1. | 1.225325 | .5346357 | 2.29 | 0.028 | .1420501 | 2.3086 |
| L2. | .3031446 | .36933 | 0.82 | 0.417 | -.445189 | 1.051478 |
| L3. | .5551846 | .3782327 | 1.47 | 0.151 | -.2111876 | 1.321557 |
| L4. | 1.379641 | .3823295 | 3.61 | 0.001 | .6049674 | 2.154314 |
| _cons | 4.047577 | .7257703 | 5.58 | 0.000 | 2.577027 | 5.518128 |

Error-Correction Terms for GSP and Income-Transfers



Autocorrelations for GSP Error Correction Term (ec_g)



The VECM Model

1. $\Delta lrevr_t =$
 $\sum_{i=1}^p \beta_{1r}(i) \Delta lrevr_{t-i} + \sum_{i=1}^p \beta_{1g}(i) \Delta lgspr_{t-i} +$
 $\sum_{i=1}^p \beta_{1y}(i) \Delta lymtr_{t-i} + \alpha_{1g} ec_g_{t-1} + \alpha_{1y} ec_y_{t-1} +$
 $\beta_{10} + u_{1t}$
2. $\Delta lgspr_t =$
 $\sum_{i=1}^p \beta_{2r}(i) \Delta lrevr_{t-i} + \sum_{i=1}^p \beta_{2g}(i) \Delta lgspr_{t-i} +$
 $\sum_{i=1}^p \beta_{2y}(i) \Delta lymtr_{t-i} + \alpha_{2g} ec_g_{t-1} + \alpha_{2y} ec_y_{t-1} +$
 $\beta_{20} + u_{2t}$
3. $\Delta lymtr_t =$
 $\sum_{i=1}^p \beta_{3r}(i) \Delta lrevr_{t-i} + \sum_{i=1}^p \beta_{3g}(i) \Delta lgspr_{t-i} +$
 $\sum_{i=1}^p \beta_{3y}(i) \Delta lymtr_{t-i} + \alpha_{3g} ec_g_{t-1} + \alpha_{3y} ec_y_{t-1} +$
 $\beta_{30} + u_{3t}$

VECM Model Estimates

```

. var dlrevr dlgspr dlymtr, lags(1/1) exog(L.ec_g L.ec_y)
.
. Vector autoregression
.
. Sample: 1998q1 - 2011q3
. Log likelihood = 500.2322
. FPE = 4.88e-12
. Det(Sigma_ml) = 2.53e-12
. No. of obs = 55
. AIC = -17.53572
. HQIC = -17.28167
. SBIC = -16.87877
.
. Equation Parms RMSE R-sq chi2 P>chi2
.-----
. dlrevr 6 .035701 0.3895 35.08475 0.0000
. dlgspr 6 .005611 0.5275 61.40625 0.0000
. dlymtr 6 .010567 0.5185 59.23084 0.0000
.-----
.
.-----
. Coef. Std. Err. z P>|z| [95% Conf. Interval]
.-----
. dlrevr
. dlrevr L1. -.0137055 .1415883 -0.10 0.923 [-.2912136 .2638025]
. dlgspr L1. .4725516 .7533629 0.63 0.530 [-1.004013 1.949116]
. dlymtr L1. 1.580362 .3952457 4.00 0.000 [.8056952 2.35503]
. ec_g LI. .2256739 .350384 0.64 0.520 [-.4610661 .9124139]
. ec_y LI. -.6713756 .4753648 -1.41 0.158 [-1.603074 .2603224]
. _cons -.0073395 .0058534 -1.25 0.210 [-.018812 .0041329]
.-----

```

VECM Model Estimates, Continued

| | Coef. | Std. Err. | z | P> z | [95% Conf. Interval] | |
|--------|-----------|-----------|-------|-------|----------------------|-----------|
| ----- | | | | | | |
| dlgspr | | | | | | |
| dlrevr | | | | | | |
| L1. | .0391867 | .0222508 | 1.76 | 0.078 | -.0044241 | .0827975 |
| dlgspr | | | | | | |
| L1. | .2614355 | .1183922 | 2.21 | 0.027 | .0293911 | .4934798 |
| dlymtr | | | | | | |
| L1. | .2683569 | .0621135 | 4.32 | 0.000 | .1466167 | .390097 |
| ec_g | | | | | | |
| L1. | .0241871 | .0550634 | 0.44 | 0.660 | -.0837352 | .1321093 |
| ec_y | | | | | | |
| L1. | -.0618759 | .0747043 | -0.83 | 0.408 | -.2082937 | .0845419 |
| _cons | .0023456 | .0009199 | 2.55 | 0.011 | .0005426 | .0041485 |
| ----- | | | | | | |
| dlymtr | | | | | | |
| dlrevr | | | | | | |
| L1. | -.0322506 | .0419082 | -0.77 | 0.442 | -.1143891 | .0498879 |
| dlgspr | | | | | | |
| L1. | .6404445 | .2229849 | 2.87 | 0.004 | .2034022 | 1.077487 |
| dlymtr | | | | | | |
| L1. | .3081897 | .1169872 | 2.63 | 0.008 | .0788991 | .5374804 |
| ec_g | | | | | | |
| L1. | -.3594172 | .1037088 | -3.47 | 0.001 | -.5626826 | -.1561518 |
| ec_y | | | | | | |
| L1. | .4654486 | .1407013 | 3.31 | 0.001 | .189679 | .7412181 |
| _cons | .0005072 | .0017325 | 0.29 | 0.770 | -.0028885 | .0039029 |
| ----- | | | | | | |

Steps to Produce the n-period Forecast from $t+1$ to $t+n$

1. Use the VECM to predict $\Delta lrevr_{t+1|t}$,
 $\Delta lgspr_{t+1|t}$, $\Delta lymtr_{t+1|t}$
2. $lrevr_{t+1|t} = lrevr_t + \Delta lrevr_{t+1|t}$, etc. for
 $lgspr_{t+1|t}$, $lymtr_{t+1|t}$.
3. $ec_g_{t+1|t} = lrevr_{t+1|t} - \hat{\theta}_{g0} - \hat{\theta}_{g1} lgspr_{t+1|t}$
 $ec_y_{t+1|t} = lrevr_{t+1|t} - \hat{\theta}_{y0} - \hat{\theta}_{y1} lymtr_{t+1|t}$
4. Iterate through steps 1-3 replacing " $t + 1|t$ " by " $t + 2|t$ ", " t " by " $t + 1|t$ ", until " $t + n|t$ ".

Prediction Code for Stata After “var” Command

```
* prediction loop
* obs 58 is 2011q4, first quarter in forecast
* obs 178 is 2041q4, far in the future
*
local i=58
while `i'<=178 {
    capture drop pdlrevr
    capture drop pdlgspr
    capture drop pdlymtr

    predict pdlrevr in `i', xb equation(dlrevr)
    predict pdlgspr in `i', xb equation(dlgspr)
    predict pdlymtr in `i', xb equation(dlymtr)

    replace lrevr=l.lrevr + pdlrevr in `i'
    replace lgspr=l.lgspr + pdlgspr in `i'
    replace lyctr=l.lyctr + pdlymtr in `i'

    replace dlrevr=d.lrevr in `i'
    replace dlgspr=d.lgspr in `i'
    replace dlyctr=d.lyctr in `i'

    replace ec_g = lrevr - bconsg - bg*lgspr in `i'
    replace ec_y = lrevr - bconsy - bymt*lyctr in `i'

    local i=`i'+1
}
```

Estimation of the Beveridge-Nelson (BN) Trend

To estimate the Beveridge-Nelson trend, calculate the slope of the long-term trend in the far future and extrapolate this linear trend backward to the end of history.

This is easily done by estimating an OLS regression of $lrevr$ on time near the end of the long-term forecast and “backcasting” the fitted line back to the end of history.

Calculation of the BN Trend

```

. *
. * Calculate the BN Trend
. *
.
.
. regress lrevr time if tin(2025q1,2041q4)
.
.
. Source | SS df MS Number of obs =
68 -----+----- F( 1, 66)
. Model | .619436925 1 .619436925 Prob > F =
0.0000 Residual | 5.8334e-09 66 8.8385e-11 R-squared =
1.0000 -----+----- Adj R-squared =
1.0000 Total | .61943693 67 .009245327 Root MSE =
9.4e-06
.
. -----
. lrevr | Coef. Std. Err. t P>|t| [95% Conf.
Interval]
. -----+-----
. time | .0048626 5.81e-08 8.4e+04 0.000 .0048625 .
0048628
. _cons | 9.831054 .0000171 5.8e+05 0.000 9.83102
9.831088
. -----
.
. display (1+_b[time])^4-1
. .01959292
.
. predict trend_lrevr

```

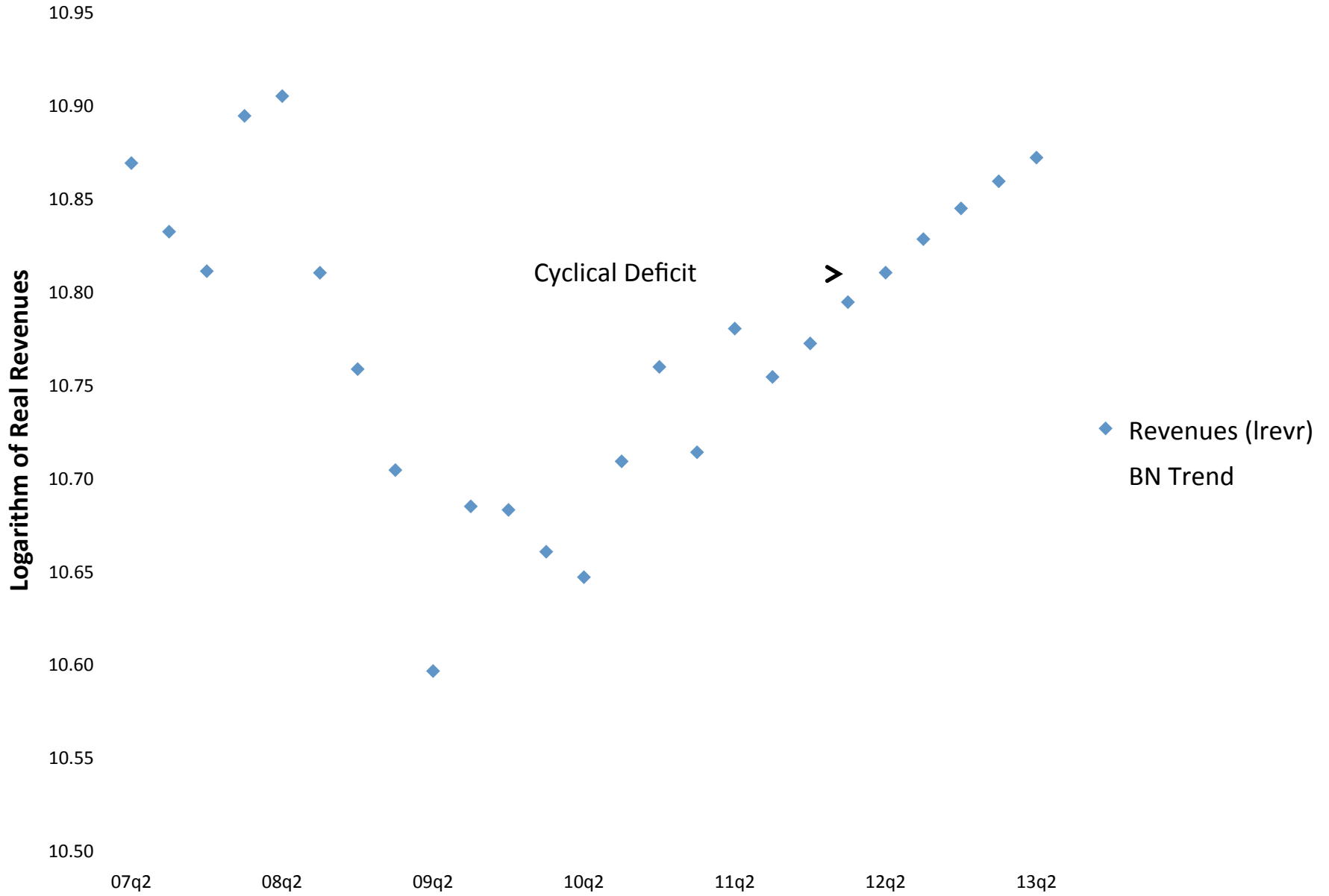
Revenue History and Forecast with BN Trend



Revenue History and Forecast with BN Trend



Revenue History and Forecast with BN Trend



References

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