Introduction to time-series commands in Stata

May 11th, 2023

Topics

Part I: Univariate time-series analysis

- Working with dates in Stata
- Declaring time-series data with **tsset**
- Plotting with **tsline**
- Testing parameter stability with **estat cusum**
- Smoothing with **tssmooth**
- Testing for unit roots with **dfuller**
- Difference and lag operators
- Visualizing autocorrelation with **ac** and **pac**
- Box-Jenkins models with **arima**
- Heteroskedasticity models with **arch**
- Forecasting with **predict**

Part II: Multivariate time-series analysis

- Business calendars with **bcal**
- Vector autoregression with **var** and **svar**
- Impulse-response functions with **irf**

Part I. Univariate time-series analysis

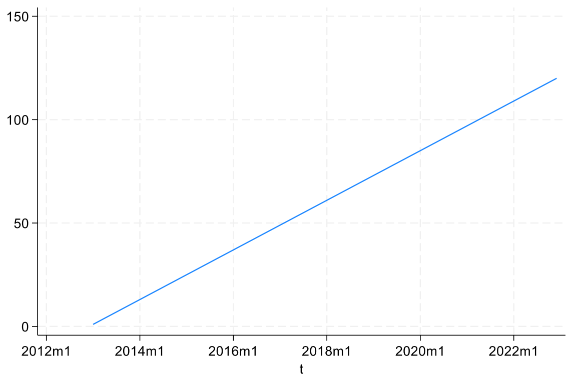
Components of a time series

$$y_t = trend_t + seasonality_t + residual_t$$

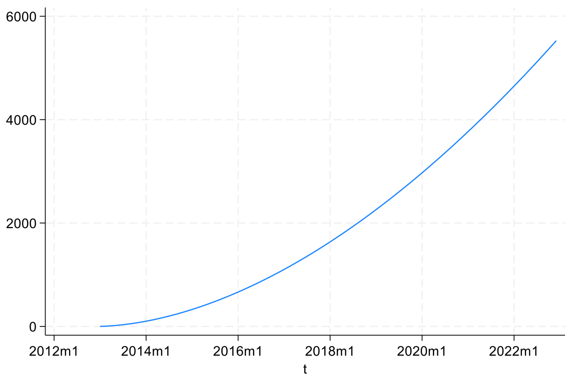
or

$$x_t = trend_t \times seasonality_t \times residual_t$$

Components of a time series

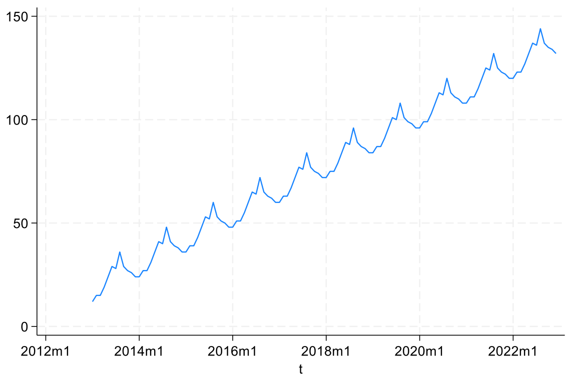


Additive trend

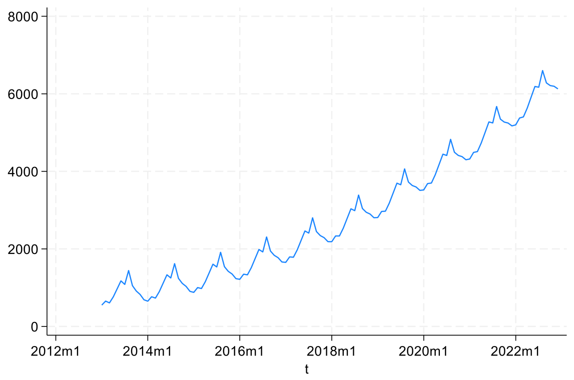


Multiplicative trend

Components of a time series

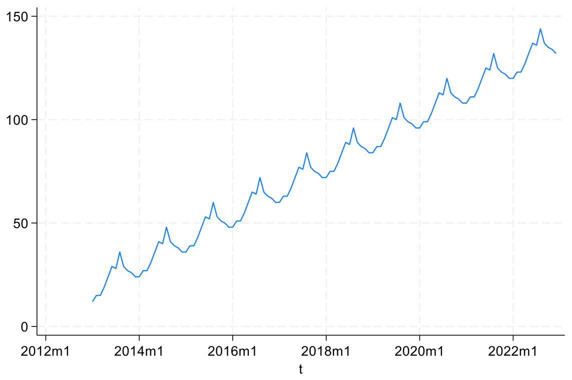


Additive trend
Additive seasonality

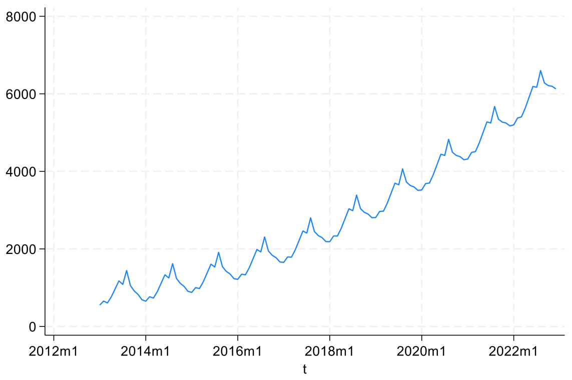


Multiplicative trend
Additive seasonality

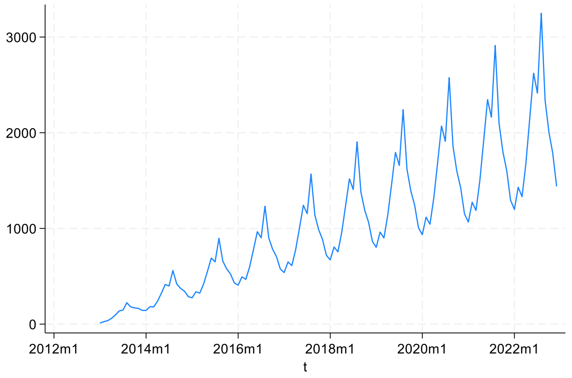
Components of a time series



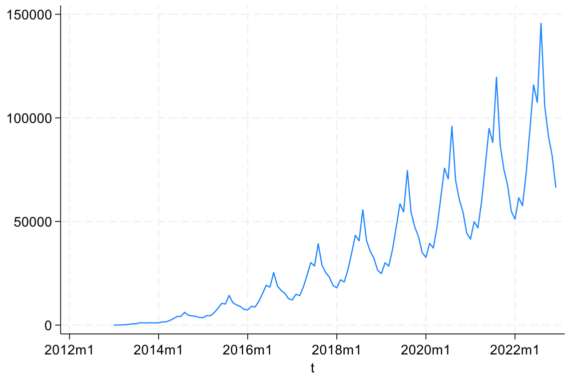
Additive trend
Additive seasonality



Multiplicative trend
Additive seasonality

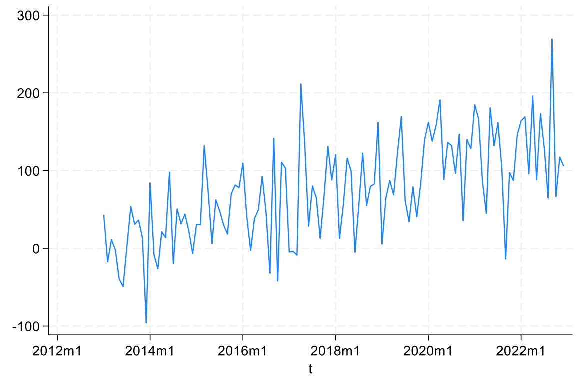


Additive trend
Multiplicative seasonality

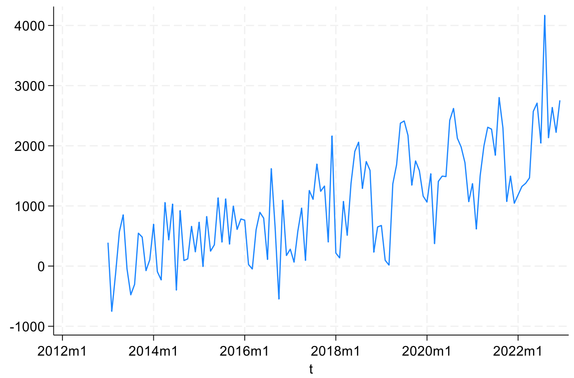


Multiplicative trend
Multiplicative seasonality

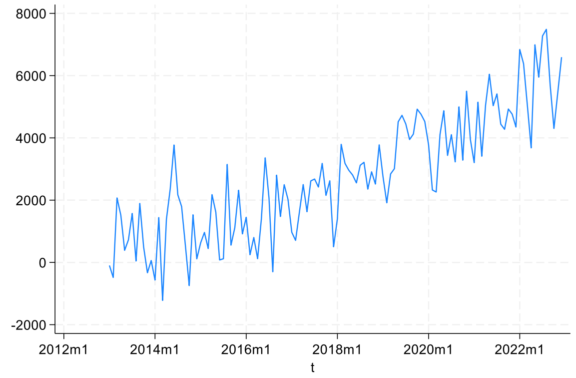
Components of a time series



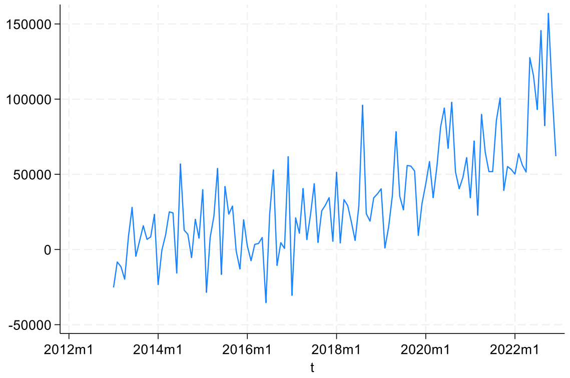
Additive trend
Additive seasonality
+ random noise



Multiplicative trend
Additive seasonality
+ random noise

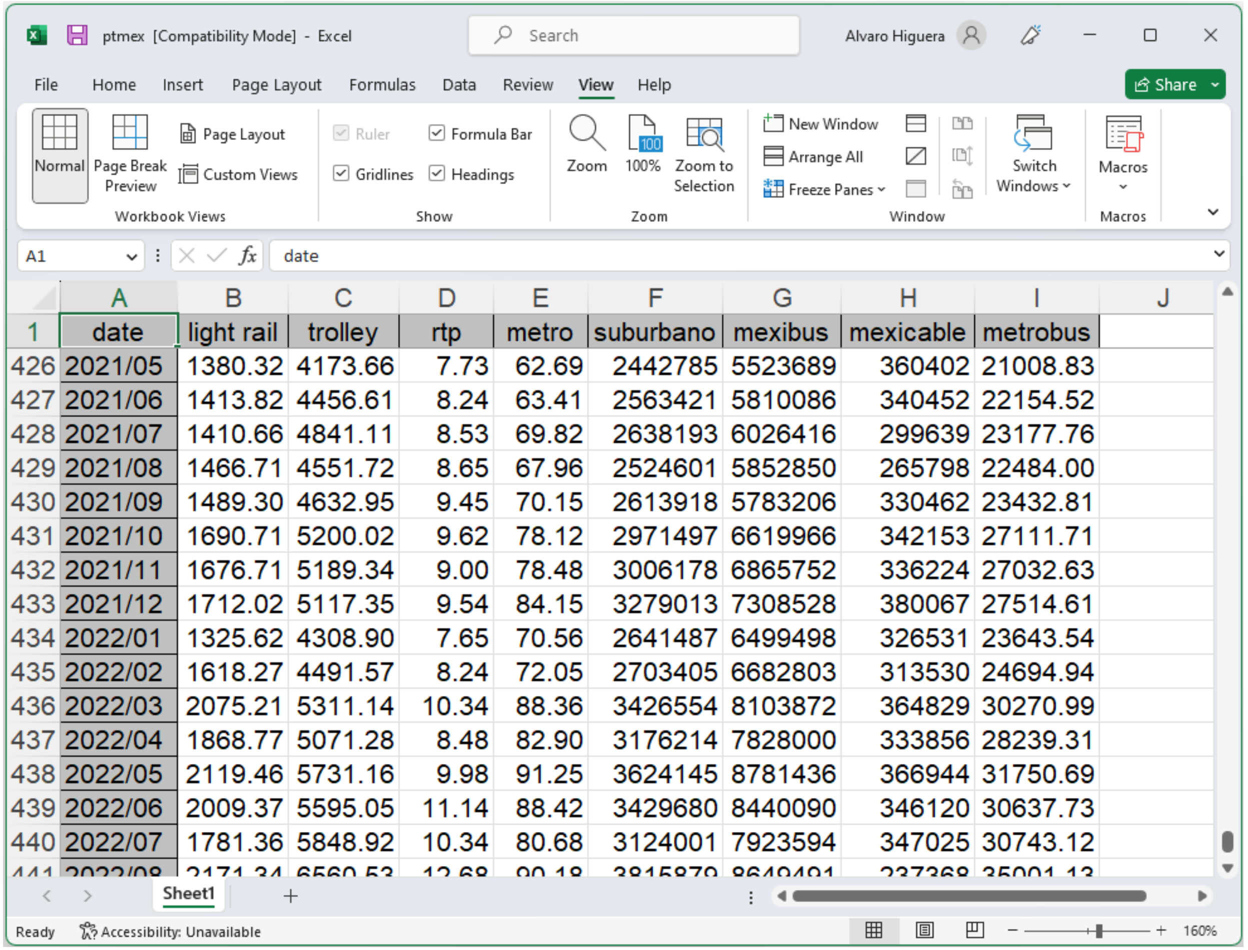


Additive trend
Multiplicative seasonality
+ random noise



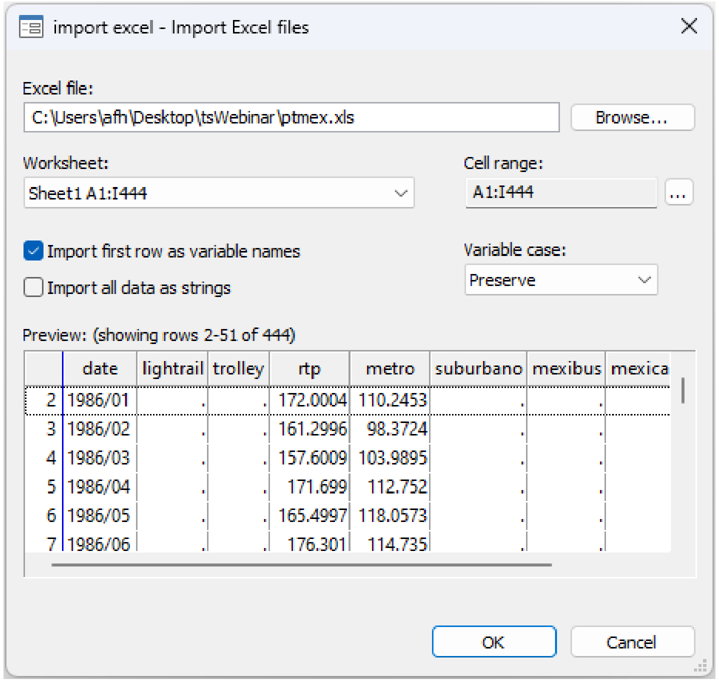
Multiplicative trend
Multiplicative seasonality
+ random noise

Public transport dataset



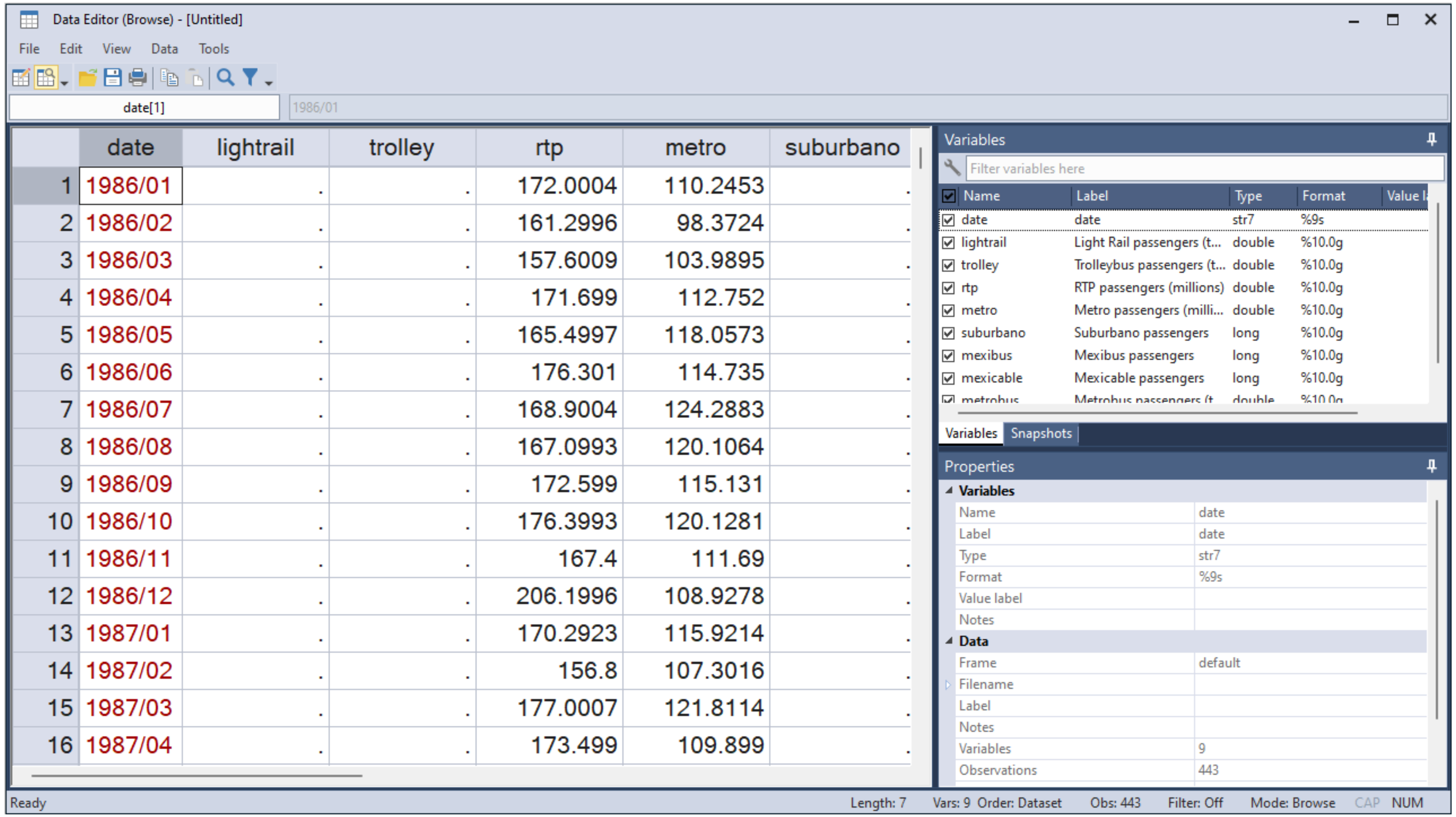
	date	light rail	trolley	rtp	metro	suburbano	mexibus	mexicable	metrobus
426	2021/05	1380.32	4173.66	7.73	62.69	2442785	5523689	360402	21008.83
427	2021/06	1413.82	4456.61	8.24	63.41	2563421	5810086	340452	22154.52
428	2021/07	1410.66	4841.11	8.53	69.82	2638193	6026416	299639	23177.76
429	2021/08	1466.71	4551.72	8.65	67.96	2524601	5852850	265798	22484.00
430	2021/09	1489.30	4632.95	9.45	70.15	2613918	5783206	330462	23432.81
431	2021/10	1690.71	5200.02	9.62	78.12	2971497	6619966	342153	27111.71
432	2021/11	1676.71	5189.34	9.00	78.48	3006178	6865752	336224	27032.63
433	2021/12	1712.02	5117.35	9.54	84.15	3279013	7308528	380067	27514.61
434	2022/01	1325.62	4308.90	7.65	70.56	2641487	6499498	326531	23643.54
435	2022/02	1618.27	4491.57	8.24	72.05	2703405	6682803	313530	24694.94
436	2022/03	2075.21	5311.14	10.34	88.36	3426554	8103872	364829	30270.99
437	2022/04	1868.77	5071.28	8.48	82.90	3176214	7828000	333856	28239.31
438	2022/05	2119.46	5731.16	9.98	91.25	3624145	8781436	366944	31750.69
439	2022/06	2009.37	5595.05	11.14	88.42	3429680	8440090	346120	30637.73
440	2022/07	1781.36	5848.92	10.34	80.68	3124001	7923594	347025	30743.12

Importing data




```
. import excel "C:\Users\afh\Desktop\tsWebinar\ptmex.xls",
  sheet("Sheet1") firstrow
```

Date variable



	date	lightrail	trolley	rtp	metro	suburbano
1	1986/01	.	.	172.0004	110.2453	.
2	1986/02	.	.	161.2996	98.3724	.
3	1986/03	.	.	157.6009	103.9895	.
4	1986/04	.	.	171.699	112.752	.
5	1986/05	.	.	165.4997	118.0573	.
6	1986/06	.	.	176.301	114.735	.
7	1986/07	.	.	168.9004	124.2883	.
8	1986/08	.	.	167.0993	120.1064	.
9	1986/09	.	.	172.599	115.131	.
10	1986/10	.	.	176.3993	120.1281	.
11	1986/11	.	.	167.4	111.69	.
12	1986/12	.	.	206.1996	108.9278	.
13	1987/01	.	.	170.2923	115.9214	.
14	1987/02	.	.	156.8	107.3016	.
15	1987/03	.	.	177.0007	121.8114	.
16	1987/04	.	.	173.499	109.899	.

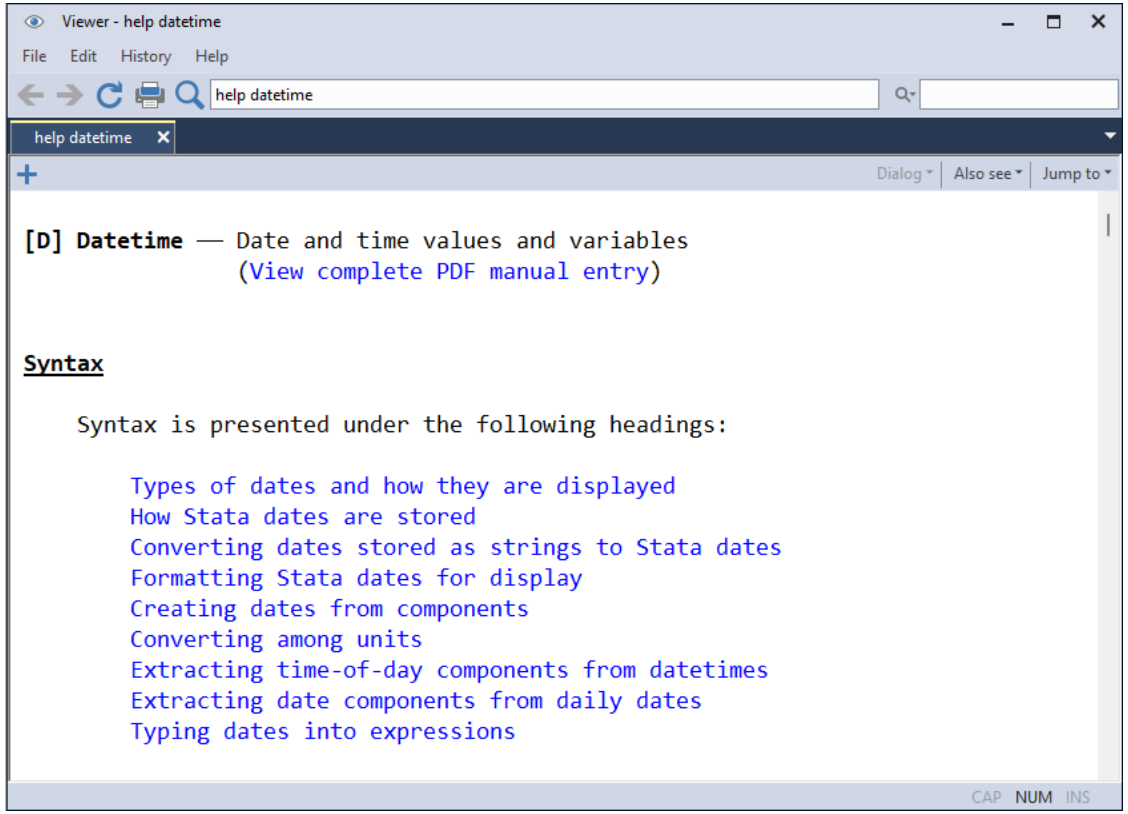
Date variable format

	date	t
1	1986/01	312
2	1986/02	313
3	1986/03	314
4	1986/04	315
5	1986/05	316
6	1986/06	317
7	1986/07	318
8	1986/08	319
9	1986/09	320
10	1986/10	321

	date	t
1	1986/01	1986m1
2	1986/02	1986m2
3	1986/03	1986m3
4	1986/04	1986m4
5	1986/05	1986m5
6	1986/06	1986m6
7	1986/07	1986m7
8	1986/08	1986m8
9	1986/09	1986m9
10	1986/10	1986m10

```
. generate t = monthly(date, "YM")

. format t %tm
```

Date variables help


Viewer - help datetime

File Edit History Help

help datetime

Dialog Also see Jump to

[D] **Datetime** — Date and time values and variables
(View complete PDF manual entry)

Syntax

Syntax is presented under the following headings:

Types of dates and how they are displayed
How Stata dates are stored
Converting dates stored as strings to Stata dates
Formatting Stata dates for display
Creating dates from components
Converting among units
Extracting time-of-day components from datetimes
Extracting date components from daily dates
Typing dates into expressions

CAP NUM INS

```
. help datetime
```

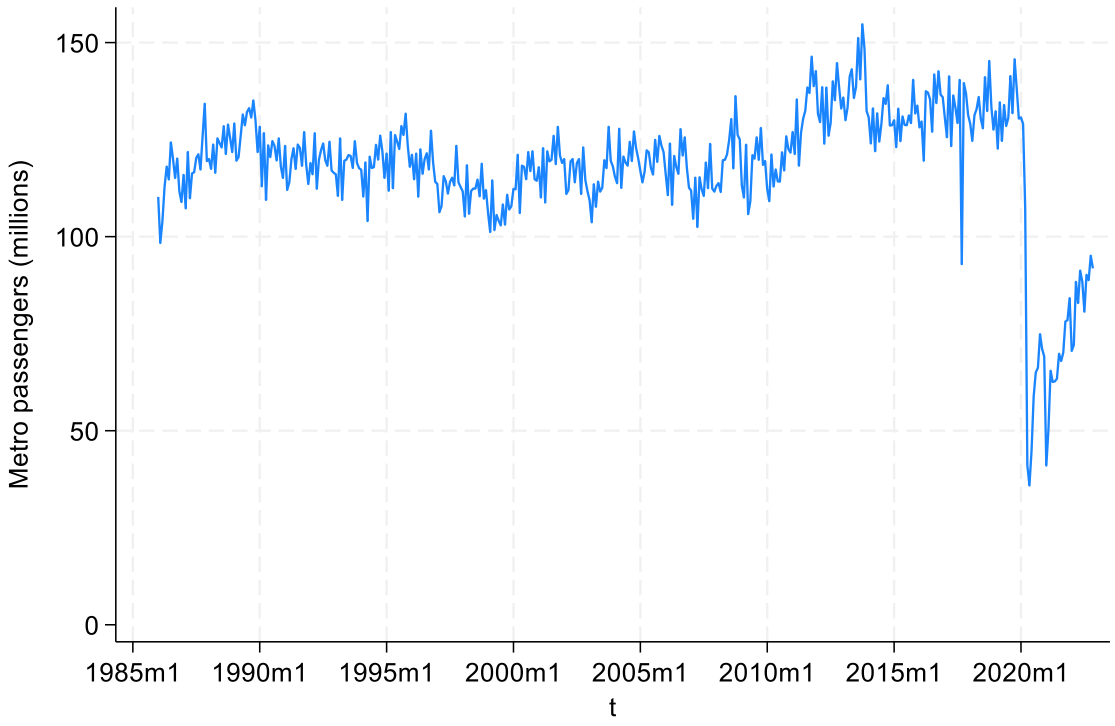
Declaring time-series data

```
. tsset t

Time variable: t, 1986m1 to 2022m11
        Delta: 1 month
```

Metro

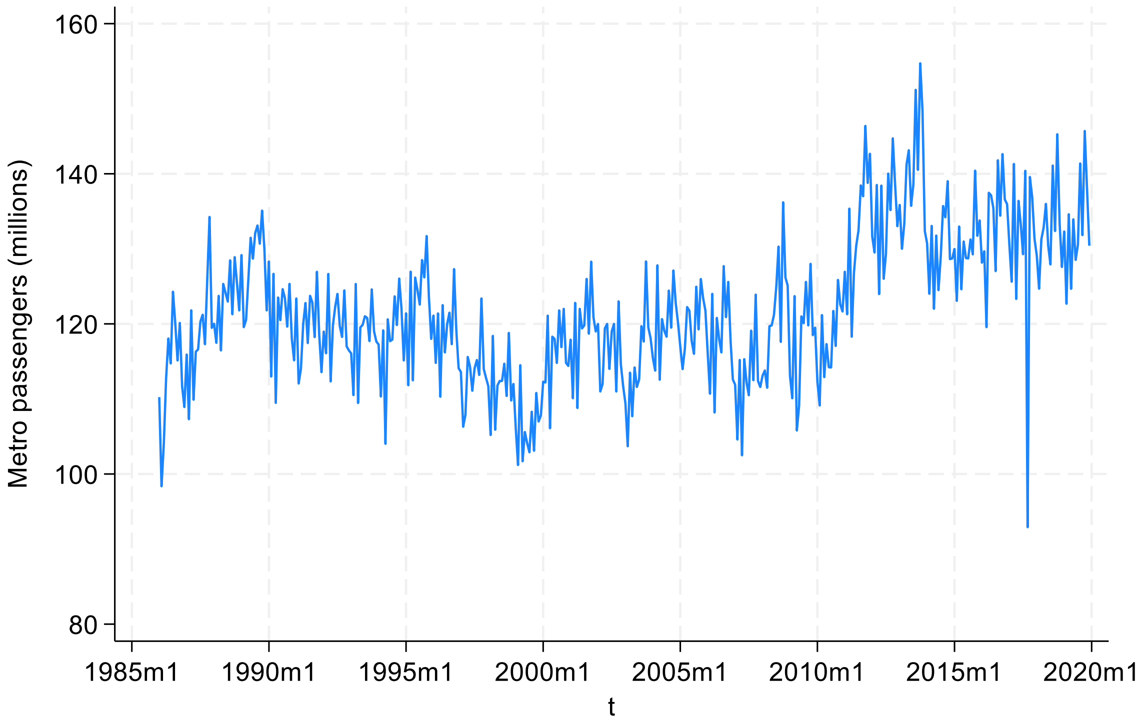

El Rosario
Tezozomoc
Aquiles Serdán
Azcapotzalco
Ferrería / Arena Ciudad de México
Norte 45
Vallejo
Instituto del Petróleo
Politécnico
Lindavista
Deportivo 18 de Marzo
Indios Verdes
Martín Carrera
Camarones
Refinería
Autobuses del Norte
Potrero
La Villa-Basílica
Talismán
La Raza
Cuatro Caminos
Panteones
Tacuba
Cuitláhuac
Popotla
Colegio Militar
Normal
San Cosme
Revolución
Misterios
Valle Gómez
Consulado
Eduardo Molina
Aragón
Bondojito
Tlatelolco
Guerrero
Garibaldi / Lagunilla
Buenavista
Hidalgo
Bellas Artes
Allende
Zócalo
Tepito
Lagunilla
Morelos
Canal del Norte
Romero Rubio
Oceanía
Deportivo Oceanía
Bosque de Aragón
Villa de Aragón
Nezahualcóyotl
Impulsora
Río de los Remedios
Múzquiz
Ecatepec
Olímpica
Plaza Aragón
Ciudad Azteca
San Joaquín
Polanco
Auditorio
Constituyentes
Chapultepec
Sevilla
Insurgentes
Cuauhtémoc
Balderas
Juárez
Salto del Agua
San Juan de Letrán
Isabel la Católica
Pino Suárez
Merced
Candelaria
San Lázaro
Moctezuma
Balbuena
Boulevard Pto. Aéreo
Gómez Farías
Zaragoza
Pantitlán
Flores Magón
Terminal Aérea
Hangares
Fray Servando
Niños Héroes
Doctores
Obrera
San Antonio Abad
Hospital General
Juanacatlán
Tacubaya
Observatorio
Patriotismo
Chilpancingo
Centro Médico
Lázaro Cárdenas
Chabacano
Jamaica
Mixiuhca
Velódromo
Ciudad Deportiva
Puebla
Agrícola Oriental
Canal de San Juan
Tepalcates
Guelatao
Peñón Viejo
Acatitla
Santa Marta
Los Reyes
La Paz
La Viga
Santa Anita
Viaducto
Coyuya
Etiopía / Plaza de la Transparencia
Xola
Villa de Cortés
Iztacalco
Eugenia
Nativitas
Apatlaco
San Pedro de los Pinos
San Antonio
Mixcoac
Insurgentes Sur
División del Norte
Zapata
Portales
Hospital 20 de Noviembre
Parque de los Venados
Ermita
Aculco
Escuadrón 201
Barranca del Muerto
Coyoacán
Eje Central
Mexicaltzingo
Atlalilco
Iztapalapa
C. de la Estrella
U.A.M. I
Const. de 1917
Viveros / Derechos Humanos
General Anaya
Miguel Ángel de Quevedo
Tasqueña
Culhuacán
Copilco
Universidad
Conexión con Tren Ligero
Dirección Xochimilco
San Andrés Tomatlán
Lomas Estrella
Calle 11
Periférico Ote.
Tezonco
Olivos
Nopalera
Zapotitlán
Tlaltenco
Tláhuac
ANILLO PERIFÉRICO
CIRCUITO INTERIOR

Metro: Time-series line plot



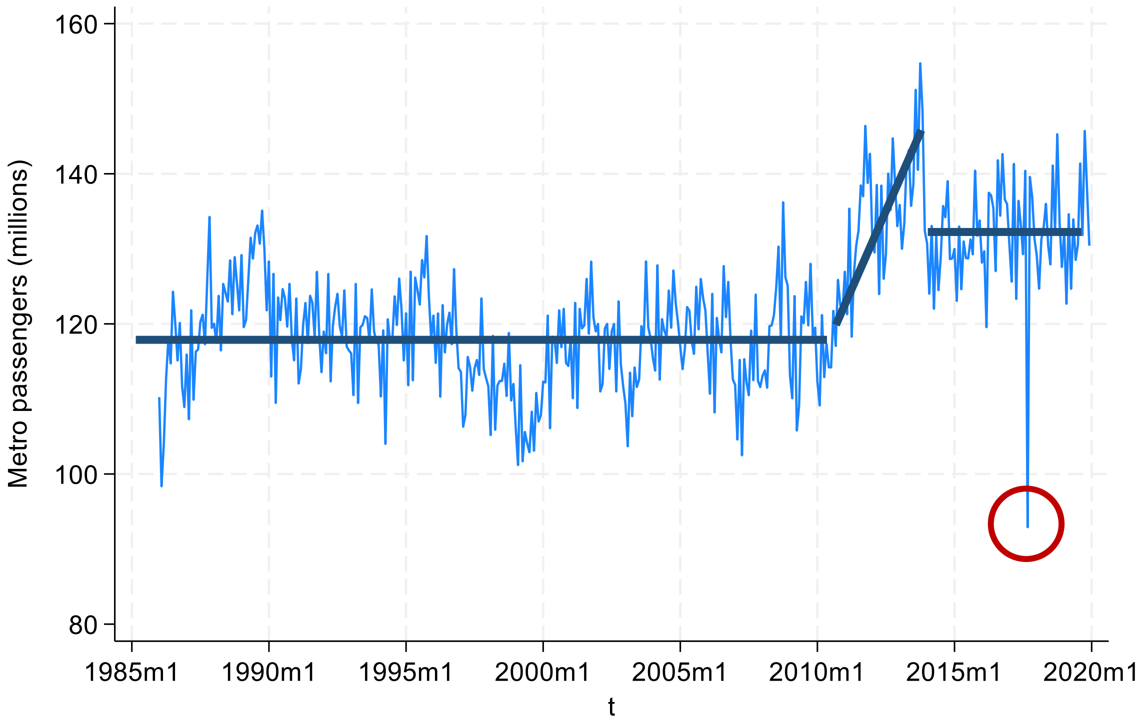

```
. tsline metro
```

Metro: Removing the pandemic




```
. keep if tin(1986m1, 2019m12)

. tsline metro
```

Metro: First impression



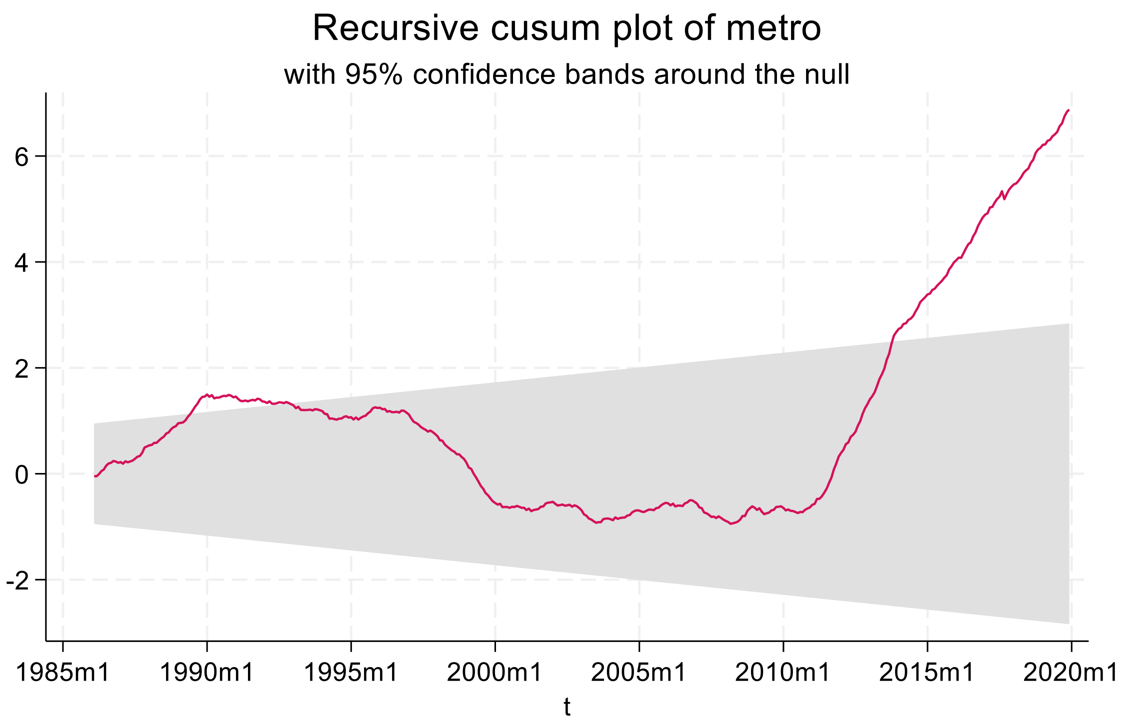
Metro: Parameter stability

Source	SS	df	MS			
Model	0	0	.	Number of obs	=	408
Residual	38300.6572	407	94.1048088	F(0, 407)	=	0.00
				Prob > F	=	.
Total	38300.6572	407	94.1048088	R-squared	=	0.0000
				Adj R-squared	=	0.0000
				Root MSE	=	9.7008

metro	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
_cons	121.8943	.4802593	253.81	0.000	120.9502	122.8384

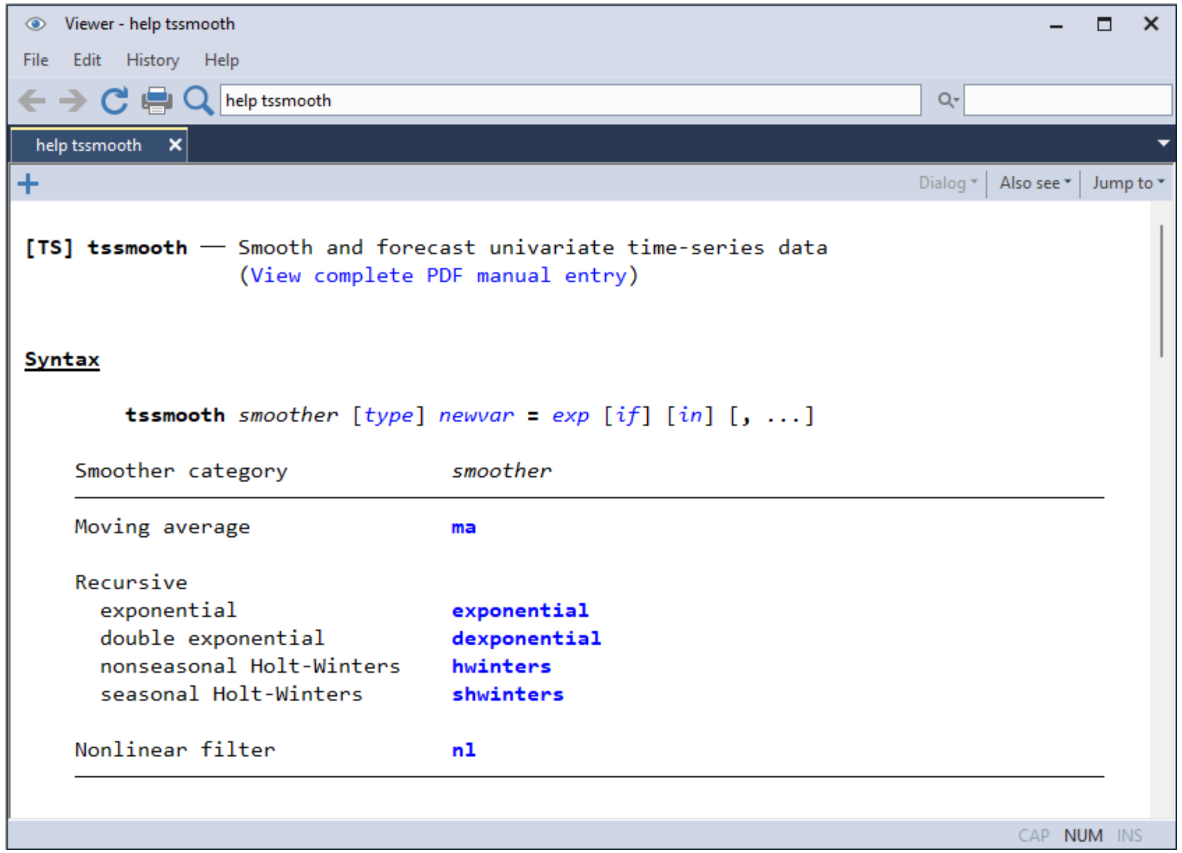
```
. regress metro
```

Metro: Parameter stability



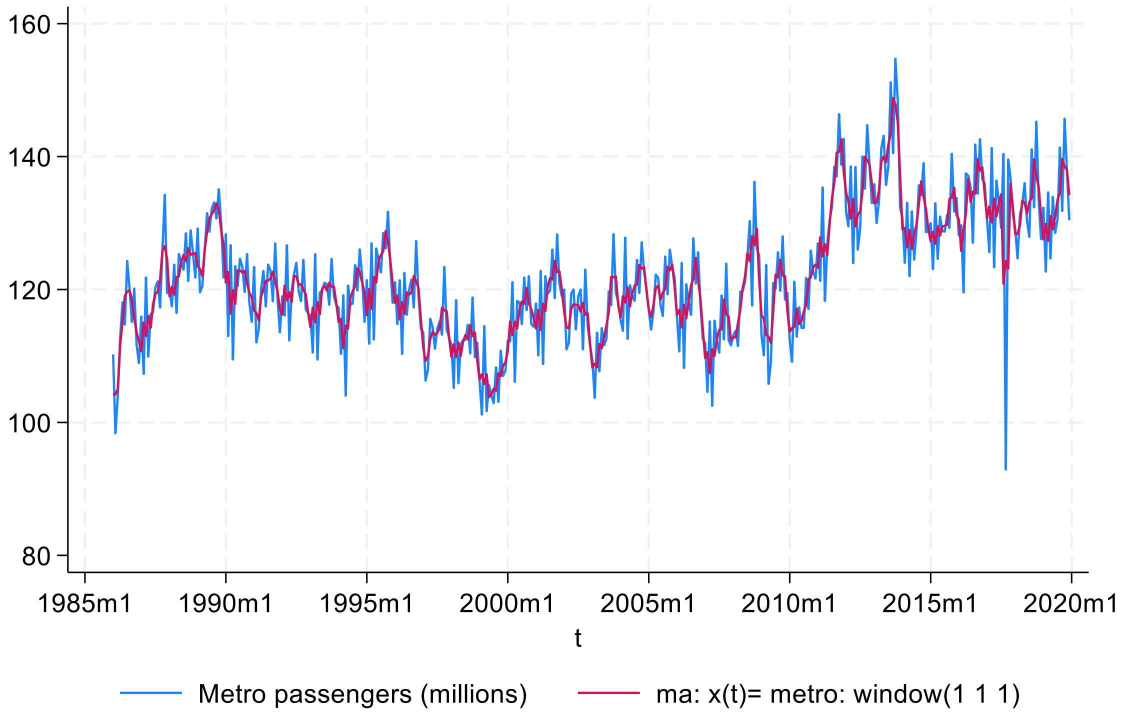

```
. estat sbcusum
```

Smoothers in Stata



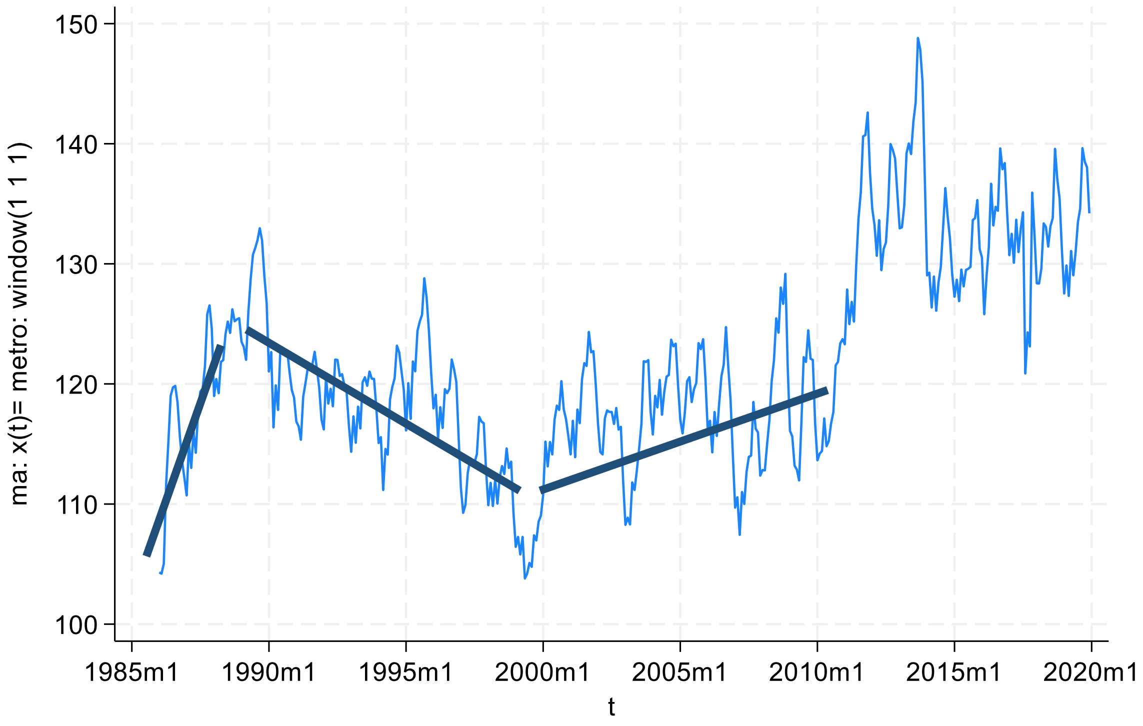

```
. help tssmooth
```

Metro: Moving average (1 1 1) smoother



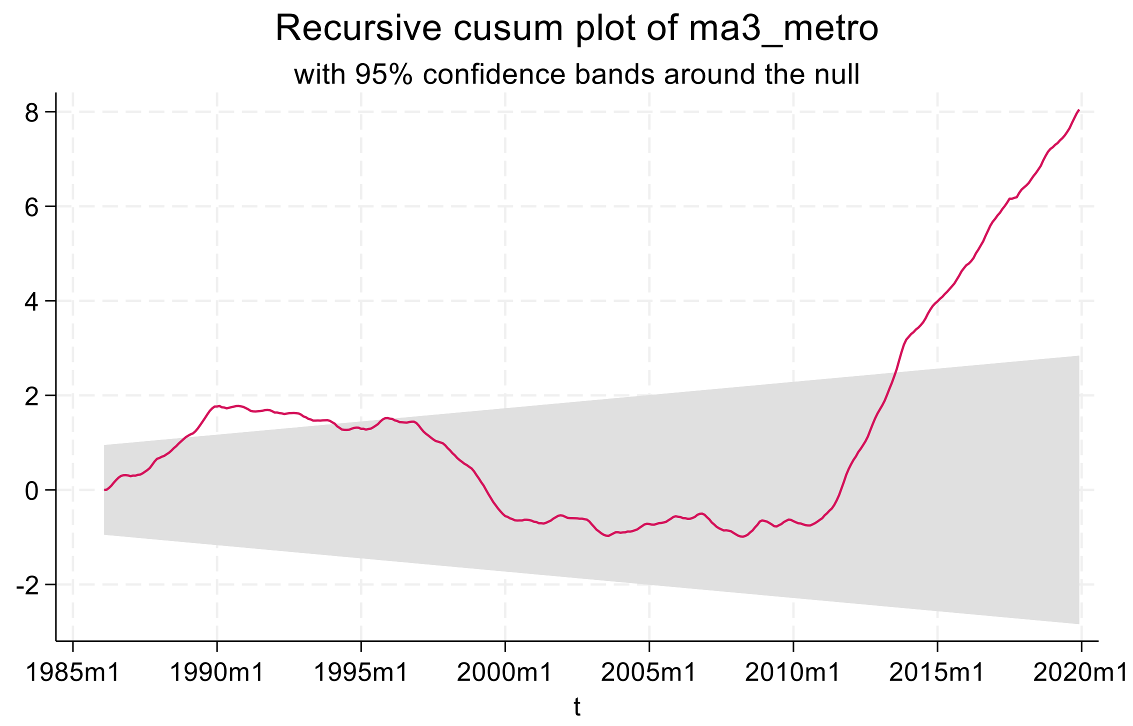

```
. tssmooth ma ma3_metro = metro,
  window(1 1 1)

. tsline metro ma3_metro
```

Metro: Moving average (1 1 1) smoother



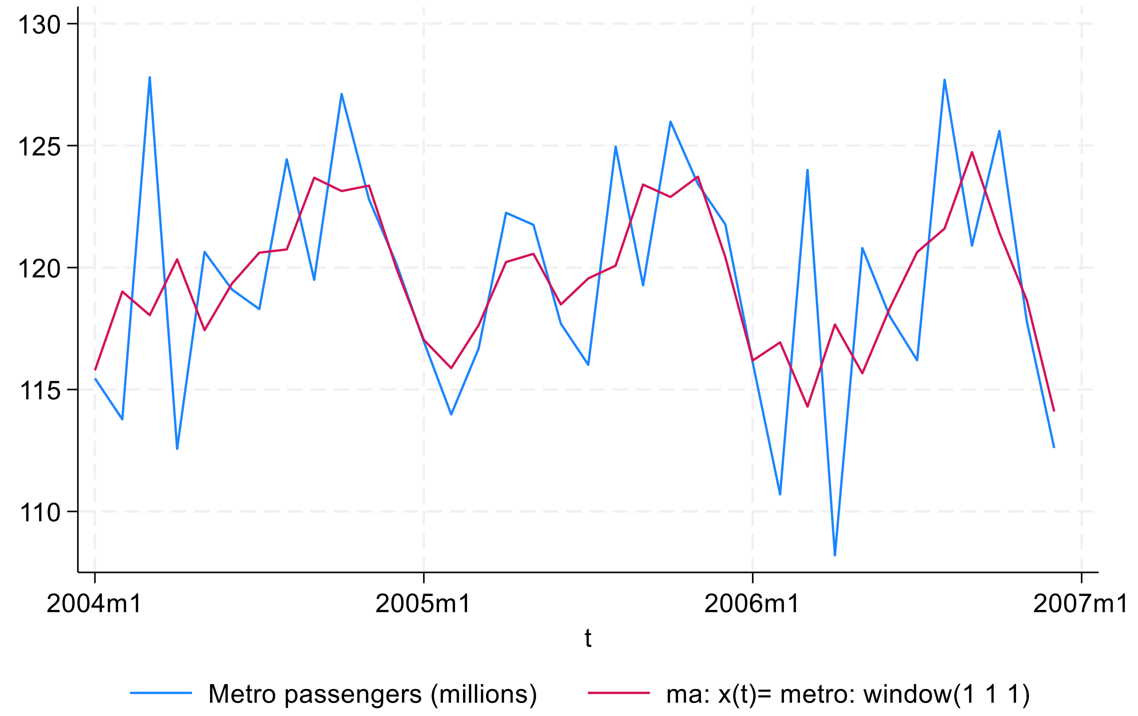

```
. tsline ma3_metro
```

Metro: Moving average (1 1 1) smoother



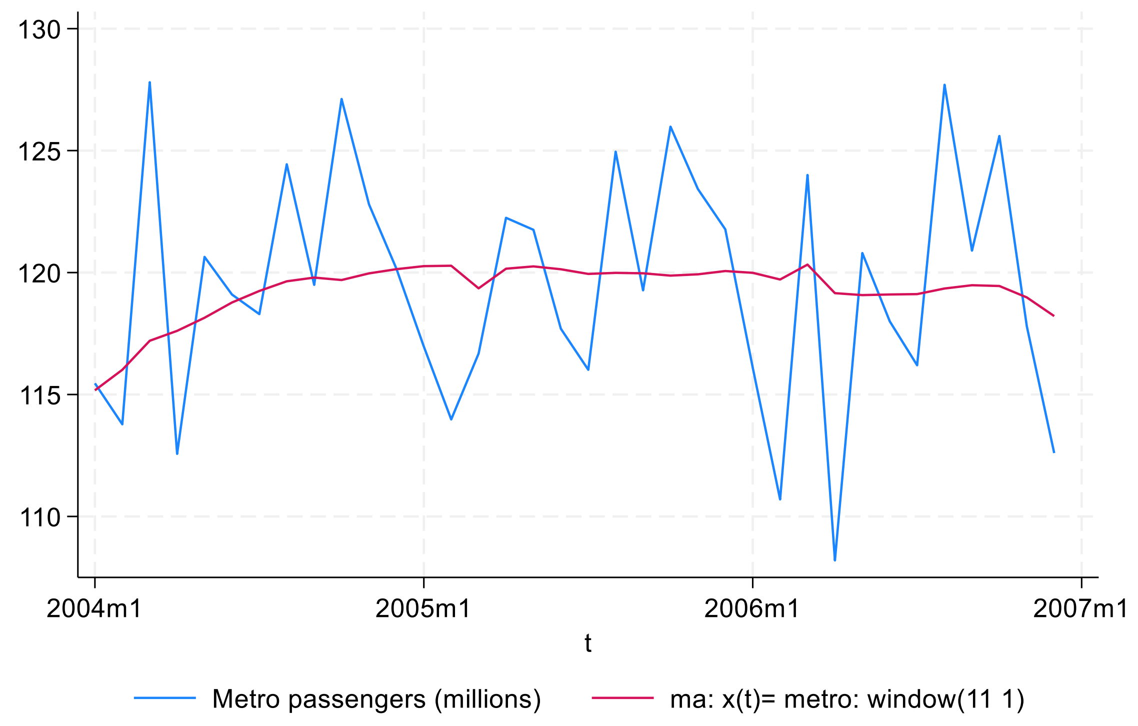

```
. regress ma3_metro

. estat sbcusum
```

Metro: Seasonality



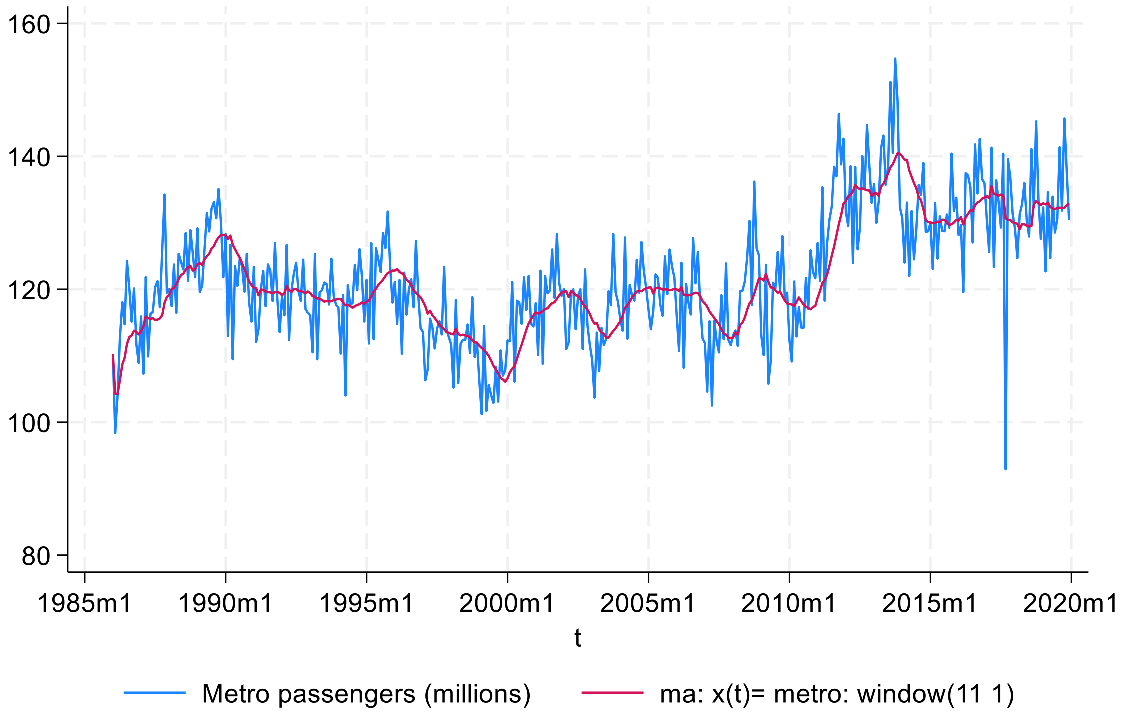

```
. tsline metro ma3_metro if tin(2004m1,
  2006m12)
```

Metro: Moving average (11 1) smoother



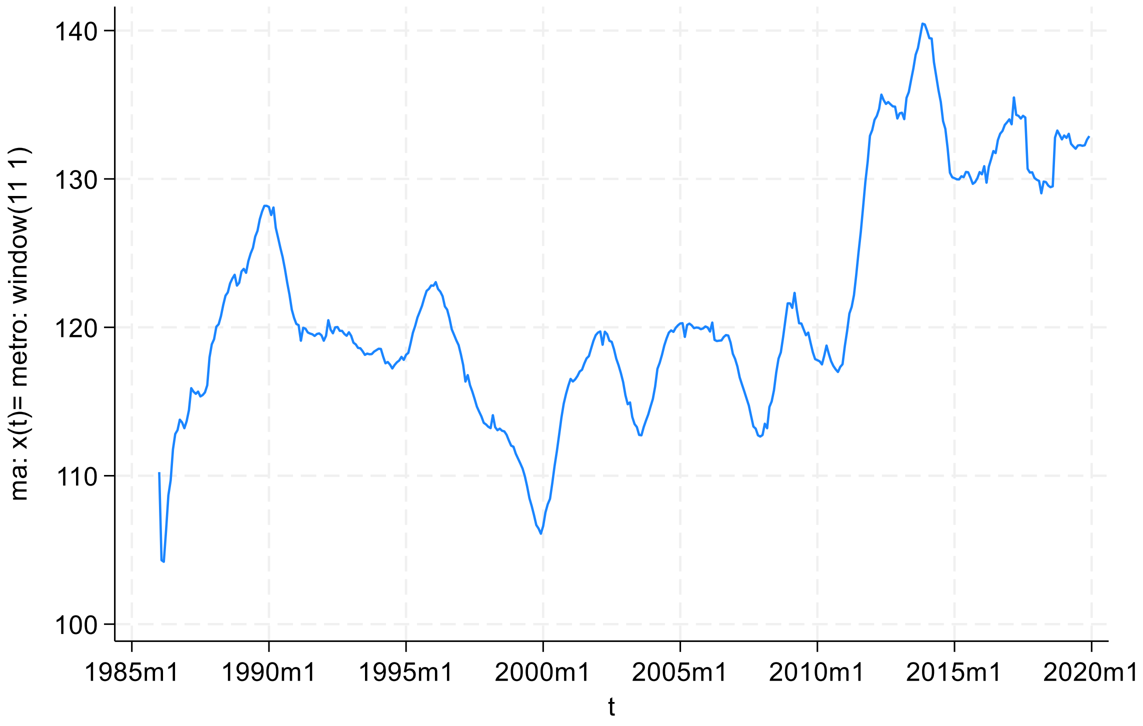

```
. tssmooth ma ma12_metro = metro,
  window(11 1)

. tsline metro ma12_metro if
  tin(2004m1, 2006m12)
```

Metro: Moving average (11 1) smoother



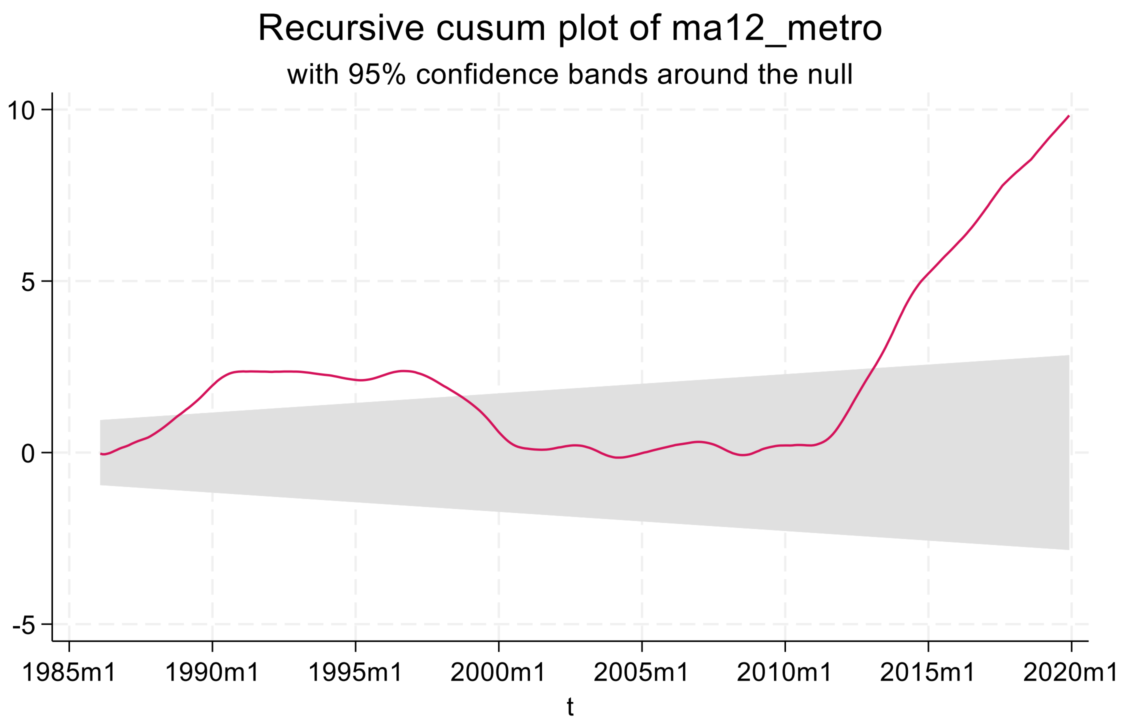

```
. tsline metro ma12_metro
```

Metro: Moving average (11 1) smoother



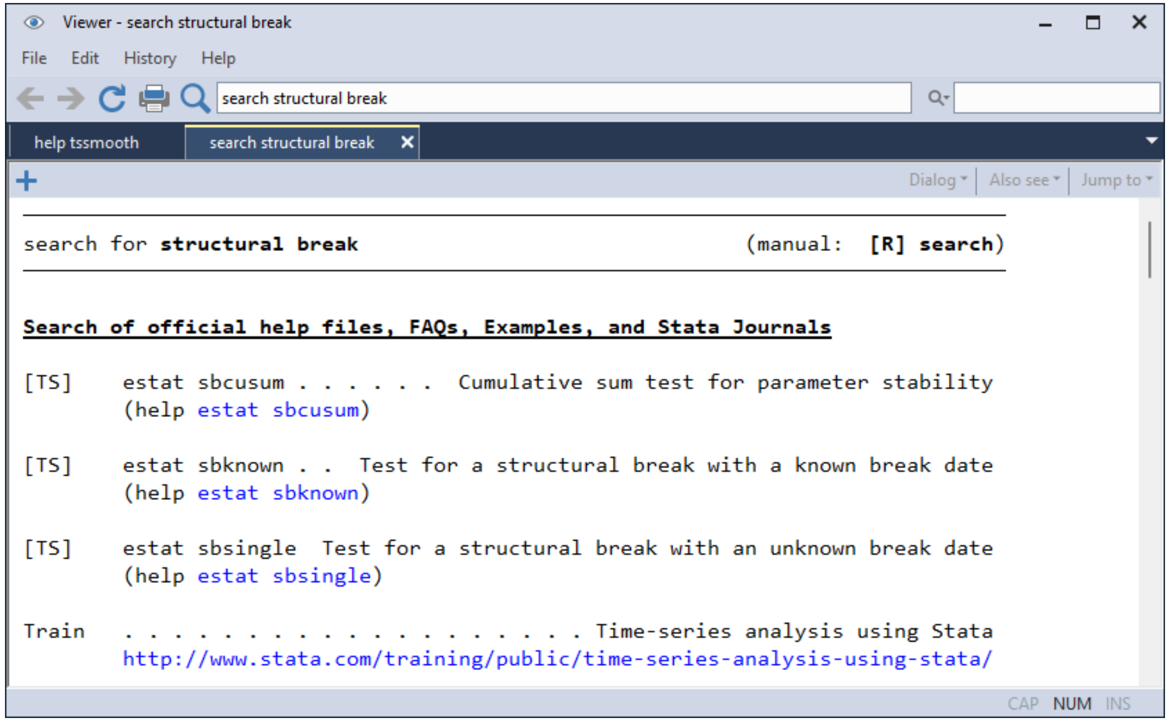

```
. tsline ma12_metro
```

Metro: Moving average (11 1) smoother




```
. regress ma12_metro

. estat sbcusum
```

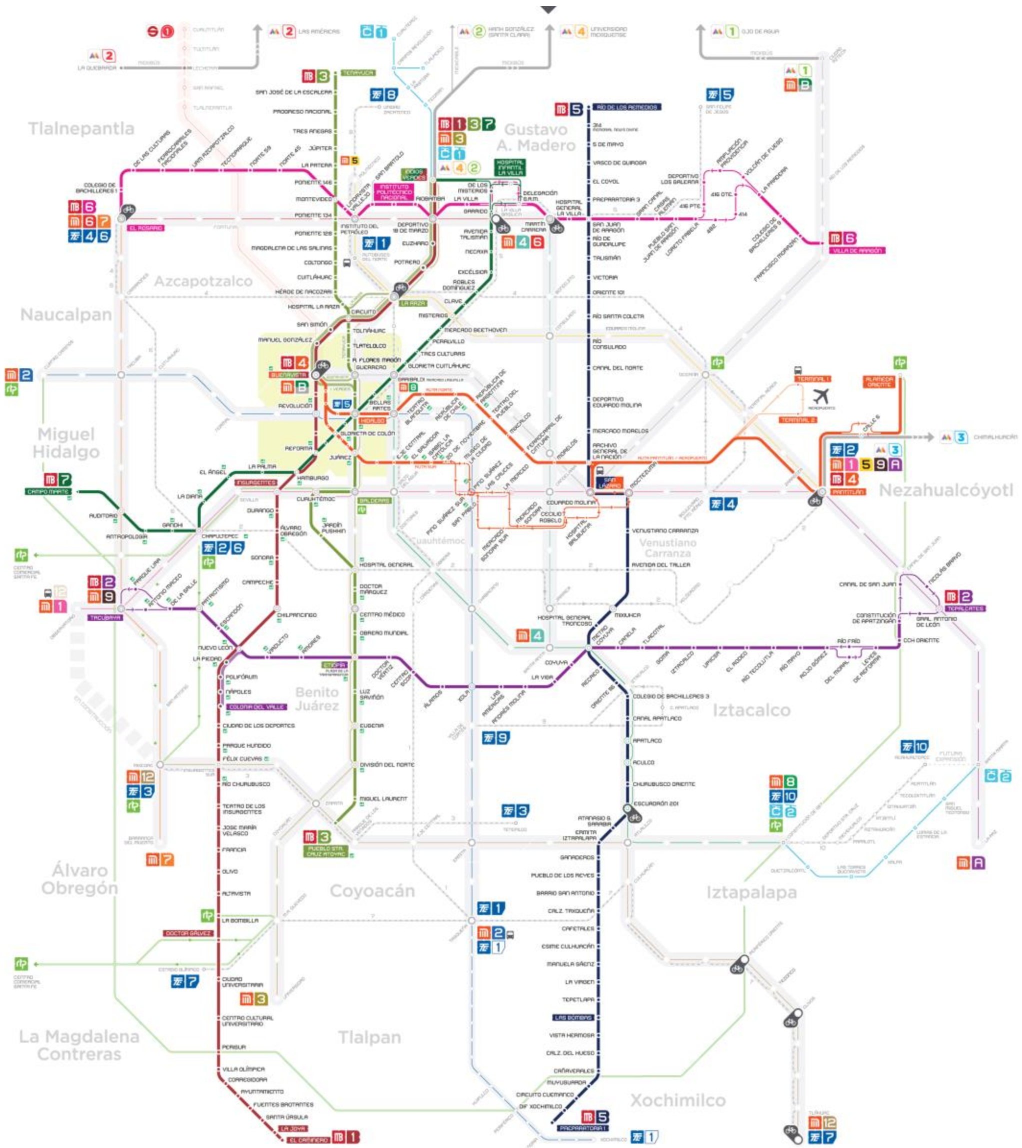
Other structural break tests




```
. search structural break
```

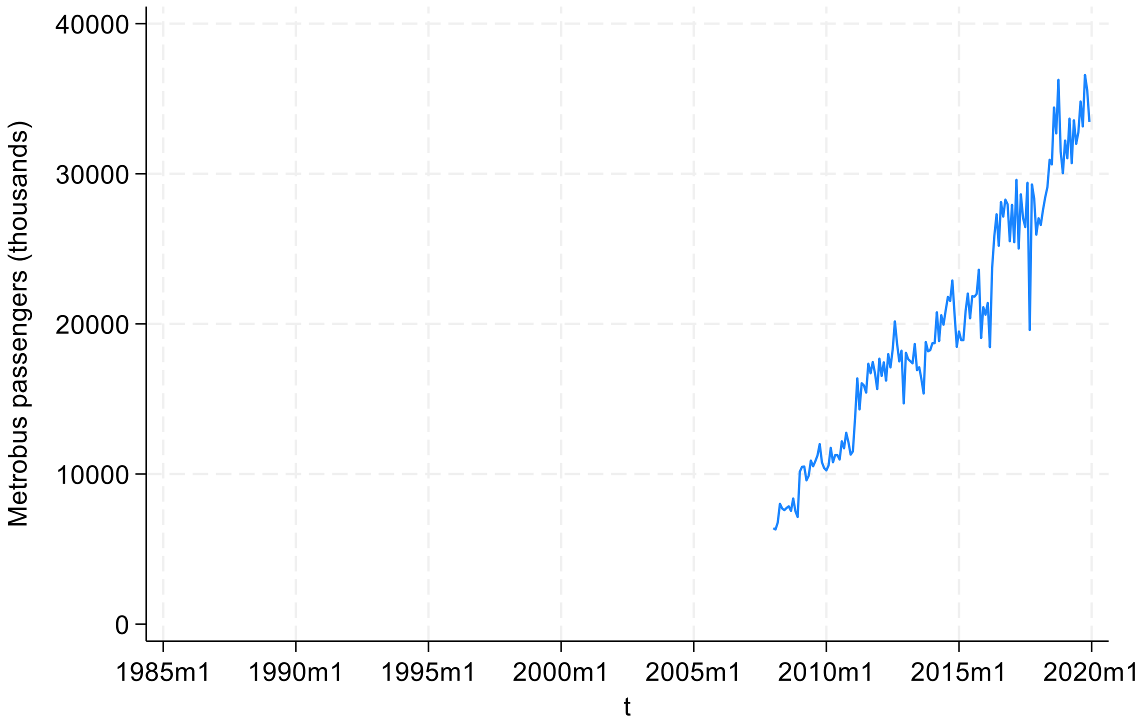
Metrobus

RIO TIBER
CTO. INTERIOR
EJE 2 PONIENTE
Metrobús



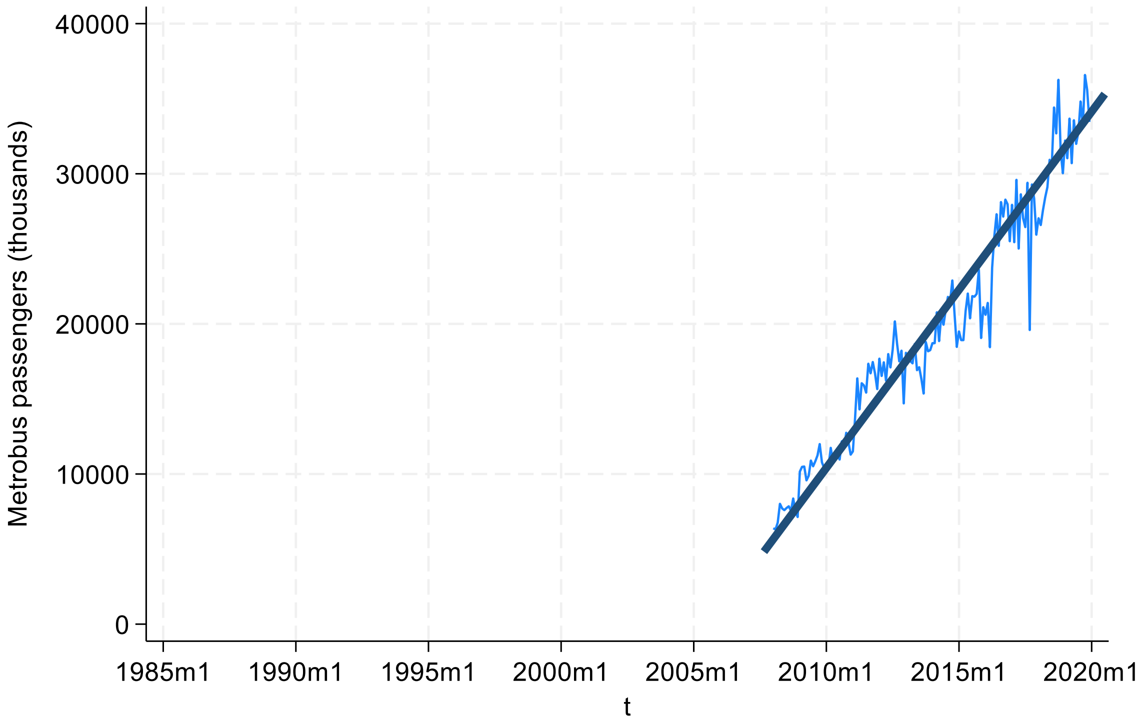
Tlalnepantla
Gustavo A. Madero
Azcapotzalco
Naucalpan
Miguel Hidalgo
Nezahualcóyotl
Venustiano Carranza
Cuauhtémoc
Benito Juárez
Iztacalco
Álvaro Obregón
Coyoacán
Iztapalapa
La Magdalena Contreras
Tlalpan
Xochimilco

Metrobus: Time series line plot

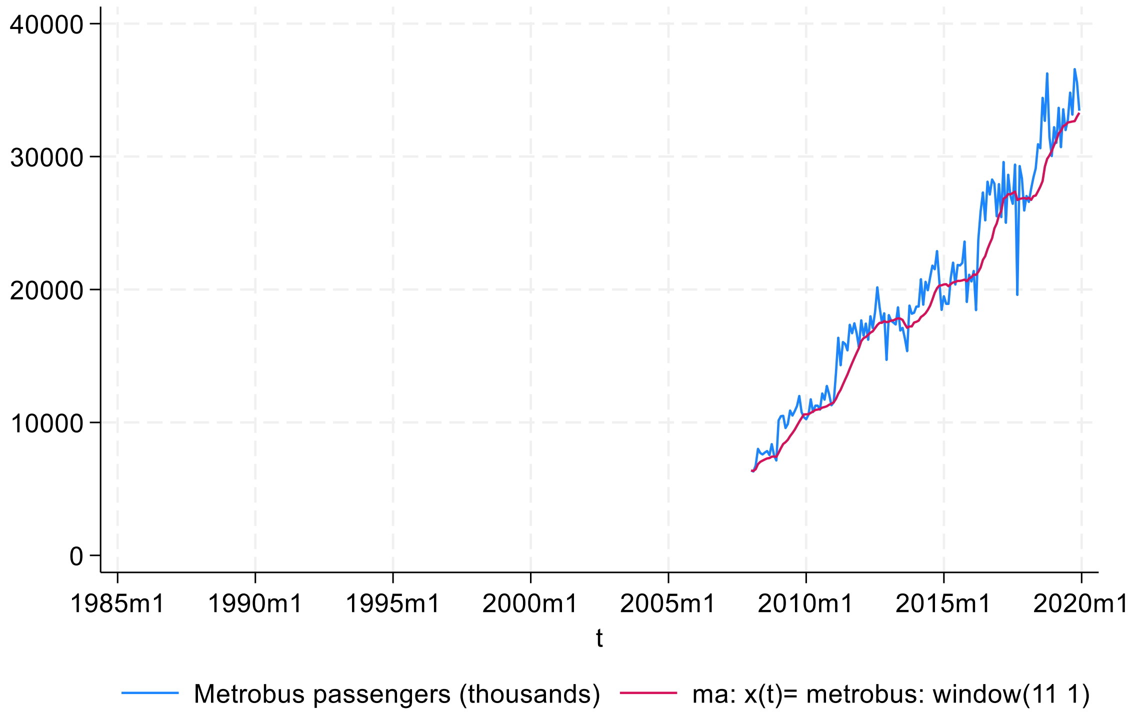



```
. tsline metrobus
```

Metrobus: Time series line plot

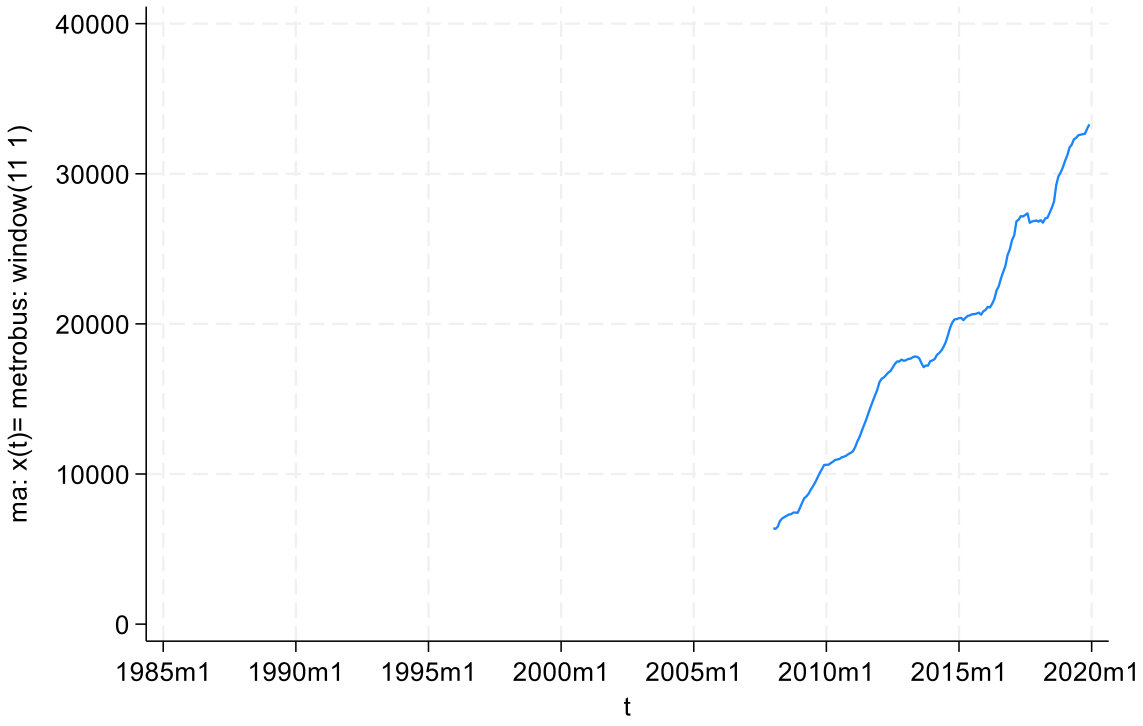


Metrobus: ma window(11 1) smoother




```
. tssmooth ma ma12_metrobus = metrobus,
  window(11 1)

. tsline metrobus ma12_metrobus
```

Metrobus: ma window(11 1) smoother



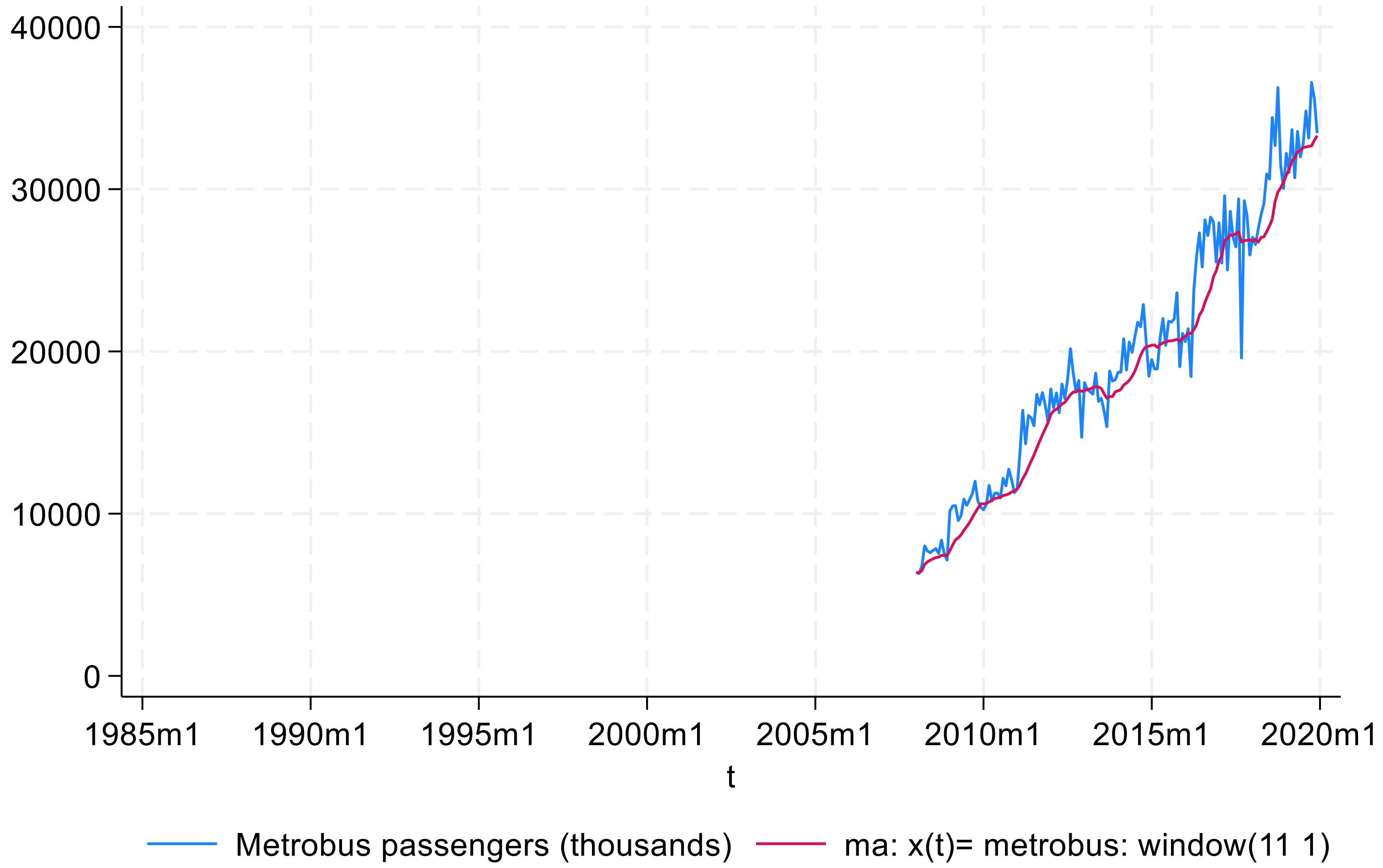

```
. tsline ma12_metrobus
```

Metrobus: Unit-root test

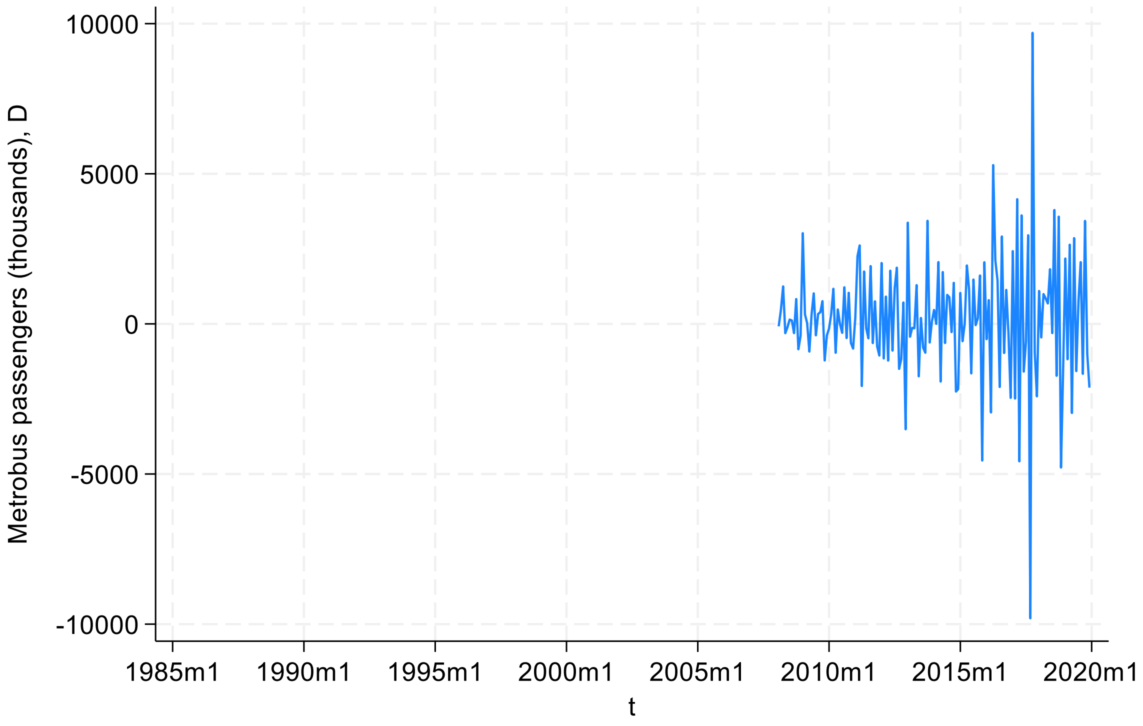
```
Dickey-Fuller test for unit root              Number of obs  = 143
Variable: metrobus                            Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test        -------- critical value ---------
              statistic           1%           5%           10%
-----------------------------------------------------------------
 Z(t)            -1.576       -3.496       -2.887        -2.577
-----------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.4956.
```

```
. dfuller metrobus
```

Metrobus: Unit-root test



Metrobus: First differences




```
. tsline D.metrobus
```

Aside: Difference and lag operators

Differences

`D.`*variable*
`D2.`*variable*
etc...

Lags

`L.`*variable*
`L2.`*variable*
etc...

Leads

`F.`*variable*
`F2.`*variable*
etc...

Seasonal difference

`S4.`*variable*
`S12.`*variable*

Metrobus: Unit-root test

```
Dickey-Fuller test for unit root          Number of obs  = 143
Variable: metrobus                        Number of lags =   0

H0: Random walk with or without drift

                                       Dickey-Fuller
                   Test      -------- critical value ---------
              statistic           1%           5%          10%
--------------------------------------------------------------
 Z(t)            -7.560       -4.026       -3.444       -3.144
--------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
. dfuller metrobus, trend
```

Metrobus: Unit-root test

```
Dickey-Fuller test for unit root          Number of obs  = 142
Variable: D.metrobus                      Number of lags =   0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test        ──────── critical value ────────
              statistic            1%           5%          10%
──────────────────────────────────────────────────────────────
 Z(t)           -22.508        -3.496       -2.887       -2.577
──────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

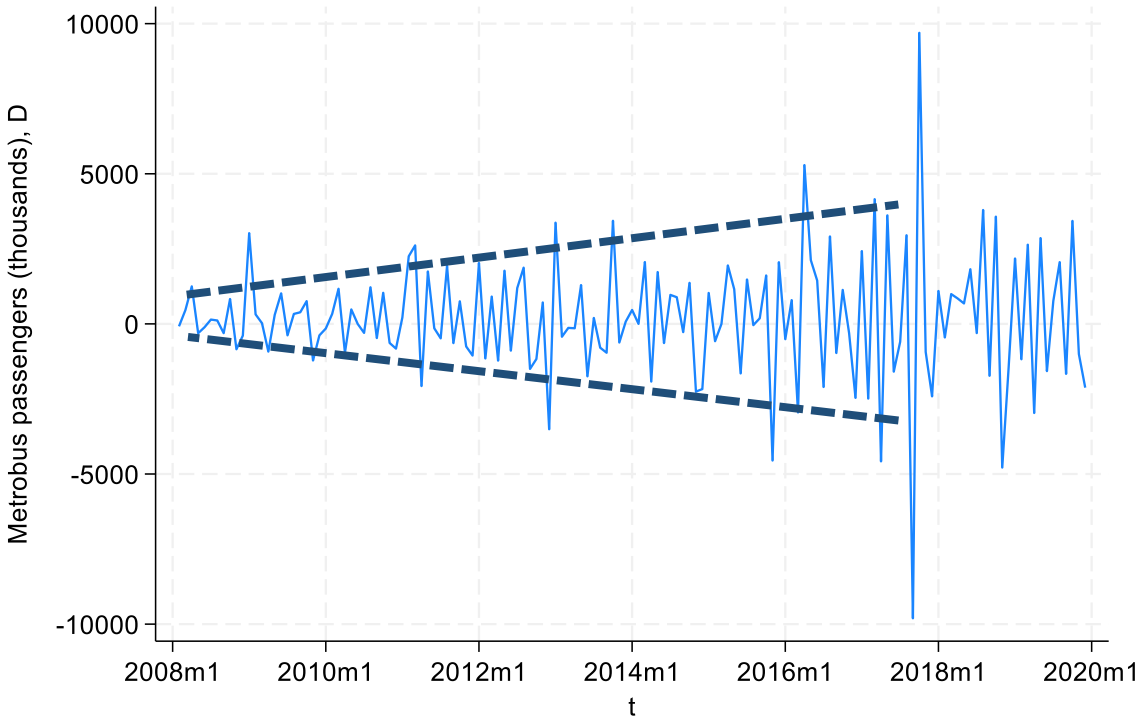
```
. dfuller D.metrobus
```

Other unit-root tests

```
Viewer - search unit root
File  Edit  History  Help
search unit root

search unit root
Dialog  Also see  Jump to

search for unit root                                    (manual:  [R] search)

Search of official help files, FAQs, Examples, and Stata Journals

[TS]    dfgls . . . . . . . . . . . . . . . . . . . . .  DF-GLS unit-root test
        (help dfgls)

[TS]    dfuller . . . . . . . . . . . . Augmented Dickey-Fuller unit-root test
        (help dfuller)

[TS]    pperron . . . . . . . . . . . . . . . . Phillips-Perron unit-root test
        (help pperron)

[XT]    xtunitroot  . . . . . . . . . . . . . . . . Panel-data unit-root tests
        (help xtunitroot)

Blog    . . . . . . . . . . . . . . . . . . . . . . . Unit-root tests in Stata
        . . . . . . . . . . . . . . . . . . . . . . . . . . . . A. Rajbhandari
        6/16    http://blog.stata.com/2016/06/21/unit-root-tests-in-stata/

CAP  NUM  INS
```

```
. search unit root
```

Metrobus: Constant variance?



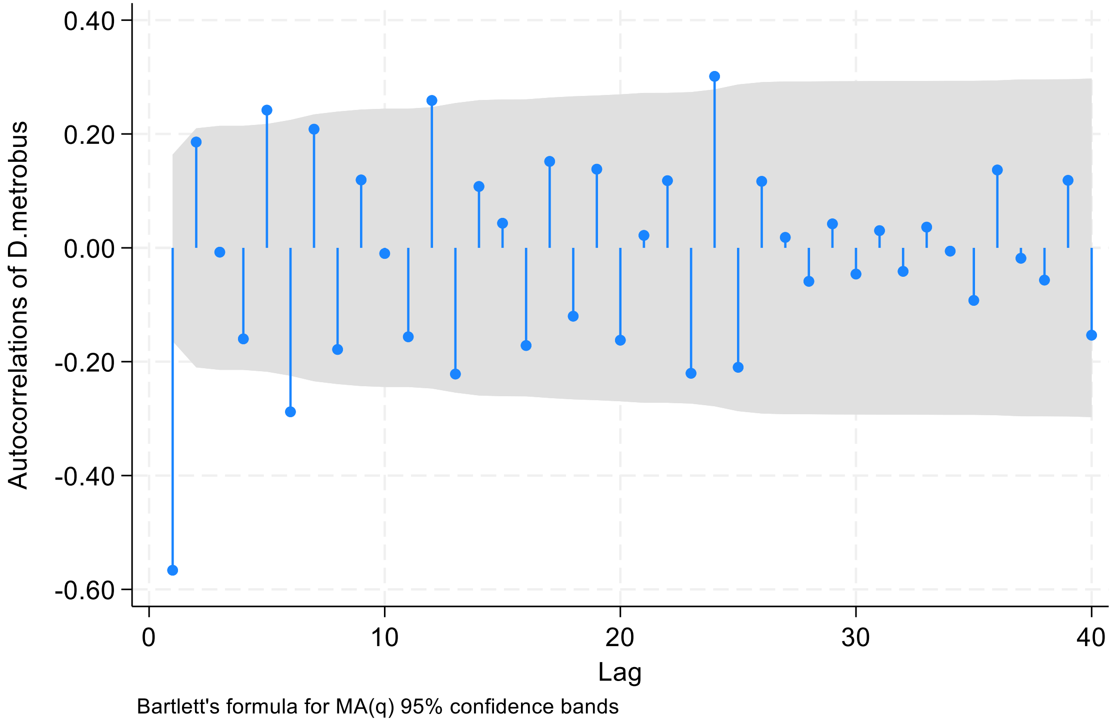

```
. tsline D.metrobus if tin(2008m1,
  2019m12)
```

Metrobus: ARIMA

$$d.metrobus_t = \mu + \phi_1 d.metrobus_{t-1} + \cdots + \phi_p d.metrobus_{t-p}$$

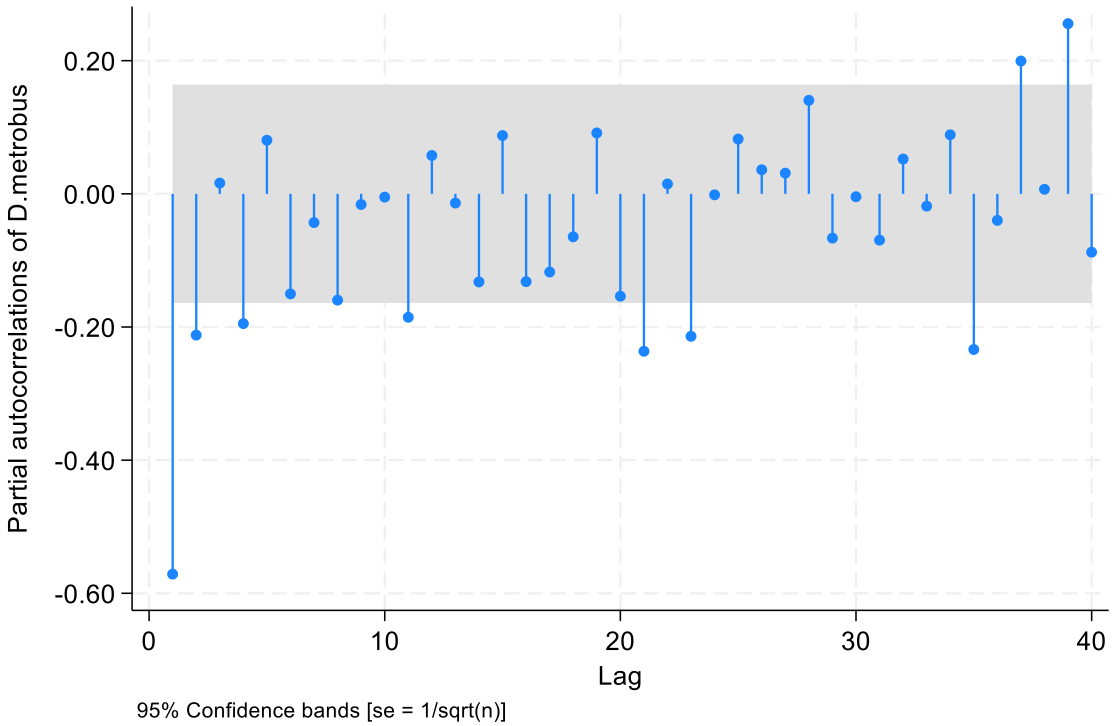
$$+ \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_p \epsilon_{t-q}$$

Autocorrelogram




```
. ac D.metrobus
```

Partial autocorrelogram




```
. pac D.metrobus
```

Model selection with `arimasoc`

```
Lag-order selection criteria

Sample: 2008m2 thru 2019m12                   Number of obs = 143
```

Model	LL	df	AIC	BIC	HQIC
ARMA(0,0)	-1296.576	2	2597.151	2603.077	2599.559
ARMA(0,1)	-1267.407	3	2540.814	2549.702	2544.426
ARMA(0,2)	-1266.229	4	2540.459	2552.31	2545.274
ARMA(1,0)	-1268.825	3	2543.65	2552.539	2547.262
ARMA(1,1)	-1265.545	4	2539.09	2550.941	2543.906
ARMA(1,2)	-1265.508	5	2541.017	2555.831	2547.037
ARMA(2,0)	-1265.658	4	2539.317	2551.168	2544.133
ARMA(2,1)	-1263.476	5	2536.951	2551.766	2542.971
ARMA(2,2)	-1263.171	6	2538.342	2556.12	2545.566

```
Selected (max) LL:   ARMA(2,2)
Selected (min) AIC:  ARMA(2,1)
Selected (min) BIC:  ARMA(0,1)
Selected (min) HQIC: ARMA(2,1)
```

```
. arimasoc D.metrobus
```

Metrobus: ARIMA(2, 1, 1)

```
ARIMA regression

Sample: 2008m2 thru 2019m12                     Number of obs     =        143
                                                Wald chi2(3)      =     536.43
Log likelihood = -1263.476                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
  D.metrobus | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
metrobus     |
       _cons |   197.8784   87.02933     2.27   0.023     27.30409    368.4528
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |  -1.381551   .1067587   -12.94   0.000    -1.590794   -1.172307
         L2. |  -.5842782   .0561559   -10.40   0.000    -.6943418   -.4742146
             |
          ma |
         L1. |   .7644672   .1315618     5.81   0.000     .5066109    1.022324
-------------+----------------------------------------------------------------
      /sigma |   1659.666   72.87977    22.77   0.000     1516.824    1802.508
------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.
```

```
. arima metrobus, arima(2, 1, 1)

. estimates store arima21
```

Metrobus: ARCH

$$d.metrobus_t = \mu + \phi_1 d.metrobus_{t-1} + \cdots + \phi_p d.metrobus_{t-p}$$
$$+ \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_p \epsilon_{t-q}$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 \epsilon_{t-1}^2 + \cdots + \gamma_m \epsilon_{t-m}^2$$

Metrobus: ARCH effects test

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(*p*)	chi2	df	Prob > chi2
1	32.956	1	0.0000

H0: no ARCH effects vs. H1: ARCH(*p*) disturbance

```
. quietly regress D.metrobus

. estat archlm, lags(1)
```

Metrobus: ARMA(2,1) with ARCH(1) disturbances

```
ARCH family regression -- ARMA disturbances

Sample: 2008m2 thru 2019m12                     Number of obs     =        143
                                                Wald chi2(3)      =     182.94
Log likelihood = -1253.196                      Prob > chi2       =     0.0000
```

D.metrobus	Coefficient	OPG std. err.	z	P>|z|	[95% conf.	interval]
metrobus						
_cons	146.1883	69.72694	2.10	0.036	9.525977	282.8505
ARMA						
ar						
L1.	-1.168511	.4180182	-2.80	0.005	-1.987812	-.3492107
L2.	-.4133894	.2131822	-1.94	0.052	-.8312189	.0044401
ma						
L1.	.5519442	.4585955	1.20	0.229	-.3468865	1.450775
ARCH						
arch						
L1.	.6602451	.213515	3.09	0.002	.2417633	1.078727
_cons	1395431	256825.7	5.43	0.000	892062.1	1898800

```
. arch D.metrobus, ar(1 2) ma(1)
  arch(1)
```

Metrobus: AR(2) with ARCH(1) disturbances

```
ARCH family regression -- AR disturbances

Sample: 2008m2 thru 2019m12                     Number of obs     =        143
                                                Wald chi2(2)      =      73.36
Log likelihood = -1253.454                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
  D.metrobus | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
metrobus     |
       _cons |   155.7661   62.14133     2.51   0.012     33.97133    277.5609
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |  -.6555086   .1004949    -6.52   0.000     -.852475   -.4585421
         L2. |  -.1295425   .0979355    -1.32   0.186    -.3214926    .0624076
-------------+----------------------------------------------------------------
ARCH         |
        arch |
         L1. |    .703343   .1981944     3.55   0.000     .3148891    1.091797
             |
       _cons |    1362397   240384.3     5.67   0.000     891252.9     1833542
------------------------------------------------------------------------------
```

```
. arch D.metrobus, ar(1 2) arch(1)
```

Metrobus: AR(1) with ARCH(1) disturbances

```
ARCH family regression -- AR disturbances

Sample: 2008m2 thru 2019m12                     Number of obs     =        143
                                                Wald chi2(1)      =      55.66
Log likelihood = -1254.34                       Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
  D.metrobus | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
metrobus     |
       _cons |   158.3452   70.99336     2.23   0.026     19.20079    297.4896
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |  -.5558053   .0744961    -7.46   0.000     -.701815   -.4097956
-------------+----------------------------------------------------------------
ARCH         |
        arch |
         L1. |   .6144126   .1385206     4.44   0.000     .3429173    .8859079
             |
       _cons |    1454262   221030.7     6.58   0.000      1021050     1887474
------------------------------------------------------------------------------
```

```
. arch D.metrobus, ar(1) arch(1)

. estimates store arch1
```

Metrobus: Model comparison

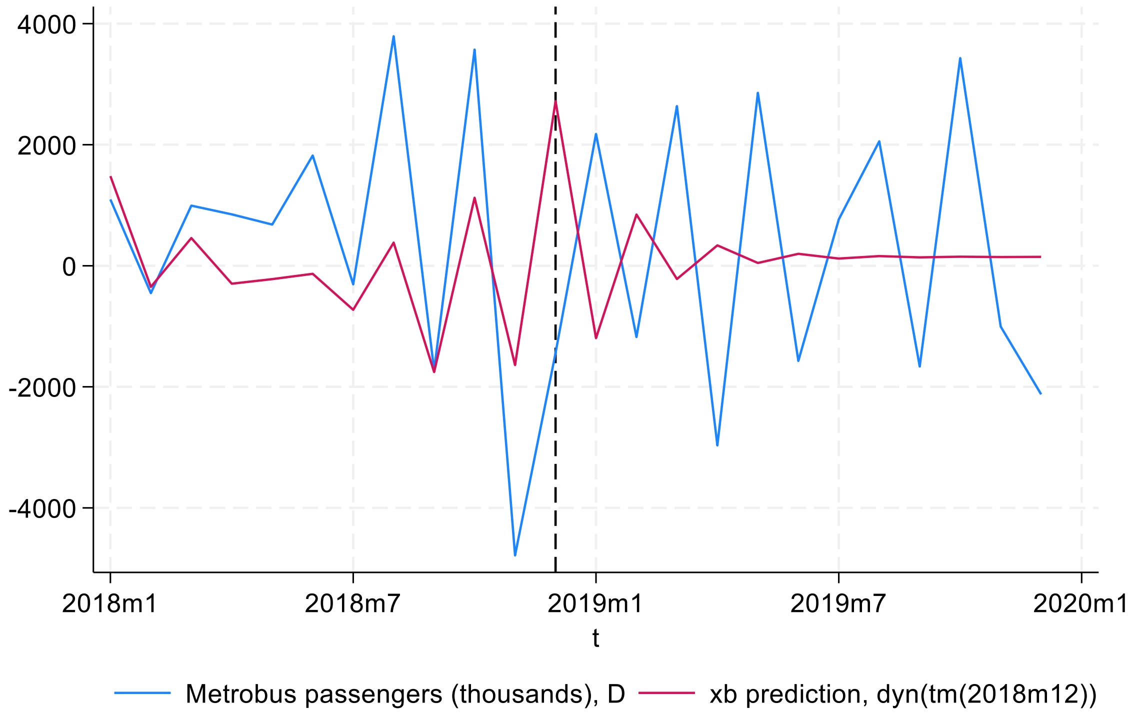
Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
arima21	143	.	-1263.476	5	2536.951	2551.766
arch1	143	.	-1254.34	4	2516.68	2528.531

Note: BIC uses N = number of observations. See [R] BIC note.

```
. estimates stats arima21 arch1
```

Metrobus: 2019 forecast

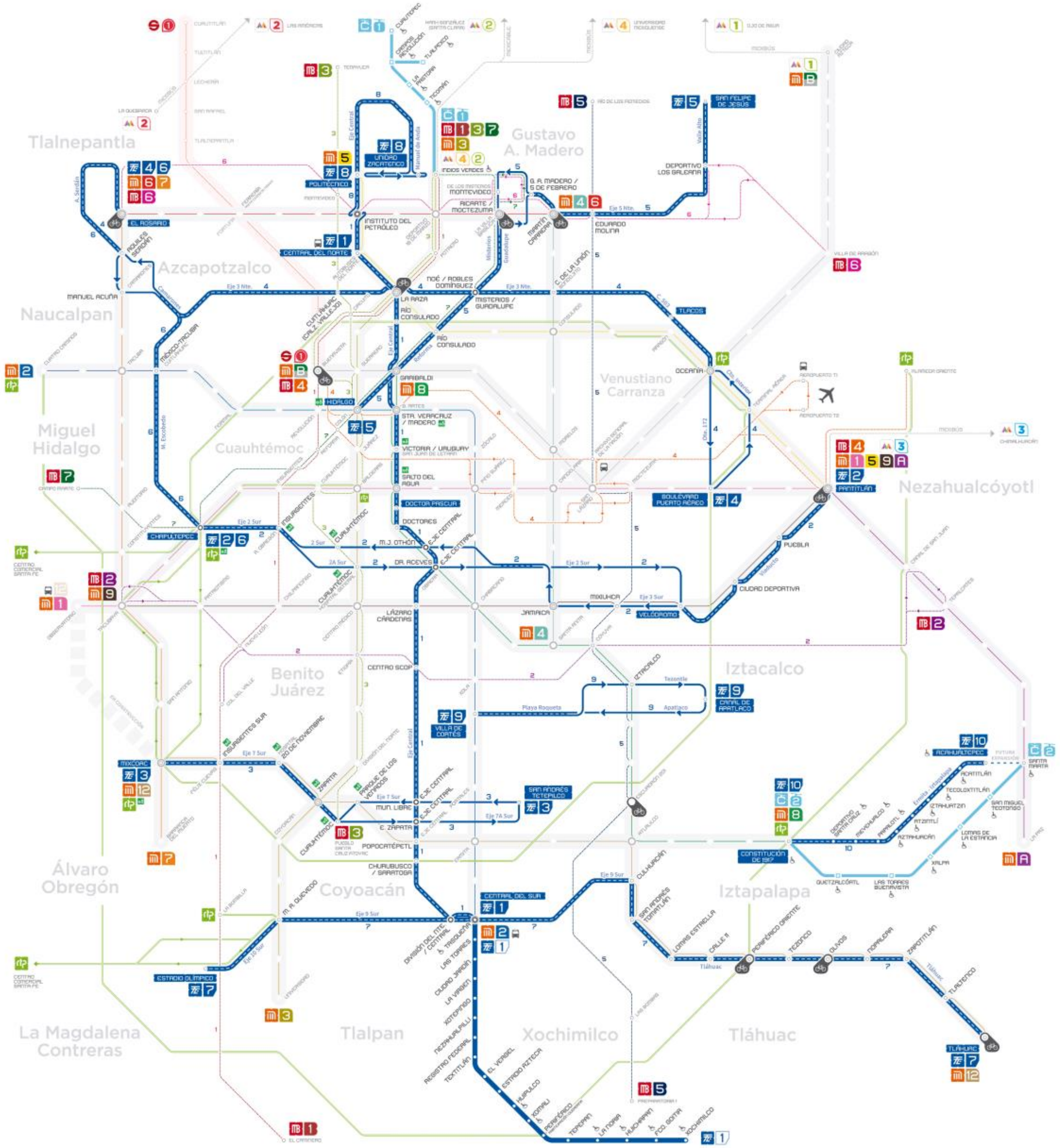



```
. arch D.metrobus if
  tin(2008m1, 2018m12), ar(1) arch(1)

. predict fcst_arch1 in tin(2008m1,
  2019m12), dynamic(tm(2018m12))

. tsline D.metrobus fcst_arch1
  if tin(2018m1, 2019m12),
  tline(2018m12)
```

Part II. Multivariate time-series analysis

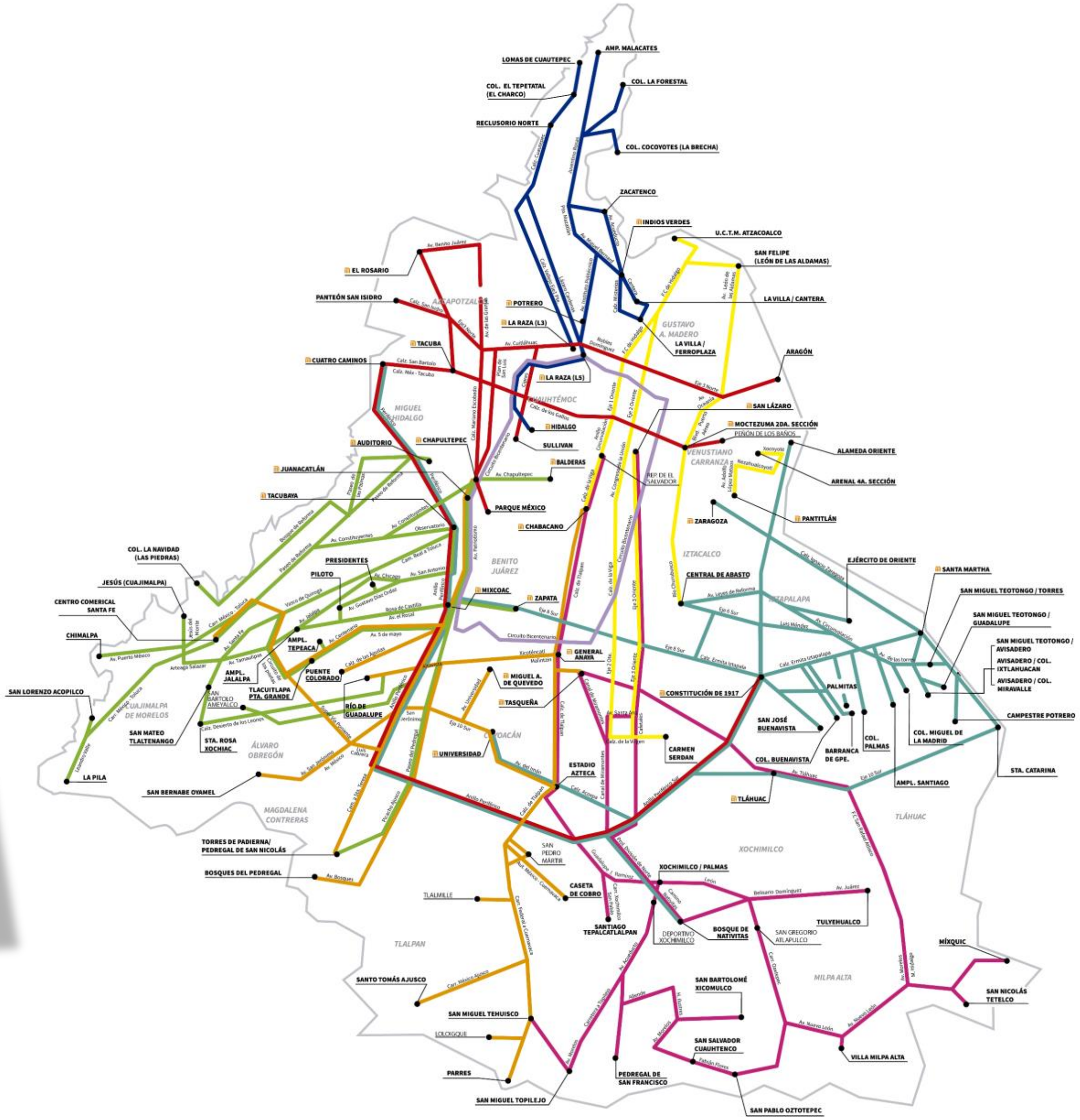
Trolley bus


20013

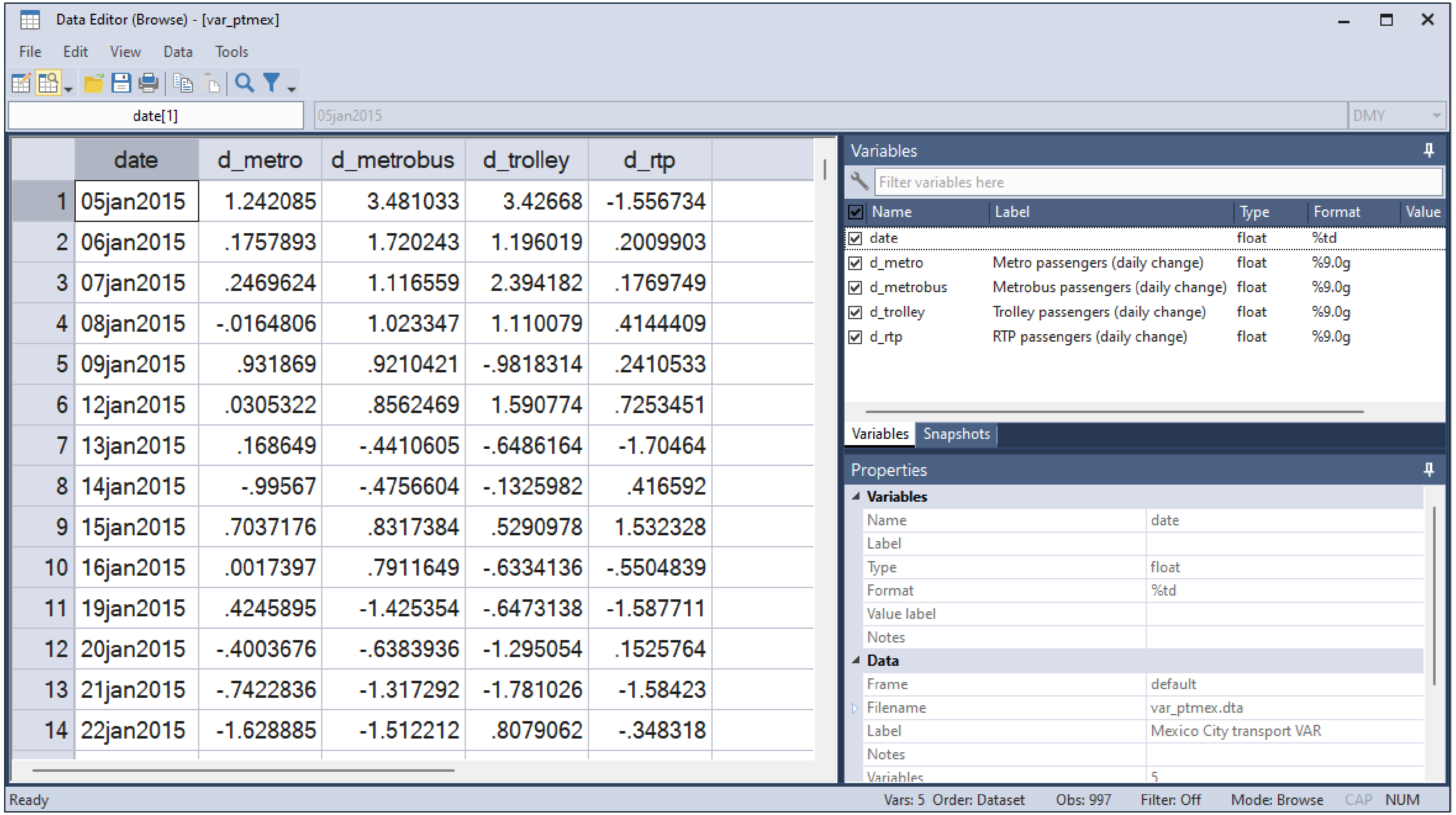

Tlalnepantla
Gustavo A. Madero
Azcapotzalco
Naucalpan
Venustiano Carranza
Miguel Hidalgo
Cuauhtémoc
Nezahualcóyotl
Benito Juárez
Iztacalco
Álvaro Obregón
Coyoacán
Iztapalapa
La Magdalena Contreras
Tlalpan
Xochimilco
Tláhuac

RTP


7107
Torino


LOMAS DE CUAUTEPEC
AMP. MALACATES
COL. LA FORESTAL
COL. EL TEPETATAL (EL CHARCO)
RECLUSORIO NORTE
COL. COCOYOTES (LA BRECHA)
ZACATENCO
INDIOS VERDES
U.C.T.M. ATZACOALCO
SAN FELIPE (LEÓN DE LAS ALDAMAS)
EL ROSARIO
PANTEÓN SAN ISIDRO
POTRERO
LA VILLA / CANTERA
LA RAZA (L3)
TACUBA
LA VILLA / FERROPLAZA
ARAGÓN
CUATRO CAMINOS
LA RAZA (L5)
SAN LÁZARO
HIDALGO
MOCTEZUMA 2DA. SECCIÓN
AUDITORIO
CHAPULTEPEC
SULLIVAN
ALAMEDA ORIENTE
BALDERAS
JUANACATLÁN
ARENAL 4A. SECCIÓN
TACUBAYA
PARQUE MÉXICO
PANTITLÁN
CHABACANO
ZARAGOZA
COL. LA NAVIDAD (LAS PIEDRAS)
PRESIDENTES
EJÉRCITO DE ORIENTE
SANTA MARTHA
PILOTO
CENTRAL DE ABASTO
JESÚS (CUAJIMALPA)
MIXCOAC
ZAPATA
SAN MIGUEL TEOTONGO / TORRES
CENTRO COMERICAL SANTA FE
SAN MIGUEL TEOTONGO / GUADALUPE
CHIMALPA
AMPL. TEPEACA
GENERAL ANAYA
SAN MIGUEL TEOTONGO / AVISADERO
AMPL. JALALPA
PUENTE COLORADO
MIGUEL A. DE QUEVEDO
SAN LORENZO ACOPILCO
TLACUITLAPA PTA. GRANDE
TASQUEÑA
CONSTITUCIÓN DE 1917
PALMITAS
RÍO DE GUADALUPE
CAMPESTRE POTRERO
SAN MATEO TLALTENANGO
SAN JOSÉ BUENAVISTA
COL. MIGUEL DE LA MADRID
STA. ROSA XOCHIAC
UNIVERSIDAD
CARMEN SERDAN
COL. PALMAS
BARRANCA DE GPE.
LA PILA
ESTADIO AZTECA
COL. BUENAVISTA
STA. CATARINA
SAN BERNABE OYAMEL
AMPL. SANTIAGO
TLÁHUAC
TORRES DE PADIERNA/ PEDREGAL DE SAN NICOLÁS
XOCHIMILCO / PALMAS
BOSQUES DEL PEDREGAL
CASETA DE COBRO
TLALMILLE
TULYEHUALCO
SANTIAGO TEPALCATLALPAN
BOSQUE DE NATIVITAS
MÍXQUIC
SANTO TOMÁS AJUSCO
SAN BARTOLOMÉ XICOMULCO
SAN NICOLÁS TETELCO
SAN MIGUEL TEHUISCO
SAN SALVADOR CUAHTENCO
VILLA MILPA ALTA
PARRES
PEDREGAL DE SAN FRANCISCO
SAN MIGUEL TOPILEJO
SAN PABLO OZTOTEPEC

The dataset



Data Editor (Browse) - [var_ptmex]

File Edit View Data Tools

date[1] 05jan2015 DMY

	date	d_metro	d_metrobus	d_trolley	d_rtp
1	05jan2015	1.242085	3.481033	3.42668	-1.556734
2	06jan2015	.1757893	1.720243	1.196019	.2009903
3	07jan2015	.2469624	1.116559	2.394182	.1769749
4	08jan2015	-.0164806	1.023347	1.110079	.4144409
5	09jan2015	.931869	.9210421	-.9818314	.2410533
6	12jan2015	.0305322	.8562469	1.590774	.7253451
7	13jan2015	.168649	-.4410605	-.6486164	-1.70464
8	14jan2015	-.99567	-.4756604	-.1325982	.416592
9	15jan2015	.7037176	.8317384	.5290978	1.532328
10	16jan2015	.0017397	.7911649	-.6334136	-.5504839
11	19jan2015	.4245895	-1.425354	-.6473138	-1.587711
12	20jan2015	-.4003676	-.6383936	-1.295054	.1525764
13	21jan2015	-.7422836	-1.317292	-1.781026	-1.58423
14	22jan2015	-1.628885	-1.512212	.8079062	-.348318

Variables

Filter variables here

Name	Label	Type	Format	Value
date		float	%td	
d_metro	Metro passengers (daily change)	float	%9.0g	
d_metrobus	Metrobus passengers (daily change)	float	%9.0g	
d_trolley	Trolley passengers (daily change)	float	%9.0g	
d_rtp	RTP passengers (daily change)	float	%9.0g	

Variables Snapshots

Properties

Variables	
Name	date
Label	
Type	float
Format	%td
Value label	
Notes	
Data	
Frame	default
Filename	var_ptmex.dta
Label	Mexico City transport VAR
Notes	
Variables	5

Ready Vars: 5 Order: Dataset Obs: 997 Filter: Off Mode: Browse CAP NUM

The dataset

```
. tsset date

Time variable: date, 05jan2015 to 30oct2018, but with gaps
        Delta: 1 day
```

```
. tsset date
```

The dataset

date
05jan2015
06jan2015
07jan2015
08jan2015
09jan2015
12jan2015
13jan2015
14jan2015
15jan2015
16jan2015

Step 1: Create a business calendar

```
. bcal create mycal, from(date)
```

```
Business calendar mycal (format %tbmycal):

  Purpose:

    Range: 05jan2015  30oct2018
               20093      21487    in %td units
                   0        996    in %tbmycal units

   Center: 05jan2015
               20093               in %td units
                   0               in %tbmycal units

  Omitted:       398               days
                 104.2             approx. days/year

 Included:       997               days
                 261.0             approx. days/year

Notes:

  Business calendar file mycal.stbcal saved.
```

Step 2: Load the business calendar

```
loading .\mycal.stbcal ...

     1. * Business calendar "mycal" created by -bcal create-
     2. * Created/replaced on 13 Mar 2023
     3.
     4. version 17
     5. dateformat ymd
     6.
     7. range 2015jan05 2018oct30
     8. centerdate 2015jan05
     9.
    10. omit dayofweek (Sa Su)

(calendar loaded successfully)
```

```
. bcal load mycal
```

Step 3: Generate business calendar variable

	date	d_metro	d_metrobus	d_trolley	d_rtp	bcaldate
1	05jan2015	1.242085	3.481033	3.42668	-1.556734	0
2	06jan2015	.1757893	1.720243	1.196019	.2009908	1
3	07jan2015	.2469624	1.116559	2.394182	.1769749	2
4	08jan2015	-.0164806	1.023347	1.110079	.4144409	3
5	09jan2015	.931869	.9210421	-.9818314	.2410538	4
6	12jan2015	.0305322	.8562469	1.590774	.7253451	5
7	13jan2015	.168649	-.4410605	-.6486164	-1.70464	6
8	14jan2015	-.99567	-.4756604	-.1325982	.416592	7
9	15jan2015	.7037176	.8317384	.5290978	1.532328	8
10	16jan2015	.0017397	.7911649	-.6334136	-.5504839	9
11	19jan2015	.4245895	-1.425354	-.6473138	-1.587711	10
12	20jan2015	-.4003676	-.6383936	-1.295054	.1525764	11
13	21jan2015	-.7422836	-1.317292	-1.781026	-1.58428	12
14	22jan2015	-1.628885	-1.512212	.8079062	-.348318	13

```
. generate bcaldate = bofd("mycal",
  date)
```

Step 4: Format business calendar variable

	date	d_metro	d_metrobus	d_trolley	d_rtp	bcaldate
1	05jan2015	1.242085	3.481033	3.42668	-1.55673	05jan2015
2	06jan2015	.1757893	1.720243	1.196019	.200990	06jan2015
3	07jan2015	.2469624	1.116559	2.394182	.176974	07jan2015
4	08jan2015	-.0164806	1.023347	1.110079	.414440	08jan2015
5	09jan2015	.931869	.9210421	-.9818314	.241053	09jan2015
6	12jan2015	.0305322	.8562469	1.590774	.725345	12jan2015
7	13jan2015	.168649	-.4410605	-.6486164	-1.7046	13jan2015
8	14jan2015	-.99567	-.4756604	-.1325982	.41659	14jan2015
9	15jan2015	.7037176	.8317384	.5290978	1.53232	15jan2015
10	16jan2015	.0017397	.7911649	-.6334136	-.550483	16jan2015
11	19jan2015	.4245895	-1.425354	-.6473138	-1.58771	19jan2015
12	20jan2015	-.4003676	-.6383936	-1.295054	.152576	20jan2015
13	21jan2015	-.7422836	-1.317292	-1.781026	-1.5842	21jan2015
14	22jan2015	-1.628885	-1.512212	.8079062	-.34831	22jan2015

```
. format %tbmycal bcaldate
```

Business calendar variable

```
. tsset bcaldate

Time variable: bcaldate, 05jan2015 to 30oct2018
        Delta: 1 day
```

```
. tsset bcaldate
```

Vector autoregression intuition

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + ... + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR intuition: Contemporaneous effects

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR intuition: Contemporaneous effects

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR intuition: Contemporaneous effects

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

- If a commuter is not using one transportation system today, they may be using another.

VAR intuition: Lagged effects

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR intuition: Lagged effects

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

- Negative autocorrelation? Probably not. People don't go to work/school just every other day.

- Positive autocorrelation? Maybe, because days of above-average changes in passenger volumes tend to be followed by more days of above-average changes. Same for below-average days.

VAR intuition: Innovations

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR intuition: Innovations

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR theory review: Setup

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR theory review: Structural to reduced form

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

!!! !!!

VAR theory review: Structural to reduced form

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} - \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR theory review: Structural to reduced form

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} + \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} - \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

$$\underbrace{\begin{bmatrix} 1 & -a_{12} & -a_{13} & -a_{14} \\ -a_{21} & 1 & -a_{23} & -a_{24} \\ -a_{31} & -a_{32} & 1 & -a_{34} \\ -a_{41} & -a_{42} & -a_{43} & 1 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} a^1_{11} & a^1_{12} & a^1_{13} & a^1_{14} \\ a^1_{21} & a^1_{22} & a^1_{23} & a^1_{24} \\ a^1_{31} & a^1_{32} & a^1_{33} & a^1_{34} \\ a^1_{41} & a^1_{42} & a^1_{43} & a^1_{44} \end{bmatrix}}_{A_1} \underbrace{\begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix}}_{y_{t-1}} + \dots + \underbrace{\begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix}}_{B} \underbrace{\begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}}_{\epsilon_t}$$

VAR theory review: Structural to reduced form

$$Ay_t = A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t$$

VAR theory review: Structural to reduced form

$$Ay_t = A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t$$

$$y_t = \underbrace{A^{-1}A_1}_{\Phi_1} y_{t-1} + ... + \underbrace{A^{-1}A_p}_{\Phi_p} y_{t-p} + \underbrace{A^{-1}B\epsilon_t}_{u_t}$$

VAR theory review: Structural to reduced form

$$Ay_t = A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t$$

$$y_t = \underbrace{A^{-1}A_1}_{\Phi_1} y_{t-1} + ... + \underbrace{A^{-1}A_p}_{\Phi_p} y_{t-p} + \underbrace{A^{-1}B\epsilon_t}_{u_t}$$

$$y_t = \Phi_1 y_{t-1} + ... + \Phi_p y_{t-p} + u_t$$

VAR: Lag order

Lag-order selection criteria

Sample: 12jan2015 thru 30oct2018 Number of obs = 992

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4527.17				1.3e-09	-9.1193	-9.11179	-9.09954
1	6067.36	3080.4	16	0.000	6.0e-11	-12.1923	-12.1547	-12.0935
2	6153.1	171.48	16	0.000	5.2e-11	-12.3329	-12.2653	-12.155*
3	6184.62	63.04*	16	0.000	5.0e-11*	-12.3642*	-12.2665*	-12.1073
4	6192.31	15.39	16	0.496	5.1e-11	-12.3474	-12.2197	-12.0115
5	6196.83	9.0334	16	0.912	5.2e-11	-12.3243	-12.1665	-11.9094

* optimal lag
Endogenous: d_metro d_metrobus d_trolley d_rtp
Exogenous: _cons

```
. varsoc d_metro d_metrobus d_trolley
  d_rtp
```

VAR: Output

```
Vector autoregression

Sample: 08jan2015 thru 30oct2018              Number of obs     =        994
Log likelihood =  -2057.746                   AIC               =   4.244961
FPE            =   .0008197                   HQIC              =   4.342451
Det(Sigma_ml)  =   .0007383                   SBIC              =    4.50139

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
d_metro              13     .411561   0.8329   4954.318   0.0000
d_metrobus           13     .581226   0.6617   1944.278   0.0000
d_trolley            13     .925986   0.1391   160.5786   0.0000
d_rtp                13     .981036   0.0497   51.96537   0.0000
----------------------------------------------------------------
```

```
. var d_metro d_metrobus d_trolley
  d_rtp, lags(1 2 3)
```

VAR: Output

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
d_metro						
d_metro						
L1.	.0578853	.0382751	1.51	0.130	-.0171325	.1329031
L2.	.108086	.0464578	2.33	0.020	.0170304	.1991416
L3.	.1416069	.0375527	3.77	0.000	.0680049	.2152089
d_metrobus						
L1.	-.1588305	.1139093	-1.39	0.163	-.3820885	.0644276
L2.	-.2908373	.0945086	-3.08	0.002	-.4760708	-.1056038
L3.	.0977986	.0398539	2.45	0.014	.0196864	.1759108
d_trolley						
L1.	.0341848	.0200201	1.71	0.088	-.0050539	.0734234
L2.	.0284608	.0287286	0.99	0.322	-.0278462	.0847679
L3.	.0385756	.0269324	1.43	0.152	-.0142109	.091362
d_rtp						
L1.	.5980455	.074328	8.05	0.000	.4523653	.7437257
L2.	.6297207	.0803916	7.83	0.000	.4721561	.7872854
L3.	.3153713	.0453119	6.96	0.000	.2265616	.404181
_cons	-.0038782	.0129925	-0.30	0.765	-.029343	.0215867

VAR: Output

d_metrobus						
d_metro						
L1.	.3077106	.0540539	5.69	0.000	.2017669	.4136543
L2.	-.0260303	.0656099	-0.40	0.692	-.1546233	.1025628
L3.	-.0008957	.0530337	-0.02	0.987	-.10484	.1030485
d_metrobus						
L1.	.0615783	.160868	0.38	0.702	-.2537172	.3768738
L2.	-.2176465	.1334695	-1.63	0.103	-.479242	.0439489
L3.	.0721852	.0562836	1.28	0.200	-.0381286	.1824989
d_trolley						
L1.	.1889079	.0282733	6.68	0.000	.1334933	.2443225
L2.	.1050341	.0405719	2.59	0.010	.0255147	.1845536
L3.	.0957912	.0380351	2.52	0.012	.0212437	.1703387
d_rtp						
L1.	.418431	.1049695	3.99	0.000	.2126945	.6241674
L2.	.0648947	.1135328	0.57	0.568	-.1576256	.2874149
L3.	.0730707	.0639916	1.14	0.254	-.0523506	.1984919
_cons	-.0057634	.0183486	-0.31	0.753	-.041726	.0301992

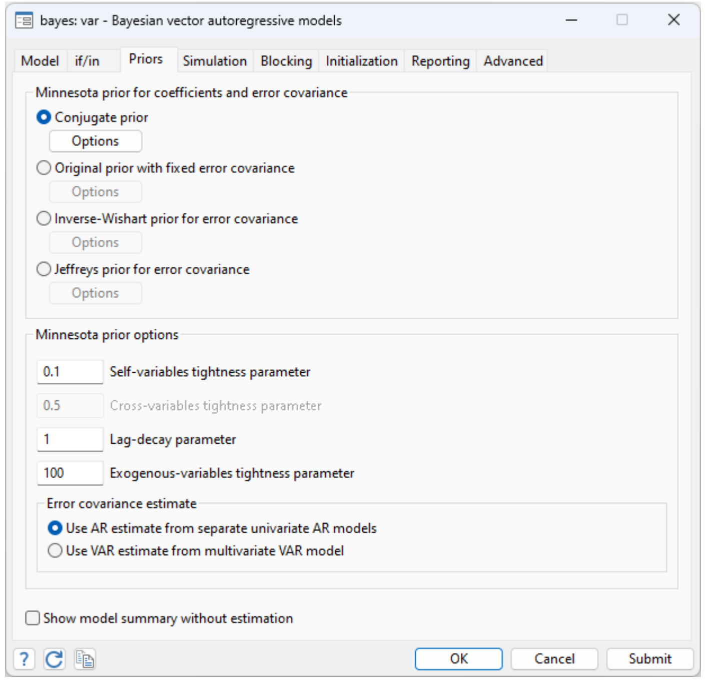
VAR: Output

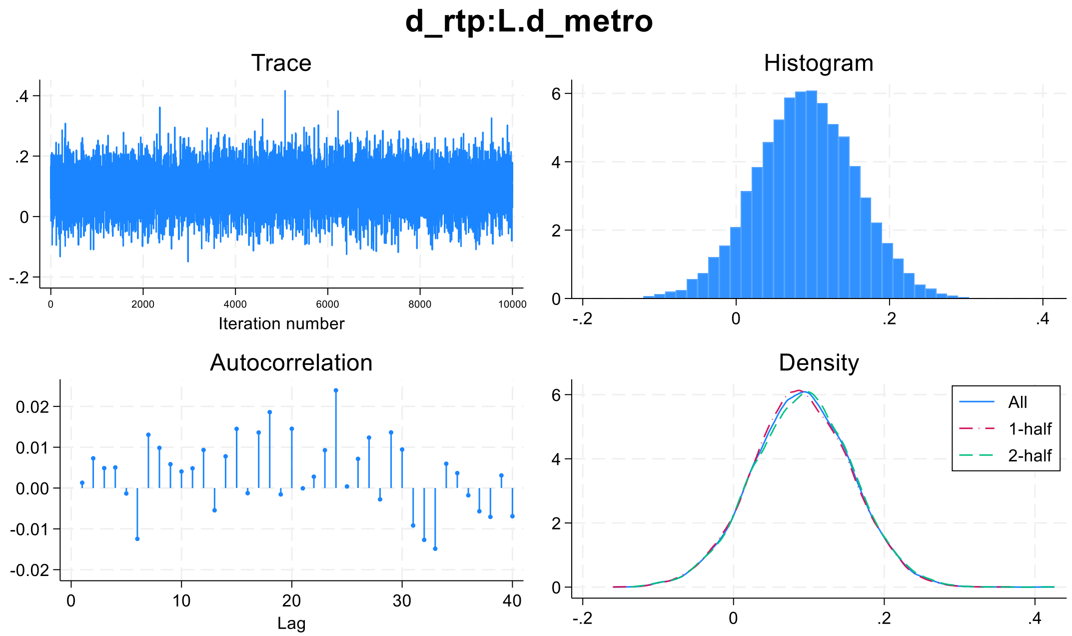
d_trolley						
d_metro						
L1.	.1137616	.0861166	1.32	0.186	-.0550238	.2825469
L2.	-.0588601	.1045272	-0.56	0.573	-.2637296	.1460094
L3.	-.0256809	.0844913	-0.30	0.761	-.1912808	.1399191
d_metrobus						
L1.	.2076194	.2562887	0.81	0.418	-.2946972	.709936
L2.	.0436953	.2126385	0.21	0.837	-.3730684	.460459
L3.	.0777061	.0896688	0.87	0.386	-.0980415	.2534537
d_trolley						
L1.	-.0152065	.0450439	-0.34	0.736	-.103491	.0730779
L2.	-.0088138	.0646376	-0.14	0.892	-.1355011	.1178735
L3.	.0516183	.0605961	0.85	0.394	-.0671479	.1703845
d_rtp						
L1.	.1036687	.1672333	0.62	0.535	-.2241027	.43144
L2.	-.0593307	.1808761	-0.33	0.743	-.4138413	.2951799
L3.	-.0253078	.101949	-0.25	0.804	-.2251241	.1745085
_cons	-.005603	.0292323	-0.19	0.848	-.0628973	.0516912

VAR: Output

d_rtp						
d_metro						
L1.	.1021072	.0912362	1.12	0.263	-.0767124	.2809268
L2.	-.0348227	.1107413	-0.31	0.753	-.2518716	.1822262
L3.	.0238819	.0895143	0.27	0.790	-.1515629	.1993267
d_metrobus						
L1.	.0221895	.271525	0.08	0.935	-.5099897	.5543687
L2.	-.4005451	.2252798	-1.78	0.075	-.8420853	.0409952
L3.	.1591715	.0949996	1.68	0.094	-.0270242	.3453672
d_trolley						
L1.	.0124564	.0477217	0.26	0.794	-.0810765	.1059893
L2.	.0050517	.0684802	0.07	0.941	-.1291671	.1392705
L3.	.0785933	.0641985	1.22	0.221	-.0472335	.2044201
d_rtp						
L1.	.0610577	.1771753	0.34	0.730	-.2861995	.408315
L2.	.2549217	.1916291	1.33	0.183	-.1206644	.6305079
L3.	.1552565	.1080098	1.44	0.151	-.0564388	.3669518
_cons	-.0000959	.0309702	-0.00	0.998	-.0607963	.0606045

The `bayes` prefix






```
. bayes: var d_metro d_metrobus d_trolley d_rtp, lags(1 2 3)
```

Structural vector autoregression

$$Ay_t = A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t$$

$$y_t = \underbrace{A^{-1}A_1}_{\Phi_1} y_{t-1} + ... + \underbrace{A^{-1}A_p}_{\Phi_p} y_{t-p} + \underbrace{A^{-1}B\epsilon_t}_{u_t}$$

$$y_t = \Phi_1 y_{t-1} + ... + \Phi_p y_{t-p} + u_t$$

SVAR

$$Ay_t = A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t$$

$$y_t = \underbrace{A^{-1}A_1}_{\Phi_1} y_{t-1} + ... + \underbrace{A^{-1}A_p}_{\Phi_p} y_{t-p} + \underbrace{A^{-1}B\epsilon_t}_{u_t}$$

$$y_t = \Phi_1 y_{t-1} + ... + \Phi_p y_{t-p} + u_t$$

$$\Rightarrow E[u_t u_t^{'}] = \Sigma$$

SVAR: Identification

Information we have

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} \end{bmatrix}$$

10 covariances

Information we want

$$A = \begin{bmatrix} 1 & -a_{12} & -a_{13} & -a_{14} \\ -a_{21} & 1 & -a_{23} & -a_{24} \\ -a_{31} & -a_{32} & 1 & -a_{34} \\ -a_{41} & -a_{42} & -a_{43} & 1 \end{bmatrix}$$

28 parameters

$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix}$$

SVAR: Cholesky decomposition

Information we have

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} \end{bmatrix}$$

10 covariances

Information we want

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -a_{21} & 1 & 0 & 0 \\ -a_{31} & -a_{32} & 1 & 0 \\ -a_{41} & -a_{42} & -a_{43} & 1 \end{bmatrix}$$

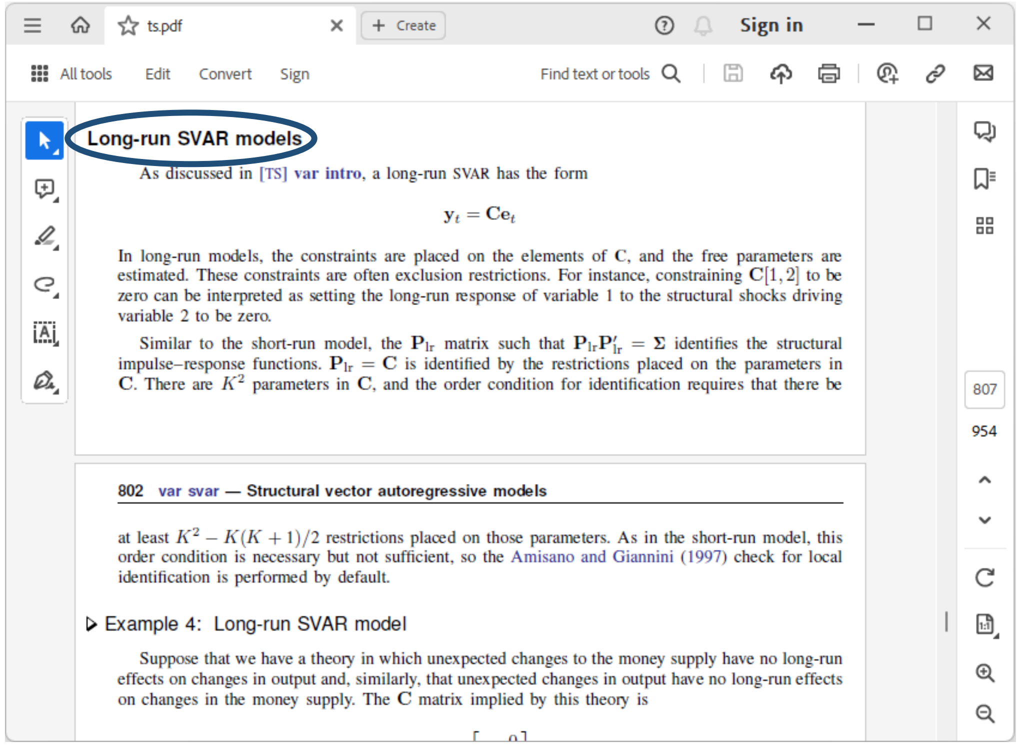
10 parameters

$$B = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 \\ 0 & 0 & b_{33} & 0 \\ 0 & 0 & 0 & b_{44} \end{bmatrix}$$

SVAR ordering

$$\begin{bmatrix} rtp_t \\ trolley_t \\ metrobus_t \\ metro_t \end{bmatrix}$$

SVAR: Other identification strategies


Long-run SVAR models

As discussed in [TS] var intro, a long-run SVAR has the form

$$y_t = Ce_t$$

In long-run models, the constraints are placed on the elements of C, and the free parameters are estimated. These constraints are often exclusion restrictions. For instance, constraining $C[1,2]$ to be zero can be interpreted as setting the long-run response of variable 1 to the structural shocks driving variable 2 to be zero.

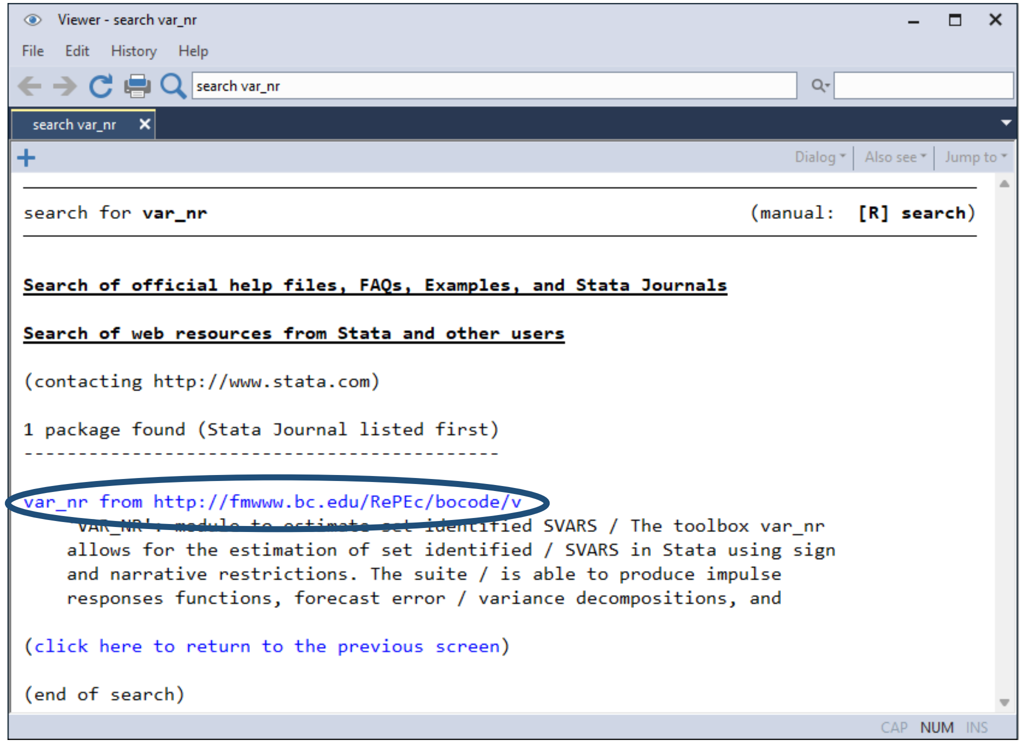
Similar to the short-run model, the P_{lr} matrix such that $P_{lr}P_{lr}' = \Sigma$ identifies the structural impulse–response functions. $P_{lr} = C$ is identified by the restrictions placed on the parameters in C. There are K^2 parameters in C, and the order condition for identification requires that there be

802 var svar — Structural vector autoregressive models

at least $K^2 - K(K+1)/2$ restrictions placed on those parameters. As in the short-run model, this order condition is necessary but not sufficient, so the Amisano and Giannini (1997) check for local identification is performed by default.

Example 4: Long-run SVAR model

Suppose that we have a theory in which unexpected changes to the money supply have no long-run effects on changes in output and, similarly, that unexpected changes in output have no long-run effects on changes in the money supply. The C matrix implied by this theory is



SVAR(3)

```
Sample: 08jan2015 thru 30oct2018                Number of obs     =        994
Exactly identified model                        Log likelihood    =  -2057.746

------------------------------------------------------------------------------
             | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
/A           |
         1_1 |          1  (constrained)
         2_1 |  -.5707443    .023845   -23.94   0.000    -.6174796   -.5240089
         3_1 |  -.5982546   .0047149  -126.89   0.000    -.6074956   -.5890136
         4_1 |  -.8871721   .0558795   -15.88   0.000    -.9966938   -.7776504
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
         3_2 |   .0319603   .0049952     6.40   0.000     .0221699    .0417506
         4_2 |   .2263981   .0145668    15.54   0.000     .1978476    .2549485
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |          1  (constrained)
         4_3 |   1.031821   .0906478    11.38   0.000     .8541541    1.209487
         1_4 |          0  (constrained)
         2_4 |          0  (constrained)
         3_4 |          0  (constrained)
         4_4 |          1  (constrained)
-------------+----------------------------------------------------------------
/B           |
         1_1 |   .9745992   .0218584    44.59   0.000     .9317576    1.017441
         2_1 |          0  (constrained)
         3_1 |          0  (constrained)
         4_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   .7326836   .0164327    44.59   0.000     .7004761     .764891
         3_2 |          0  (constrained)
         4_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |   .1153879   .0025879    44.59   0.000     .1103156    .1204601
         4_3 |          0  (constrained)
         1_4 |          0  (constrained)
         2_4 |          0  (constrained)
         3_4 |          0  (constrained)
         4_4 |   .3297697   .0073961    44.59   0.000     .3152736    .3442658
------------------------------------------------------------------------------
```

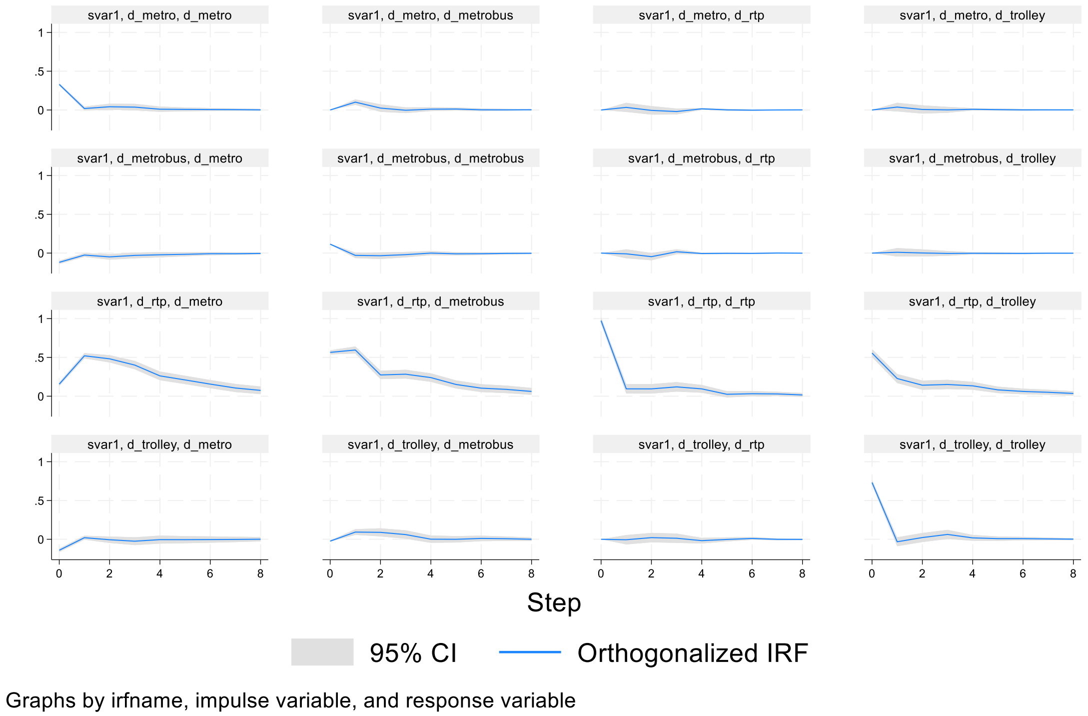
```
matrix input A =  ( 1,  0,  0,  0\ ///
                   .,  1,  0,  0\ ///
                   .,  .,  1,  0\ ///
                   .,  .,  .,  1)

matrix input B =   ( .,  0,  0,  0\ ///
                     0,  .,  0,  0\ ///
                     0,  0,  .,  0\ ///
                     0,  0,  0,  .)

. svar d_rtp d_trolley d_metrobus
  d_metro, aeq(A) beq(B) lags(1 2 3)
```

Impulse-response Function

```
. irf set "myIRF"
(file myIRF.irf created)
(file myIRF.irf now active)

. irf create svar1
(file myIRF.irf updated)
```

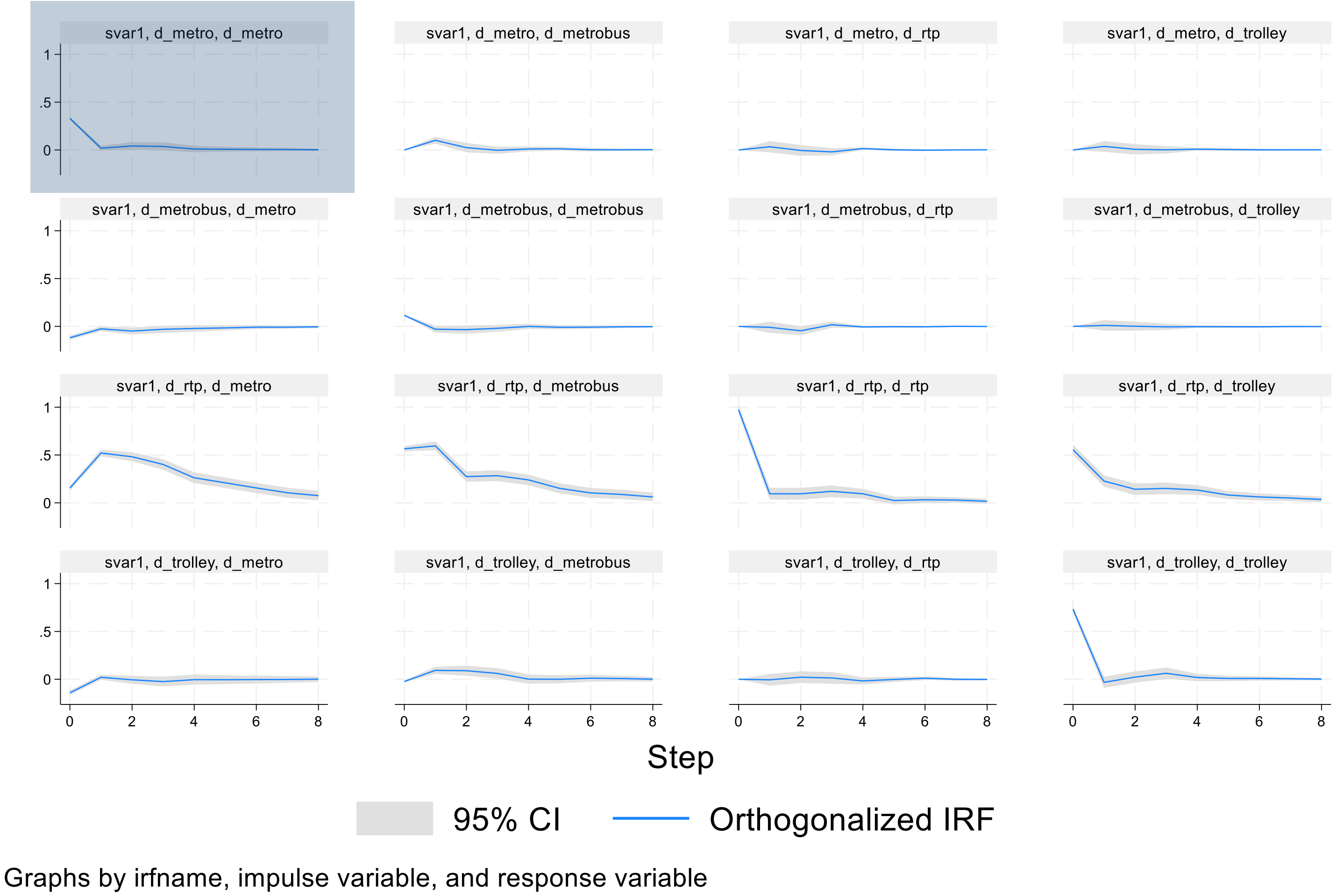
```
. irf set "myIRF"

. irf create svar1
```

IRF graphs




```
. irf graph oirf
```

IRF graphs



svar1, d_metro, d_metro
svar1, d_metro, d_metrobus
svar1, d_metro, d_rtp
svar1, d_metro, d_trolley
svar1, d_metrobus, d_metro
svar1, d_metrobus, d_metrobus
svar1, d_metrobus, d_rtp
svar1, d_metrobus, d_trolley
svar1, d_rtp, d_metro
svar1, d_rtp, d_metrobus
svar1, d_rtp, d_rtp
svar1, d_rtp, d_trolley
svar1, d_trolley, d_metro
svar1, d_trolley, d_metrobus
svar1, d_trolley, d_rtp
svar1, d_trolley, d_trolley
1
.5
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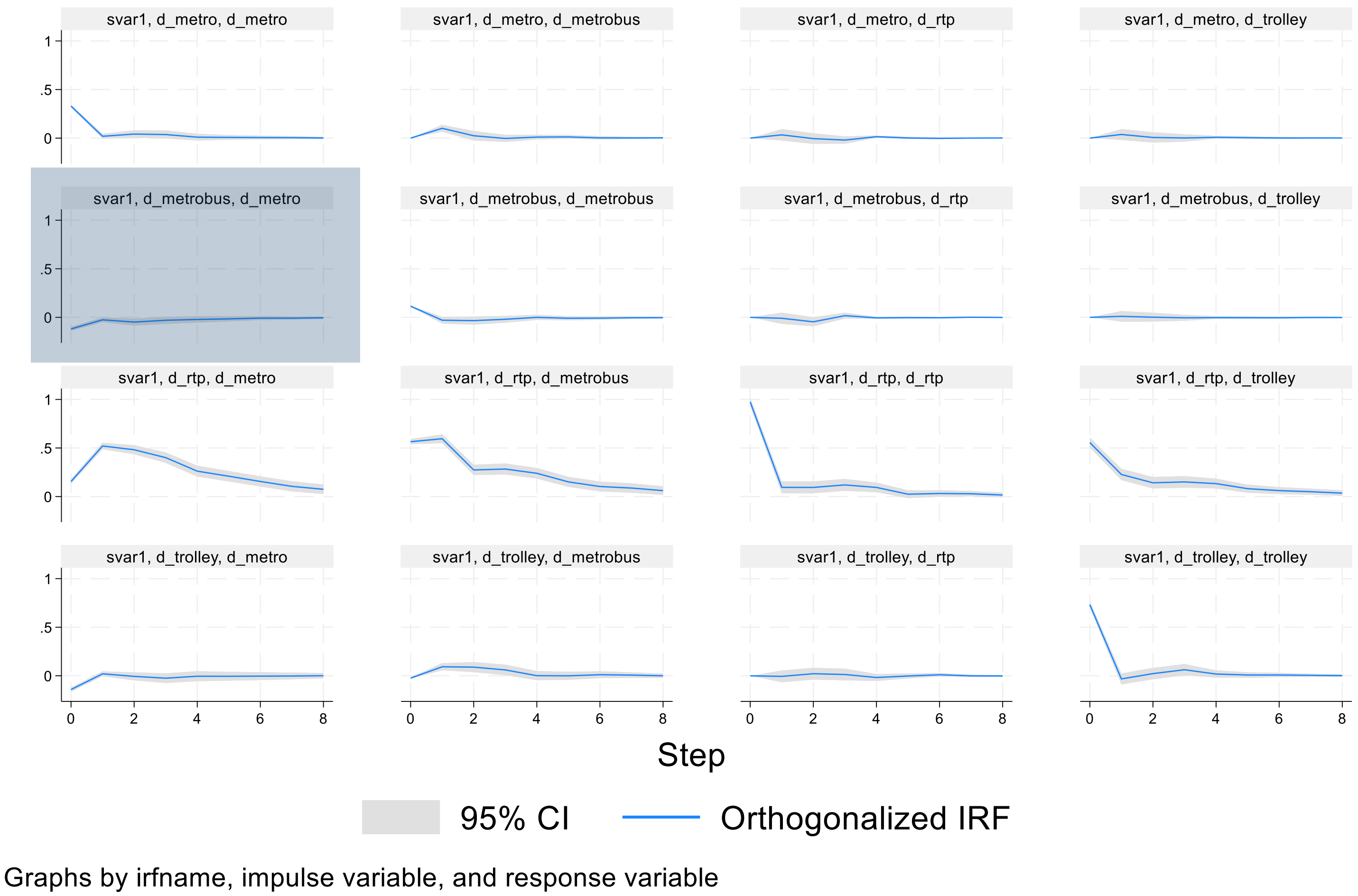
2
4
6
8
Step
95% CI
Orthogonalized IRF
Graphs by irfname, impulse variable, and response variable

IRF graphs



svar1, d_metro, d_metro
svar1, d_metro, d_metrobus
svar1, d_metro, d_rtp
svar1, d_metro, d_trolley
svar1, d_metrobus, d_metro
svar1, d_metrobus, d_metrobus
svar1, d_metrobus, d_rtp
svar1, d_metrobus, d_trolley
svar1, d_rtp, d_metro
svar1, d_rtp, d_metrobus
svar1, d_rtp, d_rtp
svar1, d_rtp, d_trolley
svar1, d_trolley, d_metro
svar1, d_trolley, d_metrobus
svar1, d_trolley, d_rtp
svar1, d_trolley, d_trolley
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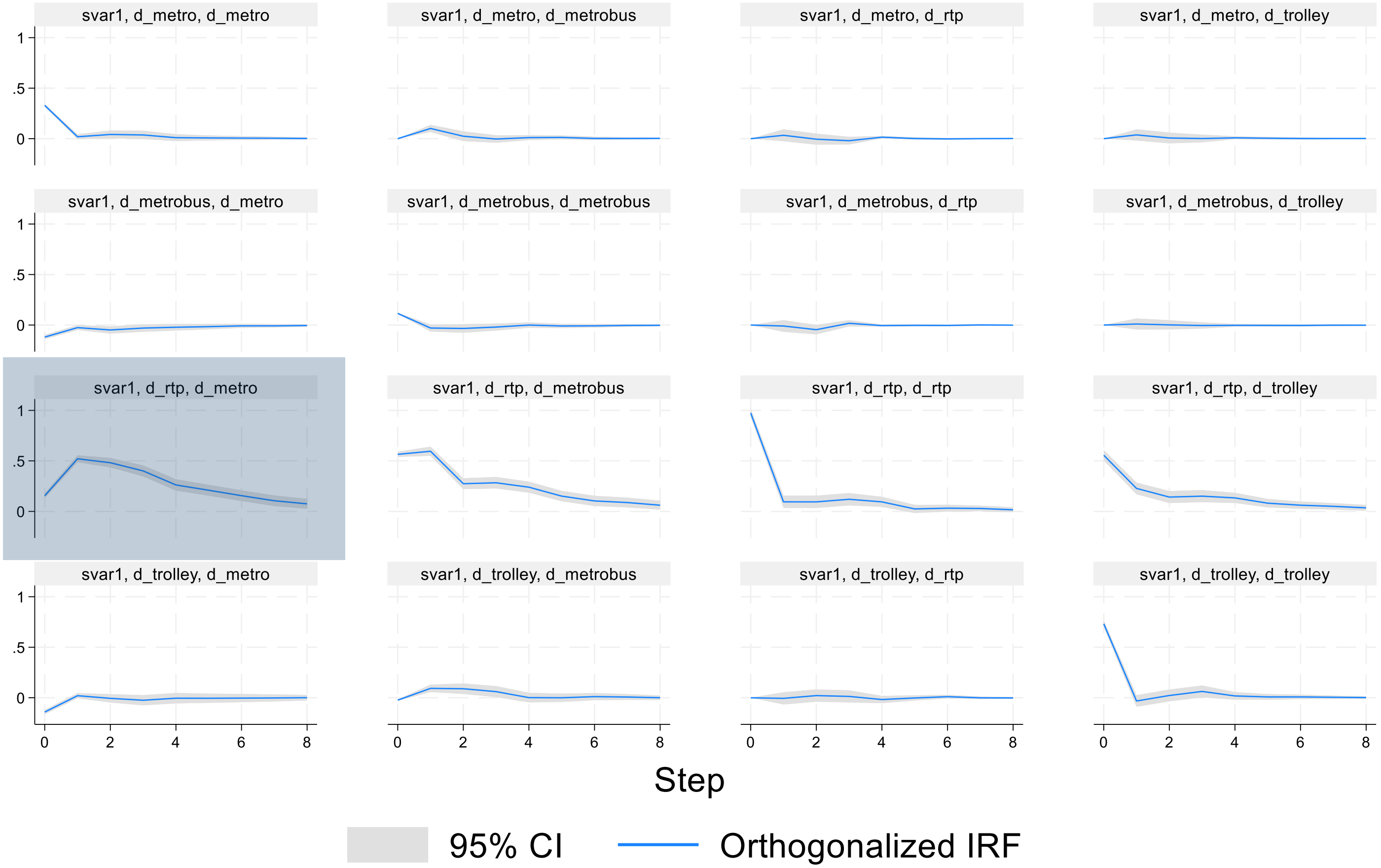
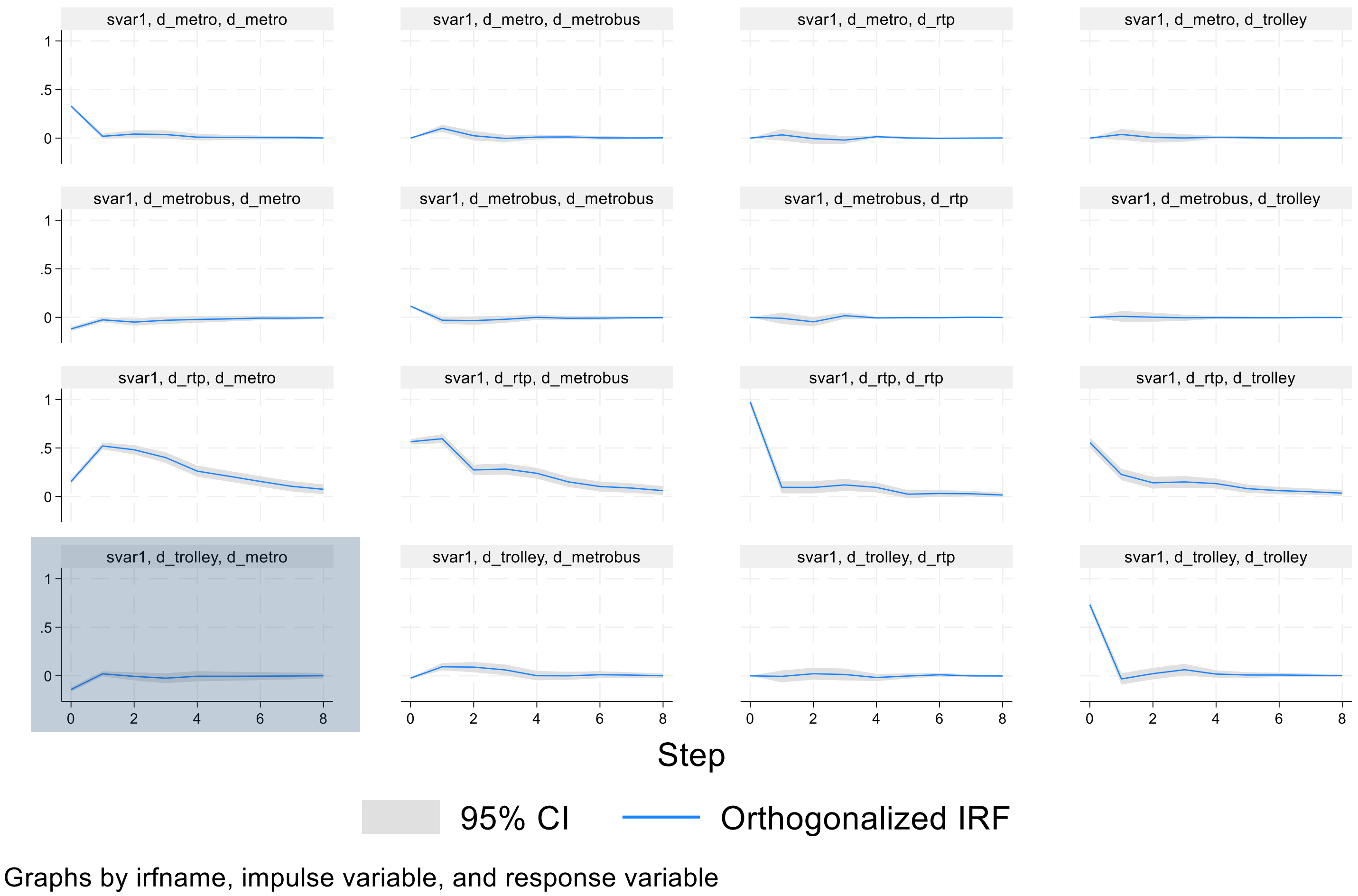
Step
95% CI
Orthogonalized IRF
Graphs by irfname, impulse variable, and response variable

IRF graphs



Graphs by irfname, impulse variable, and response variable

IRF graphs



svar1, d_metro, d_metro
svar1, d_metro, d_metrobus
svar1, d_metro, d_rtp
svar1, d_metro, d_trolley
svar1, d_metrobus, d_metro
svar1, d_metrobus, d_metrobus
svar1, d_metrobus, d_rtp
svar1, d_metrobus, d_trolley
svar1, d_rtp, d_metro
svar1, d_rtp, d_metrobus
svar1, d_rtp, d_rtp
svar1, d_rtp, d_trolley
svar1, d_trolley, d_metro
svar1, d_trolley, d_metrobus
svar1, d_trolley, d_rtp
svar1, d_trolley, d_trolley
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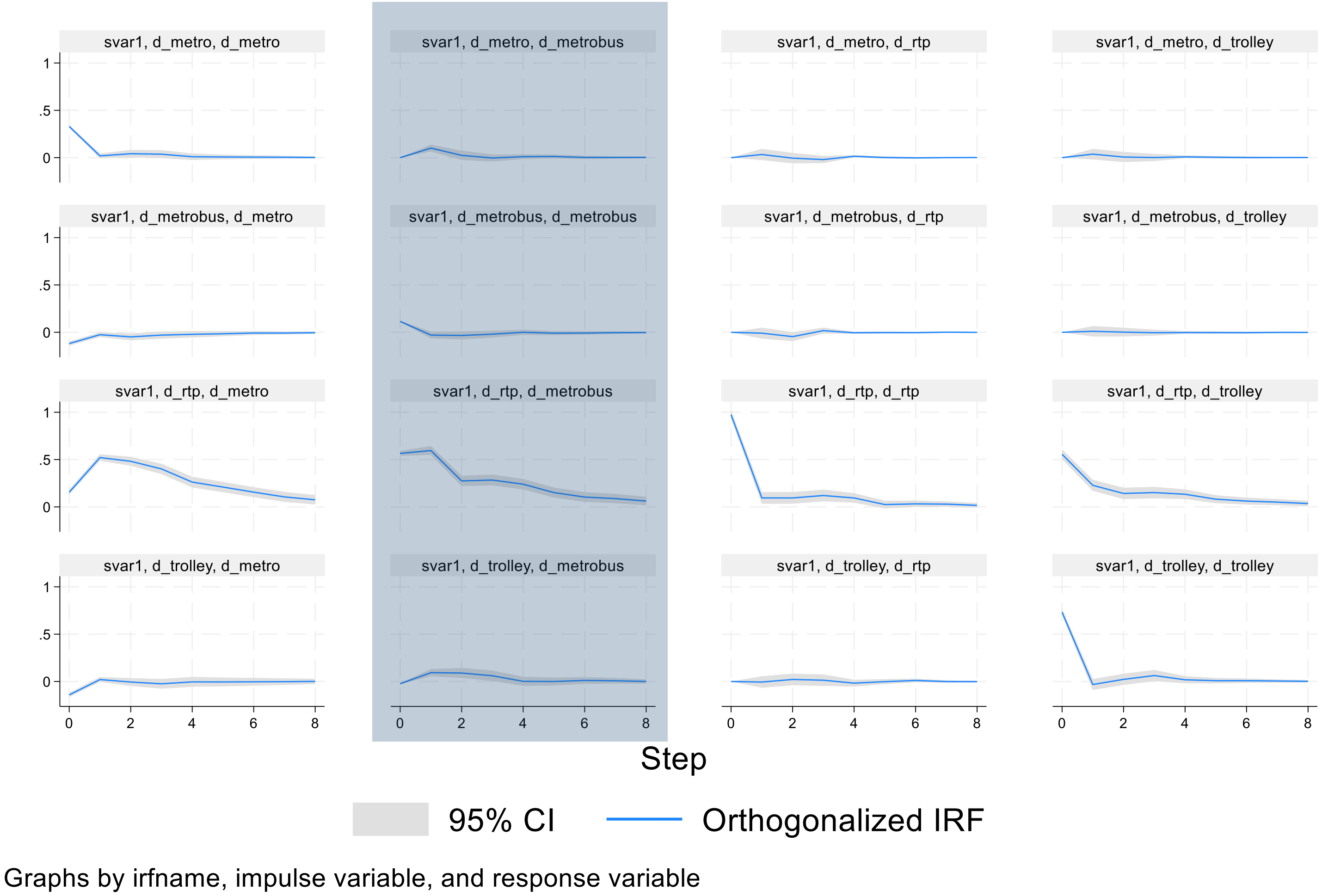
8
Step
95% CI
Orthogonalized IRF
Graphs by irfname, impulse variable, and response variable

IRF graphs


svar1, d_metro, d_metro
svar1, d_metro, d_metrobus
svar1, d_metro, d_rtp
svar1, d_metro, d_trolley
svar1, d_metrobus, d_metro
svar1, d_metrobus, d_metrobus
svar1, d_metrobus, d_rtp
svar1, d_metrobus, d_trolley
svar1, d_rtp, d_metro
svar1, d_rtp, d_metrobus
svar1, d_rtp, d_rtp
svar1, d_rtp, d_trolley
svar1, d_trolley, d_metro
svar1, d_trolley, d_metrobus
svar1, d_trolley, d_rtp
svar1, d_trolley, d_trolley
1
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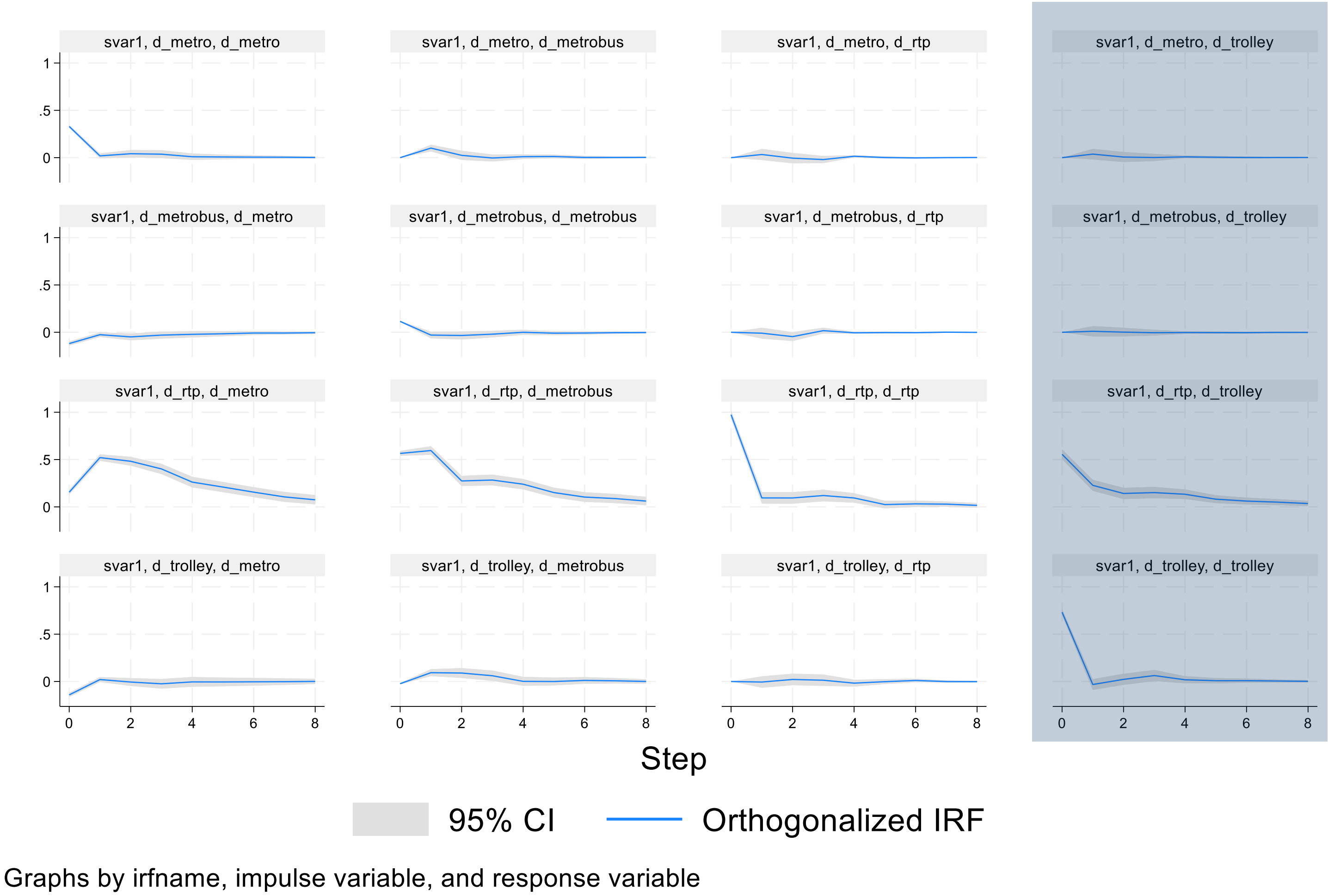
0
2
4
6
8
Step
95% CI
Orthogonalized IRF
Graphs by irfname, impulse variable, and response variable

IRF graphs


svar1, d_metro, d_metro
svar1, d_metro, d_metrobus
svar1, d_metro, d_rtp
svar1, d_metro, d_trolley
svar1, d_metrobus, d_metro
svar1, d_metrobus, d_metrobus
svar1, d_metrobus, d_rtp
svar1, d_metrobus, d_trolley
svar1, d_rtp, d_metro
svar1, d_rtp, d_metrobus
svar1, d_rtp, d_rtp
svar1, d_rtp, d_trolley
svar1, d_trolley, d_metro
svar1, d_trolley, d_metrobus
svar1, d_trolley, d_rtp
svar1, d_trolley, d_trolley
1
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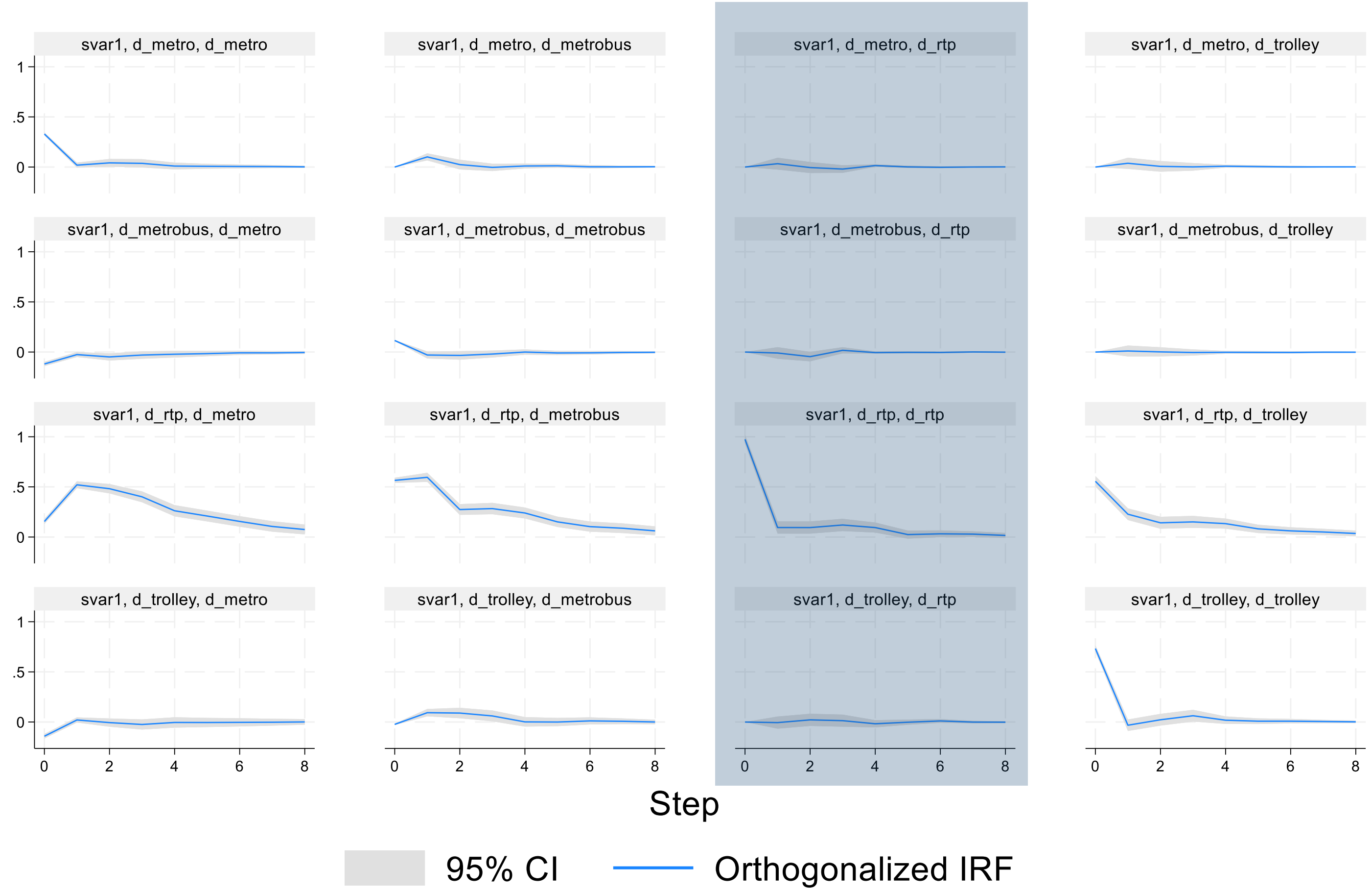
6
8
Step
95% CI
Orthogonalized IRF
Graphs by irfname, impulse variable, and response variable

IRF graphs



Graphs by irfname, impulse variable, and response variable

Thank you for joining us!

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