

Introduction to time-series commands in Stata

September 24th, 2024



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
- Lag order selection with **arimasoc**
- 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

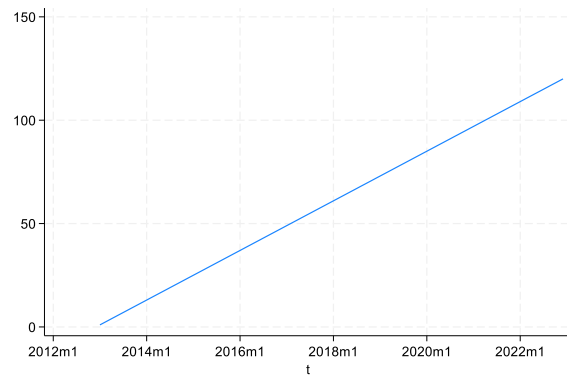
Components of a time series

$$y_t = trend_t + seasonality_t + residual_t$$

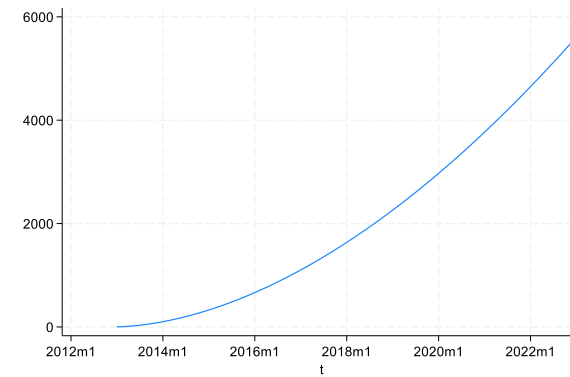
or

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

Components of a time series

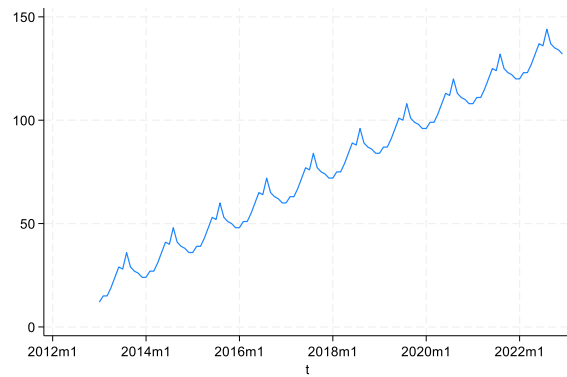


Additive trend



Multiplicative trend

Components of a time series

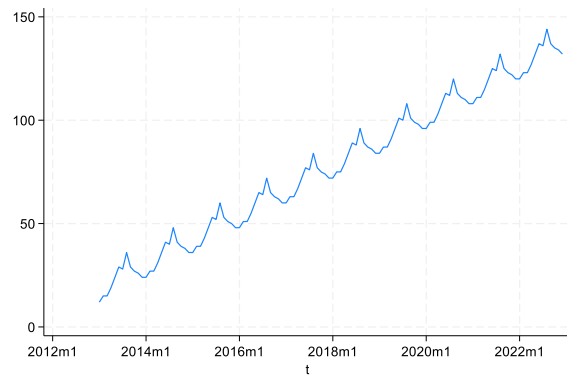


Additive trend
Additive seasonality



Multiplicative trend
Additive seasonality

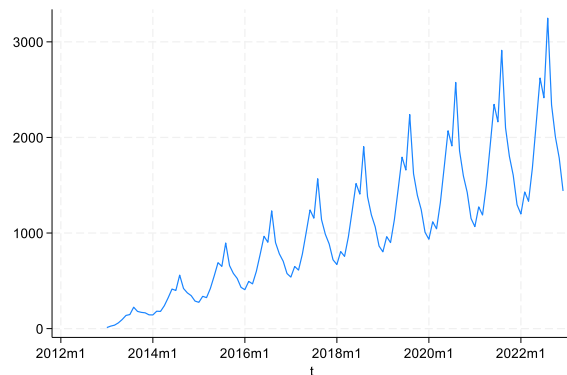
Components of a time series



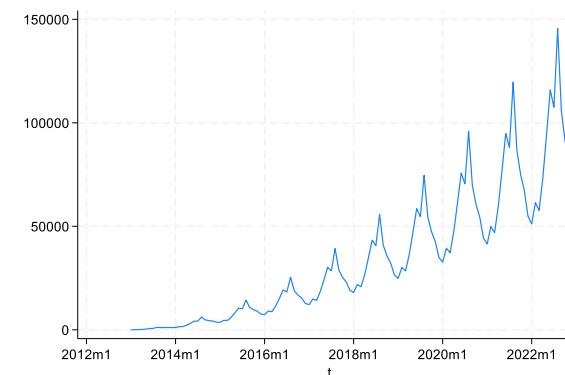
Additive trend
Additive seasonality



Multiplicative trend
Additive seasonality

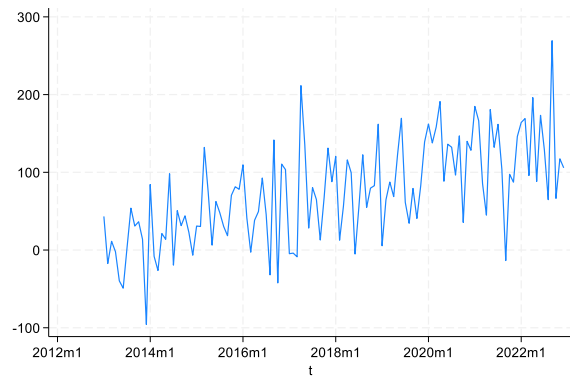


Additive trend
Multiplicative seasonality

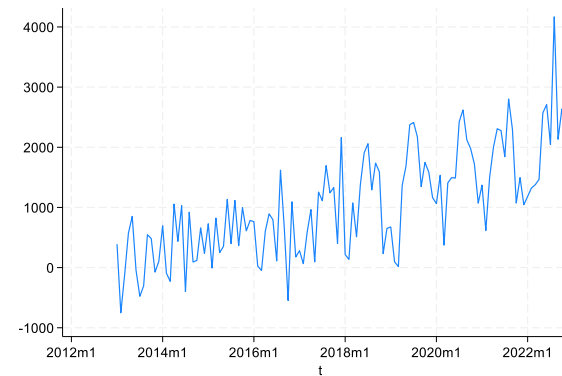


Multiplicative trend
Multiplicative seasonality

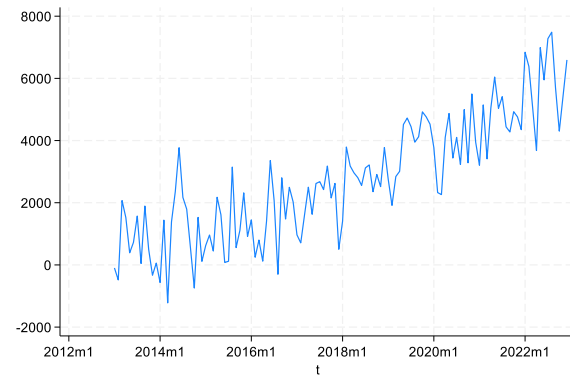
Components of a time series



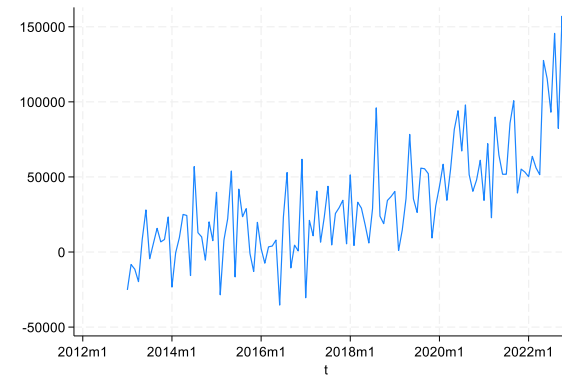
Additive trend
Additive seasonality
+ random noise



Multiplicative trend
Additive seasonality
+ random noise



Additive trend
Multiplicative seasonality
+ random noise



Multiplicative trend
Multiplicative seasonality
+ random noise

Public transport dataset

ptmex [Compatibility Mode] - Excel

File Home Insert Page Layout Formulas Data Review View Help

Normal Page Break Preview Custom Views Ruler Formula Bar Gridlines Headings Zoom 100% Zoom to Selection New Window Arrange All Freeze Panes Switch Windows Macros

A1 : X ✓ fx date

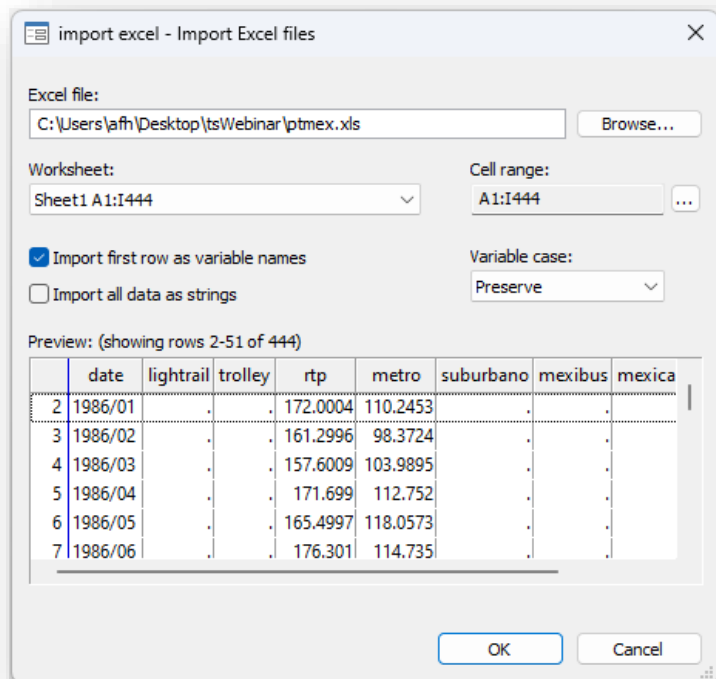
	A	B	C	D	E	F	G	H	I	J
1	date	light rail	trolley	rtp	metro	suburbano	mexibus	mexicable	metrobus	
426	2021/05	1380.32	4173.66	7.73	62.69	2442785	5523689	360402	21008.83	
427	2021/06	1413.82	4456.61	8.24	63.41	2563421	5810086	340452	22154.52	
428	2021/07	1410.66	4841.11	8.53	69.82	2638193	6026416	299639	23177.76	
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	
441	2022/08	2171.34	6560.53	12.68	90.18	3815870	8610101	337368	35001.13	

Sheet1

Ready Accessibility: Unavailable

160%

Importing data



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

Date variable

Data Editor (Browse) - [Untitled]

File Edit View Data Tools

date[1] 1986/01

	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	.

Variables

Filter variables here

Name	Label	Type	Format	Value Labels
<input checked="" type="checkbox"/> date	date	str7	%9s	
<input checked="" type="checkbox"/> lightrail	Light Rail passengers (t...	double	%10.0g	
<input checked="" type="checkbox"/> trolley	Trolleybus passengers (t...	double	%10.0g	
<input checked="" type="checkbox"/> rtp	RTP passengers (millions)	double	%10.0g	
<input checked="" type="checkbox"/> metro	Metro passengers (milli...	double	%10.0g	
<input checked="" type="checkbox"/> suburbano	Suburbano passengers	long	%10.0g	
<input checked="" type="checkbox"/> mexibus	Mexibus passengers	long	%10.0g	
<input checked="" type="checkbox"/> mexicable	Mexicable passengers	long	%10.0g	
<input checked="" type="checkbox"/> metrobuc	Metrobuc passengers (t...	double	%10.0g	

Variables Snapshots

Properties

Variables

Name	date
Label	date
Type	str7
Format	%9s
Value label	
Notes	

Data

Frame	default
Filename	
Label	
Notes	
Variables	9
Observations	443

Ready Length: 7 Vars: 9 Order: Dataset Obs: 443 Filter: Off Mode: Browse CAP NUM

Date variable format

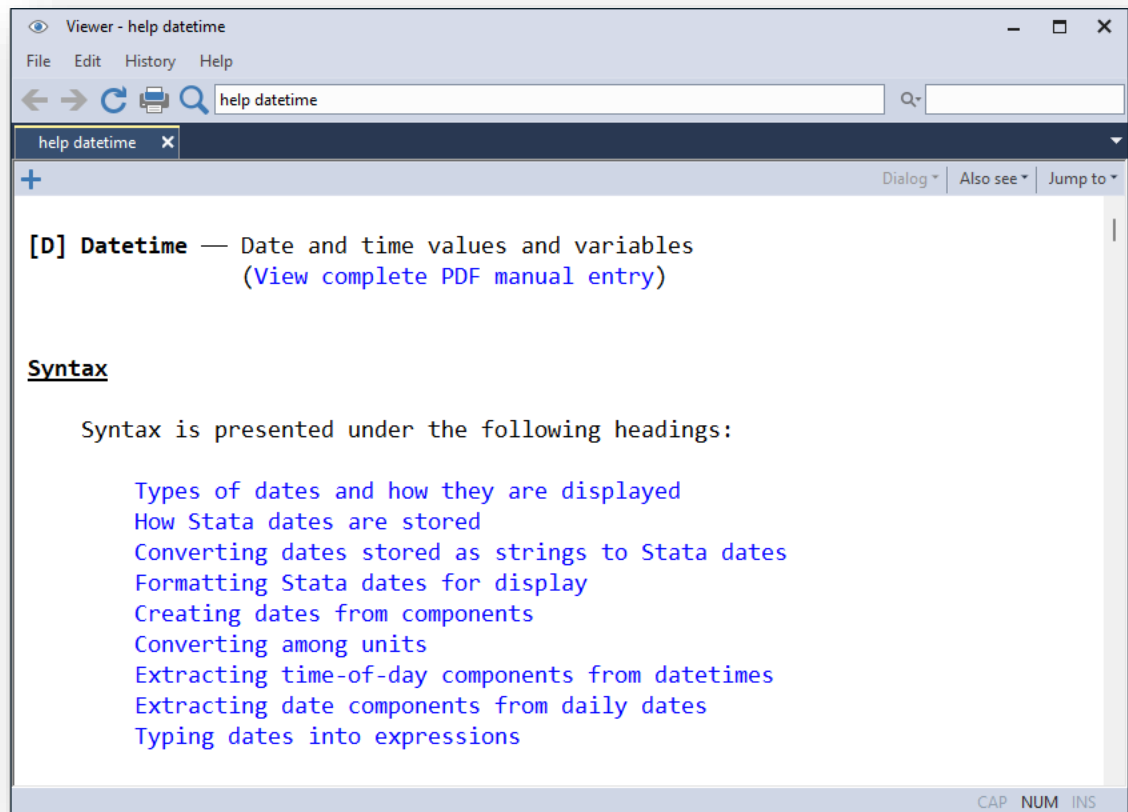
	date	t
1	1986/01	312
2	1986/02	313
3	1986/03	314
4	1986/04	315
5	1986/05	316
6	1986/06	317
7	1986/07	318
8	1986/08	319
9	1986/09	320
10	1986/10	321



	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



```
. help datetime
```

Declaring time-series data

```
. tsset t
```

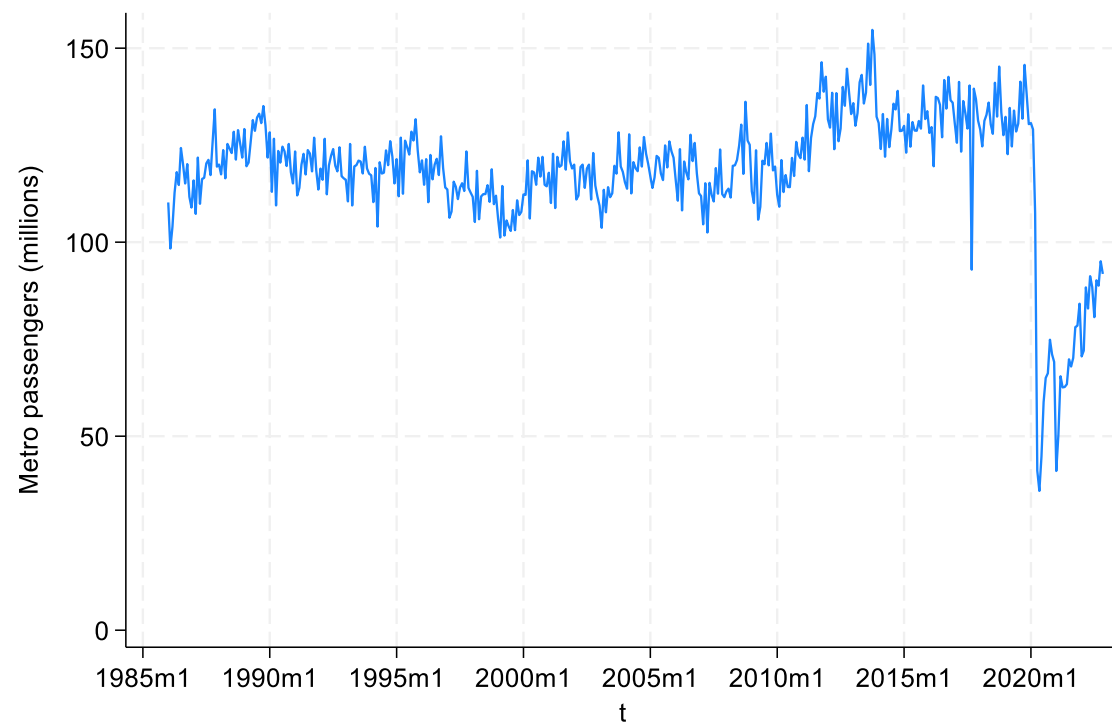
```
Time variable: t, 1986m1 to 2022m11
```

```
Delta: 1 month
```


Metro

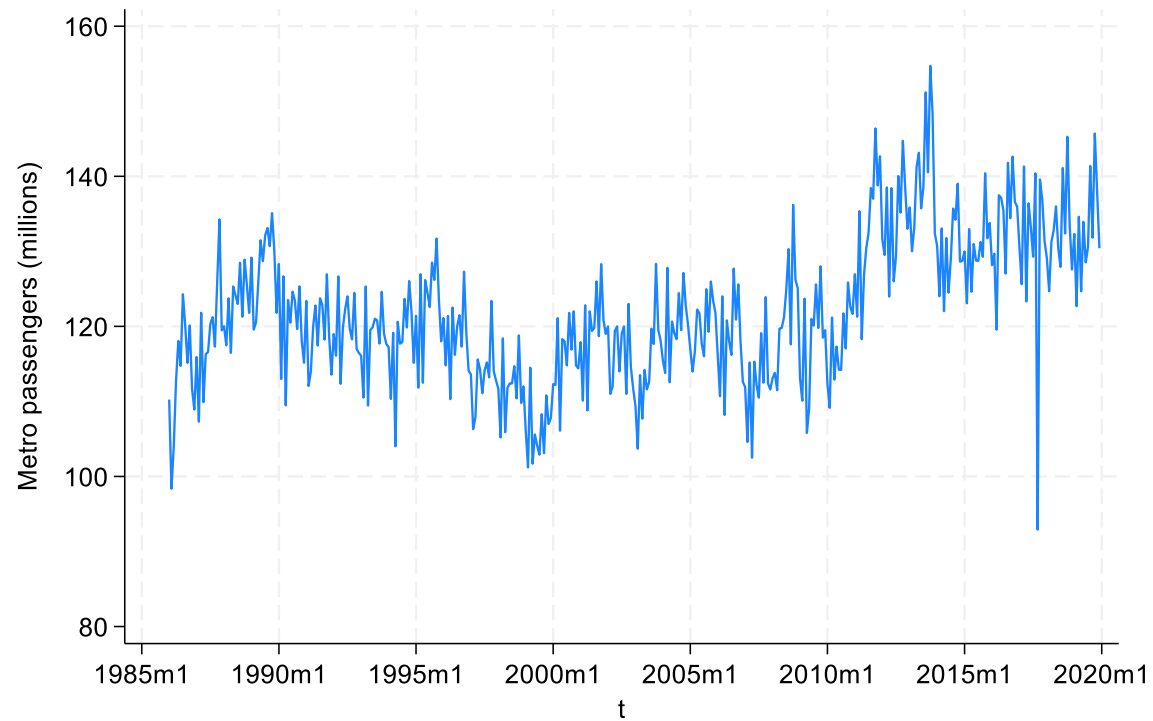


Metro: Time-series line plot



```
. tsline metro
```

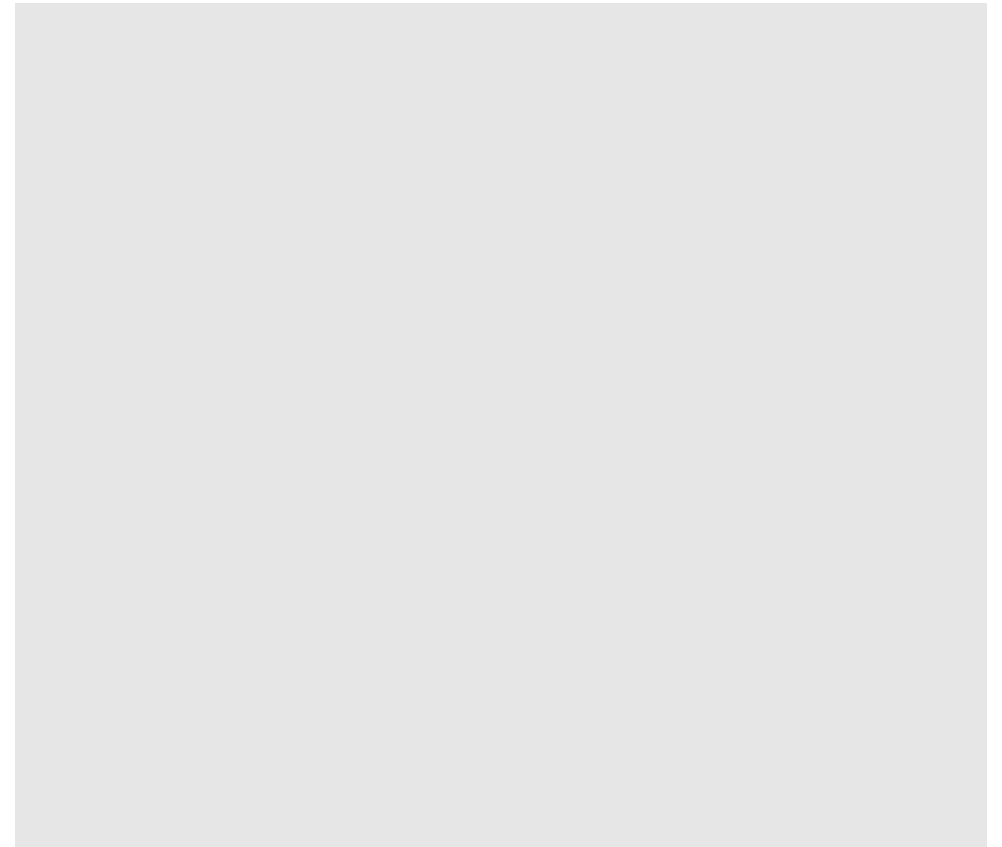
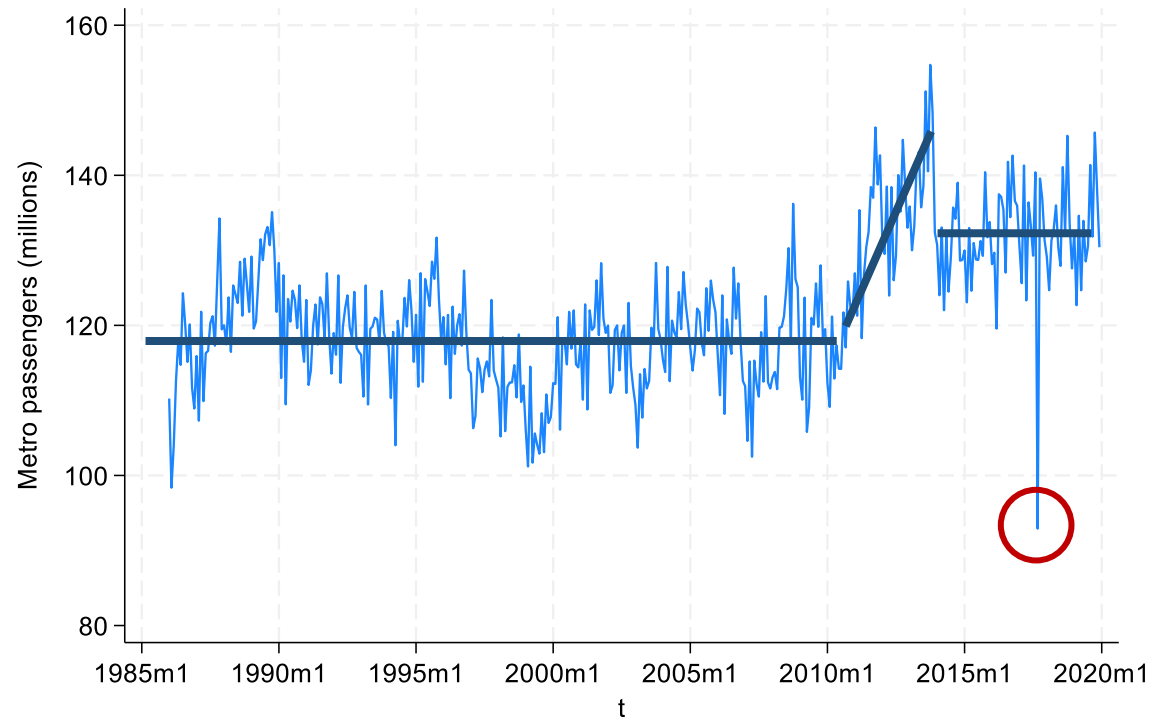

Metro: Removing the pandemic



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

```
. tsline metro
```

Metro: First impression



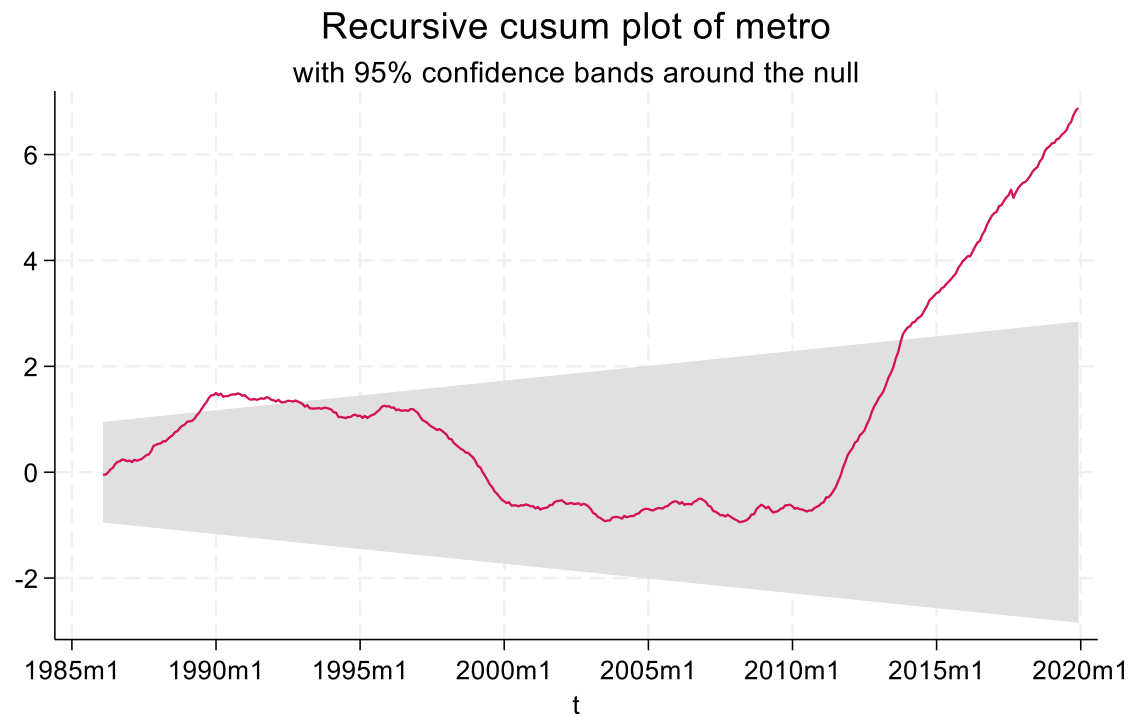
Metro: Parameter stability

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

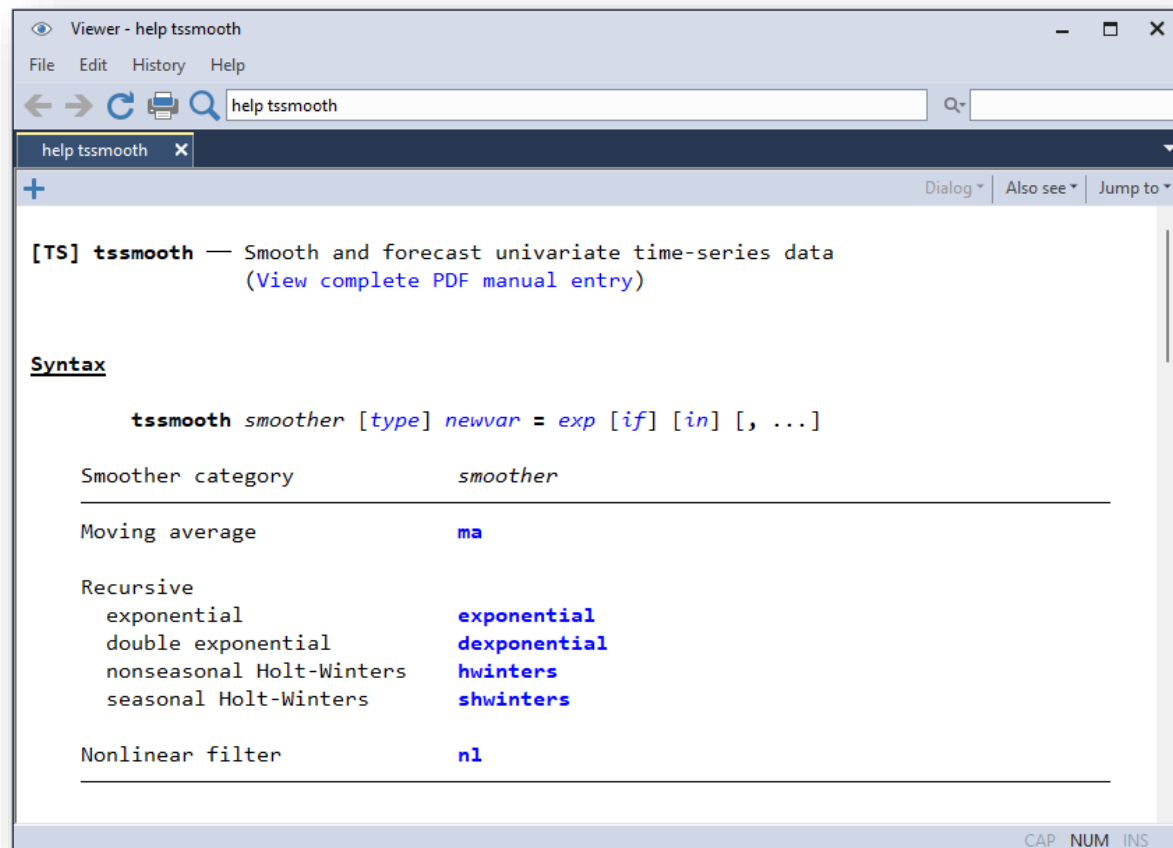
```
. regress metro
```

Metro: Parameter stability



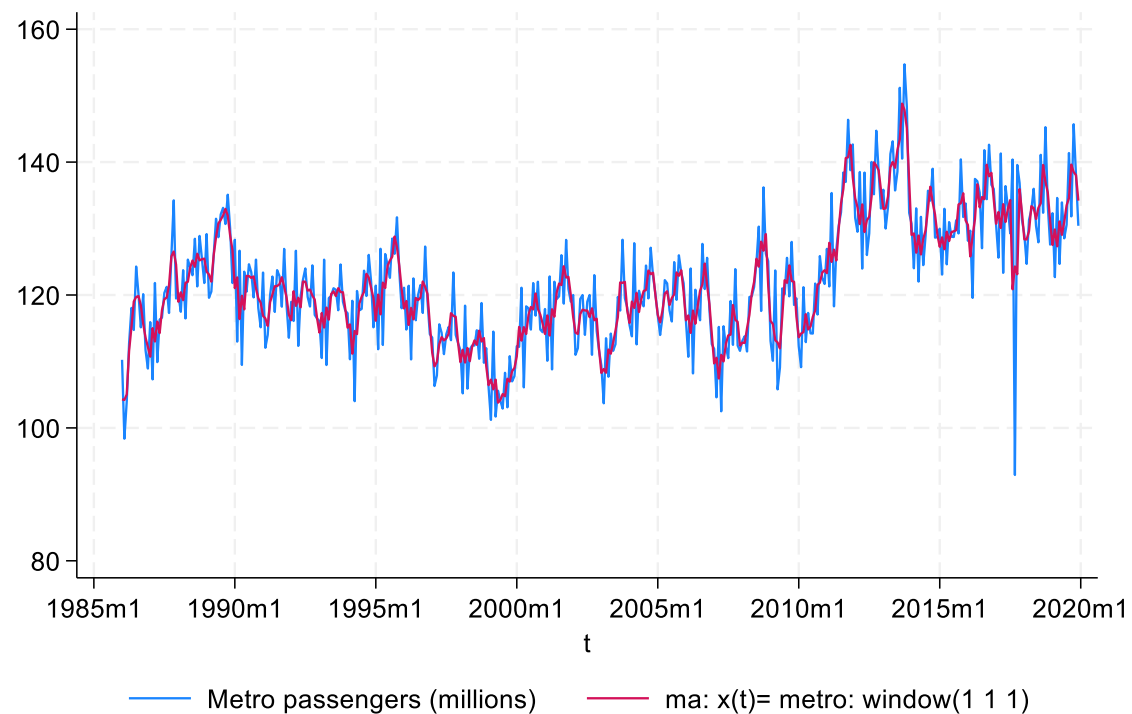
```
. estat sbcusum
```

Smoothers in Stata



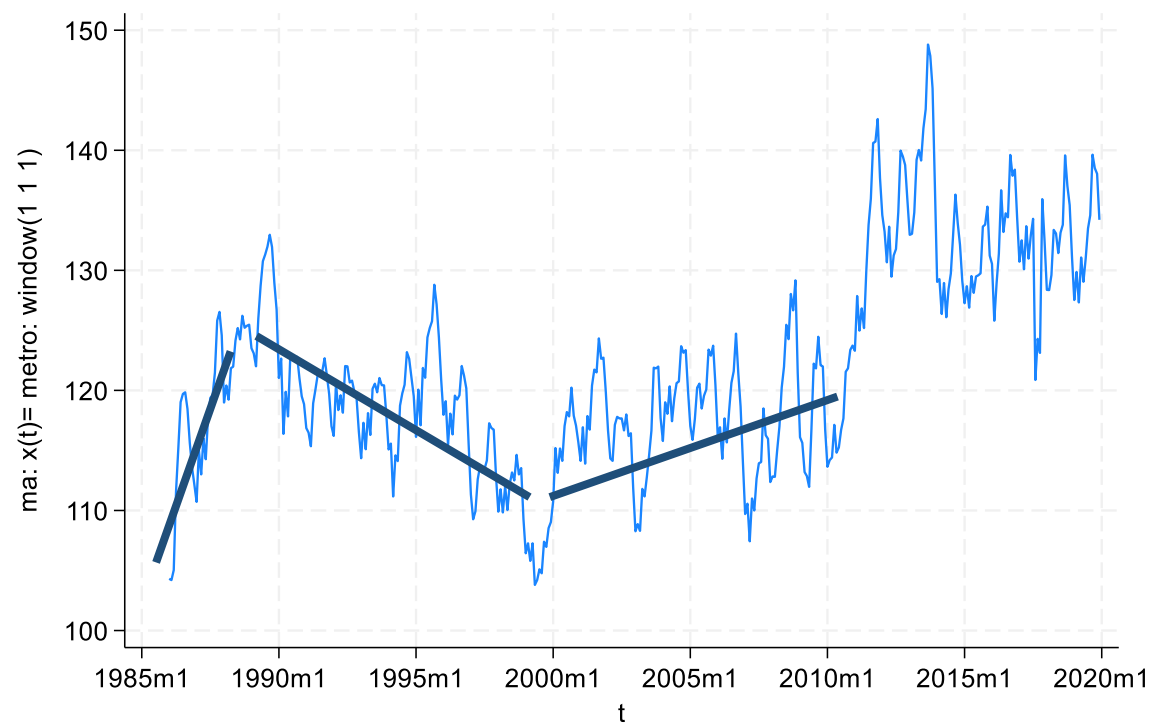
```
. help tssmooth
```

Metro: Moving average (1 1 1) smoother



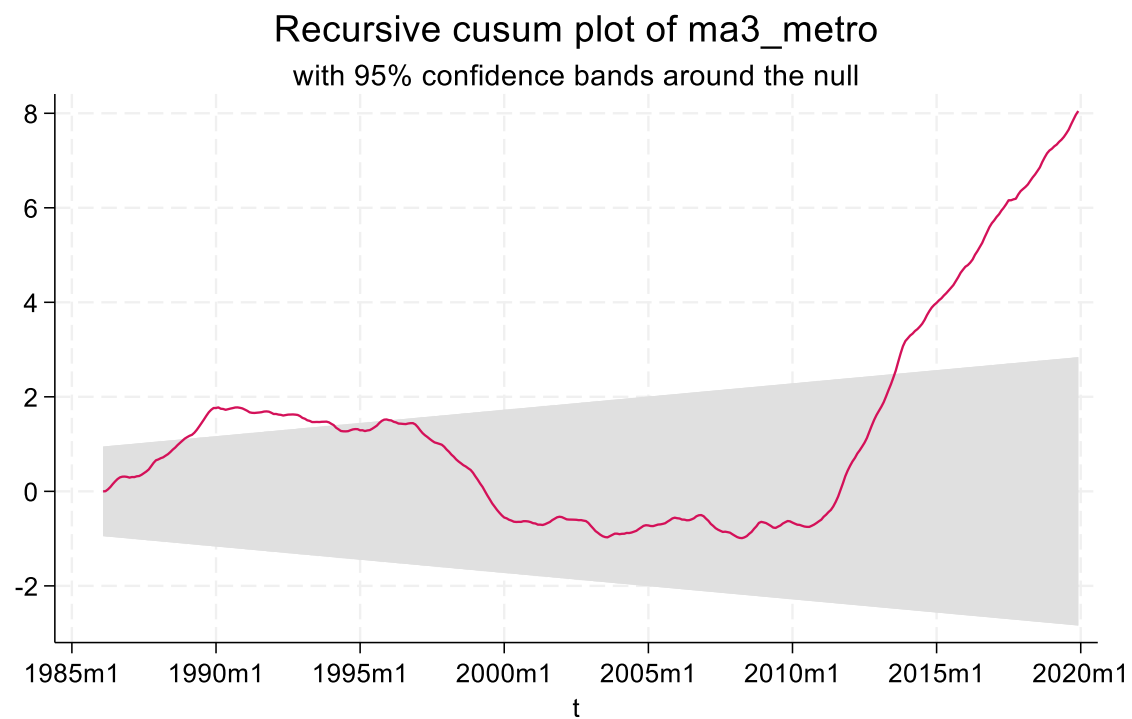
```
. tssmooth ma ma3_metro = metro,  
    window(1 1 1)  
  
. tsline metro ma3_metro
```

Metro: Moving average (1 1 1) smoother



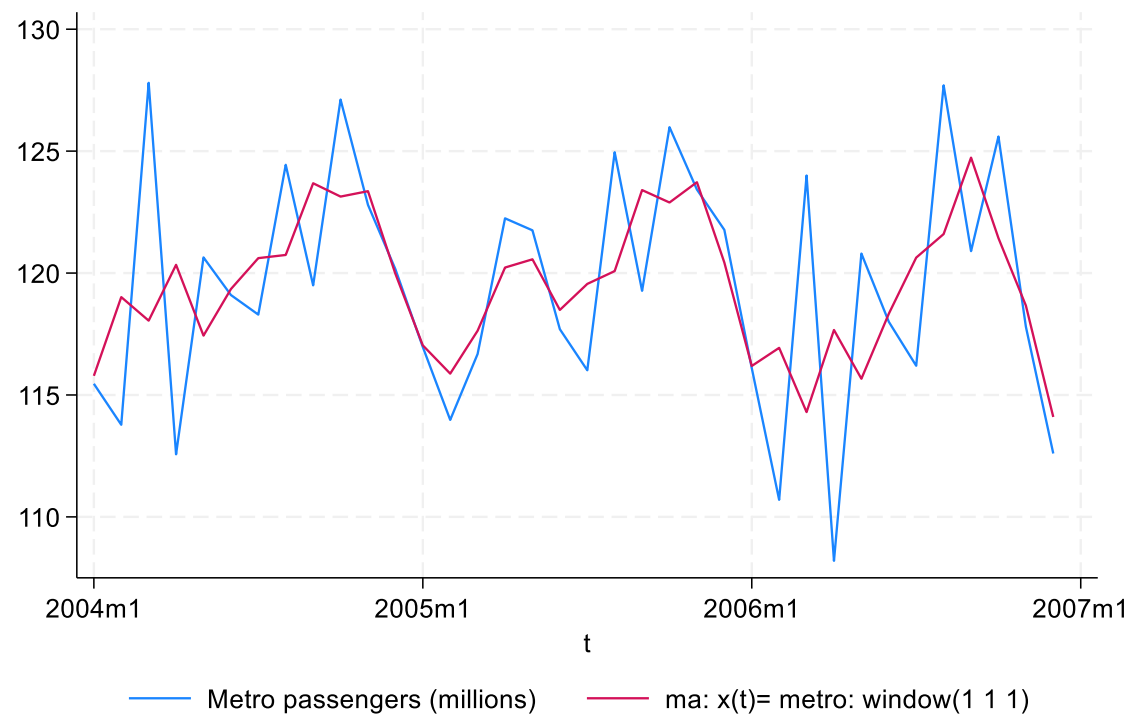
```
. tsline ma3_metro
```

Metro: Moving average (1 1 1) smoother



```
. regress ma3_metro  
  
. estat sbcusum
```


Metro: Seasonality



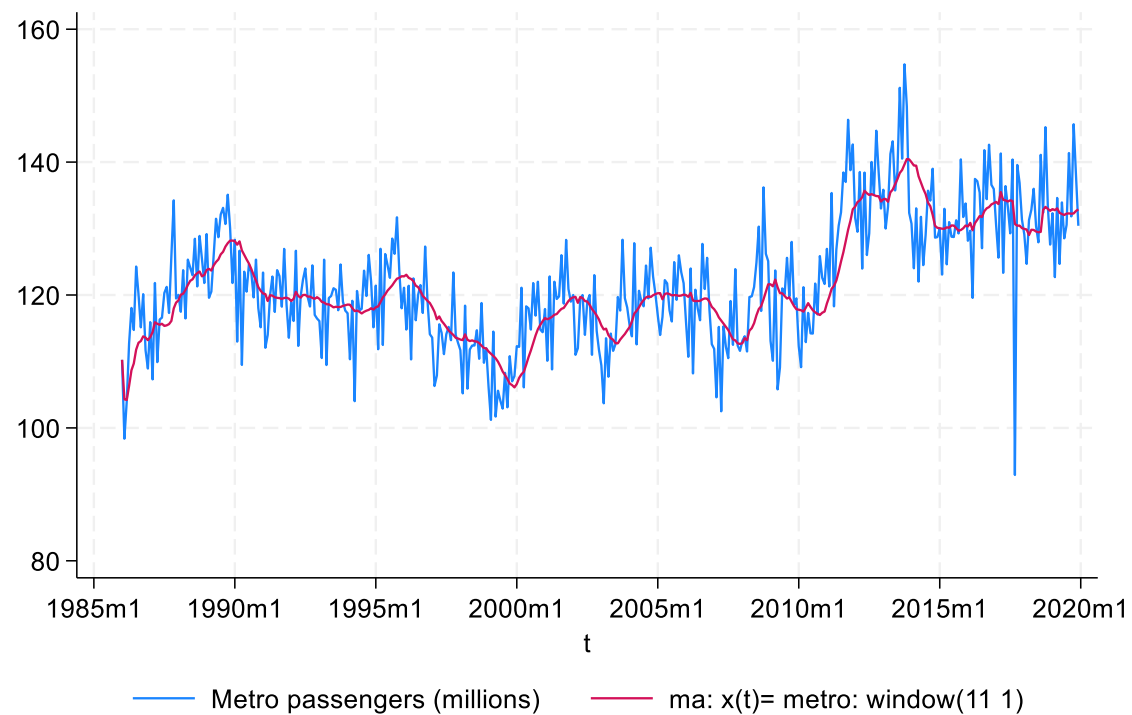
```
. tsline metro ma3_metro if tin(2004m1,  
2006m12)
```

Metro: Moving average (11 1) smoother



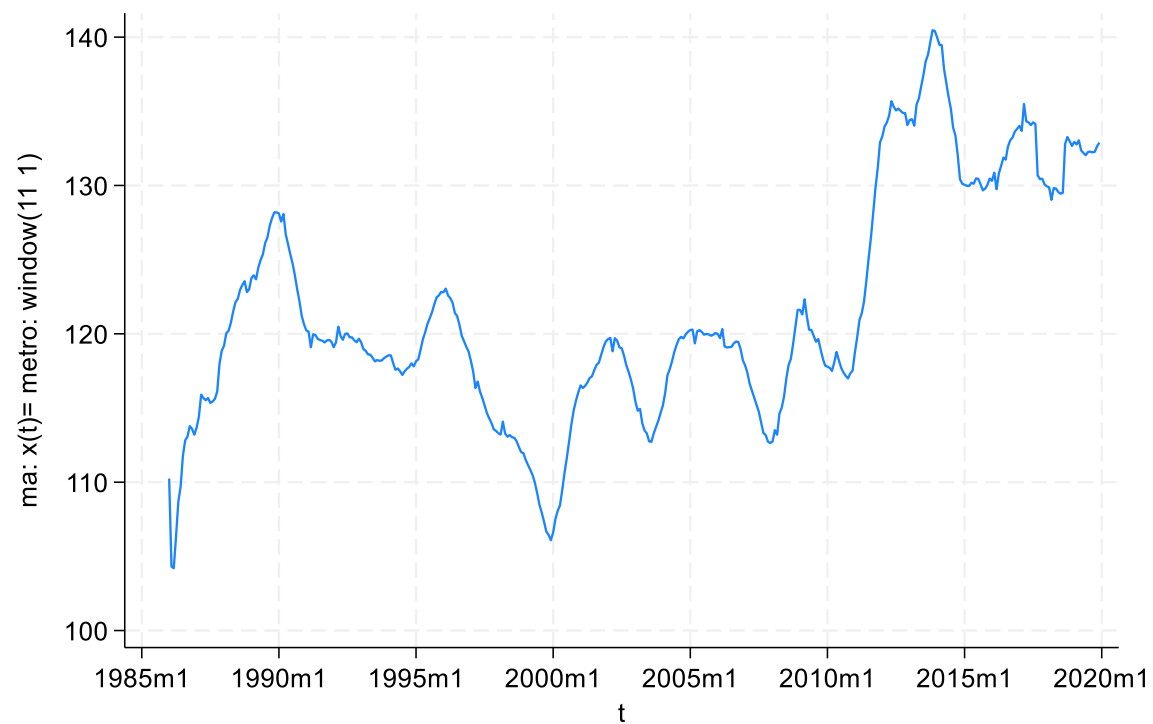
```
. tssmooth ma ma12_metro = metro,  
    window(11 1)  
  
. tsline metro ma12_metro if  
    tin(2004m1, 2006m12)
```

Metro: Moving average (11 1) smoother



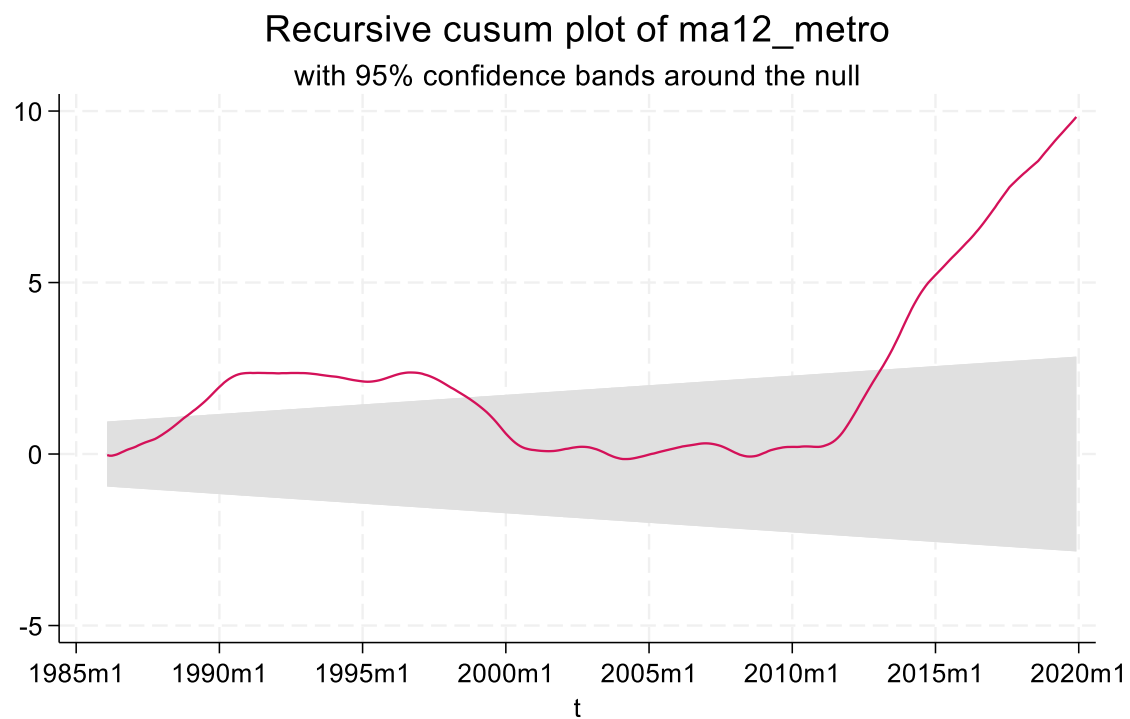
```
. tsline metro ma12_metro
```

Metro: Moving average (11 1) smoother



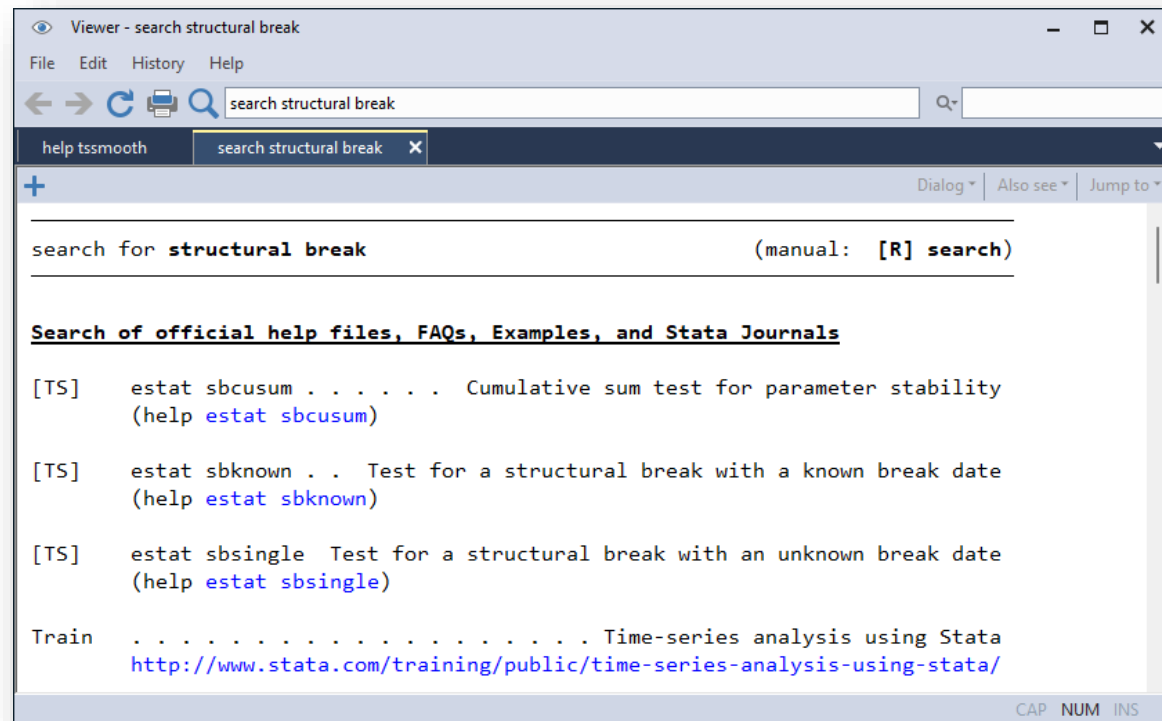
```
. tsline ma12_metro
```

Metro: Moving average (11 1) smoother



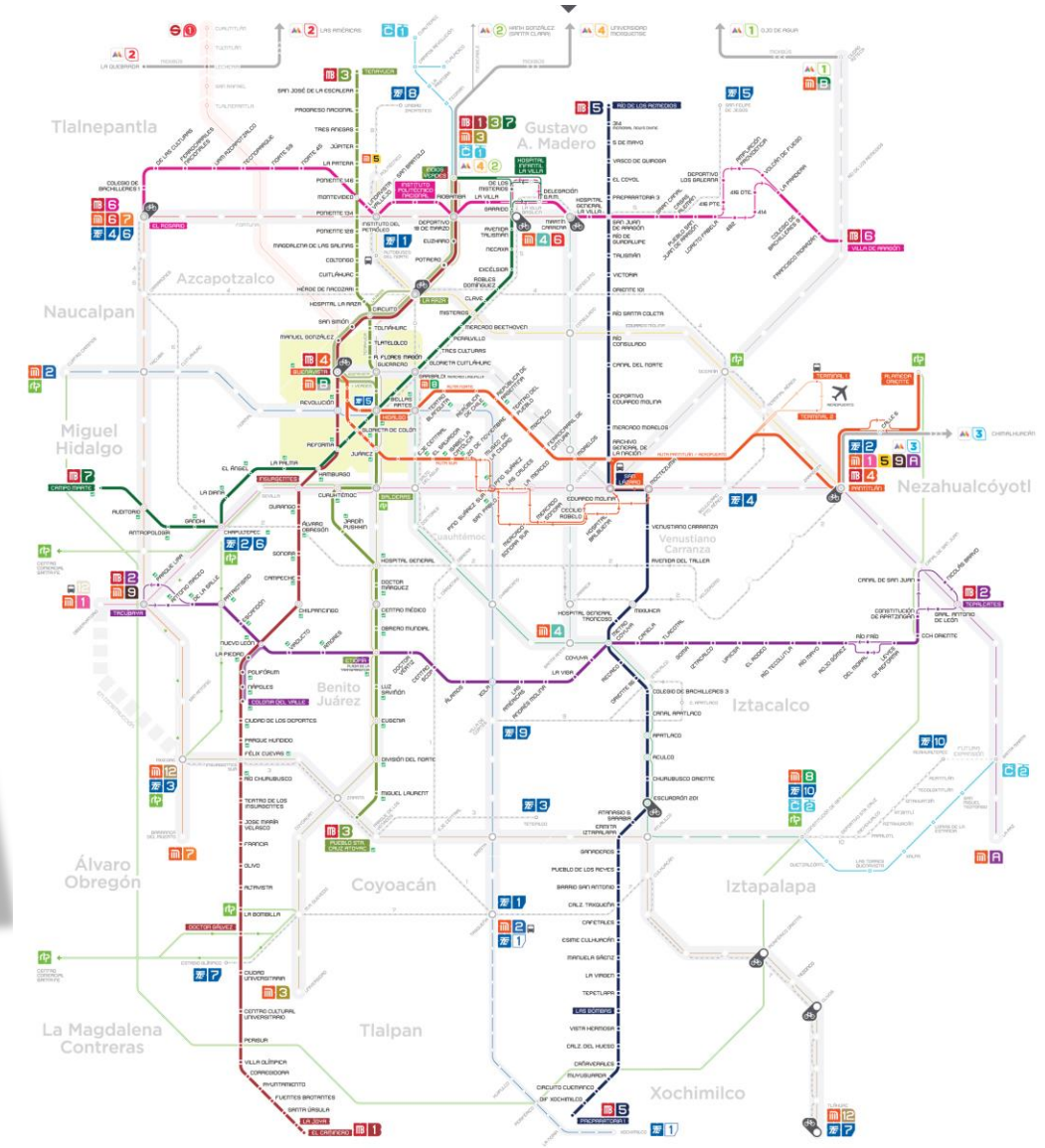
```
. regress ma12_metro  
  
. estat sbcusum
```

Other structural break tests

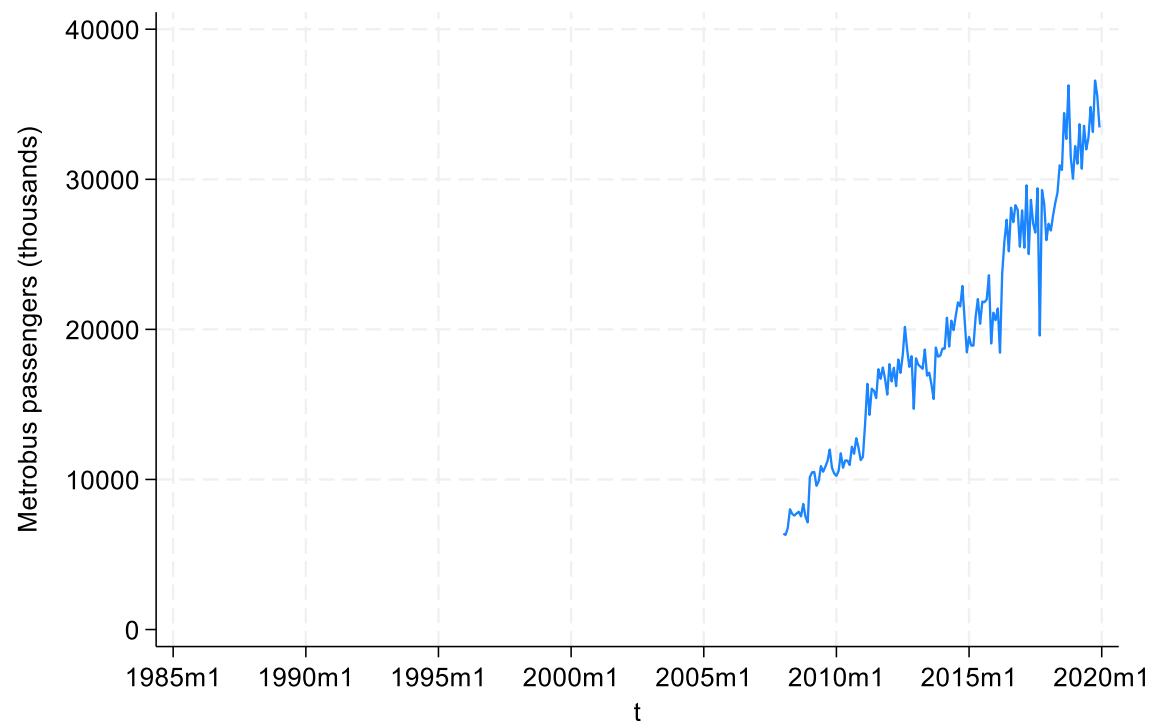


```
. search structural break
```

Metrobus

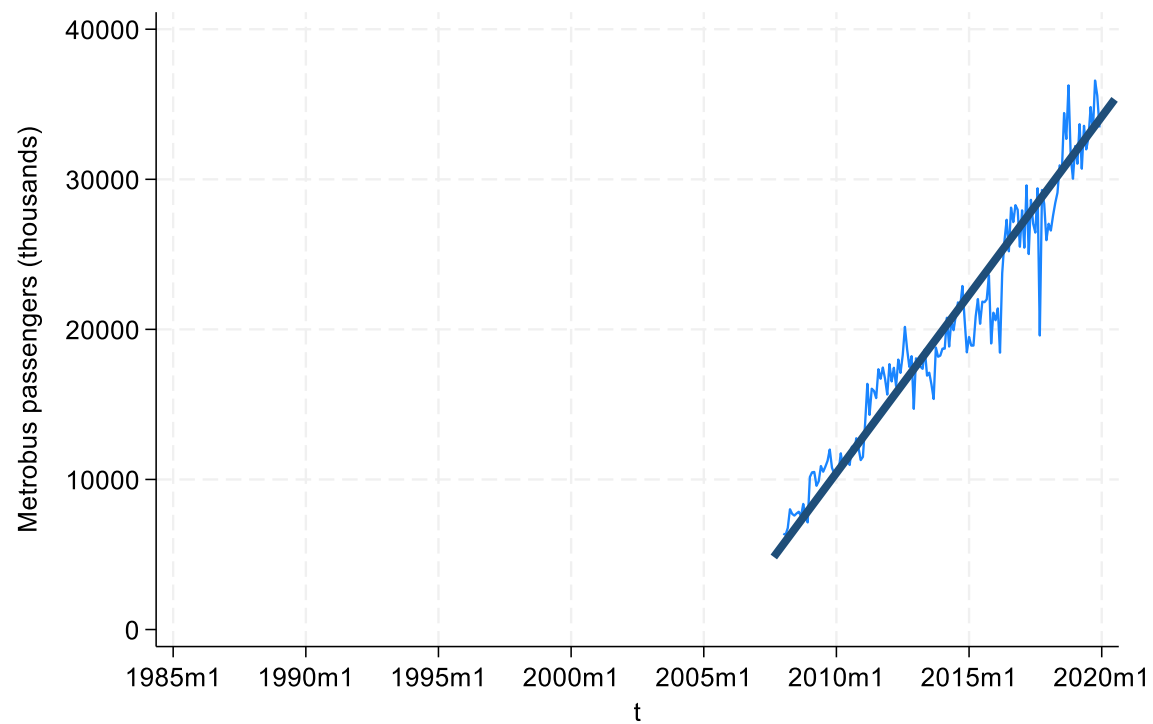


Metrobus: Time series line plot

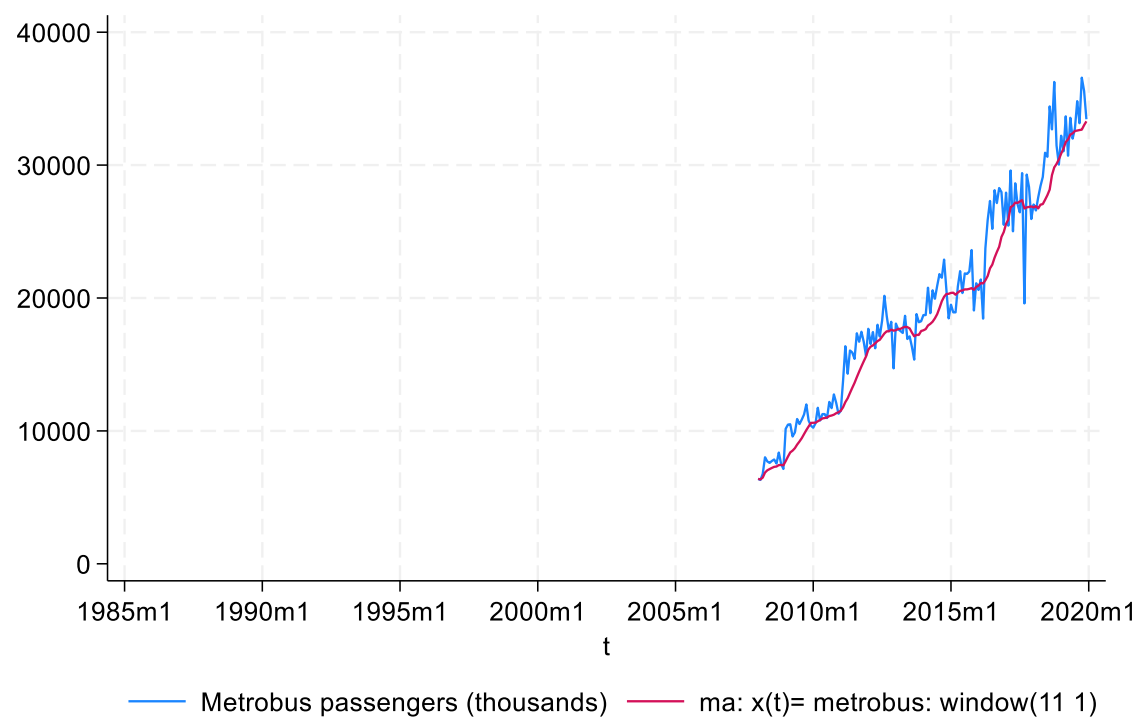


```
. tsline metrobus
```


Metrobus: Time series line plot

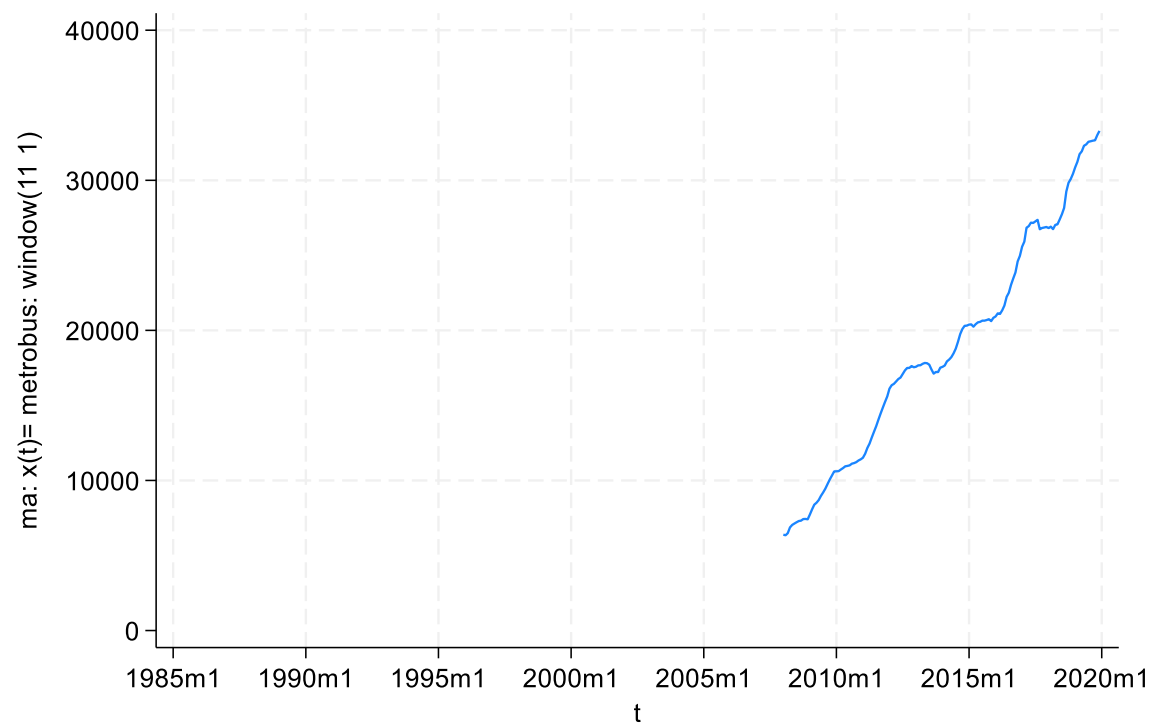


Metrobus: ma window(11 1) smoother



```
. 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

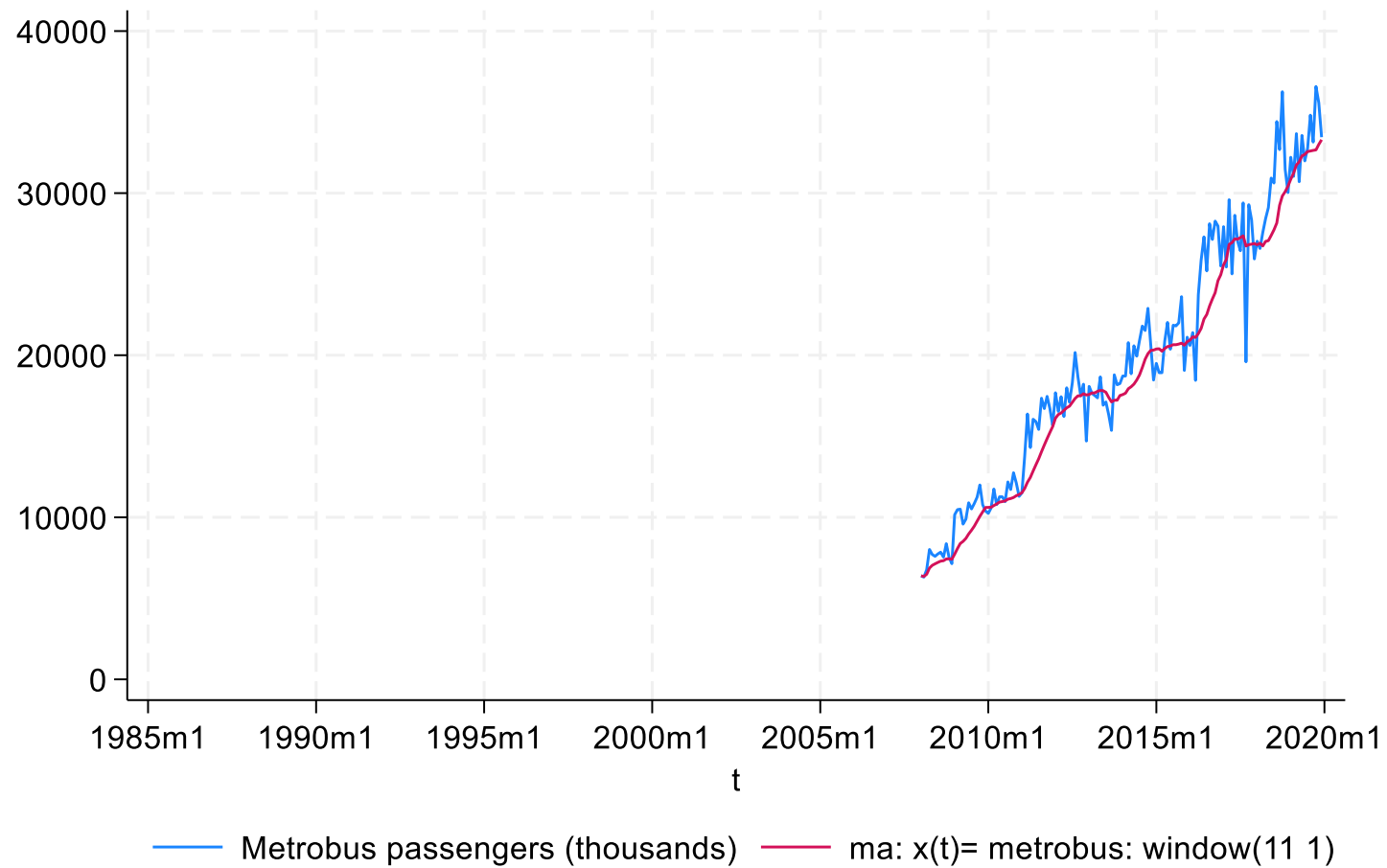
H0: Random walk without drift, d = 0

Test statistic	Dickey-Fuller critical value			
	1%	5%	10%	
Z(t)	-1.576	-3.496	-2.887	-2.577

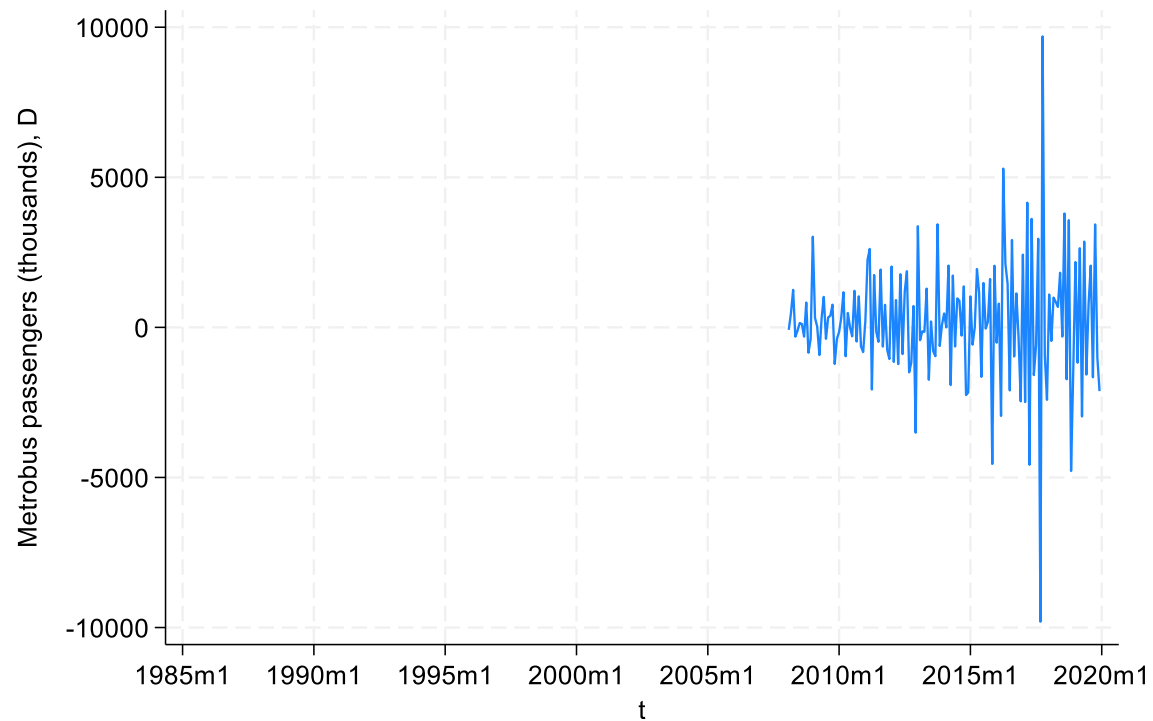
MacKinnon approximate *p*-value for Z(t) = 0.4956.

```
. 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

Test statistic	Dickey-Fuller critical value		
	1%	5%	10%
Z(t)	-7.560	-4.026	-3.444

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

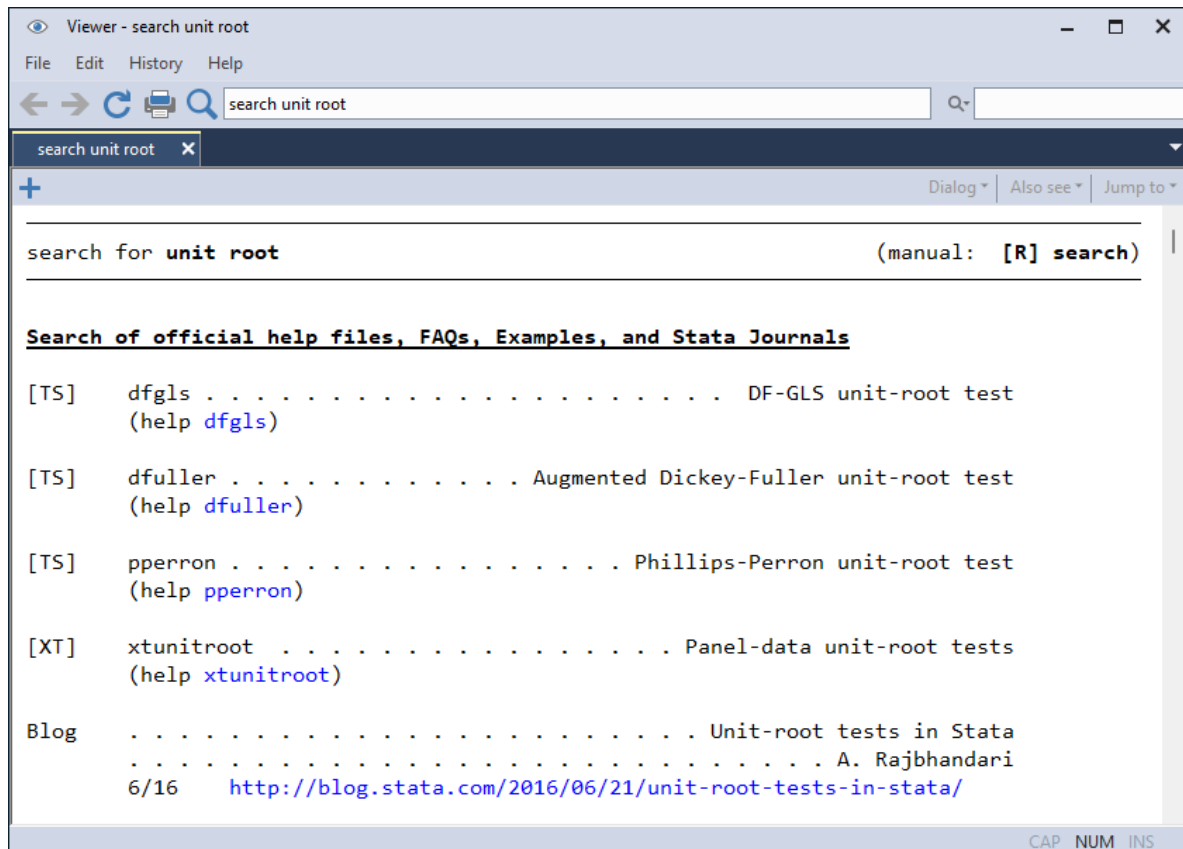
H0: Random walk without drift, $d = 0$

Test statistic	Dickey-Fuller critical value			
	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



The screenshot shows the Stata Viewer window titled "Viewer - search unit root". The search bar contains "search unit root". Below the search bar, there is a tab labeled "search unit root". The main content area displays the search results for "unit root". The results are organized into sections: "Search of official help files, FAQs, Examples, and Stata Journals". The results list several unit-root tests:

- [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](#))

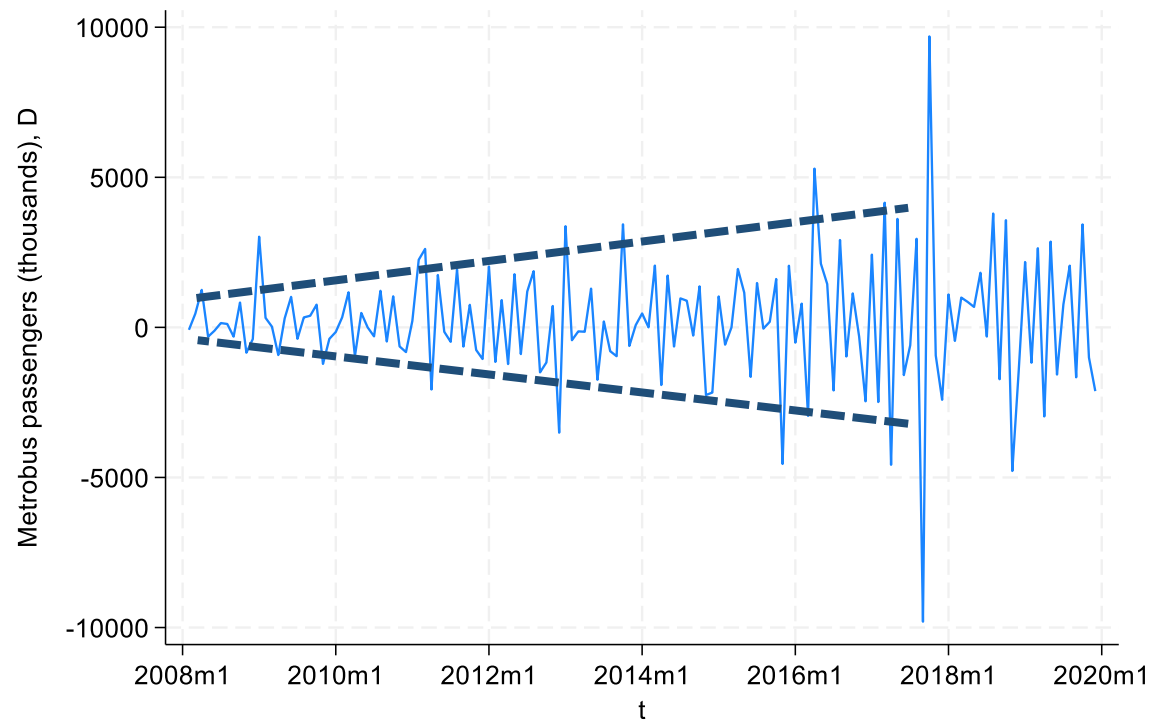
Below the search results, there is a "Blog" section with the following entry:

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

The bottom status bar shows "CAP NUM INS".

```
. search unit root
```

Metrobus: Constant variance?

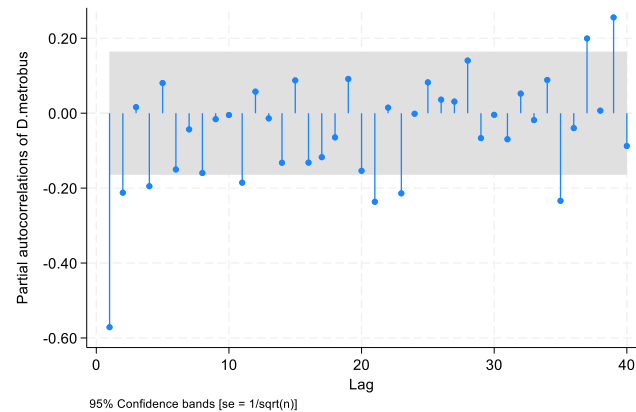
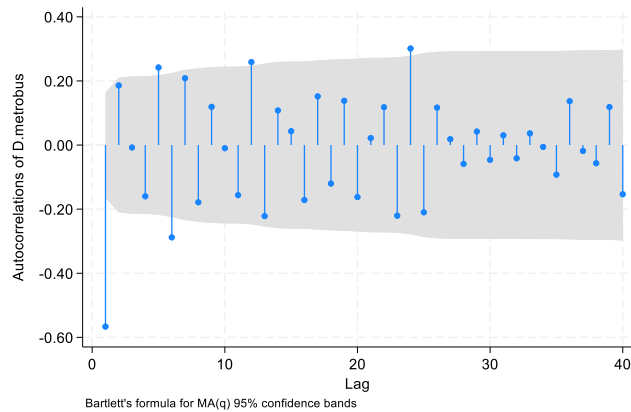


```
. tsline D.metrobus if tin(2008m1,  
2019m12)
```

Metrobus: ARIMA

$$\begin{aligned} d.metrobus_t = & \mu + \phi_1 d.metrobus_{t-1} + \cdots + \phi_p d.metrobus_{t-p} \\ & + \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} \end{aligned}$$

Autocorrelograms



- . ac D.metrobus
- . 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

D.metrobus	OPG		z	P> z	[95% conf. interval]	
	Coefficient	std. err.				
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

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

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

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		OPG		z	P> z	[95% conf. interval]	
		Coefficient	std. err.				
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		z	P> z	[95% conf. interval]	
D.metrobus		Coefficient	std. err.				
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
Log likelihood = -1254.34 Wald chi2(1) = 55.66
 Prob > chi2 = 0.0000

		OPG		z	P> z	[95% conf. interval]	
D.metrobus		Coefficient	std. err.				
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

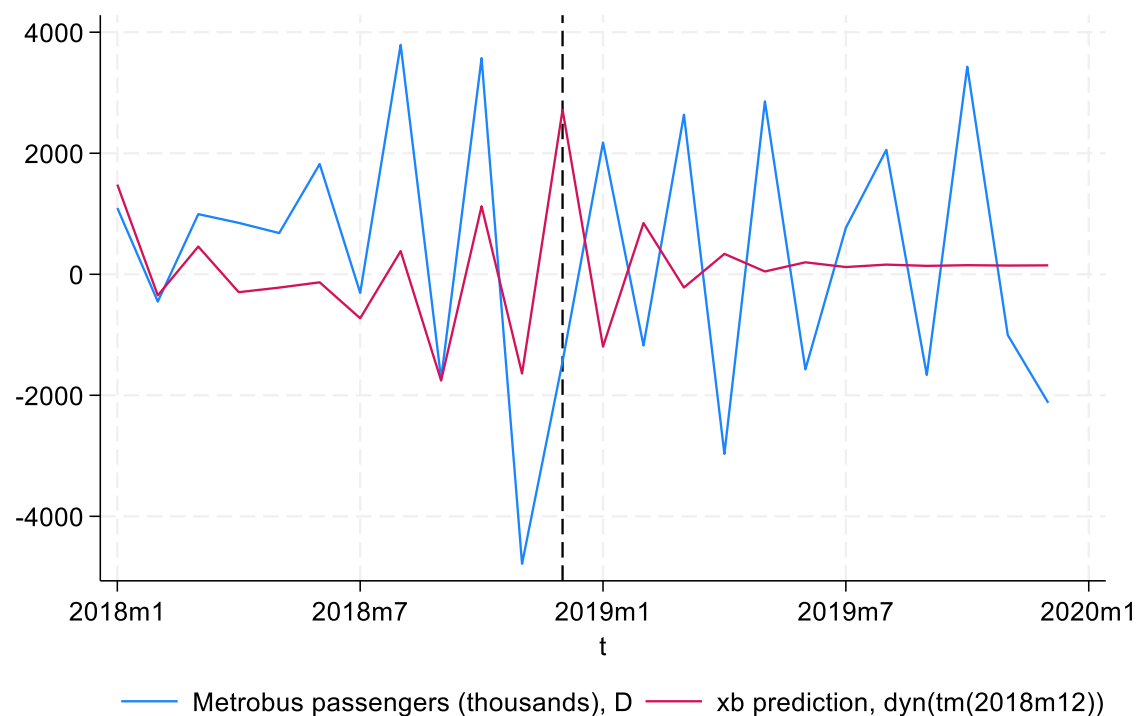
Akaike's information criterion and Bayesian information criterion

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
```

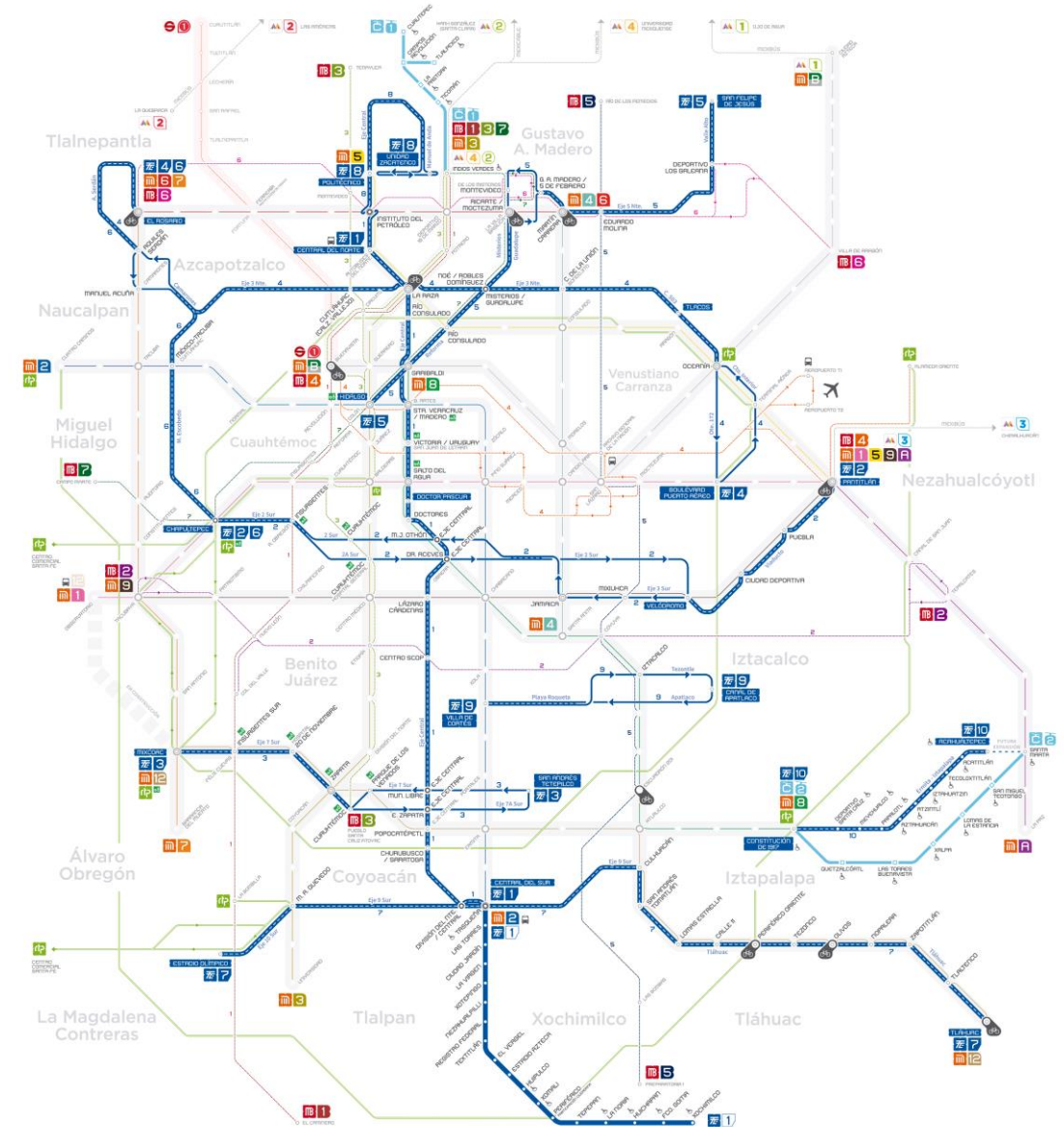
Metrobus: 2019 forecast



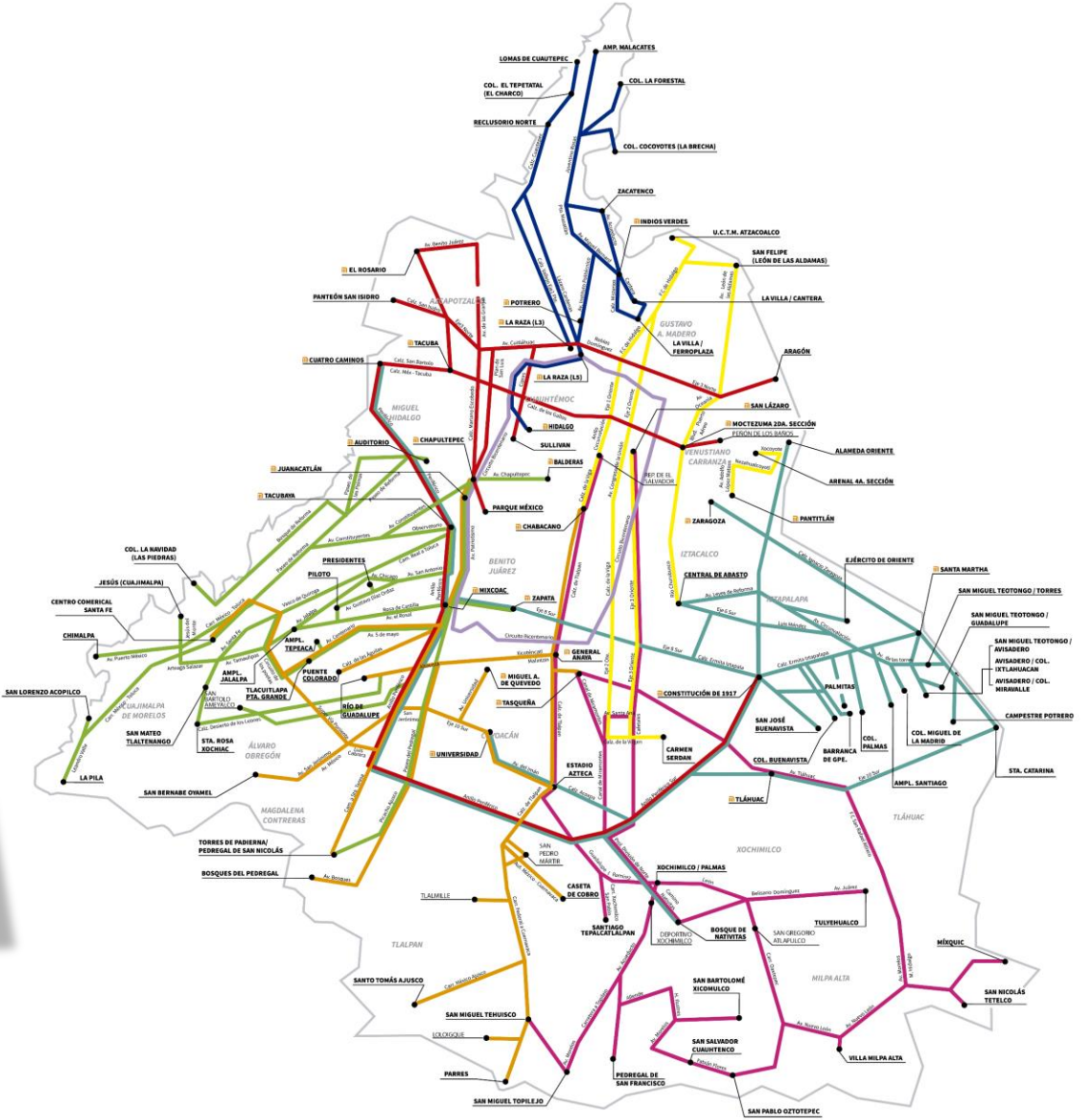
```
. arch D.metrobus if  
tin(2008m1, 2018m12), ar(1) arch(1)  
  
. predict fcst_arch1 in tin(2008m1,  
2019m12), dynamic(tm(2018m12))  
  
. tsline D.metrobus fcst_arch1  
if tin(2018m1, 2019m12),  
tline(2018m12)
```

Part II. Multivariate time-series analysis

Trolley bus



RTP



The dataset

Data Editor (Browse) - [ptransport]

File Edit View Data Tools

var10[2]

	date	d_rtp	d_trolley	d_metrob...	d_metro
1	05jan2015	-.0171005	-.000195	-.0013514	-.0363334
2	06jan2015	-.0234868	-.02486	.15454	.3625203
3	07jan2015	-.0573256	-.1347515	-.1284905	.9931831
4	08jan2015	.1846544	.1073546	.0101083	-.3816748
5	09jan2015	.1332417	-.0303602	.0055859	.2086876
6	12jan2015	.0599145	.0428238	-.1342604	.7170889
7	13jan2015	.114902	.1268956	.1558118	-.1072412
8	14jan2015	.0696713	.0355576	.0401537	-.5000088
9	15jan2015	-.1307284	-.0612663	-.1287204	.3434627
10	16jan2015	-.0486425	-.0000602	-.1231952	-.4428777
11	19jan2015	.0010848	-.0909132	-.0246318	-.1547228
12	20jan2015	-.105676	-.0431311	-.0981248	.2385716
13	21jan2015	-.0326804	-.0105127	-.1483197	.2185136
14	22jan2015	.0236691	.0028431	-.0146791	.2391467

Variables

Filter variables here

<input checked="" type="checkbox"/>	Name	Label	Type	Format	Value
<input checked="" type="checkbox"/>	date		float	%td	
<input checked="" type="checkbox"/>	d_rtp	RTP passengers daily ch...	float	%9.0g	
<input checked="" type="checkbox"/>	d_trolley	Trolley passengers daily ...	float	%9.0g	
<input checked="" type="checkbox"/>	d_metrobus	Metrobus passengers d...	float	%9.0g	
<input checked="" type="checkbox"/>	d_metro	Metro passengers daily ...	float	%9.0g	
<input checked="" type="checkbox"/>	closed_mtro	# of unavailable metro s...	float	%9.0g	
<input checked="" type="checkbox"/>	closed_mbus	# of unavailable metrob...	float	%9.0g	
<input checked="" type="checkbox"/>	protest	Protest on main road	float	%9.0g	

Variables Snapshots

Properties

Variables

Name	Label
Type	
Format	
Value label	
Notes	

Data

Frame	default

Ready Vars: 8 Order: Dataset Obs: 1,302 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

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.

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

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_rtp	d_trolley	d_metrob...	d_metro	bcaldate
1	05jan2015	-.0171005	-.000195	-.0013514	-.0363334	0
2	06jan2015	-.0234868	-.02486	.15454	.3625203	1
3	07jan2015	-.0573256	-.1347515	-.1284905	.993183	2
4	08jan2015	.1846544	.1073546	.0101083	-.3816748	3
5	09jan2015	.1332417	-.0303602	.0055859	.2086876	4
6	12jan2015	.0599145	.0428238	-.1342604	.7170889	5
7	13jan2015	.114902	.1268956	.1558118	-.1072412	6
8	14jan2015	.0696713	.0355576	.0401537	-.5000088	7
9	15jan2015	-.1307284	-.0612663	-.1287204	.3434627	8
10	16jan2015	-.0486425	-.0000602	-.1231952	-.4428777	9
11	19jan2015	.0010848	-.0909132	-.0246318	-.1547228	10
12	20jan2015	-.105676	-.0431311	-.0981248	.2385716	11
13	21jan2015	-.0326804	-.0105127	-.1483197	.2185136	12
14	22jan2015	.0236691	.0028431	-.0146791	.2391467	13

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

Step 4: Format business calendar variable

	date	d_rtp	d_trolley	d_metrob...	d_metro	bcaldate
1	05jan2015	-.0171005	-.000195	-.0013514	-.036333	05jan2015
2	06jan2015	-.0234868	-.02486	.15454	.362520	06jan2015
3	07jan2015	-.0573256	-.1347515	-.1284905	.993183	07jan2015
4	08jan2015	.1846544	.1073546	.0101083	-.381674	08jan2015
5	09jan2015	.1332417	-.0303602	.0055859	.208687	09jan2015
6	12jan2015	.0599145	.0428238	-.1342604	.717088	12jan2015
7	13jan2015	.114902	.1268956	.1558118	-.107241	13jan2015
8	14jan2015	.0696713	.0355576	.0401537	-.500008	14jan2015
9	15jan2015	-.1307284	-.0612663	-.1287204	.343462	15jan2015
10	16jan2015	-.0486425	-.0000602	-.1231952	-.442877	16jan2015
11	19jan2015	.0010848	-.0909132	-.0246318	-.154722	19jan2015
12	20jan2015	-.105676	-.0431311	-.0981248	.238571	20jan2015
13	21jan2015	-.0326804	-.0105127	-.1483197	.218513	21jan2015
14	22jan2015	.0236691	.0028431	-.0146791	.239146	22jan2015

```
. format %tbmycal bcaldate
```


Business calendar variable

```
. tsset bcaldate
```

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

```
. tsset bcaldate
```

Vector autoregression intuition

$$\begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} metro_t \\ metrobus_t \\ trolley_t \\ rtp_t \end{bmatrix}}_1 + \underbrace{\begin{bmatrix} a_{11}^1 & a_{12}^1 & a_{13}^1 & a_{14}^1 \\ a_{21}^1 & a_{22}^1 & a_{23}^1 & a_{24}^1 \\ a_{31}^1 & a_{32}^1 & a_{33}^1 & a_{34}^1 \\ a_{41}^1 & a_{42}^1 & a_{43}^1 & a_{44}^1 \end{bmatrix} \begin{bmatrix} metro_{t-1} \\ metrobus_{t-1} \\ trolley_{t-1} \\ rtp_{t-1} \end{bmatrix}}_2 + \dots + \underbrace{\begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}}_3$$

VAR intuition: Contemporaneous effects

$$\begin{bmatrix} \text{metro}_t \\ \text{metrobus}_t \\ \text{trolley}_t \\ \text{rtp}_t \end{bmatrix} = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ a_{21} & 0 & a_{23} & a_{24} \\ a_{31} & a_{32} & 0 & a_{34} \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix} \begin{bmatrix} \text{metro}_t \\ \text{metrobus}_t \\ \text{trolley}_t \\ \text{rtp}_t \end{bmatrix} + \begin{bmatrix} a_{11}^1 & a_{12}^1 & a_{13}^1 & a_{14}^1 \\ a_{21}^1 & a_{22}^1 & a_{23}^1 & a_{24}^1 \\ a_{31}^1 & a_{32}^1 & a_{33}^1 & a_{34}^1 \\ a_{41}^1 & a_{42}^1 & a_{43}^1 & a_{44}^1 \end{bmatrix} \begin{bmatrix} \text{metro}_{t-1} \\ \text{metrobus}_{t-1} \\ \text{trolley}_{t-1} \\ \text{rtp}_{t-1} \end{bmatrix} + \dots + \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{bmatrix}$$

VAR intuition: Contemporaneous effects

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

VAR intuition: Contemporaneous effects

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

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

VAR intuition: Lagged effects

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

VAR intuition: Lagged effects

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

- 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

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

VAR intuition: Innovations

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

VAR theory review: Setup

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

VAR theory review: Structural to reduced form

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

!!!
!!!

VAR theory review: Structural to reduced form

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



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

VAR theory review: Structural to reduced form

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

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



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

A y_t A_1 y_{t-1} B ϵ_t

VAR theory review: Structural to reduced form

$$Ay_t = A_1y_{t-1} + \dots + A_py_{t-p} + B\epsilon_t$$

VAR theory review: Structural to reduced form

$$Ay_t = A_1y_{t-1} + \dots + A_py_{t-p} + B\epsilon_t$$

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

VAR theory review: Structural to reduced form

$$Ay_t = A_1y_{t-1} + \dots + A_py_{t-p} + B\epsilon_t$$

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

$$y_t = \Phi_1y_{t-1} + \dots + \Phi_py_{t-p} + u_t$$

VAR: Lag order

Lag-order selection criteria

Sample: 09jan2015 thru 31dec2019

Number of obs = 1,298

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4631.85				9.4e-09	-7.13075	-7.12477	-7.11482
1	5477.65	1691.6	16	0.000	2.6e-09	-8.40932	-8.37944	-8.32968
2	5542.04	128.78*	16	0.000	2.4e-09*	-8.48388*	-8.43009*	-8.34053*
3	5546.37	8.6634	16	0.927	2.5e-09	-8.4659	-8.3882	-8.25884
4	5558.41	24.079	16	0.088	2.5e-09	-8.4598	-8.35819	-8.18902

* 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: 07jan2015 thru 31dec2019      Number of obs   =      1,300
Log likelihood =    5543.413           AIC              =   -8.472943
FPE           =    2.46e-09           HQIC            =   -8.419224
Det(Sigma_ml) =    2.32e-09           SBIC            =   -8.32977
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
d_metro	9	.351577	0.0226	30.0549	0.0002
d_metrobus	9	.088654	0.1608	249.1388	0.0000
d_trolley	9	.048777	0.5858	1838.351	0.0000
d_rtp	9	.044688	0.6664	2597.259	0.0000

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

VAR: Output

	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
d_metro						
d_metro						
L1.	.0963009	.0284151	3.39	0.001	.0406084	.1519935
L2.	.0585519	.0474892	1.23	0.218	-.0345252	.151629
d_metrobus						
L1.	-.0401478	.1256373	-0.32	0.749	-.2863924	.2060967
L2.	.1700553	.1237685	1.37	0.169	-.0725265	.4126371
d_trolley						
L1.	.2062568	.2582365	0.80	0.424	-.2998774	.712391
L2.	-.128315	.2390647	-0.54	0.591	-.5968732	.3402432
d_rtp						
L1.	.0382293	.2486141	0.15	0.878	-.4490453	.525504
L2.	.1260143	.2205073	0.57	0.568	-.3061721	.5582008
_cons	.0274022	.0101307	2.70	0.007	.0075463	.047258

VAR: Output

d_metrobus						
d_metro						
L1.	.0760821	.0071652	10.62	0.000	.0620386	.0901257
L2.	.0514549	.011975	4.30	0.000	.0279845	.0749254
d_metrobus						
L1.	.1994025	.0316809	6.29	0.000	.137309	.2614959
L2.	-.0160284	.0312097	-0.51	0.608	-.0771982	.0451414
d_trolley						
L1.	.033614	.0651174	0.52	0.606	-.0940136	.1612417
L2.	.1108322	.060283	1.84	0.066	-.0073202	.2289847
d_rtp						
L1.	-.1552757	.062691	-2.48	0.013	-.2781478	-.0324037
L2.	.0402314	.0556035	0.72	0.469	-.0687495	.1492123
_cons						
L1.	-.0100681	.0025546	-3.94	0.000	-.015075	-.0050612

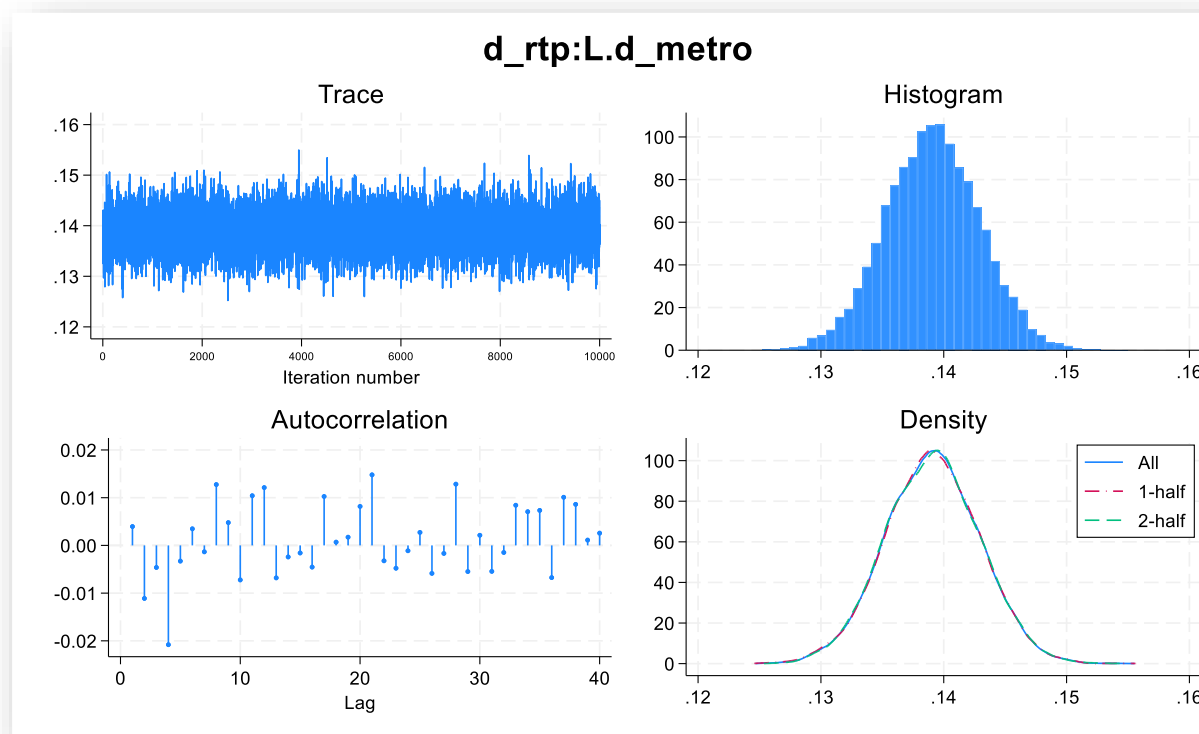
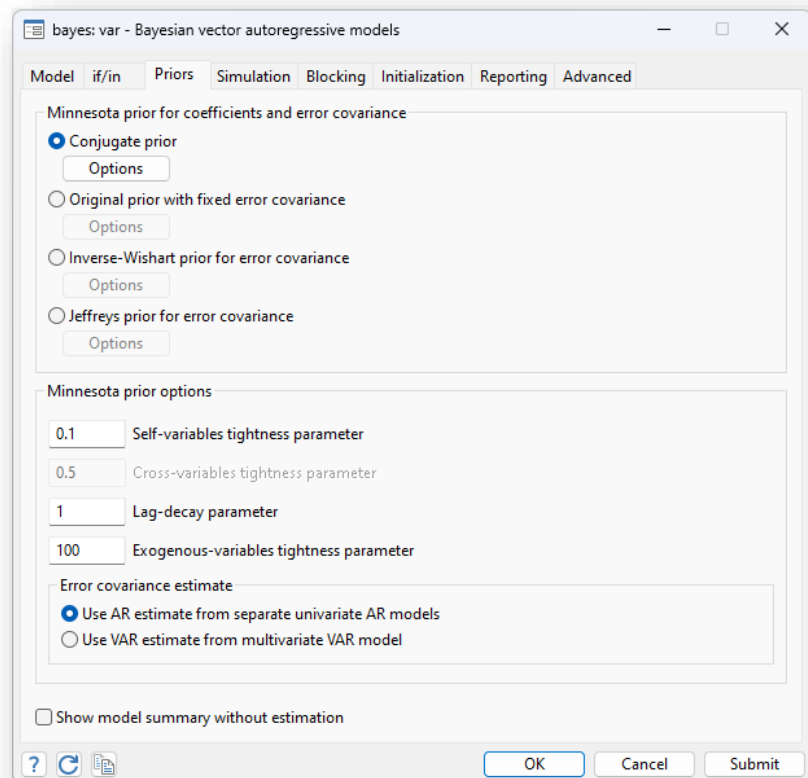
VAR: Output

d_trolley						
d_metro						
L1.	.1500006	.0039422	38.05	0.000	.142274	.1577272
L2.	.0128421	.0065885	1.95	0.051	-.0000711	.0257553
d_metrobus						
L1.	.0531633	.0174305	3.05	0.002	.0190001	.0873265
L2.	-.0245961	.0171713	-1.43	0.152	-.0582511	.009059
d_trolley						
L1.	.1128541	.0358269	3.15	0.002	.0426346	.1830736
L2.	.0781577	.0331671	2.36	0.018	.0131514	.143164
d_rtp						
L1.	.0632592	.0344919	1.83	0.067	-.0043437	.1308622
L2.	.0176976	.0305925	0.58	0.563	-.0422626	.0776578
_cons	-.0108634	.0014055	-7.73	0.000	-.0136181	-.0081086

VAR: Output

d_rtp						
d_metro						
L1.	.1464791	.0036117	40.56	0.000	.1394002	.153558
L2.	.0545522	.0060362	9.04	0.000	.0427215	.0663829
d_metrobus						
L1.	.0231037	.0159693	1.45	0.148	-.0081955	.054403
L2.	-.0176908	.0157318	-1.12	0.261	-.0485245	.0131429
d_trolley						
L1.	.0564251	.0328235	1.72	0.086	-.0079077	.120758
L2.	.0203616	.0303866	0.67	0.503	-.0391951	.0799183
d_rtp						
L1.	.1137516	.0316004	3.60	0.000	.0518159	.1756872
L2.	.0611467	.0280279	2.18	0.029	.006213	.1160803
_cons	-.0054753	.0012877	-4.25	0.000	-.0079991	-.0029515

The bayes prefix



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

Structural vector autoregression

$$Ay_t = A_1y_{t-1} + \dots + A_py_{t-p} + B\epsilon_t$$

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

$$y_t = \Phi_1y_{t-1} + \dots + \Phi_py_{t-p} + u_t$$

SVAR

$$Ay_t = A_1y_{t-1} + \dots + A_py_{t-p} + B\epsilon_t$$

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

$$y_t = \Phi_1y_{t-1} + \dots + \Phi_py_{t-p} + u_t$$

$$\Rightarrow E[u_t u_t'] = \Sigma$$

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

$$y_t = C e_t$$

In long-run models, the constraints are placed on the elements of C that are estimated. These constraints are often exclusion restrictions. For instance, the long-run response of variable 1 to a shock to variable 2 can be interpreted as setting the long-run response of variable 1 to be zero.

Similar to the short-run model, the P_{lr} matrix such that $P_{lr} = C$ is identified by the restriction $C = P_{lr}$. There are K^2 parameters in C , and the order condition for identification is necessary but not sufficient, so the Amisano and Giacomini (2007) identification is performed by default.

802 var svar — Structural vector autoregressive models

at least $K^2 - K(K+1)/2$ restrictions placed on those parameters. The order condition is necessary but not sufficient, so the Amisano and Giacomini (2007) identification is performed by default.

► **Example 4: Long-run SVAR model**

Suppose that we have a theory in which unexpected changes to output and, similarly, that unexpected changes to changes in the money supply. The C matrix implied by this theory is

Title

var ivsvar — Instrumental-variables structural vector autoregressive models*

+ This command is part of StataNow.

Description Quick start Menu Syntax
Options Remarks and examples Stored results Methods and properties
References Also see

Description

ivsvar estimates the parameters of structural vector autoregressive (SVAR) models. Instrumental-variables SVAR models are an alternative to the short-run SVAR, requiring fewer constraints than would be necessary in those models. They need fewer constraints because the shocks, are modeled using instrumental variables. The structural IRFs are the target shocks. Instrumental-variables SVAR models are also called proxy VARs. ivsvar provides two estimators: a generalized method of moments (GMM) estimator and a minimum distance estimator for multiple target shocks.

Quick start

Fit an instrumental-variables SVAR model for the variables y_1 , y_2 , and y_3 , using the GMM estimator

```
ivsvar gmm y1 y2 (y3 = z)
```

As above, but run the reduced-form vector autoregressive (VAR) model with the default 1 through 2

```
ivsvar gmm y1 y2 (y3 = z), lags(1/4)
```

Add exogenous variables x_1 and x_2

Viewer - search var_nr

File Edit History Help

search var_nr

search for var_nr (manual: [R] search)

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

Search of web resources from Stata and other users

(contacting <http://www.stata.com>)

1 package found (Stata Journal listed first)

var_nr from <http://fmwww.bc.edu/RePEc/bocode/v>

VAR_NR : module to estimate set identified SVARS / The toolbox var_nr allows for the estimation of set identified / SVARS in Stata using sign and narrative restrictions. The suite / is able to produce impulse responses functions, forecast error / variance decompositions, and

(click here to return to the previous screen)

(end of search)

SVAR(2)

Sample: 07jan2015 thru 31dec2019
Exactly identified model

Number of obs = 1,300
Log likelihood = 5543.413

	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
/A						
1_1	1	(constrained)				
2_1	-.5758992	.0257162	-22.39	0.000	-.626302	-.5254964
3_1	-.1108569	.0563891	-1.97	0.049	-.2213775	-.0003363
4_1	.6208692	.2502953	2.48	0.013	.1302994	1.111439
1_2	0	(constrained)				
2_2	1	(constrained)				
3_2	-.8365322	.0516619	-16.19	0.000	-.9377876	-.7352767
4_2	1.147998	.2510032	4.57	0.000	.656041	1.639956
1_3	0	(constrained)				
2_3	0	(constrained)				
3_3	1	(constrained)				
4_3	.1407323	.1229253	1.14	0.252	-.1001969	.3816615
1_4	0	(constrained)				
2_4	0	(constrained)				
3_4	0	(constrained)				
4_4	1	(constrained)				
/B						
1_1	.0445327	.0008734	50.99	0.000	.042821	.0462445
2_1	0	(constrained)				
3_1	0	(constrained)				
4_1	0	(constrained)				
1_2	0	(constrained)				
2_2	.0412912	.0008098	50.99	0.000	.039704	.0428783
3_2	0	(constrained)				
4_2	0	(constrained)				
1_3	0	(constrained)				
2_3	0	(constrained)				
3_3	.0769129	.0015084	50.99	0.000	.0739565	.0798693
4_3	0	(constrained)				
1_4	0	(constrained)				
2_4	0	(constrained)				
3_4	0	(constrained)				
4_4	.3408885	.0066854	50.99	0.000	.3277854	.3539916

```
. 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, .)
```

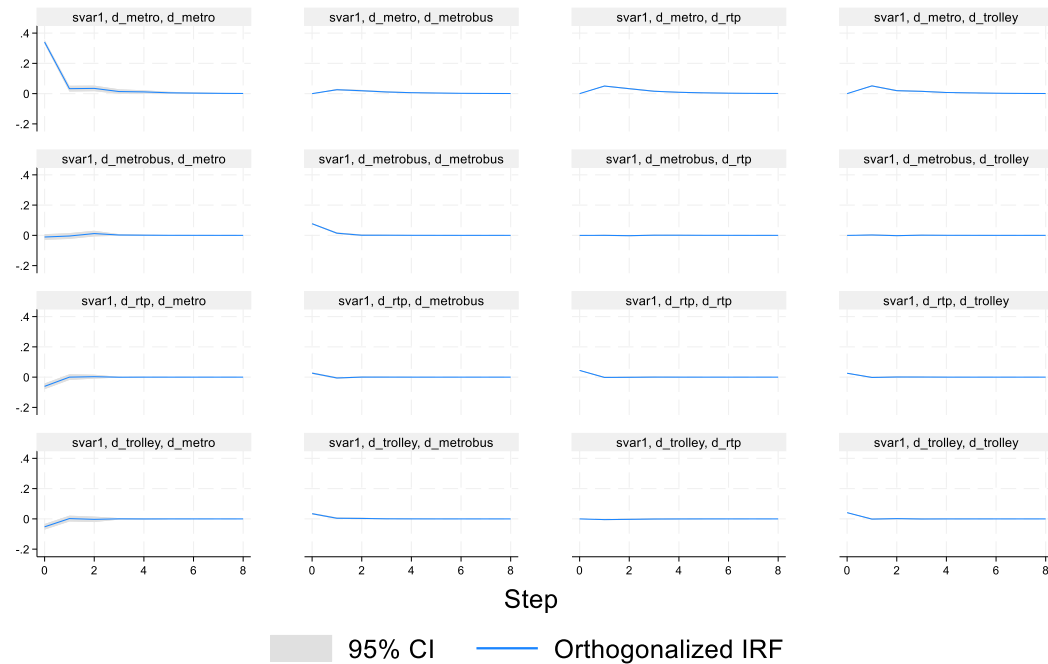
```
. svar d_rtp d_trolley d_metrobus
    d_metro, aeq(A) beq(B) lags(1 2)
```

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
```

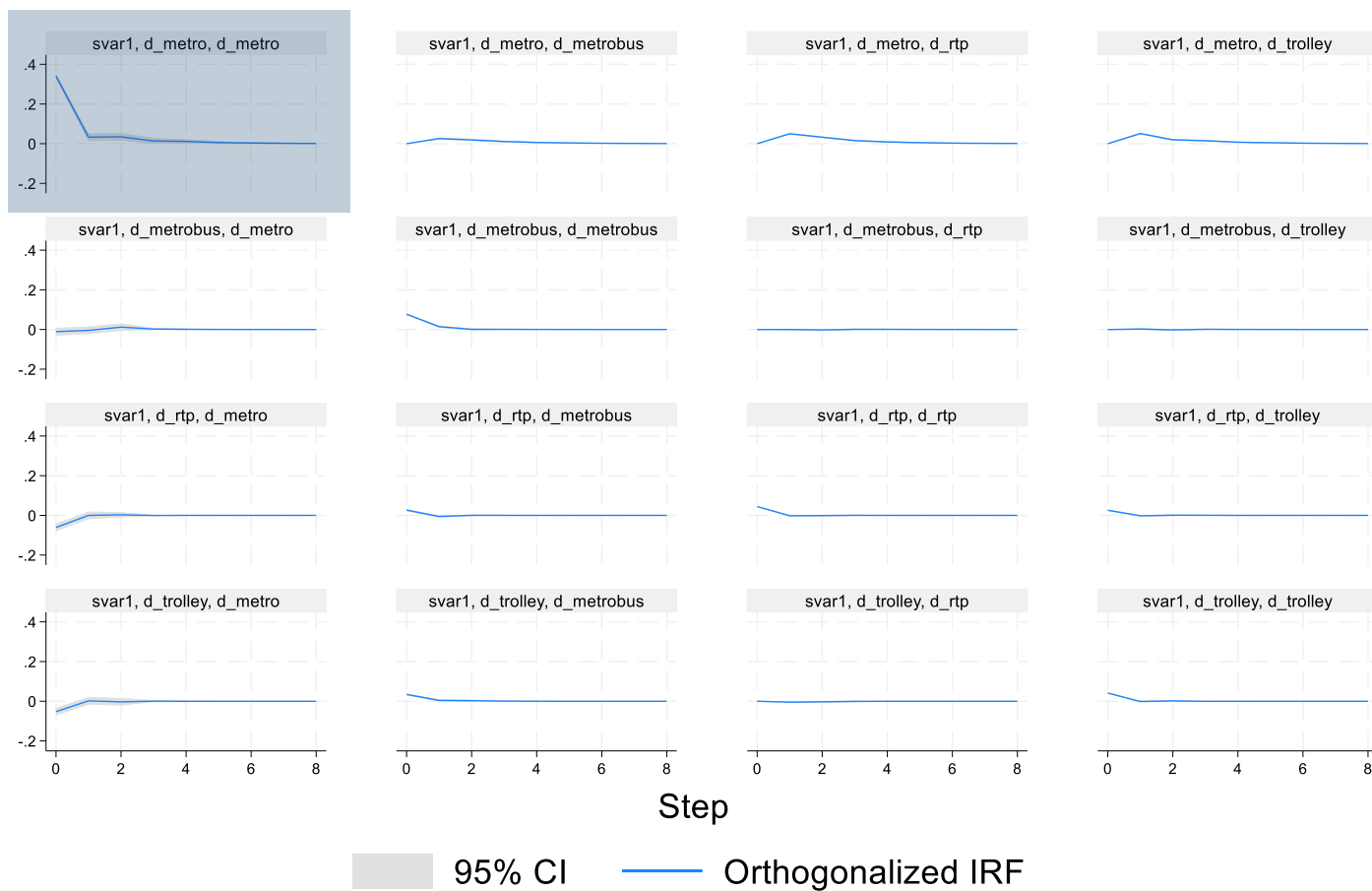
IRF graphs



Graphs by irfname, impulse variable, and response variable

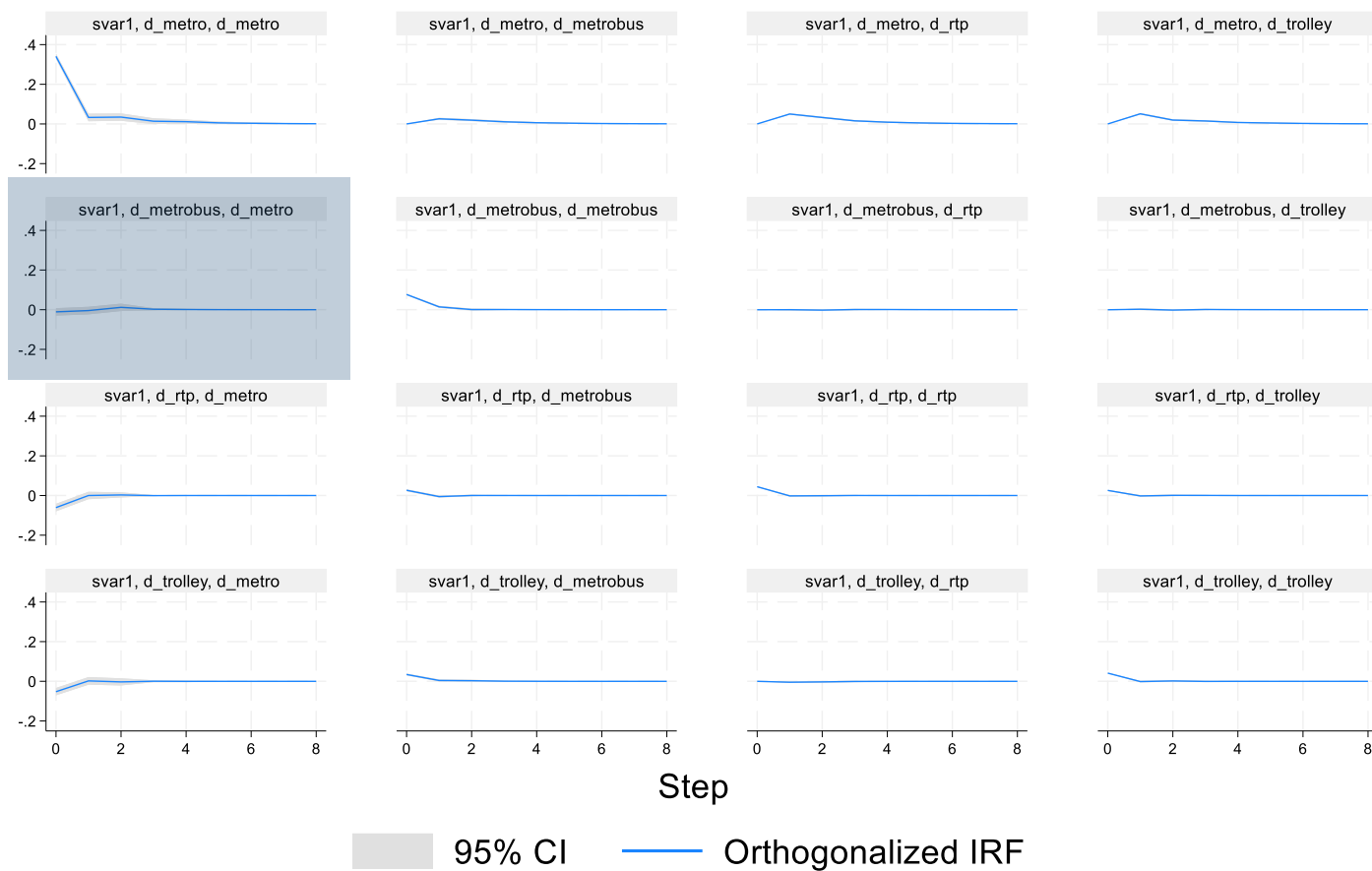
```
. irf graph oirf
```


IRF graphs



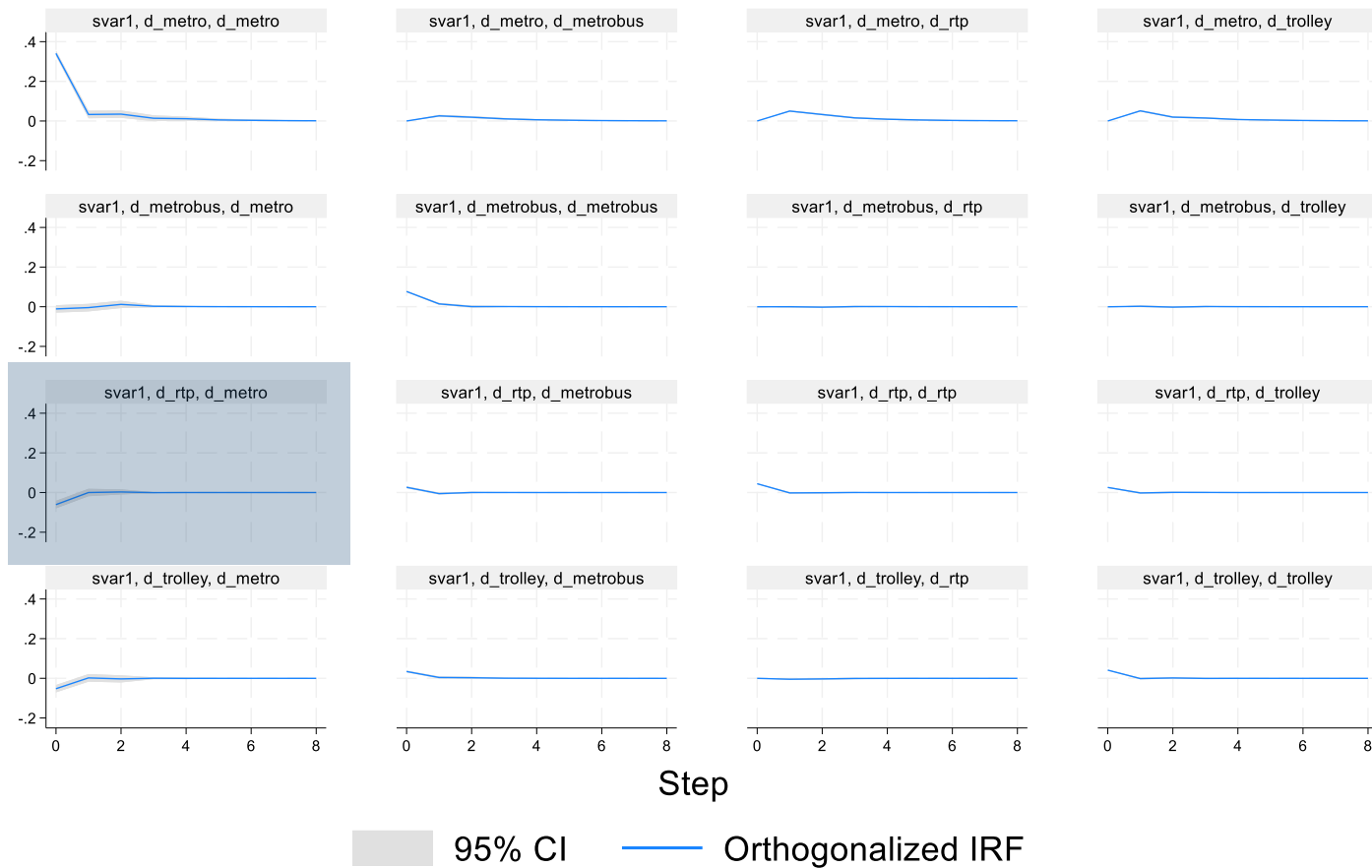
Graphs by irfname, impulse variable, and response variable

IRF graphs



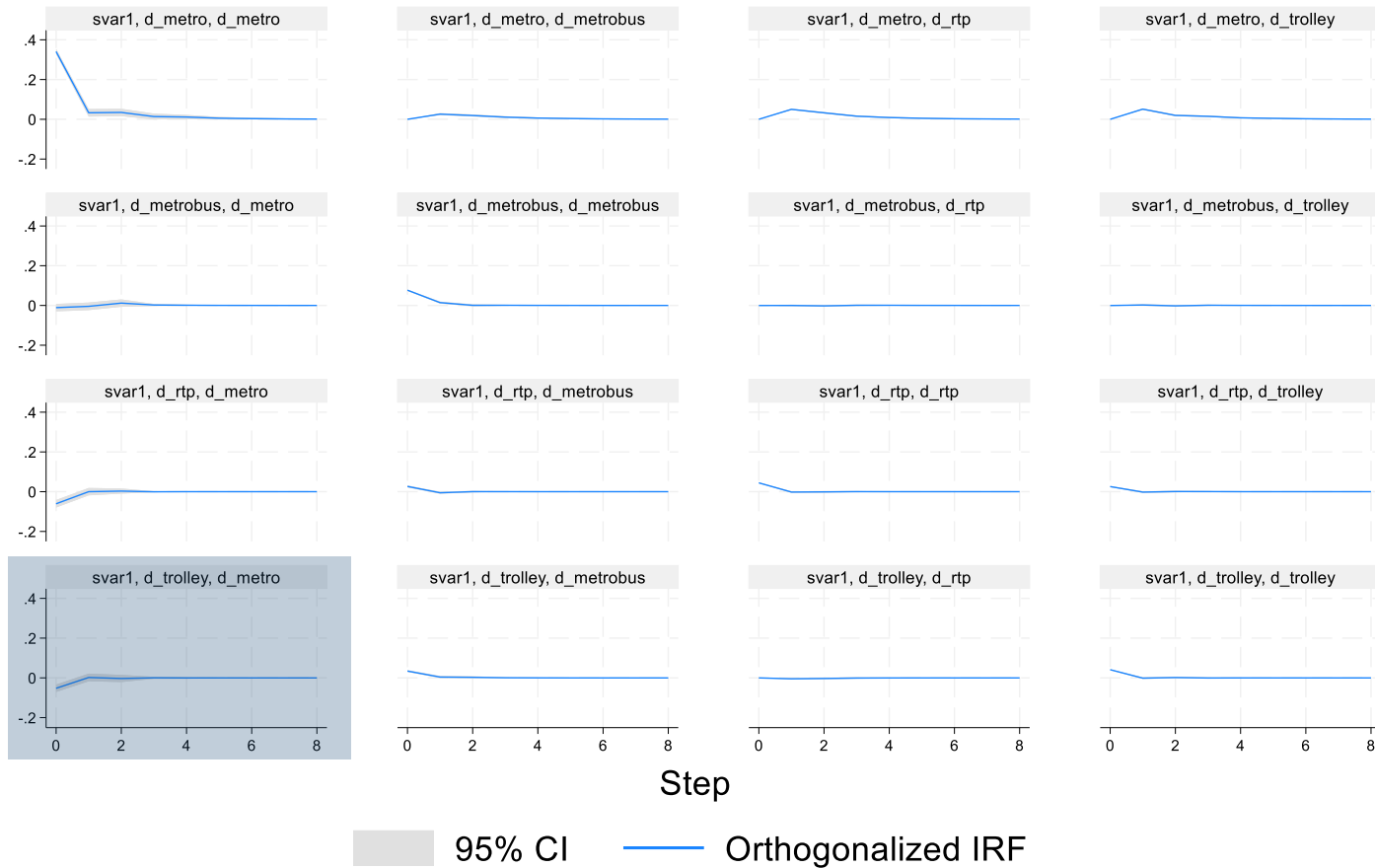
Graphs by irfname, impulse variable, and response variable

IRF graphs



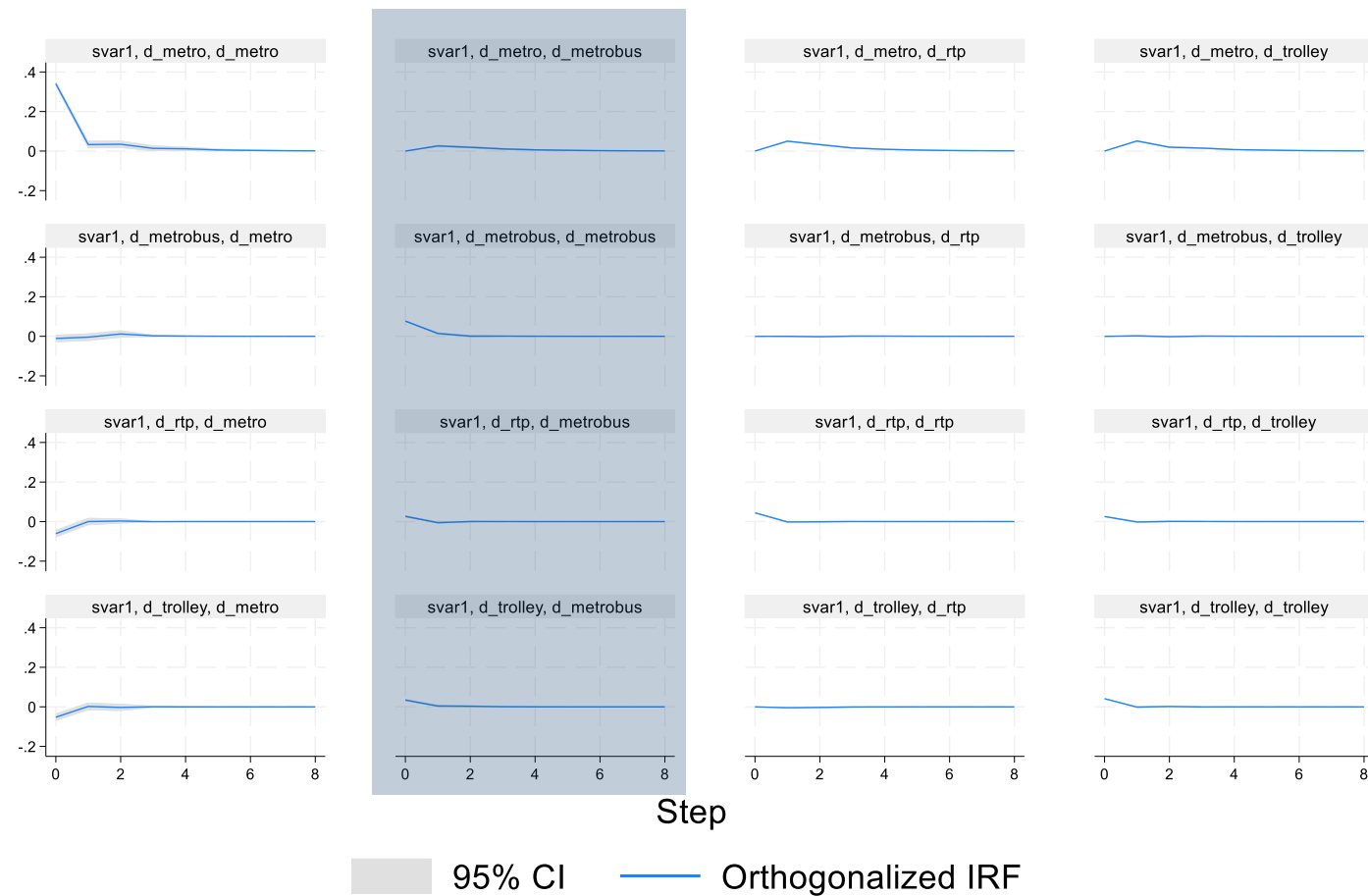
Graphs by irfname, impulse variable, and response variable

IRF graphs



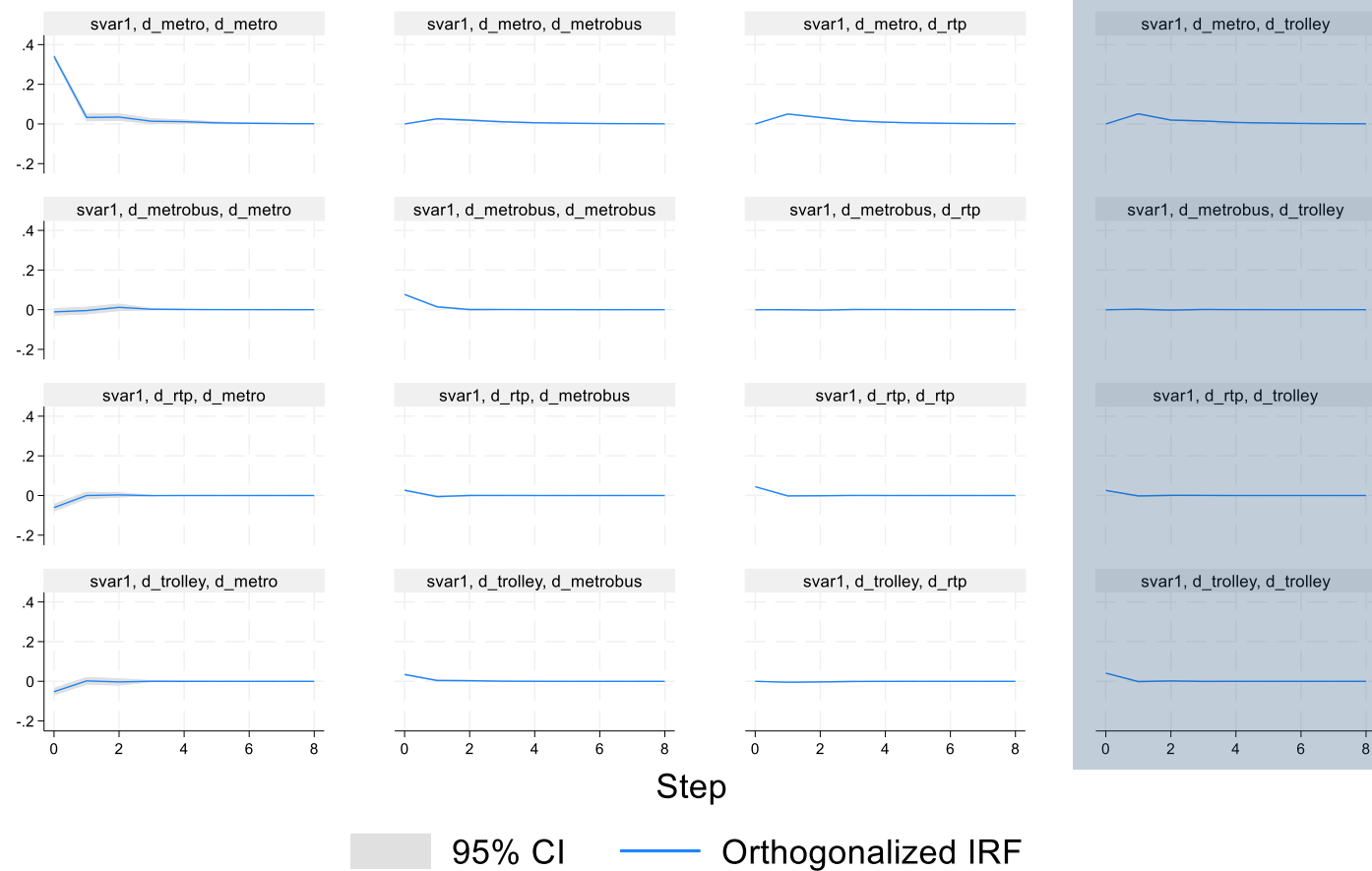
Graphs by irfname, impulse variable, and response variable

IRF graphs



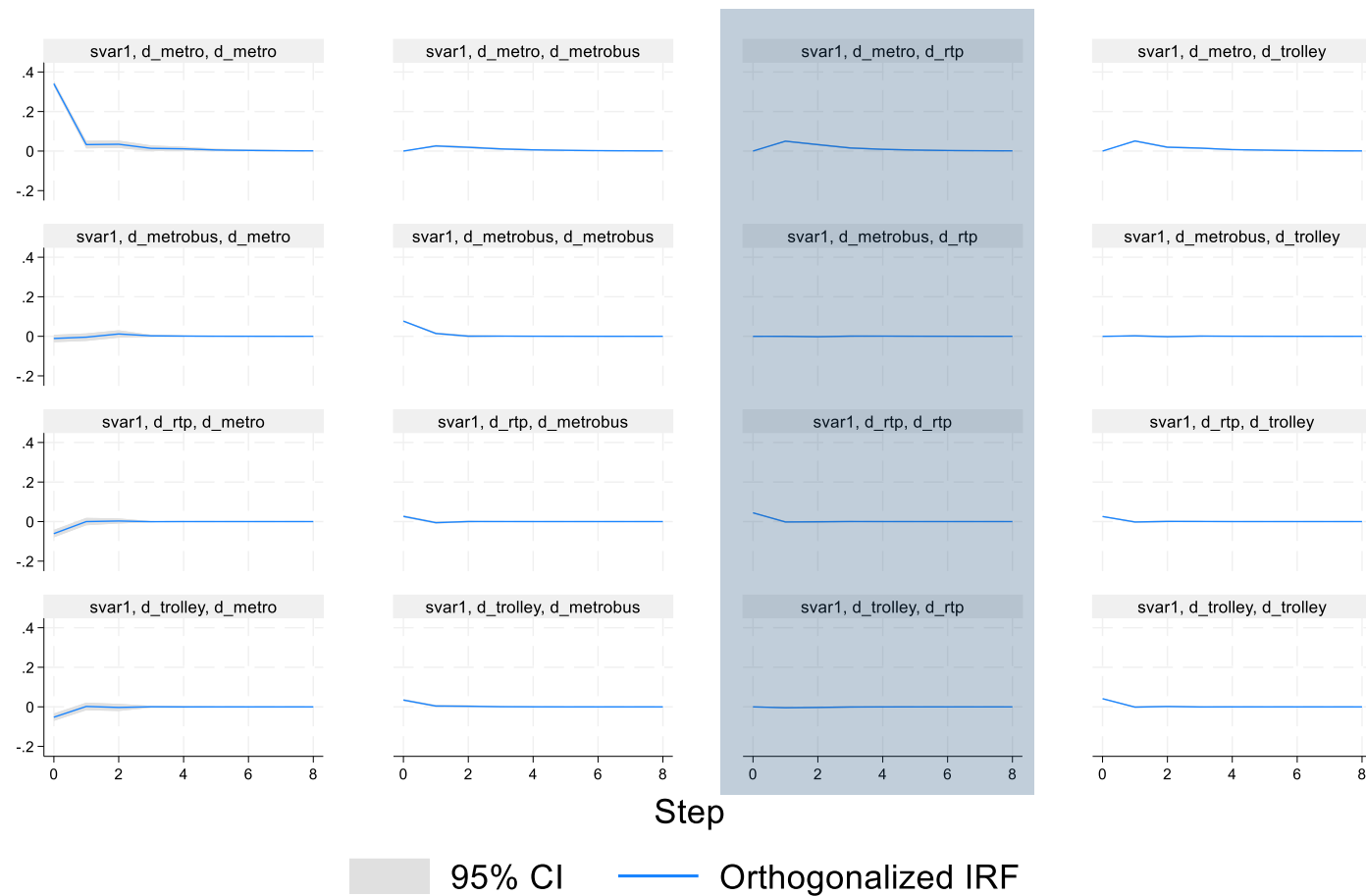
Graphs by irfname, impulse variable, and response variable

IRF graphs



Graphs by irfname, impulse variable, and response variable

IRF graphs



Graphs by irfname, impulse variable, and response variable



Thank you for joining us!

Installation and use of Stata: tech-support@stata.com

Pricing and upgrades to Stata 18: service@stata.com