

# Introducción a los comandos de series de tiempo en Stata

Septiembre 24, 2024



# Temas

## Parte I: Análisis de series univariadas

- Manejo de fechas en Stata
- Declaración de la estructura temporal con **tsset**
- Gráficos con **tsline**
- Pruebas de estabilidad de parámetros con **estat cusum**
- Suavizamiento con **tssmooth**
- Pruebas de raíz unitaria con **dfuller**
- Operadores de diferencia y rezago
- Selección de rezagos con **arimasoc**
- Modelos Box-Jenkins con **arima**
- Modelos de heteroscedasticidad con **arch**
- Pronóstico con **predict**

## Parte II: Análisis de series multivariadas

- Manejo de calendarios con **bcal**
- Vectores autorregresivos con **var** y **svar**
- Funciones impulso-respuesta con **irf**

# **Parte I. Análisis de series univariadas**

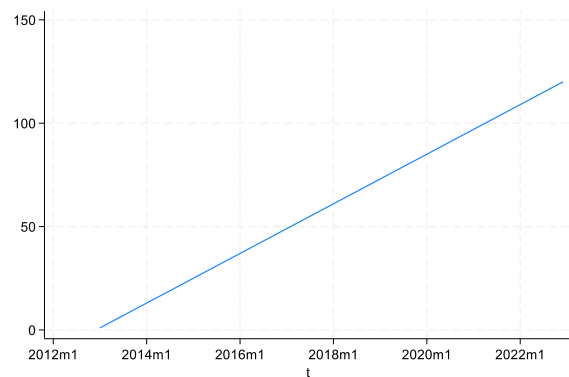
## Componentes de una serie temporal

$$y_t = \textit{tendencia}_t + \textit{estacionalidad}_t + \textit{residual}_t$$

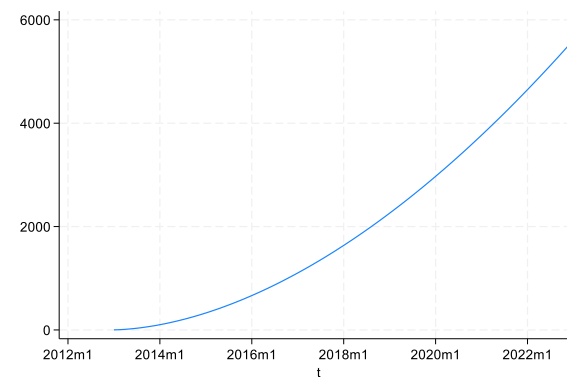
ó

$$x_t = \textit{tendencia}_t \times \textit{estacionalidad}_t \times \textit{residual}_t$$

# Componentes de una serie temporal

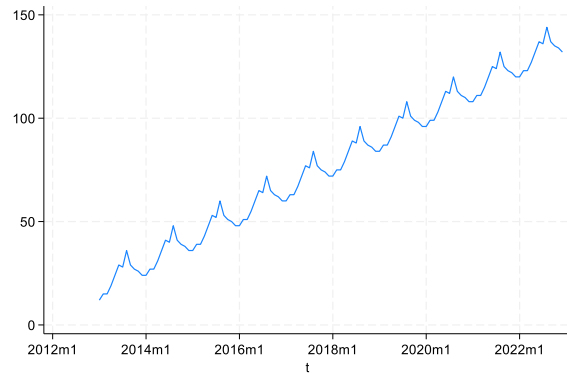


Tendencia aditiva



Tendencia multiplicativa

# Componentes de una serie temporal

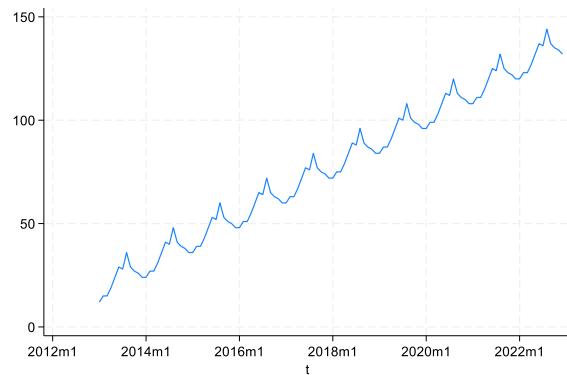


Tendencia aditiva  
Estacionalidad aditiva

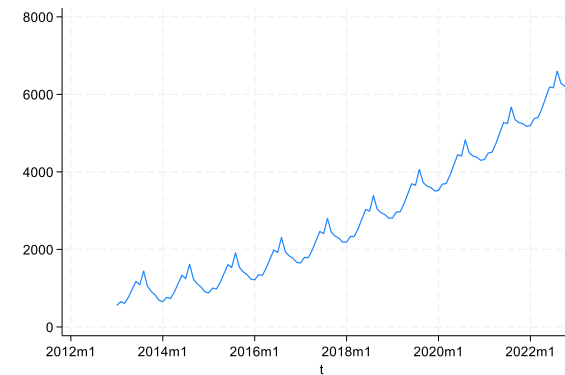


Tendencia multiplicativa  
Estacionalidad aditiva

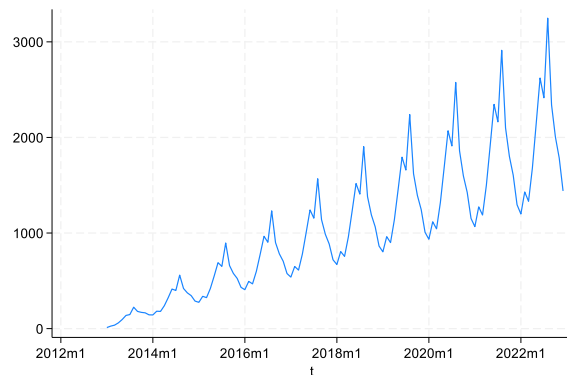
# Componentes de una serie temporal



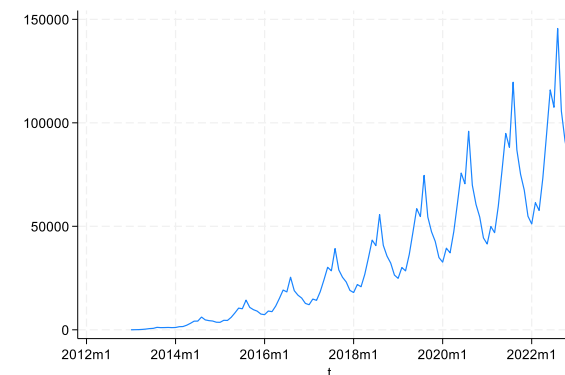
Tendencia aditiva  
Estacionalidad aditiva



Tendencia multiplicativa  
Estacionalidad aditiva

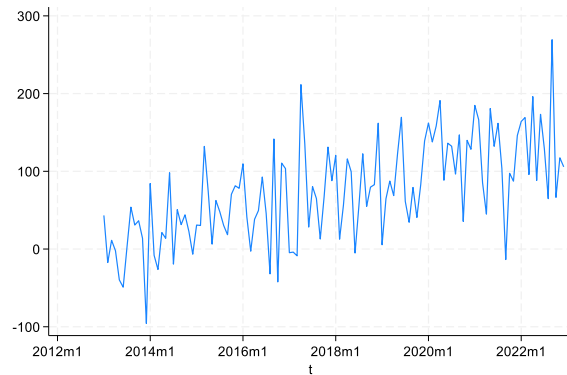


Tendencia aditiva  
Estacionalidad multiplicativa

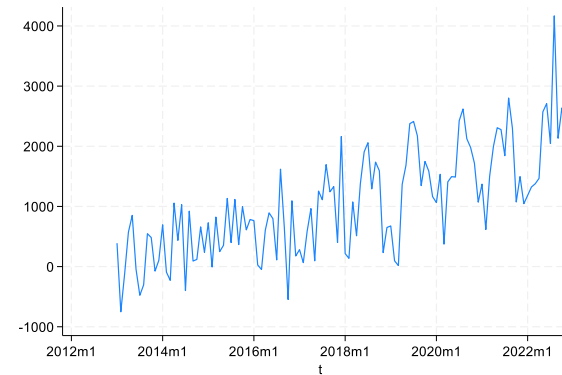


Tendencia multiplicativa  
Estacionalidad multiplicativa

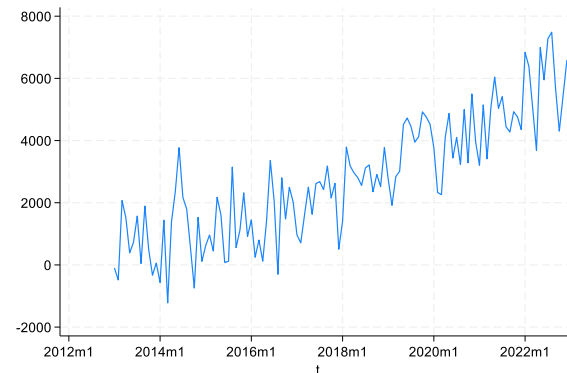
# Componentes de una serie temporal



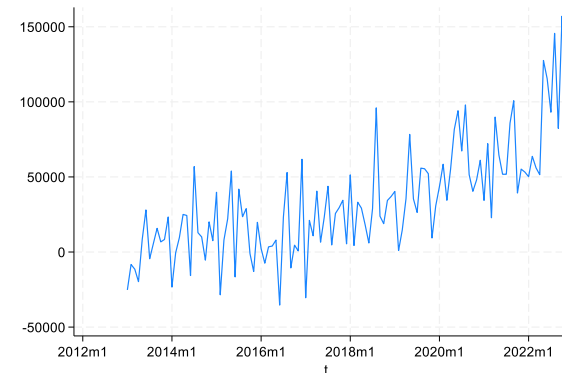
Tendencia aditiva  
Estacionalidad aditiva  
+ ruido aleatorio



Tendencia multiplicativa  
Estacionalidad aditiva  
+ ruido aleatorio



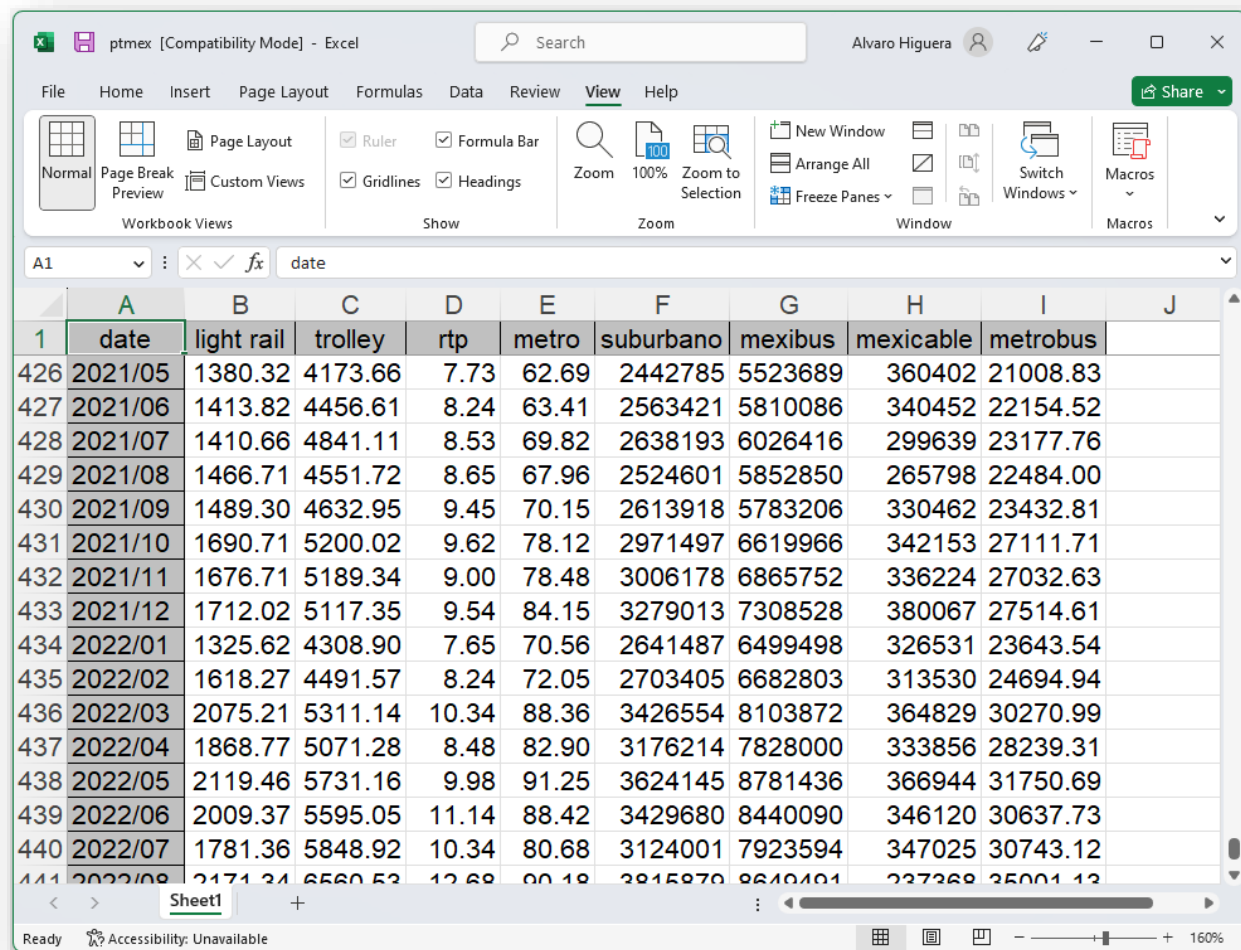
Tendencia aditiva  
Estacionalidad multiplicativa  
+ ruido aleatorio



Tendencia multiplicativa  
Estacionalidad multiplicativa  
+ ruido aleatorio



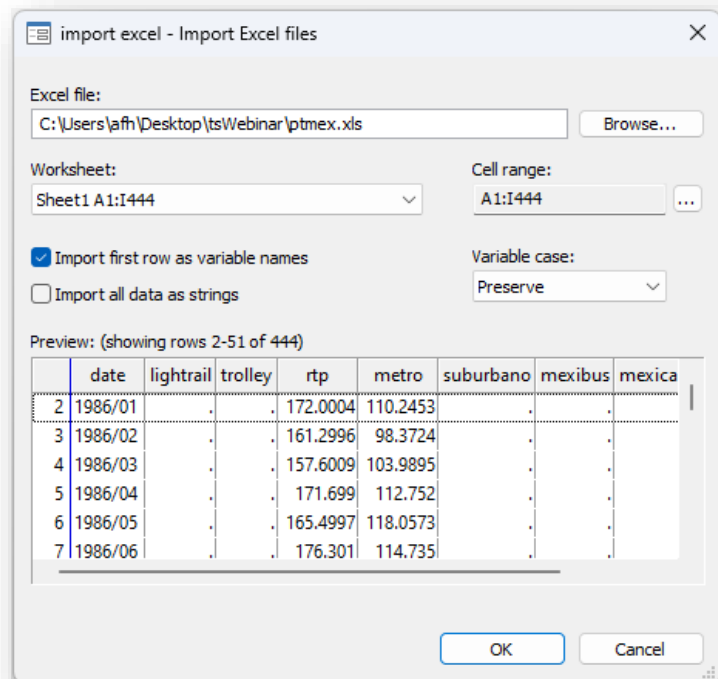
# Datos del transporte público de la Ciudad de México



The screenshot shows an Excel spreadsheet titled "ptmex [Compatibility Mode] - Excel". The ribbon includes File, Home, Insert, Page Layout, Formulas, Data, Review, View, and Help. The View tab is active, showing options for Normal, Page Break Preview, Custom Views, Ruler, Formula Bar, Gridlines, Headings, Zoom, and Window. The spreadsheet displays data for public transport in Mexico City, with columns labeled A through J. The data is organized into rows, with the first row (row 1) containing headers: date, light rail, trolley, rtp, metro, suburban, mexibus, mexicable, and metrobus. The data spans from May 2021 to July 2022, with rows numbered 1 through 440. The status bar at the bottom indicates "Ready" and "Accessibility: Unavailable".

	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	

# Importación de datos



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

# Fecha

Data Editor (Browse) - [Untitled]

File Edit View Data Tools

fecha[1] 1986/01

	fecha	lightrail	trolley	rtp	metro	suburbano	mexibus	me
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	Val
<input checked="" type="checkbox"/> fecha	date	str7	%9s	
<input checked="" type="checkbox"/> lightrail	Pasajeros tren ligero (mi...	double	%10.0g	
<input checked="" type="checkbox"/> trolley	Pasajeros trolebus (miles)	double	%10.0g	
<input checked="" type="checkbox"/> rtp	Pasajeros RTP (milliones)	double	%10.0g	
<input checked="" type="checkbox"/> metro	Pasajeros Metro (millio...	double	%10.0g	
<input checked="" type="checkbox"/> suburbano	Pasajeros Suburbano	long	%10.0g	
<input checked="" type="checkbox"/> mexibus	Pasajeros Mexibus	long	%10.0g	
<input checked="" type="checkbox"/> mexicable	Pasajeros Mexicable	long	%10.0g	
<input checked="" type="checkbox"/> metrobus	Pasajeros Metrobus (mil...	double	%10.0g	

Variables Snapshots

Properties

Variables

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

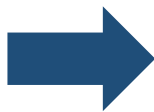
Data

Frame	default
Filename	

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

## Formateo de fecha

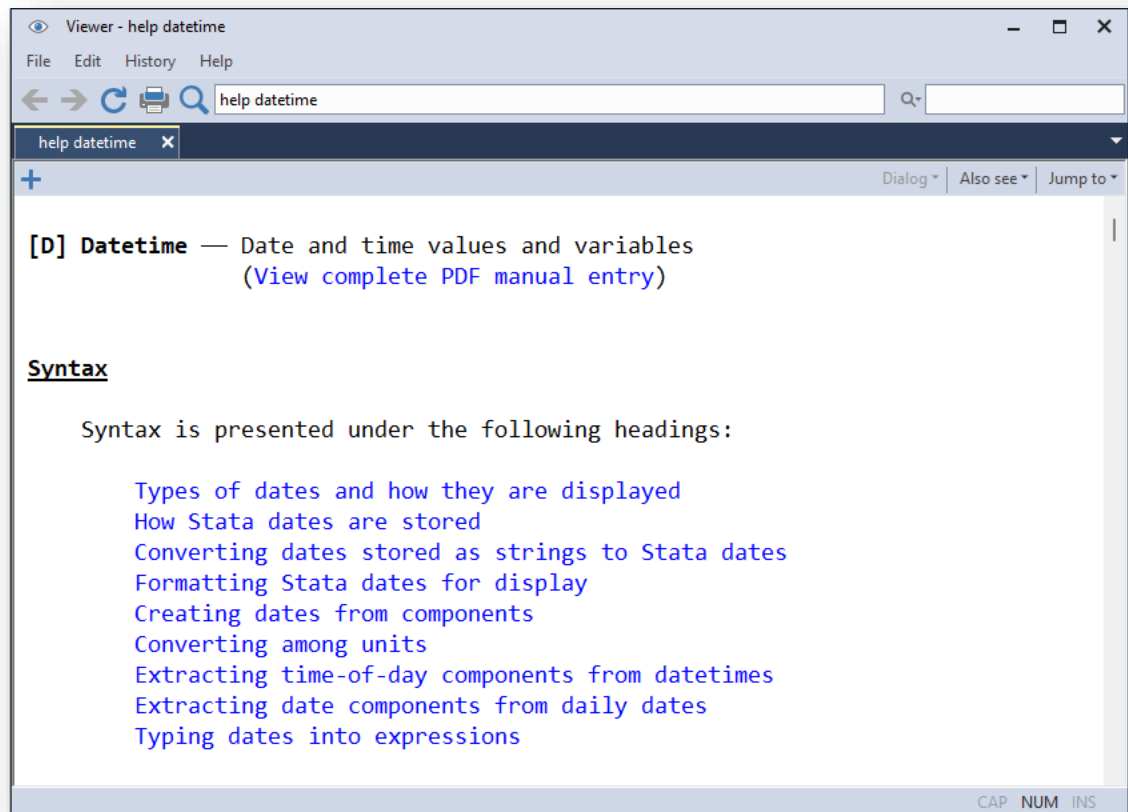
	fecha	t
1	1986/01	312
2	1986/02	313
3	1986/03	314
4	1986/04	315
5	1986/05	316
6	1986/06	317
7	1986/07	318
8	1986/08	319
9	1986/09	320
10	1986/10	321



	fecha	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(fecha, "YM")  
. format t %tm
```

# Ayuda de fechas



```
. help datetime
```

## Declaración de la estructura temporal

```
. tsset t
```

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

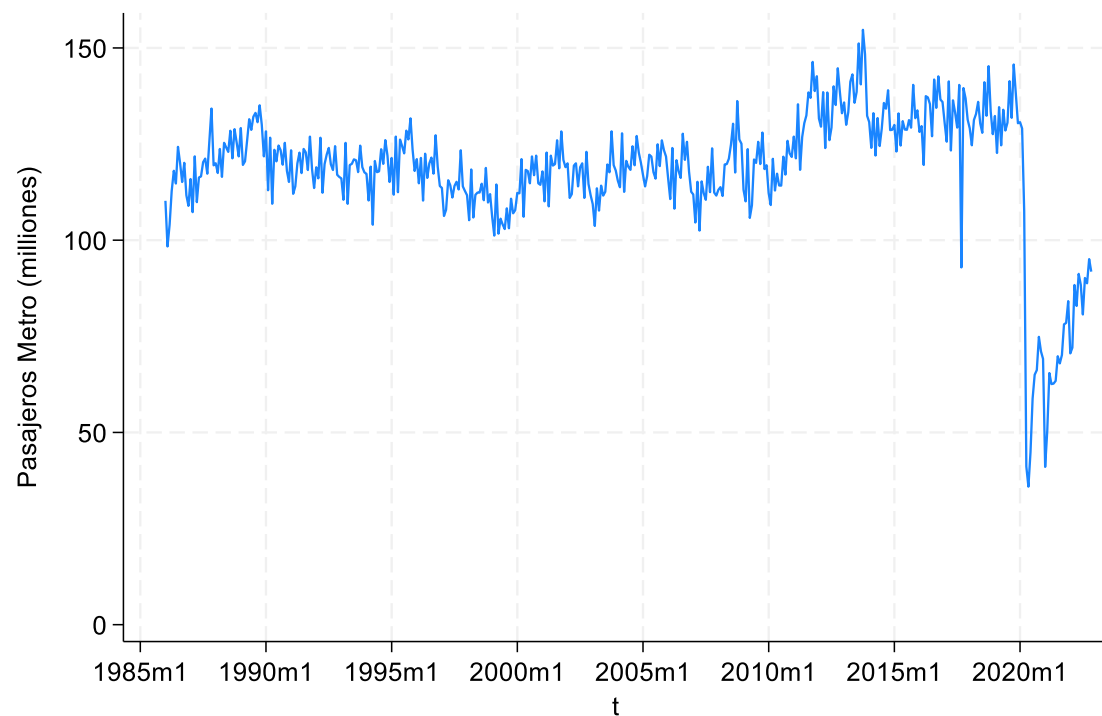
```
Delta: 1 month
```



# Metro



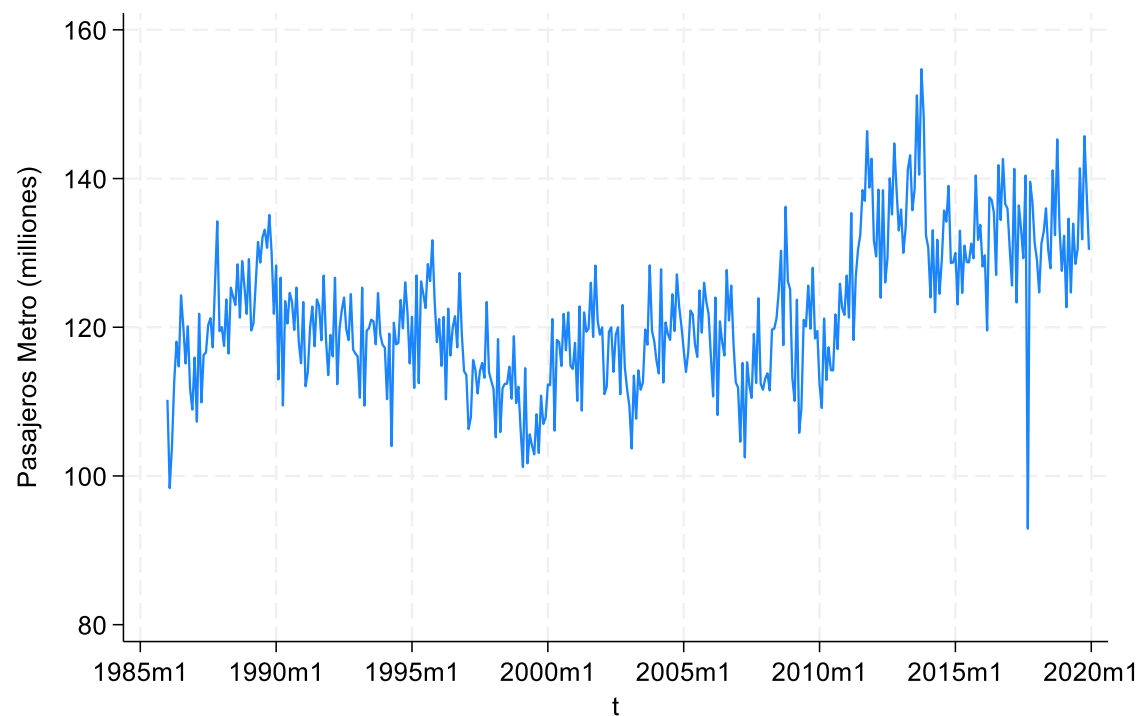
## Metro: Gráfico de línea



```
. tsline metro
```



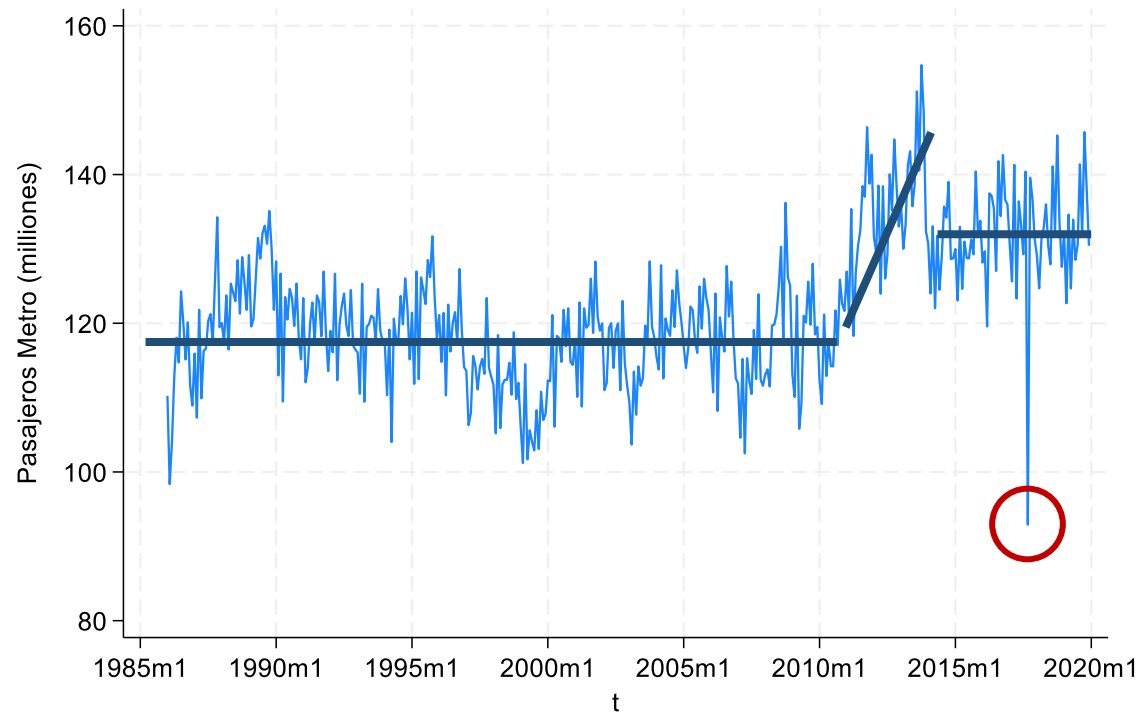
## Metro: Quitando la pandemia



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

```
. tsline metro
```

## Metro: Primera impresión



## Metro: Estimación de la media

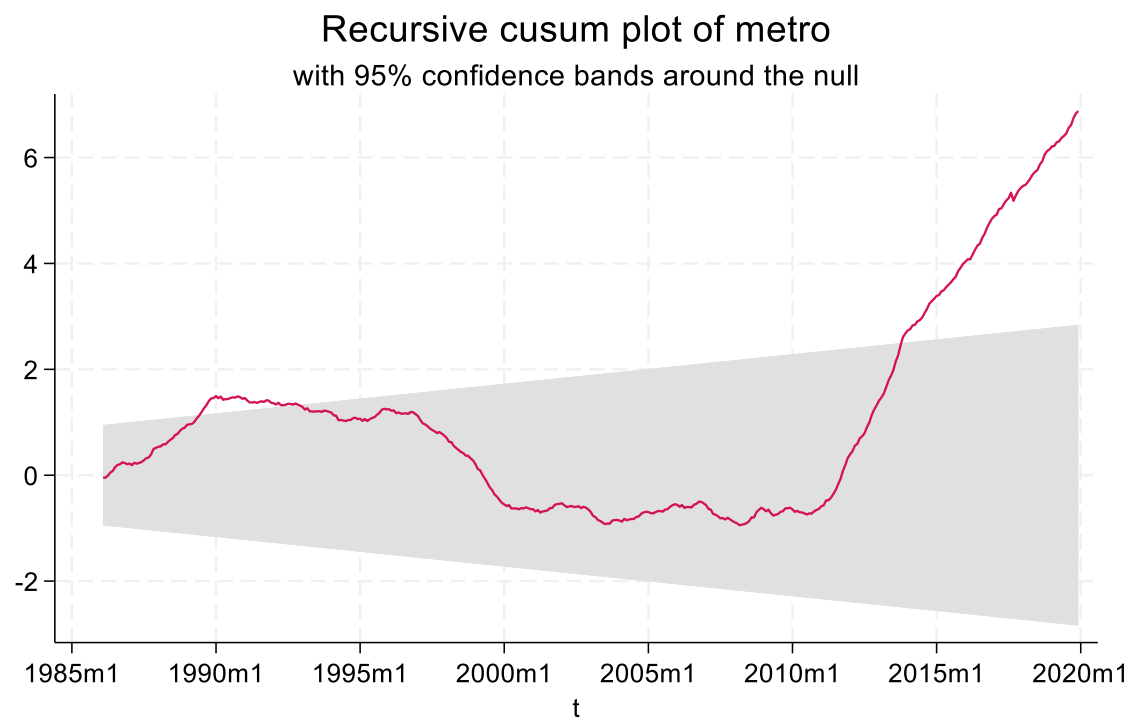
Source	SS	df	MS	Number of obs	=	408
Model	0	0	.	F(0, 407)	=	0.00
Residual	38300.6572	407	94.1048088	Prob > F	=	.
				R-squared	=	0.0000
				Adj R-squared	=	0.0000
Total	38300.6572	407	94.1048088	Root MSE	=	9.7008

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

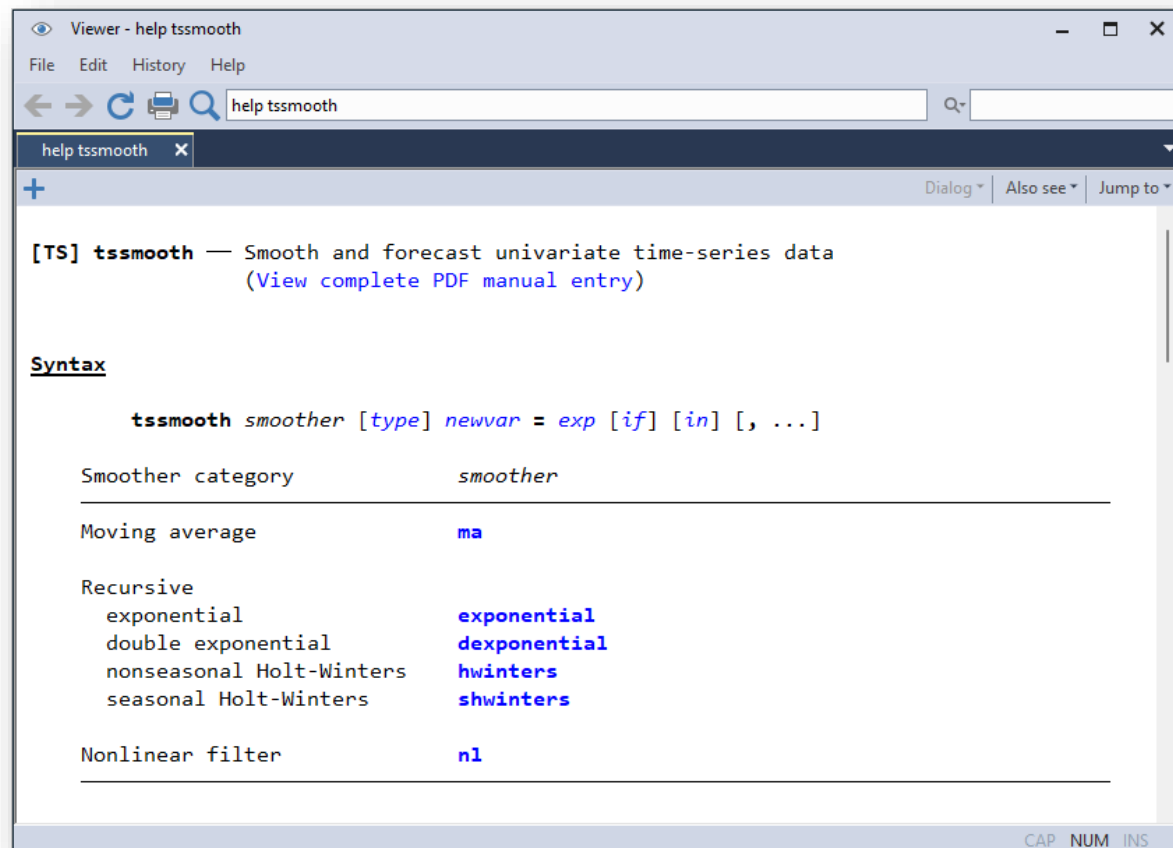
```
. regress metro
```

## Metro: Estabilidad de la media



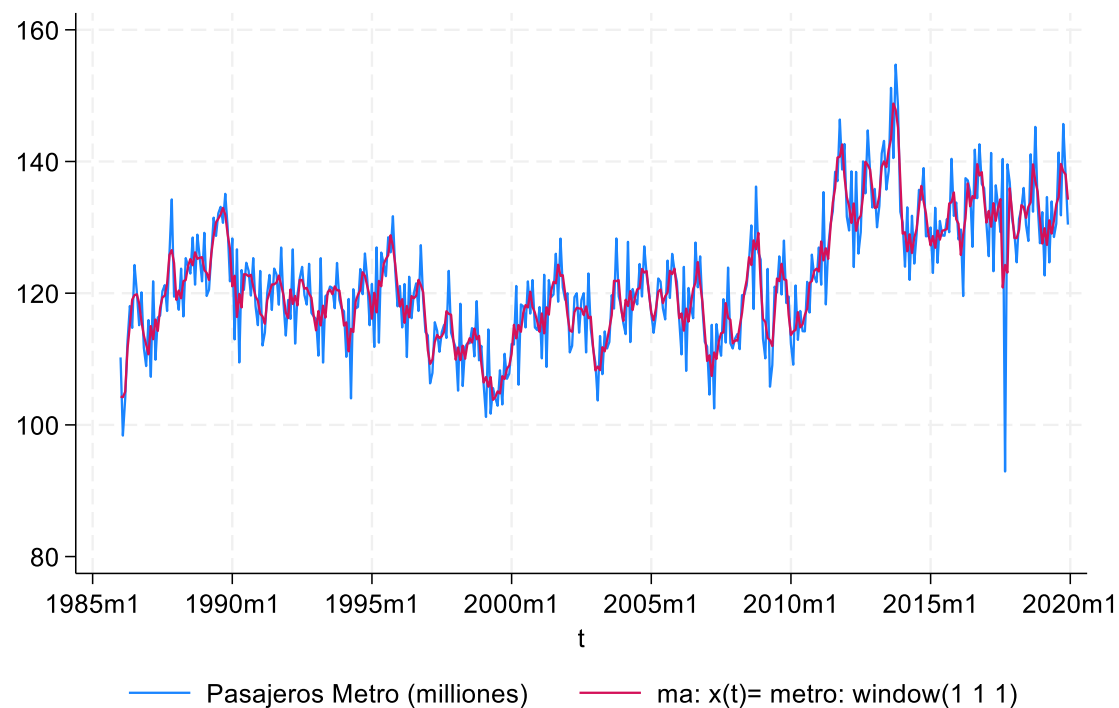
```
. estat sbcusum
```

# Suavizados en Stata



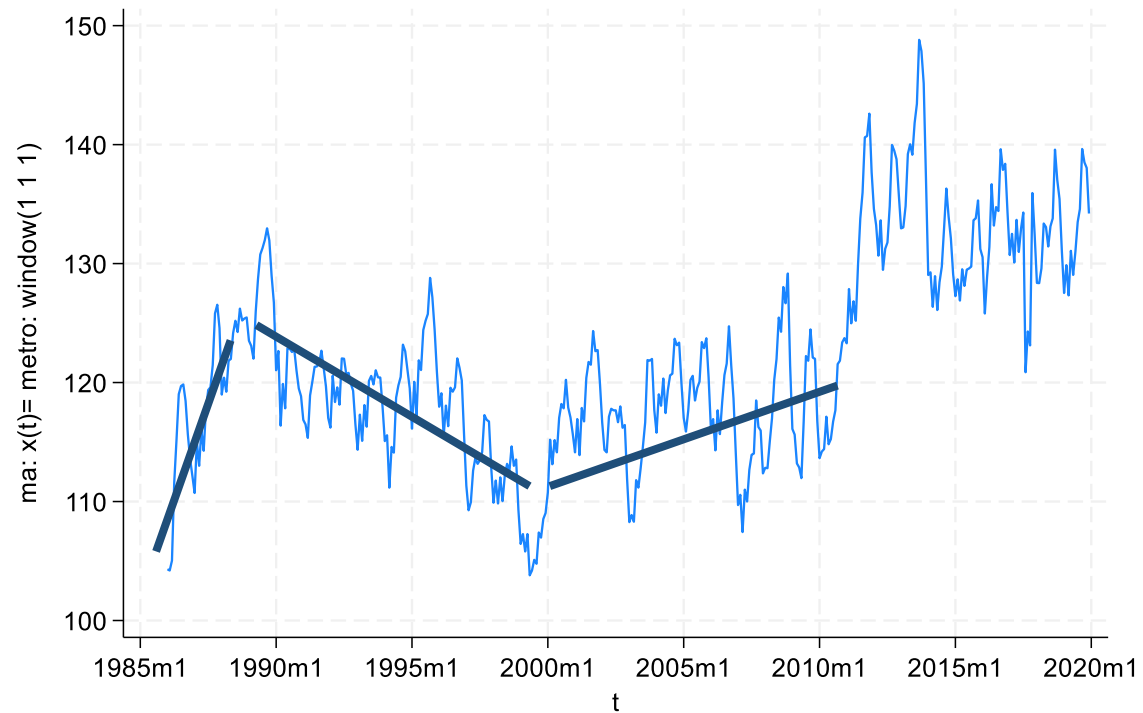
```
. help tssmooth
```

## Metro: Suavizado de medias móviles (1 1 1)



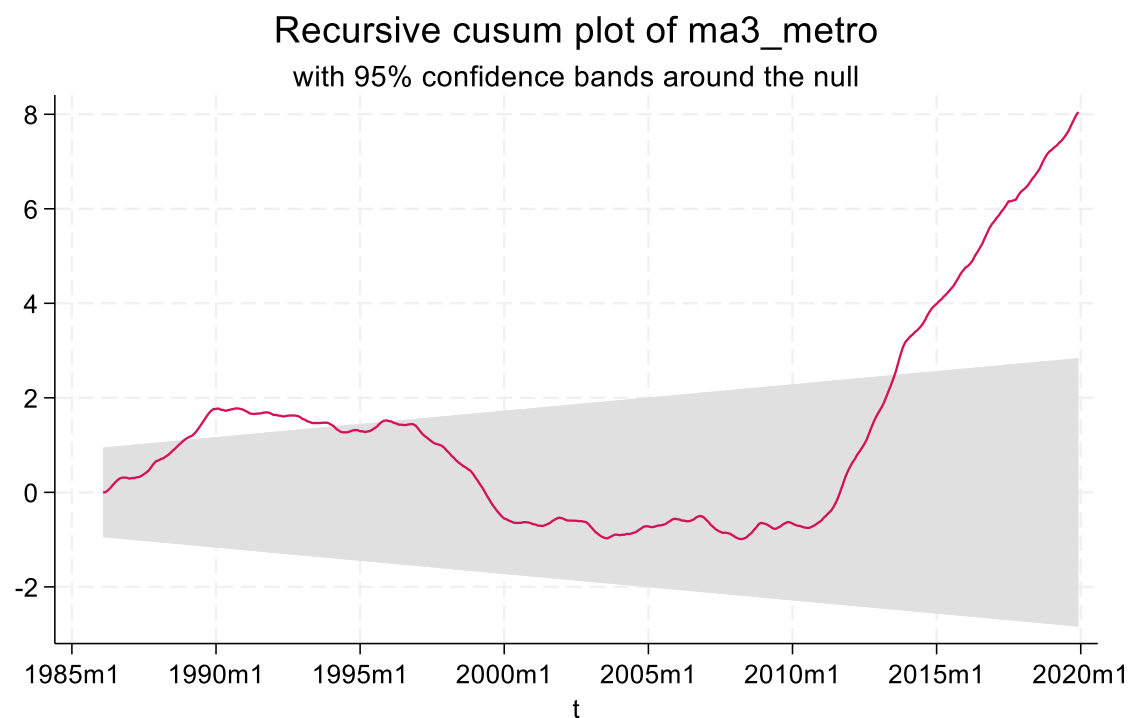
```
. tssmooth ma ma3_metro = metro,  
    window(1 1 1)  
  
. tsline metro ma3_metro
```

## Metro: Suavizado de medias móviles (1 1 1)



```
. tsline ma3_metro
```

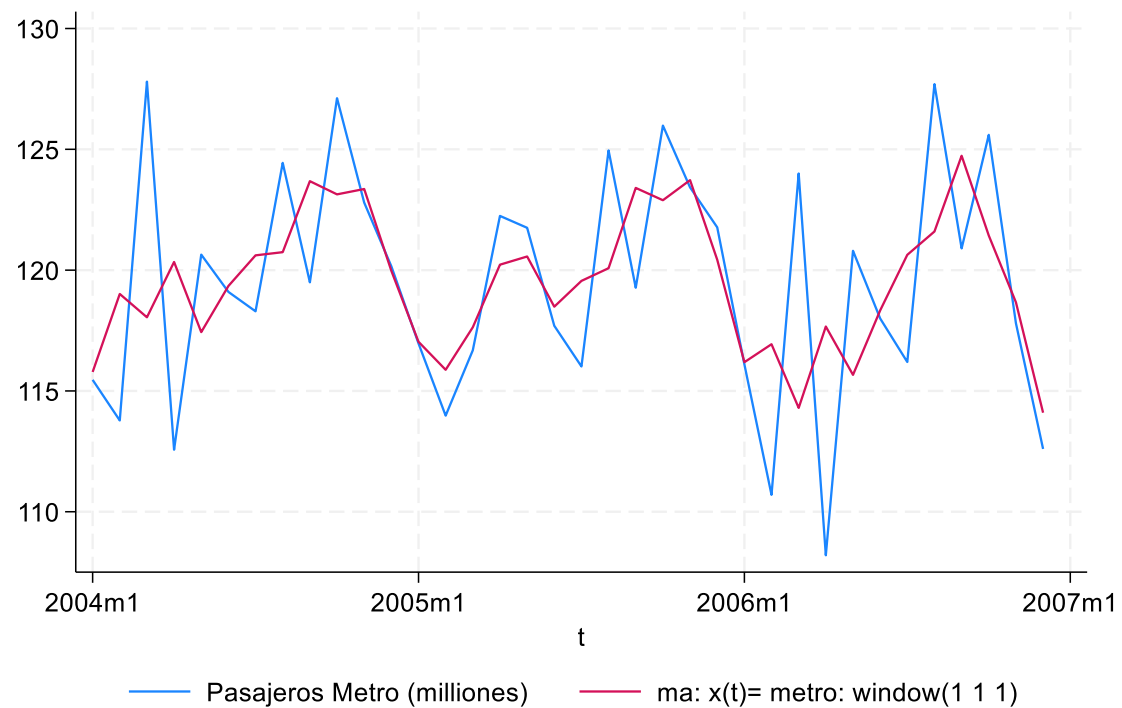
## Metro: Suavizado de medias móviles (1 1 1)



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

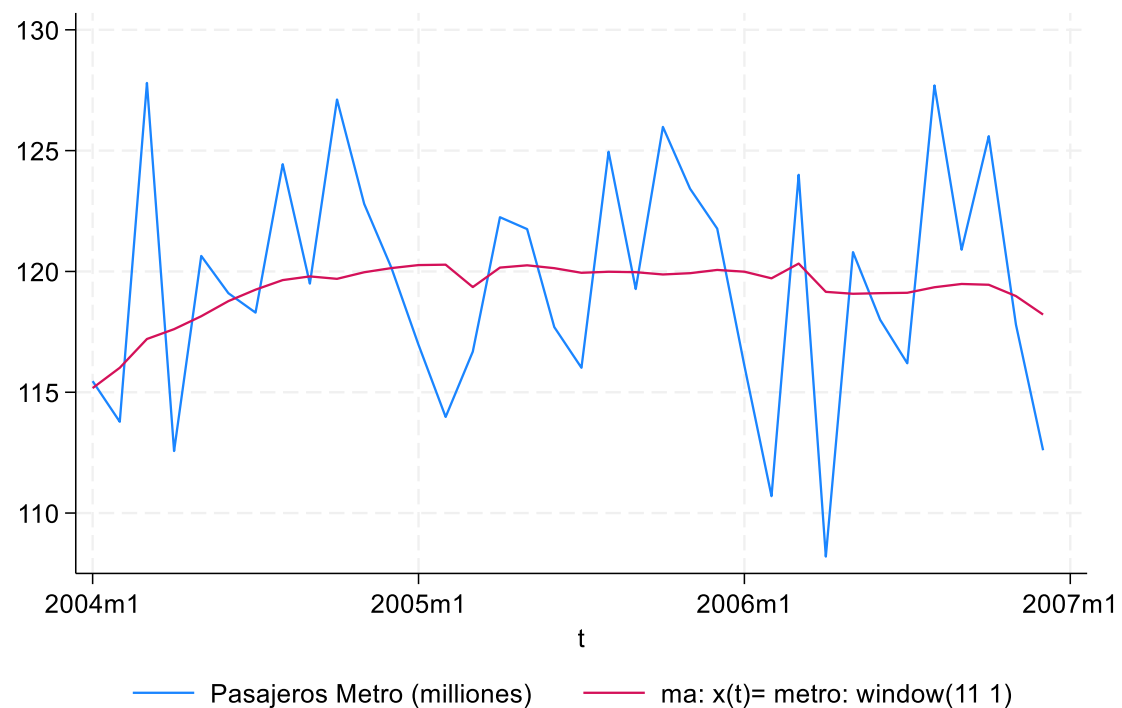


## Metro: Estacionalidad



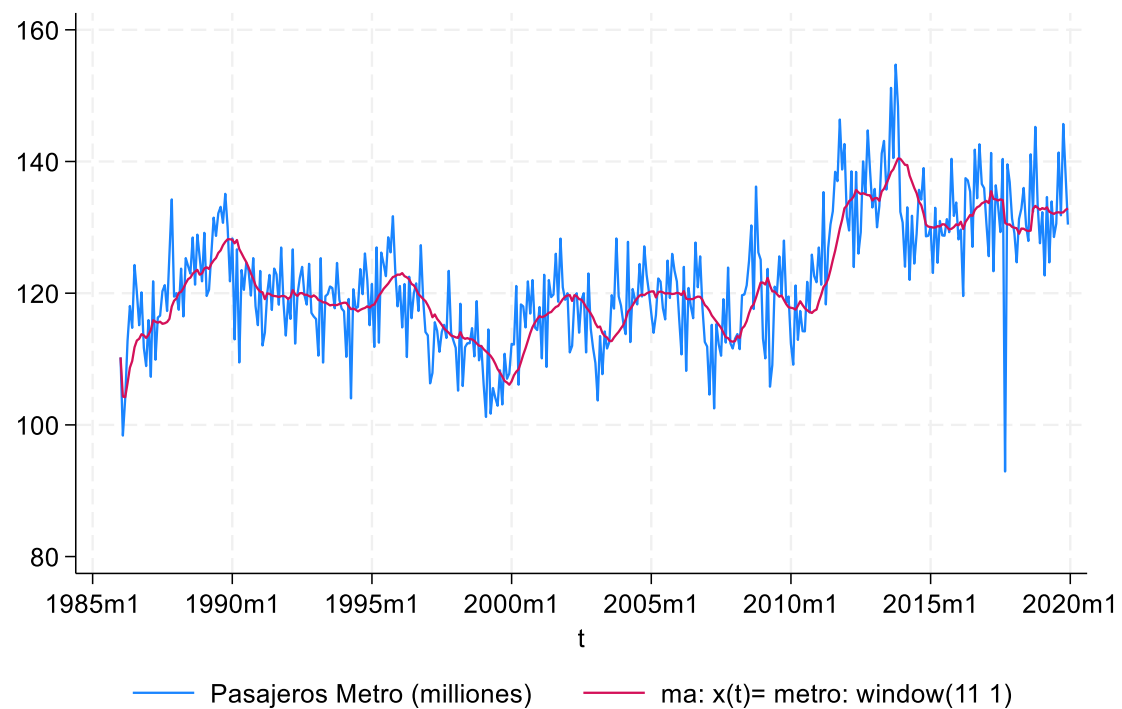
```
. tsline metro ma3_metro if tin(2004m1,  
2006m12)
```

## Metro: Suavizado de medias móviles (11 1)



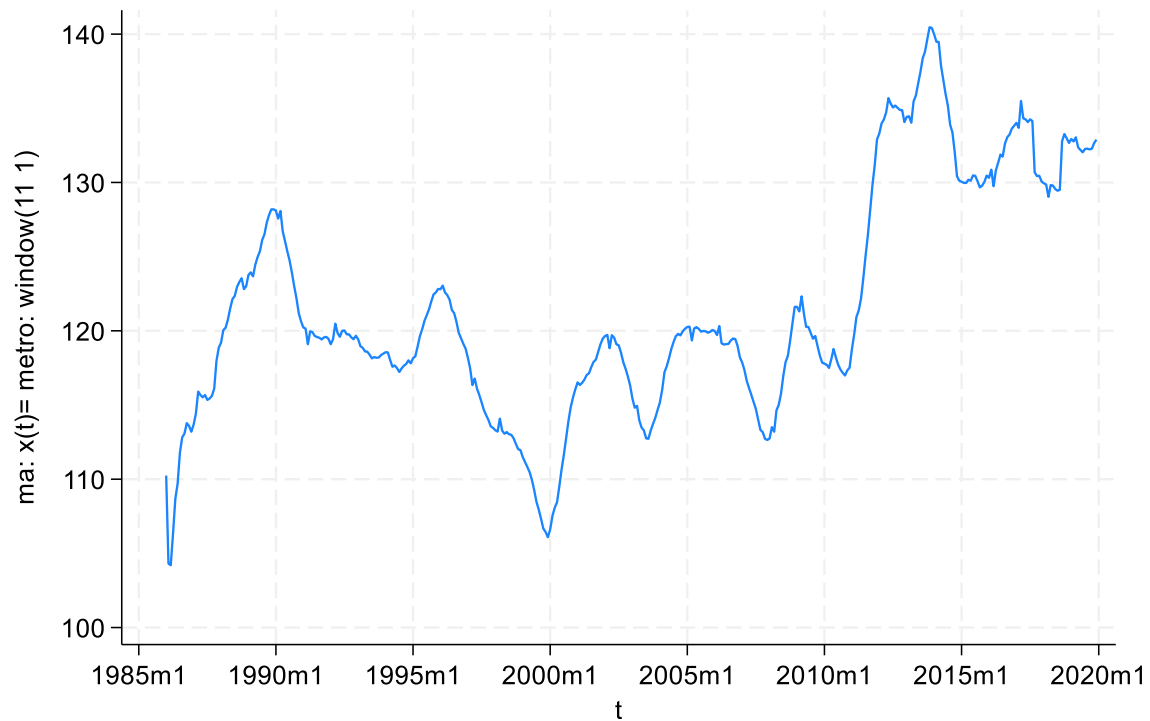
```
. tssmooth ma ma12_metro = metro,  
    window(11 1)  
  
. tsline metro ma12_metro if  
    tin(2004m1, 2006m12)
```

## Metro: Suavizado de medias móviles (11 1)



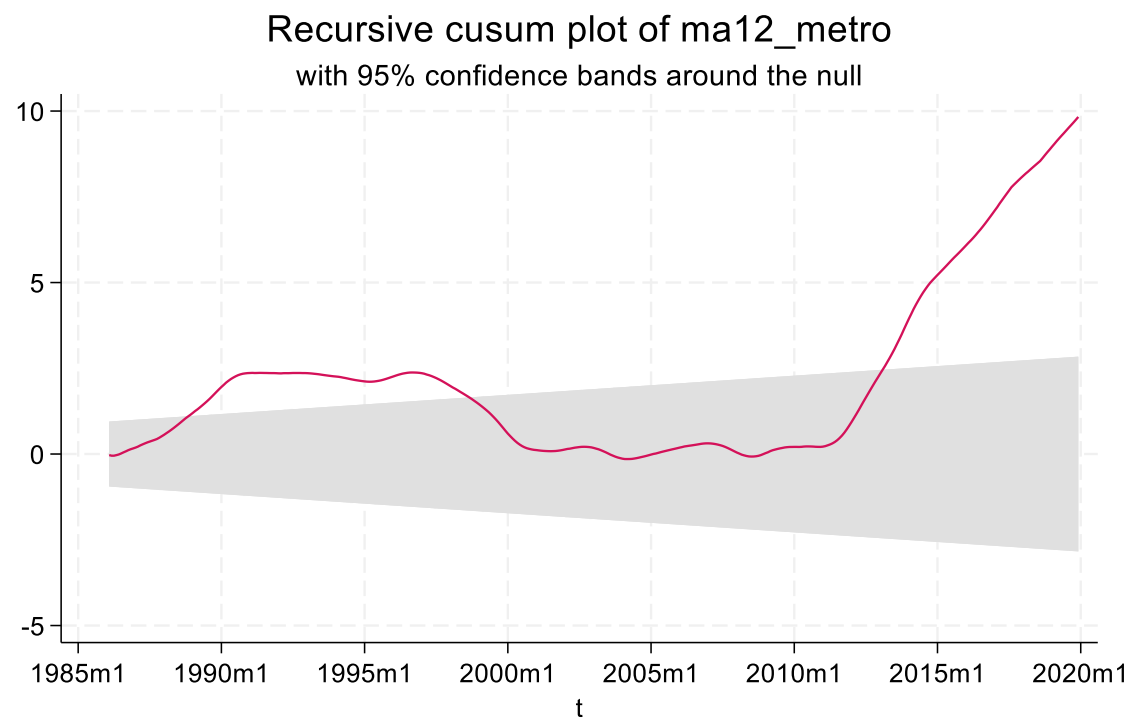
```
. tsline metro ma12_metro
```

## Metro: Suavizado de medias móviles (11 1)



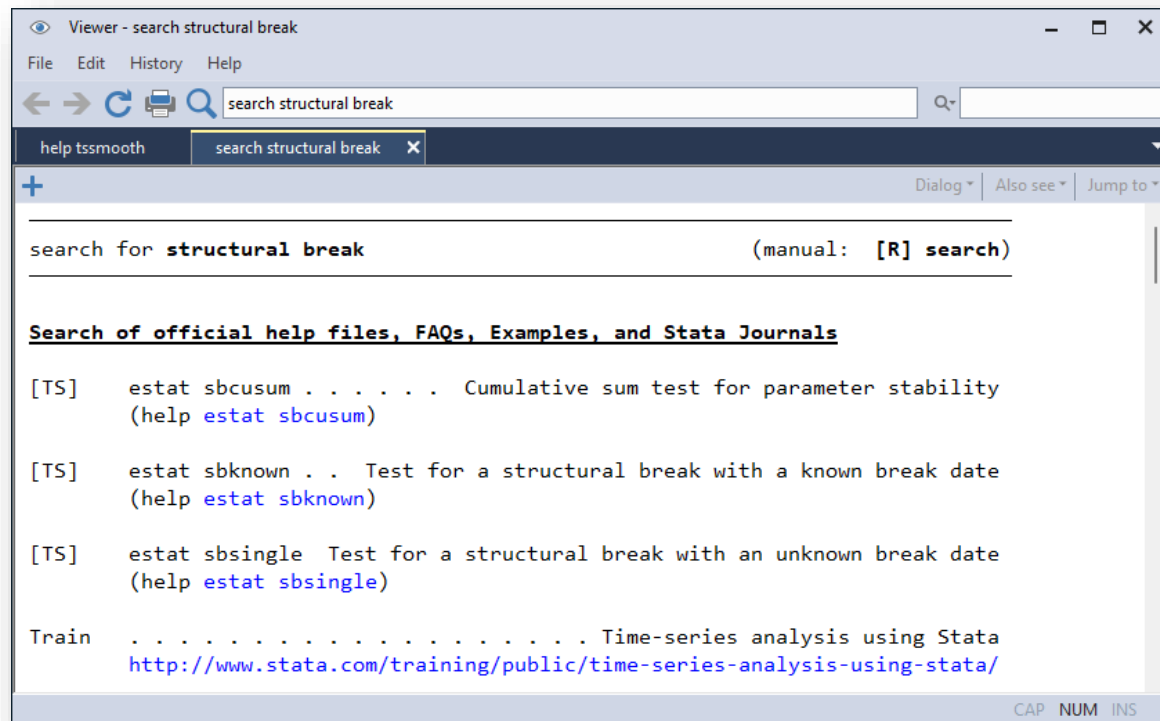
```
. tsline ma12_metro
```

## Metro: Suavizado de medias móviles (11 1)



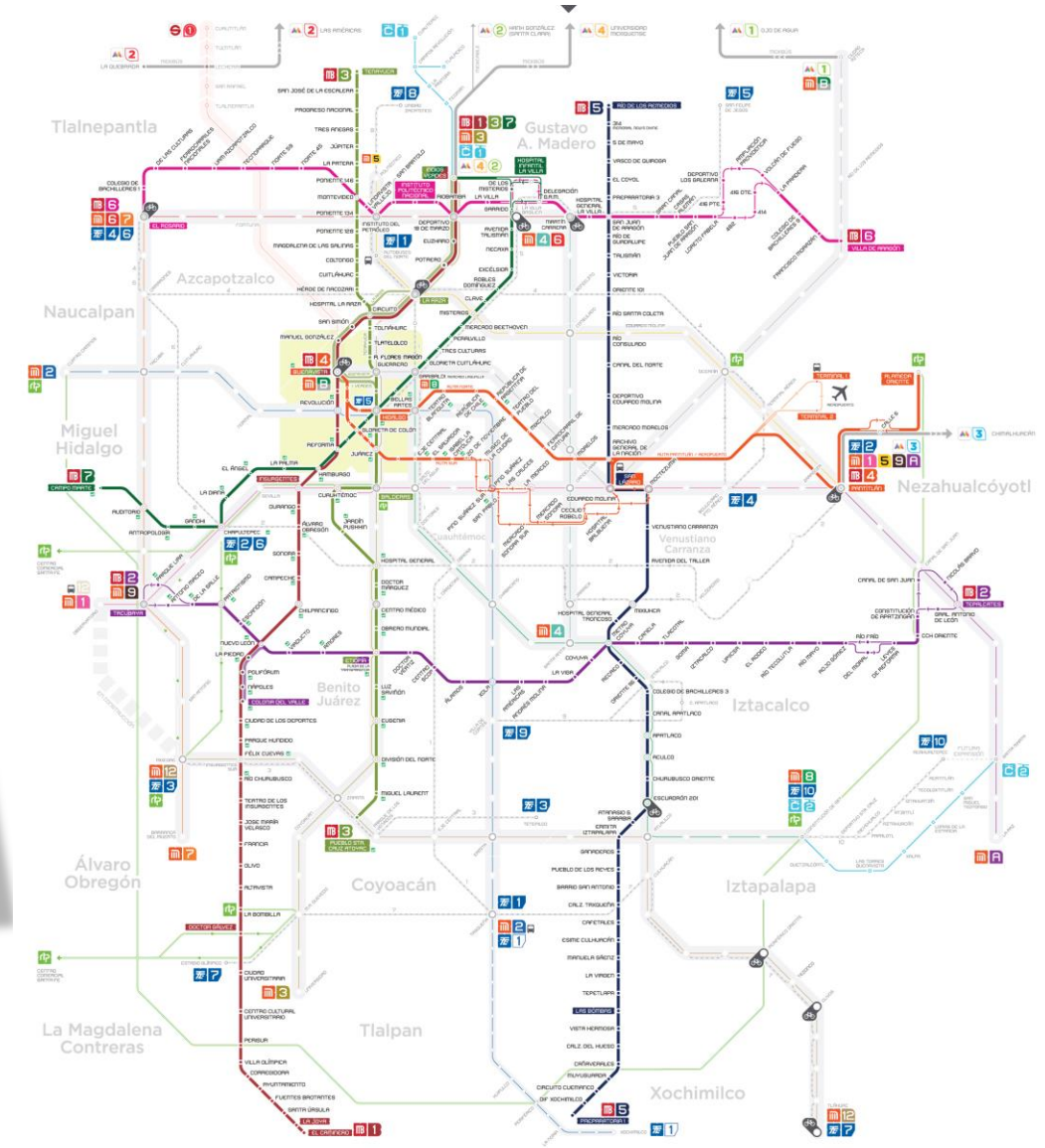
```
. regress ma12_metro  
  
. estat sbcusum
```

# Otras pruebas de cambio estructural



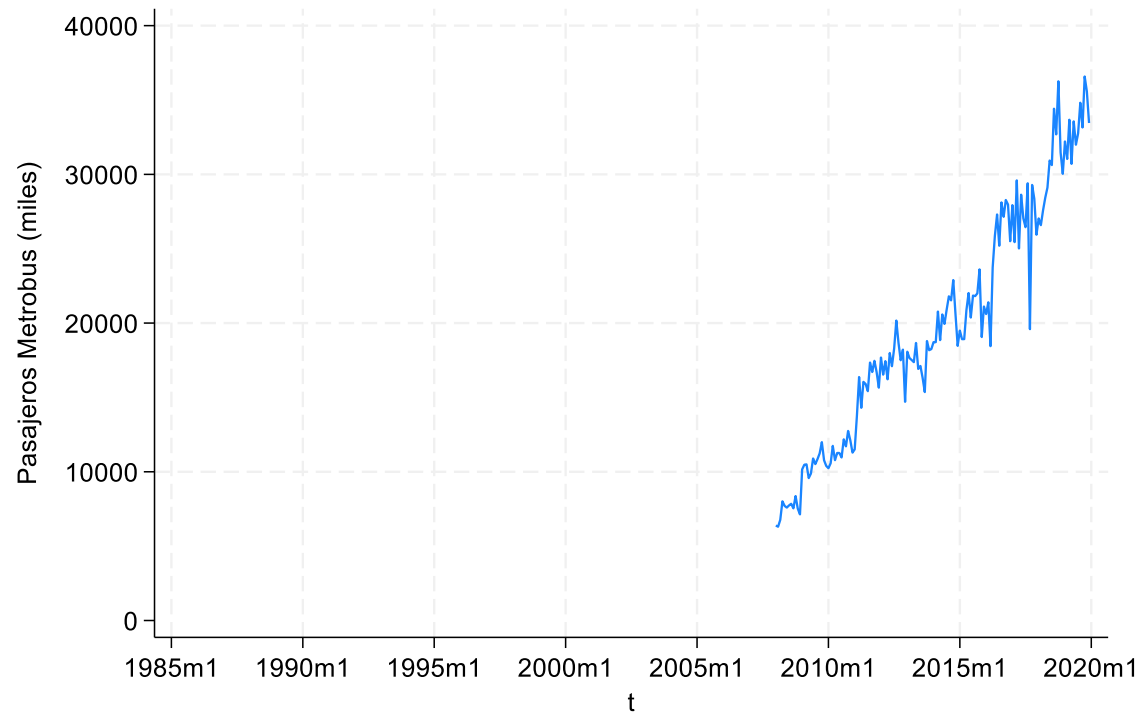
```
. search structural break
```

# Metrobús





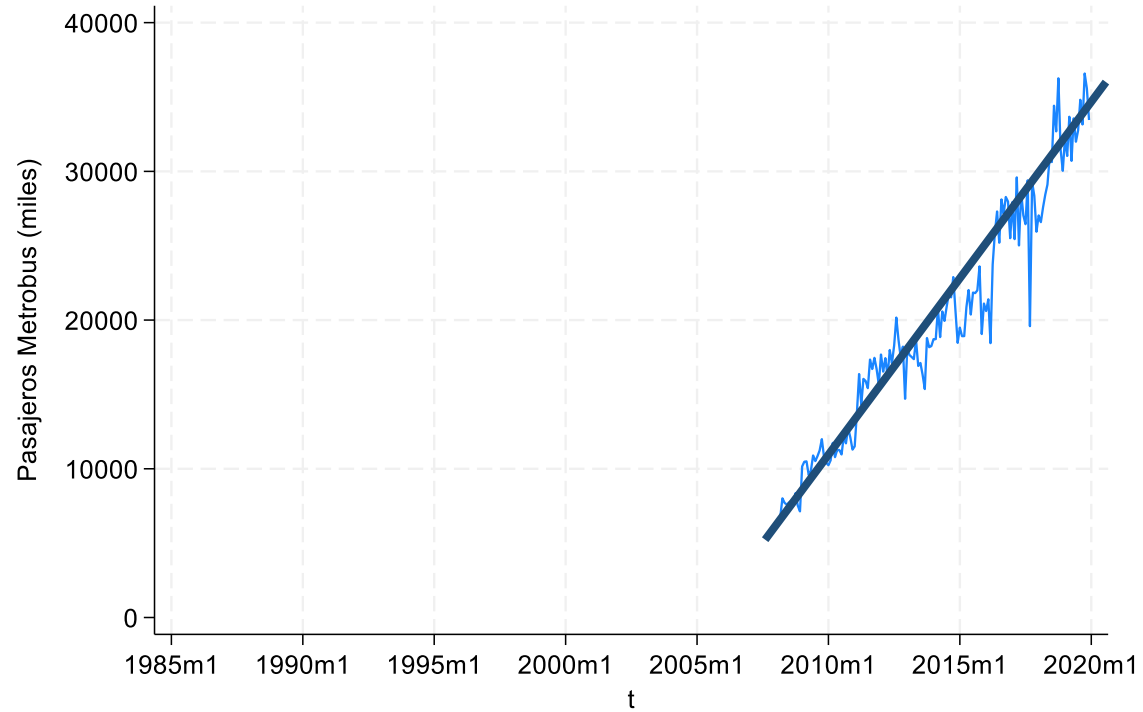
## Metrobús: Gráfico de línea



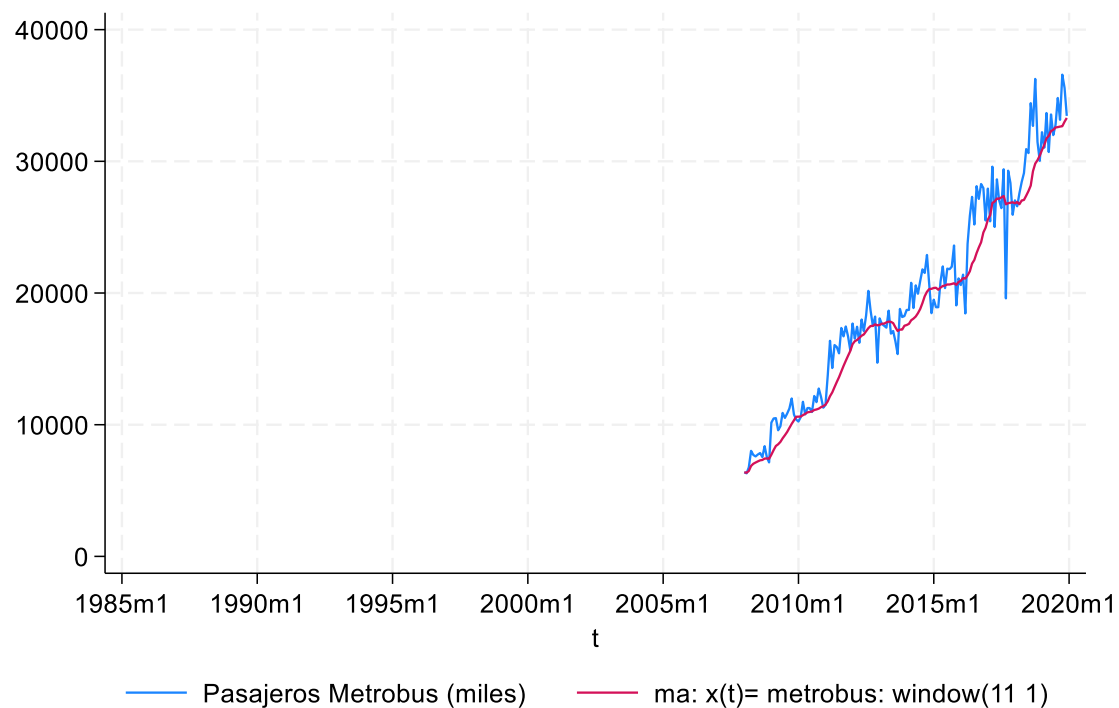
```
. tsline metrobus
```



## Metrobús: Gráfico de línea

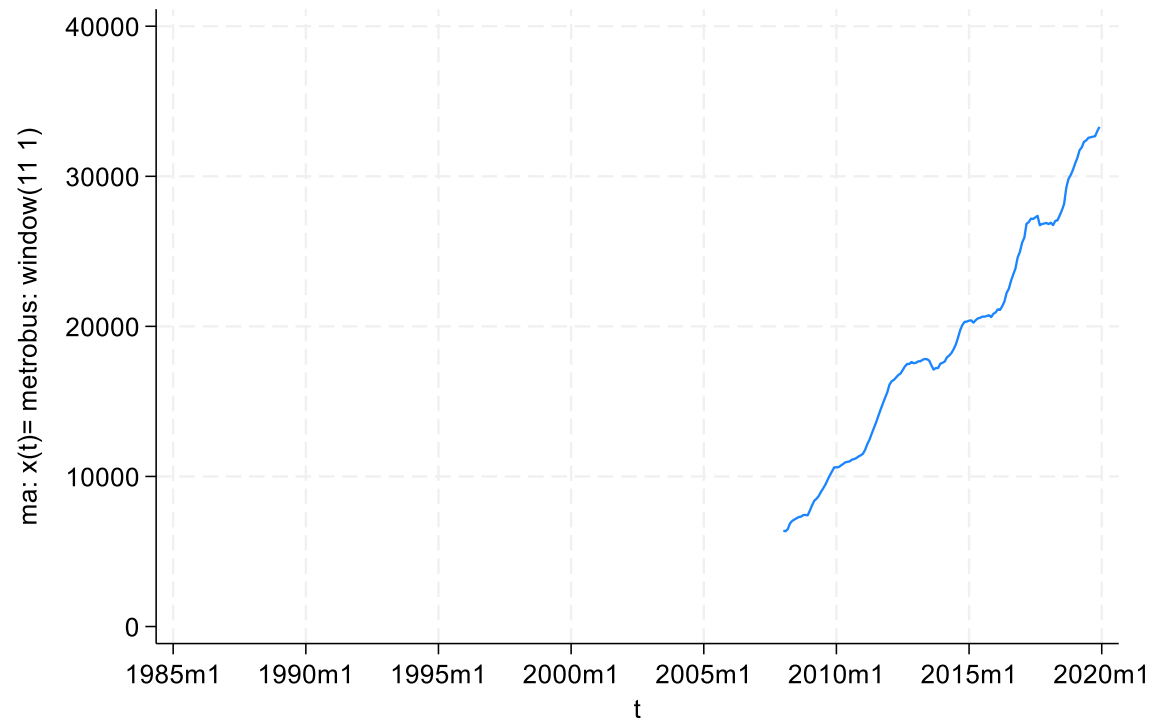


## Metrobús: suavizado ma window(11 1)



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

## Metrobús: suavizado ma window(11 1)



```
. tsline ma12_metrobus
```

# Metrobús: prueba de raíz unitaria

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

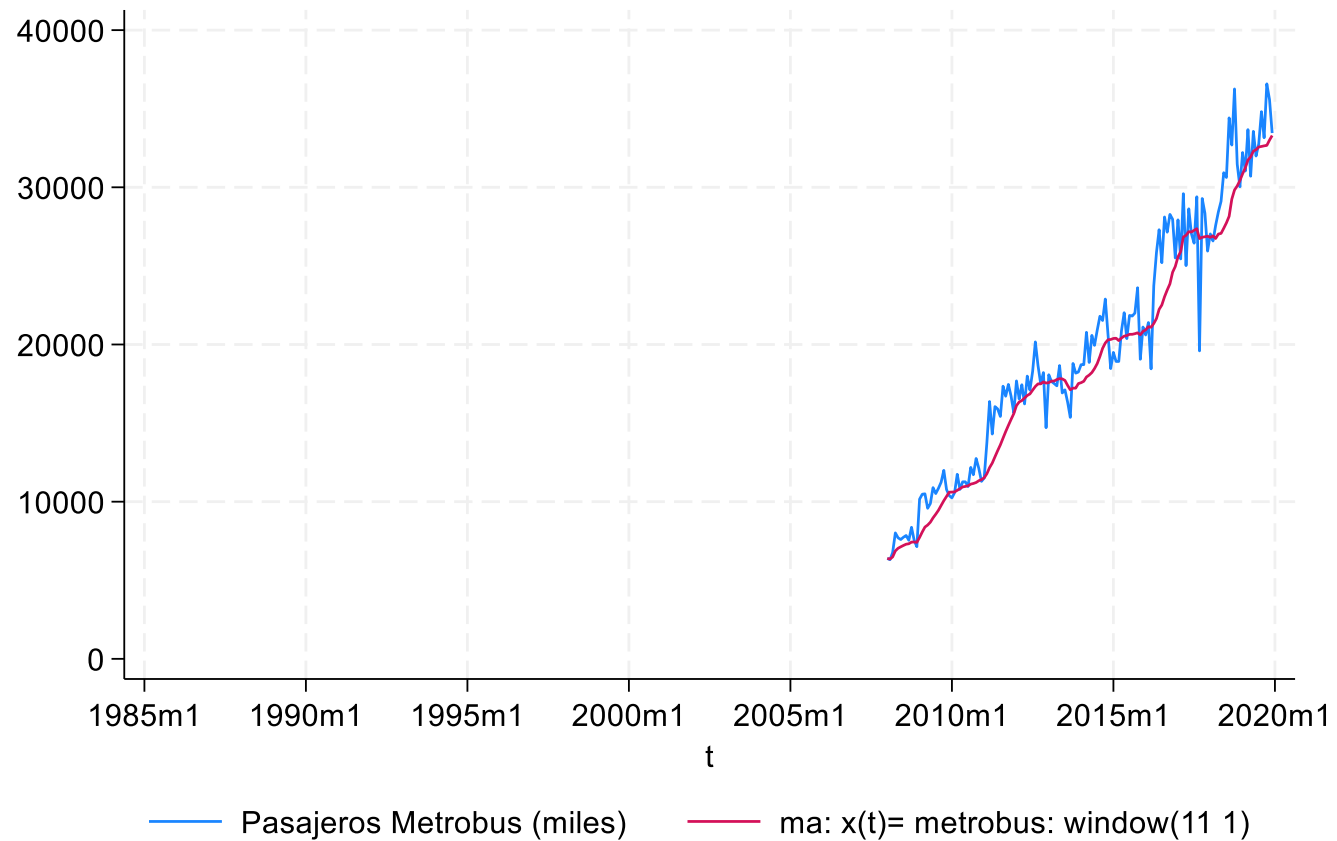
H0: Random walk without drift, d = 0

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

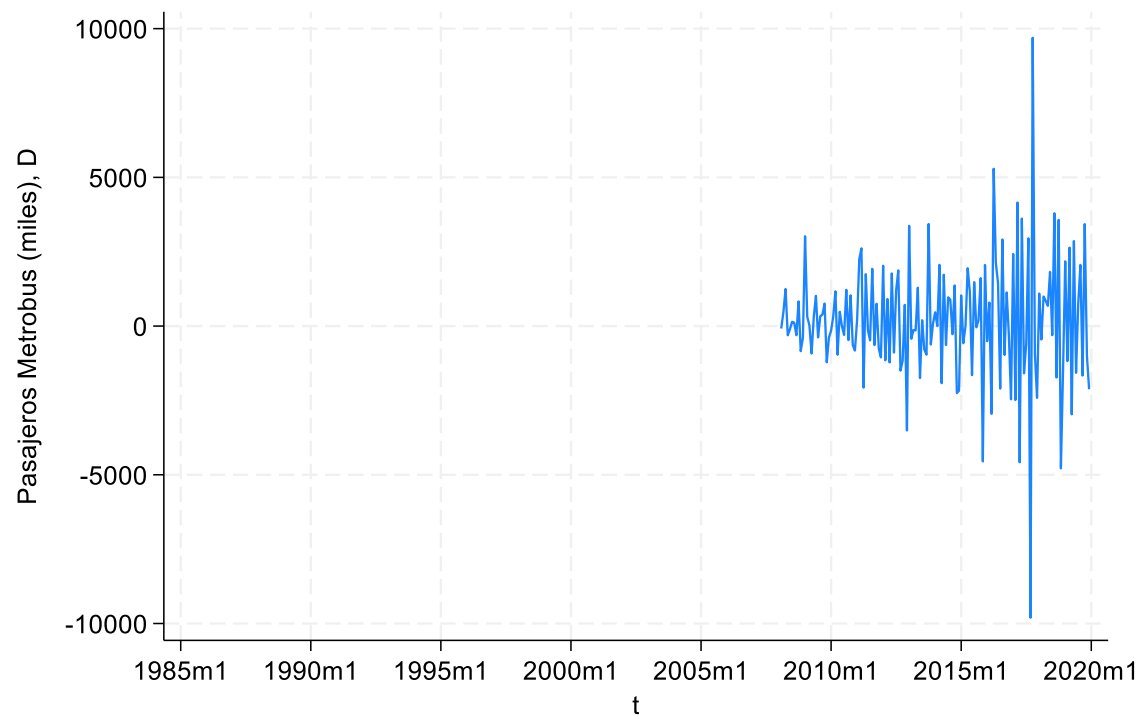
MacKinnon approximate *p*-value for Z(t) = 0.4956.

```
. dfuller metrobus
```

## Metrobús: prueba de raíz unitaria



## Metrobús: Primeras diferencias



```
. tsline D.metrobus
```

# Operadores de diferencia y rezago

## Diferencias

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

## Rezagos

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

## Adelantos

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

## Diferencias estacionales

*S4.variable*  
*S12.variable*

# Metrobús: Prueba de raíz unitaria

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
```



# Metrobús: Prueba de raíz unitaria

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

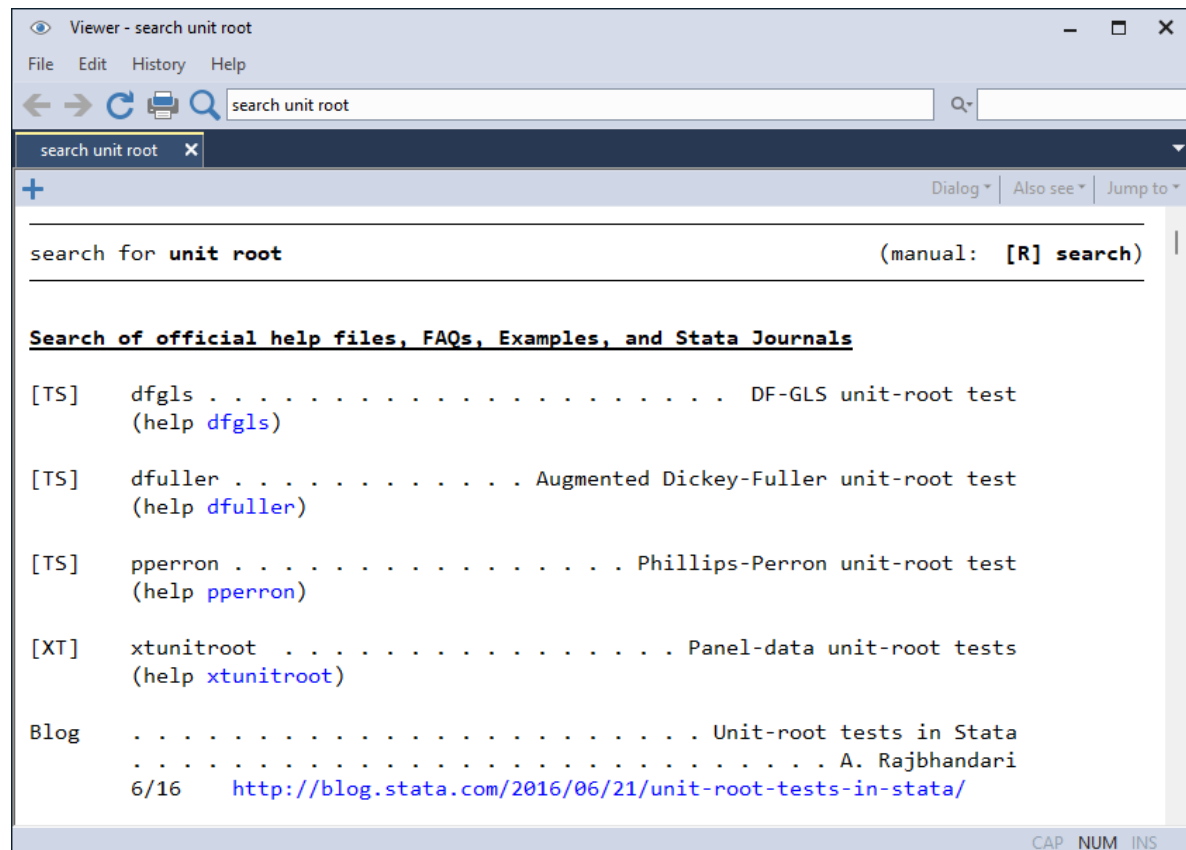
H0: Random walk without drift, d = 0

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.

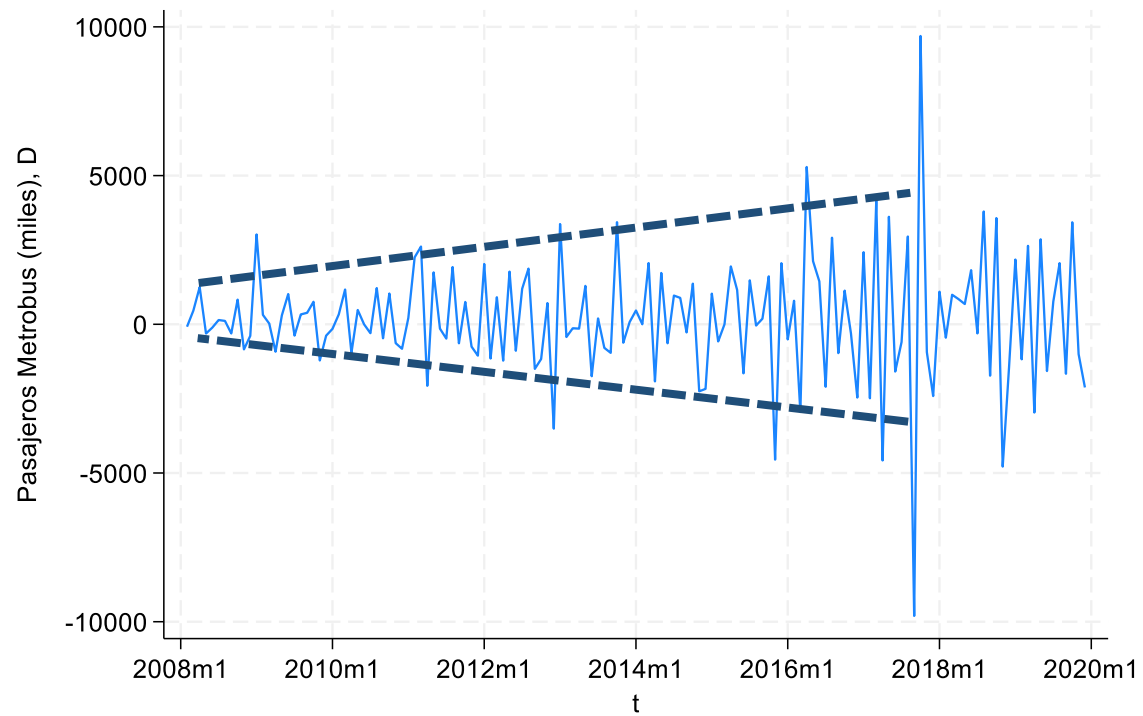
```
. dfuller D.metrobus
```

# Otras pruebas de raíz unitaria



```
. search unit root
```

## Metrobús: Varianza constante?

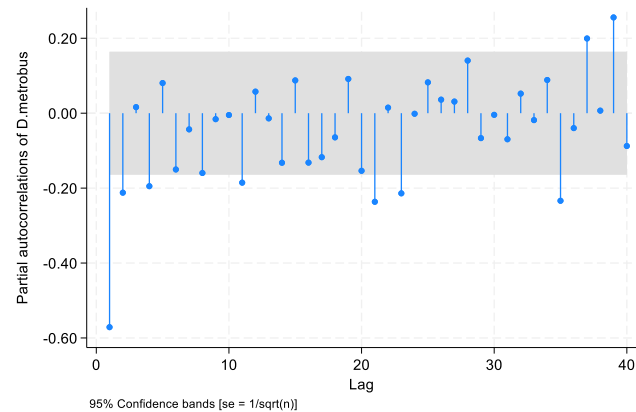
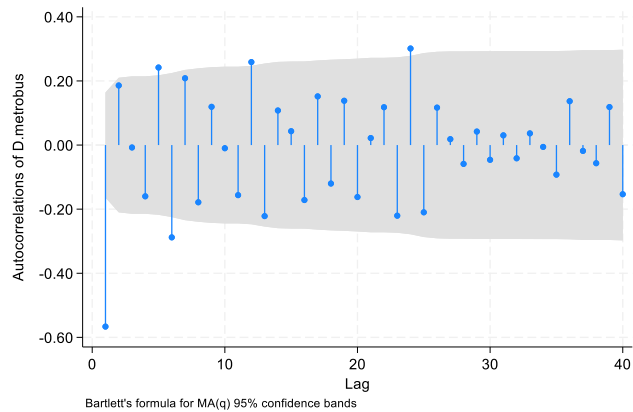


```
. tsline D.metrobus if tin(2008m1,  
2019m12)
```

## Metrobús: ARIMA

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

# Autocorrelogramas



- . ac D.metrobus
- . pac D.metrobus

# Selección de rezagos con 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
```

# Metrobús: 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					
	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
```

## Metrobús: ARCH

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

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



## Metrobús: prueba de efectos ARCH

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)
```

# Metrobús: ARMA(2,1) con errores ARCH(1)

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

		OPG		z	P> z	[95% conf. interval]	
D.metrobus		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)
```

# Metrobús: AR(2) con errores ARCH(1)

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)
```

# Metrobús: AR(1) con errores ARCH(1)

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		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
```

# Metrobús: Comparación de modelos

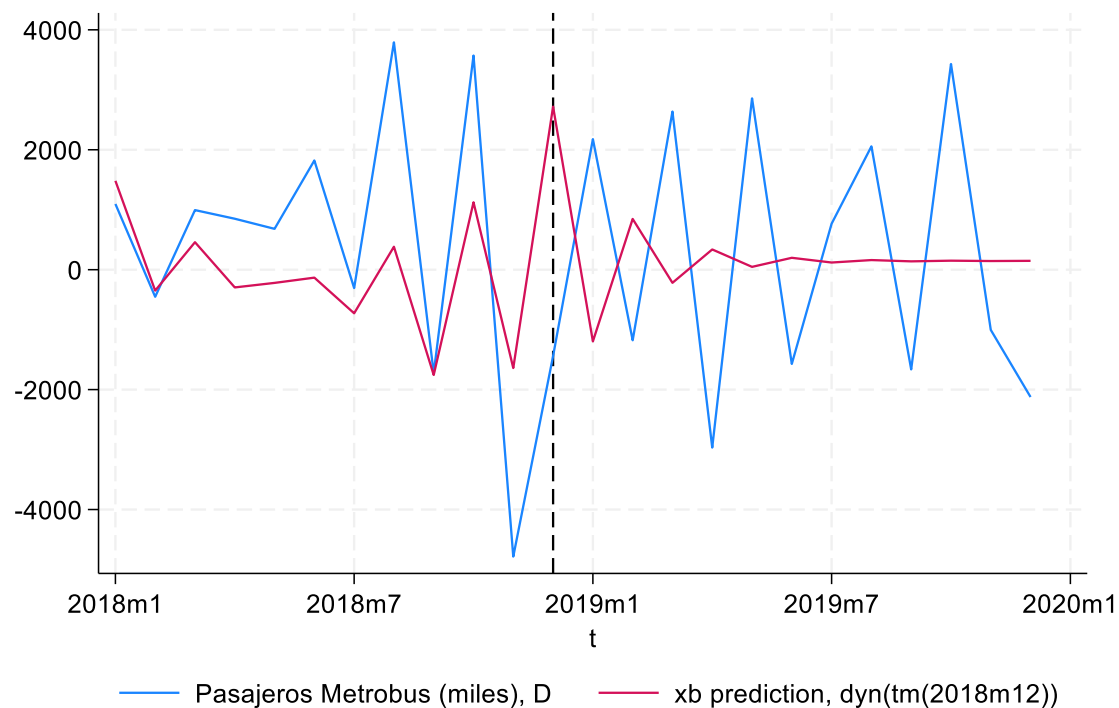
Akaike's information criterion and Bayesian information criterion

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
```

## Metrobús: Pronóstico 2019

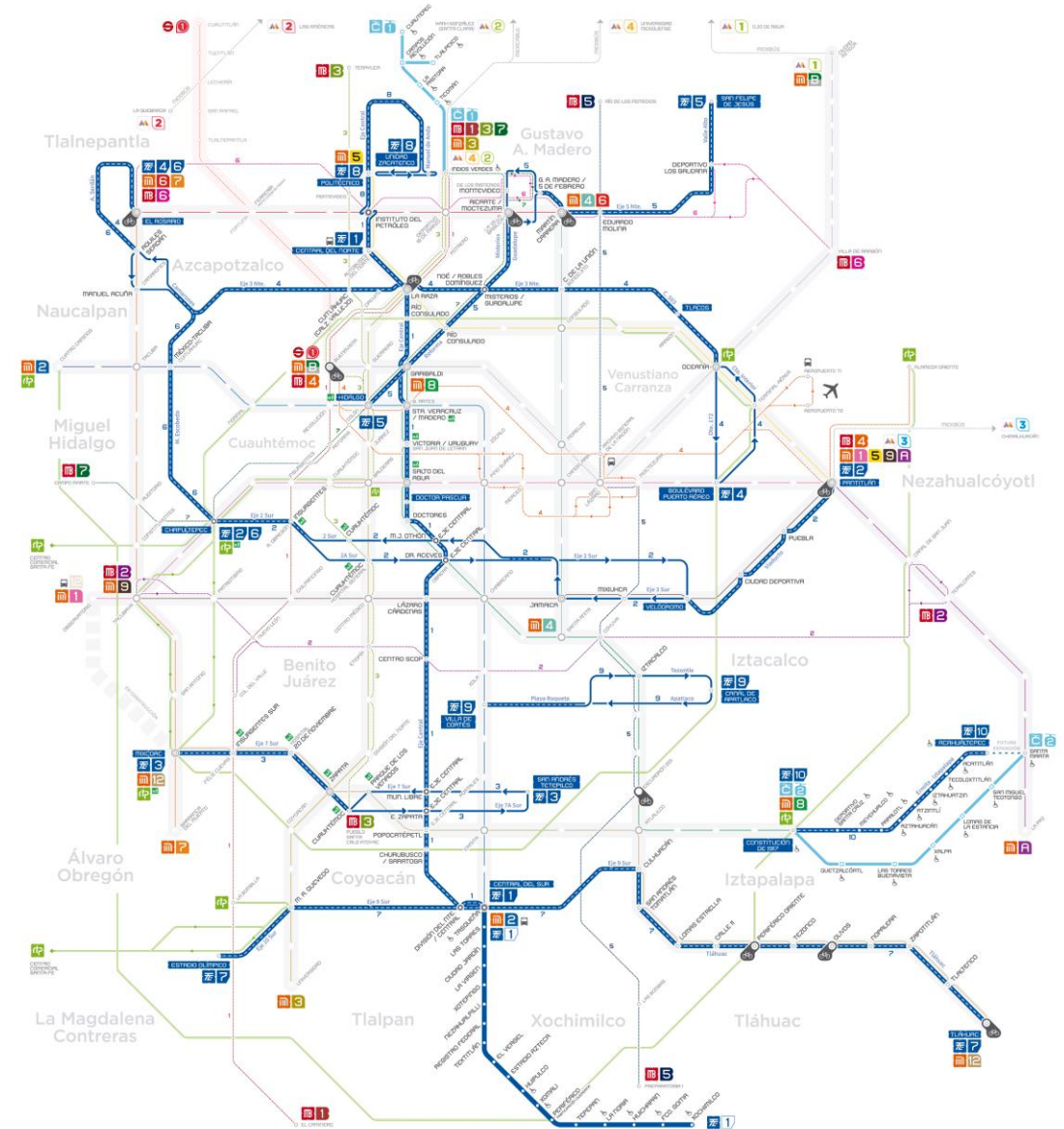


```
. arch D.metrobus if  
tin(2008m1, 2018m12), ar(1) arch(1)  
  
. predict fcst_arch1 in tin(2008m1,  
2019m12), dynamic(tm(2018m12))  
  
. tsline D.metrobus fcst_arch1  
if tin(2018m1, 2019m12),  
tline(2018m12)
```

## **Parte II. Análisis de series multivariadas**

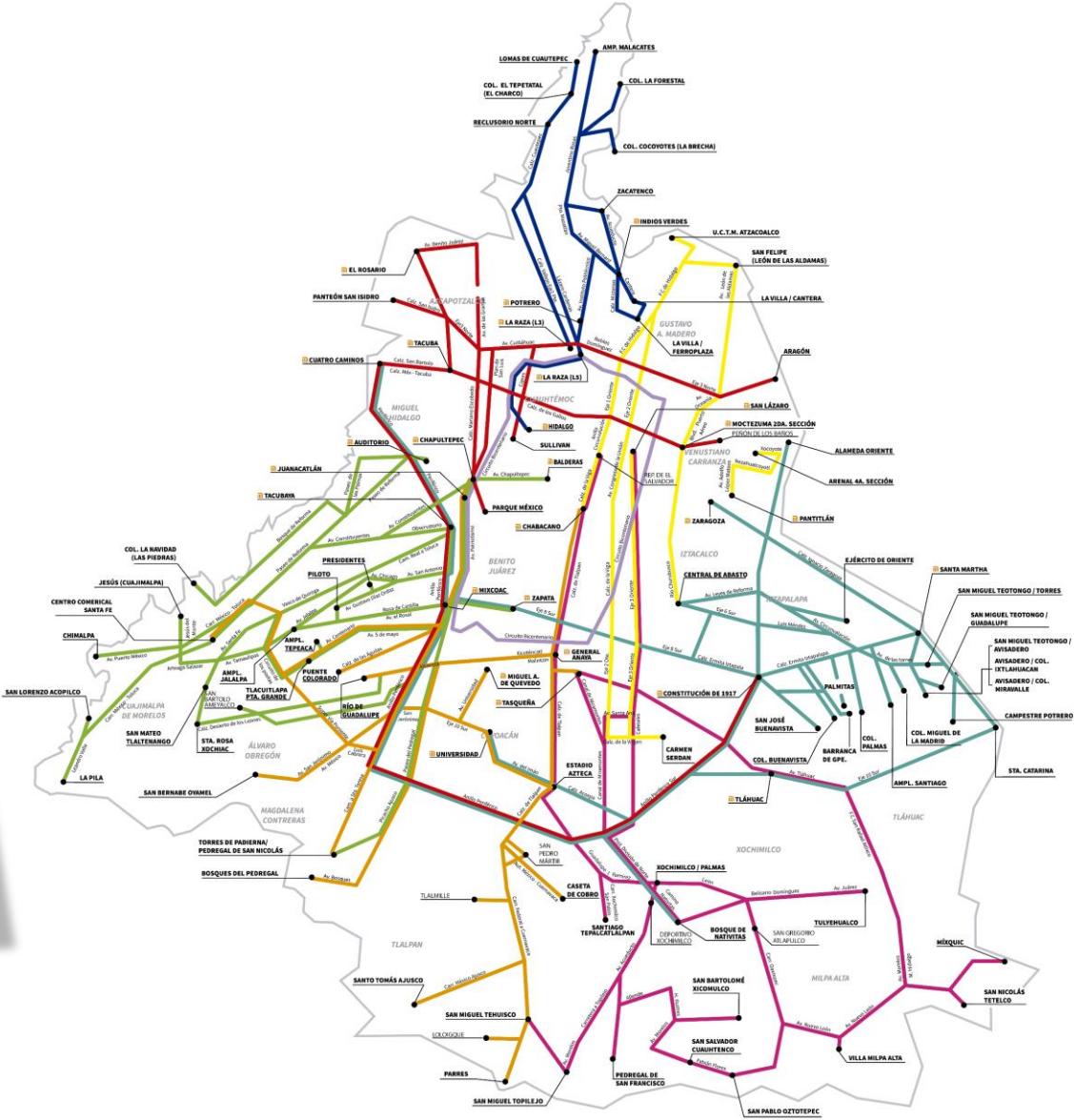


# Trolebús





RTP



# Los datos

Data Editor (Browse) - [transportep]

File Edit View Data Tools

fecha[1] 05jan2015 DMY

	fecha	d_rtp	d_trolebus	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
<input checked="" type="checkbox"/> fecha	
<input checked="" type="checkbox"/> d_rtp	Pasajeros RTP (cambio diario)
<input checked="" type="checkbox"/> d_trolebus	Pasajeros trolebús (cambio diario)
<input checked="" type="checkbox"/> d_metrobus	Pasajeros metrobús (cambio diario)
<input checked="" type="checkbox"/> d_metro	Pasajeros metro (cambio diario)
<input checked="" type="checkbox"/> cerrado_mtro	# de estaciones del metro no disponibles hoy
<input checked="" type="checkbox"/> cerrado_mbus	# de estaciones del metrobus no disponibles hoy
<input checked="" type="checkbox"/> protesta	Protesta en avenida principal

Variables Snapshots

Properties

Variables

Name	fecha
Label	
Type	float
Format	%td
Value label	
Notes	

Data

Frame	default
-------	---------

Ready Vars: 8 Order: Dataset Obs: 1,302 Filter: Off Mode: Browse CAP NUM

## Declaración de estructura temporal

```
Time variable: fecha, 05jan2015 to 31dec2019, but with gaps  
Delta: 1 day
```

```
. tsset fecha
```

## Fines de semana

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



## Paso 1: Crear calendario

```
Business calendar calendario (format %tbcalendario):
```

Purpose:

```
Range: 05jan2015 31dec2019
        20093      21914  in %td units
         0        1301  in %tbcalendario units
```

```
Center: 05jan2015
        20093      in %td units
         0        in %tbcalendario units
```

```
Omitted:    520      days
           104.2    approx. days/year
```

```
Included:   1,302    days
           261.0    approx. days/year
```

Notes:

```
Business calendar file calendario.stbcal saved.
```

```
. bcal create calendario, from(fecha)
```

## Paso 2: Cargar calendario

```
loading .\calendario.stbcal ...
```

1. \* Business calendar "calendario" created by -bcal create-
2. \* Created/replaced on 24 Sep 2024
- 3.
4. version 18.5
5. dateformat ymd
- 6.
7. range 2015jan05 2019dec31
8. centerdate 2015jan05
- 9.
10. omit dayofweek (Sa Su)

```
(calendar loaded successfully)
```

```
. bcal load calendario
```

### Paso 3: Generar variable de calendario

	fecha	d_rtp	d_trolebus	d_metrob...	d_metro	fecha2
1	05jan2015	-.0171005	-.000195	-.0013514	-.036333	0
2	06jan2015	-.0234868	-.02486	.15454	.362520	1
3	07jan2015	-.0573256	-.1347515	-.1284905	.993183	2
4	08jan2015	.1846544	.1073546	.0101083	-.381674	3
5	09jan2015	.1332417	-.0303602	.0055859	.208687	4
6	12jan2015	.0599145	.0428238	-.1342604	.717088	5
7	13jan2015	.114902	.1268956	.1558118	-.107241	6
8	14jan2015	.0696713	.0355576	.0401537	-.500008	7
9	15jan2015	-.1307284	-.0612663	-.1287204	.343462	8
10	16jan2015	-.0486425	-.0000602	-.1231952	-.442877	9
11	19jan2015	.0010848	-.0909132	-.0246318	-.154722	10
12	20jan2015	-.105676	-.0431311	-.0981248	.238571	11
13	21jan2015	-.0326804	-.0105127	-.1483197	.218513	12
14	22jan2015	.0236691	.0028431	-.0146791	.239146	13

```
. generate fecha2 = bofd("calendario",  
fecha)
```

## Paso 4: Dar formato a la variable calendario

	fecha	d_rtp	d_trolebus	d_metrob...	d_metro	fecha2
1	05jan2015	-.0171005	-.000195	-.0013514	-.0363334	05jan2015
2	06jan2015	-.0234868	-.02486	.15454	.3625208	06jan2015
3	07jan2015	-.0573256	-.1347515	-.1284905	.993183	07jan2015
4	08jan2015	.1846544	.1073546	.0101083	-.3816748	08jan2015
5	09jan2015	.1332417	-.0303602	.0055859	.2086876	09jan2015
6	12jan2015	.0599145	.0428238	-.1342604	.7170889	12jan2015
7	13jan2015	.114902	.1268956	.1558118	-.1072412	13jan2015
8	14jan2015	.0696713	.0355576	.0401537	-.5000088	14jan2015
9	15jan2015	-.1307284	-.0612663	-.1287204	.3434627	15jan2015
10	16jan2015	-.0486425	-.0000602	-.1231952	-.4428777	16jan2015
11	19jan2015	.0010848	-.0909132	-.0246318	-.1547228	19jan2015
12	20jan2015	-.105676	-.0431311	-.0981248	.2385716	20jan2015
13	21jan2015	-.0326804	-.0105127	-.1483197	.2185136	21jan2015
14	22jan2015	.0236691	.0028431	-.0146791	.2391467	22jan2015

```
. format %tbcalendario fecha2
```



## Declaración de estructura temporal

```
Time variable: fecha2, 05jan2015 to 31dec2019  
Delta: 1 day
```

```
. tsset bcaldate
```

## Intuición de vectores autorregresivos

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

## Intuición VAR: Efectos contemporáneos

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

## Intuición VAR: Efectos contemporáneos

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

## Intuición VAR: Efectos contemporáneos

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

- Si no viajo por un medio de transporte hoy, puede ser que esté usando otro para llegar a mi destino.

## Intuición VAR: Efectos rezagados

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

## Intuición VAR: Efectos rezagados

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

- Autocorrelación negativa?  
Probablemente no. La gente no trabaja/estudia sólo cada otro día.
- Autocorrelación positiva? Tal vez, porque los días con cambios por encima de la media tienden a estar acompañados de otros días con cambios por encima de la media. Igual los días con cambios inferiores a la media.

## Intuición VAR: Innovaciones

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



## Intuición VAR: Innovaciones

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

## Repaso de teoría VAR: El modelo estructural

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

## Repaso VAR: Modelo estructural a modelo reducido

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

!!!
!!!

## Repaso VAR: Modelo estructural a modelo reducido

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



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

## Repaso VAR: Modelo estructural a modelo reducido

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

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



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

$A$ 
 $y_t$ 
 $A_1$ 
 $y_{t-1}$ 
 $B$ 
 $\epsilon_t$

## Repaso VAR: Modelo estructural a modelo reducido

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

## Repaso VAR: Modelo estructural a modelo reducido

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

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

## Repaso VAR: Modelo estructural a modelo reducido

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

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

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



# VAR: Selección de rezagos

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\_trolebus d\_rtp

Exogenous: \_cons

```
. varsoc d_metro d_metrobus d_trolebus  
d_rtp
```

# VAR: Resultados

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_trolebus	9	.048777	0.5858	1838.351	0.0000
d_rtp	9	.044688	0.6664	2597.259	0.0000

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

## VAR: Resultados

	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_trolebus						
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: Resultados

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_trolebus						
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	-.0100681	.0025546	-3.94	0.000	-.015075	-.0050612

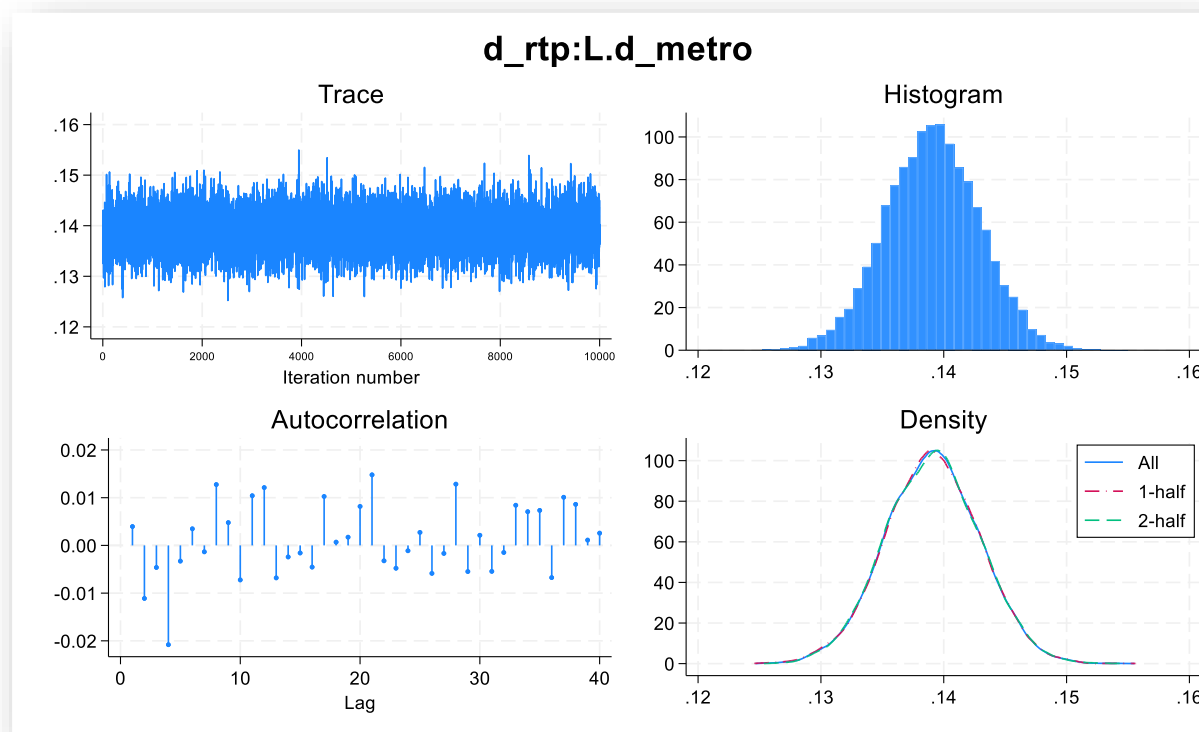
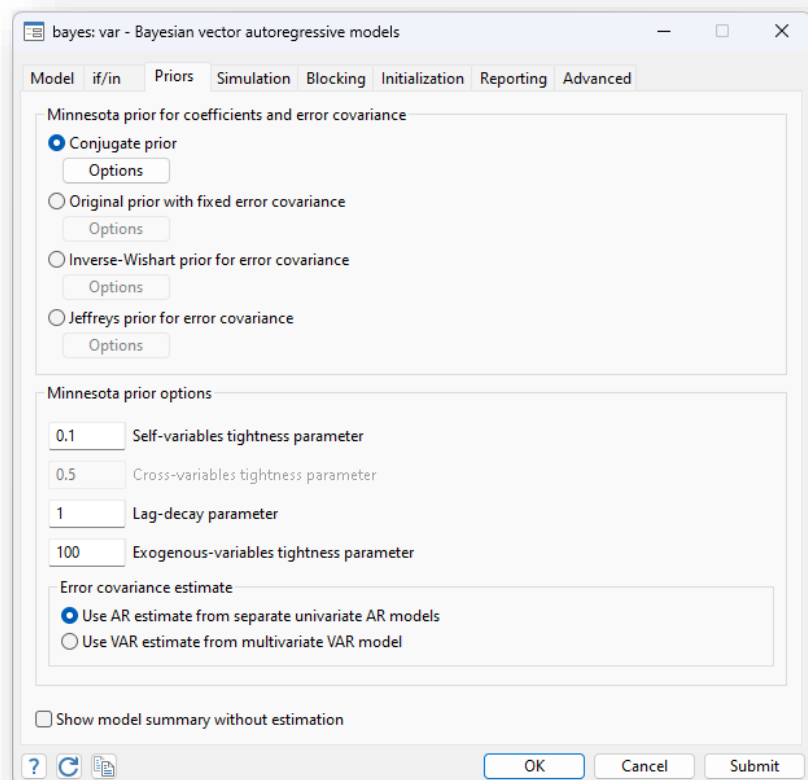
## VAR: Resultados

d_trolebus						
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_trolebus						
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: Resultados

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_trolebus						
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

# El prefijo bayes



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

## Vectores autorregresivos estructurales (SVAR)

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

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

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



# 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: Identificación

Información que tenemos

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

10 covarianzas

Información que queremos

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

28 parámetros

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

# SVAR: Descomposición de Cholesky

Información que tenemos

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

10 covarianzas

Información que queremos

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

10 parámetros

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

## SVAR: El orden con Cholesky

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

# SVAR: Otras estrategias de identificación

The image displays three overlapping screenshots from Stata documentation, illustrating different identification strategies for SVAR models.

**Left Screenshot: 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, zero can be interpreted as setting the long-run response of variable 1 to variable 2 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

**Middle Screenshot: var ivsvar**

**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 options  
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. Impulse-response functions (IRFs). 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 `y1`, `y2`, and `y3`, 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 `x1` and `x2`

**Right Screenshot: Viewer - 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: Estimación

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, .)
```

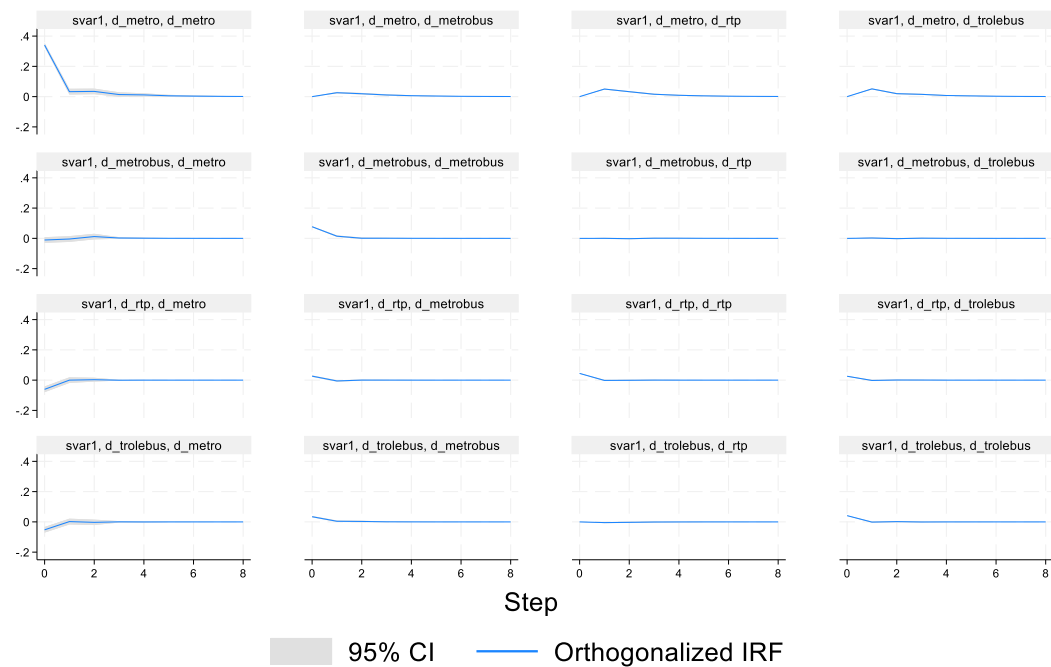
```
. svar d_rtp d_trolebus d_metrobus
    d_metro, aeq(A) beq(B) lags(1 2)
```

## Funciones de impulso-respuesta

```
. 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
```

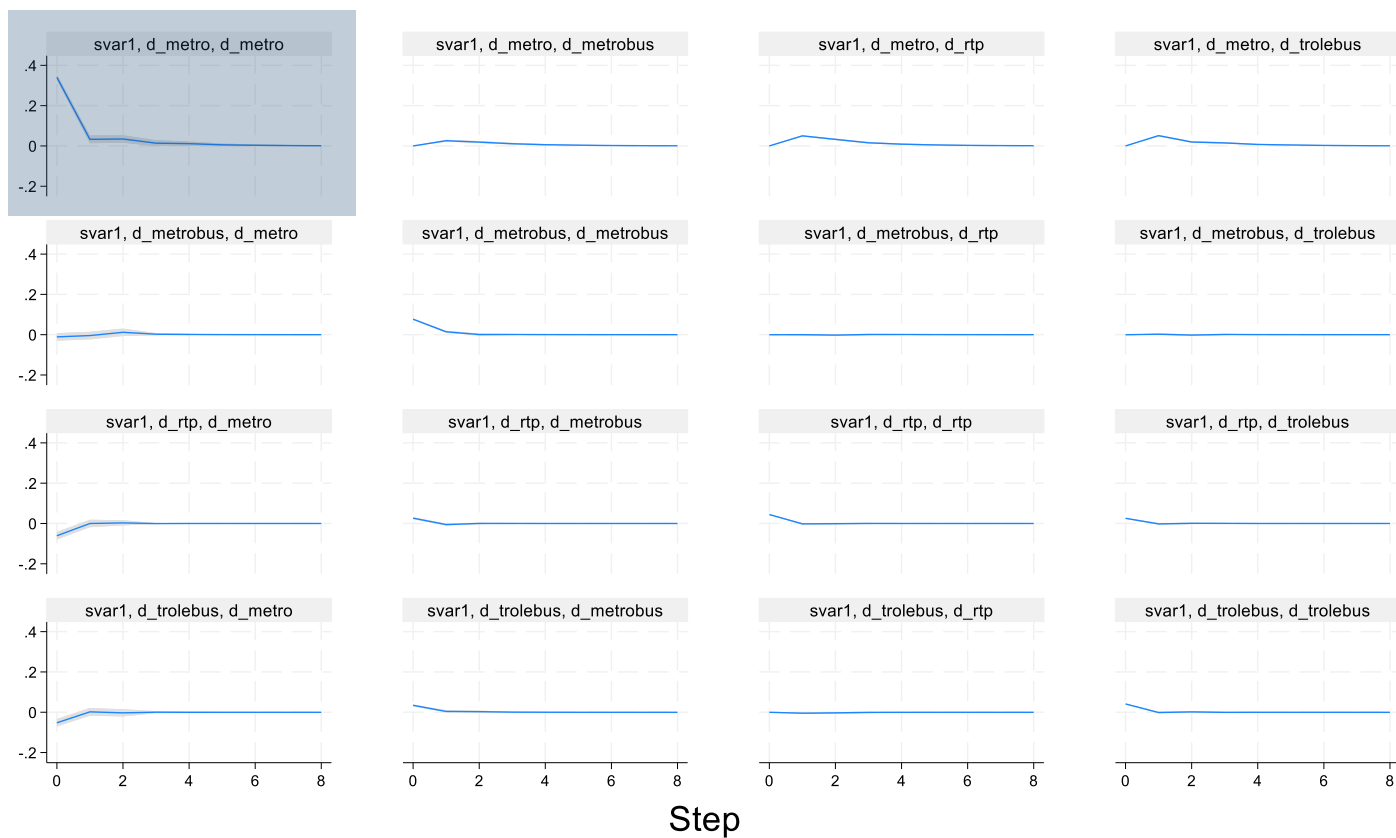
# Gráficos de impulso-respuesta



Graphs by irfname, impulse variable, and response variable

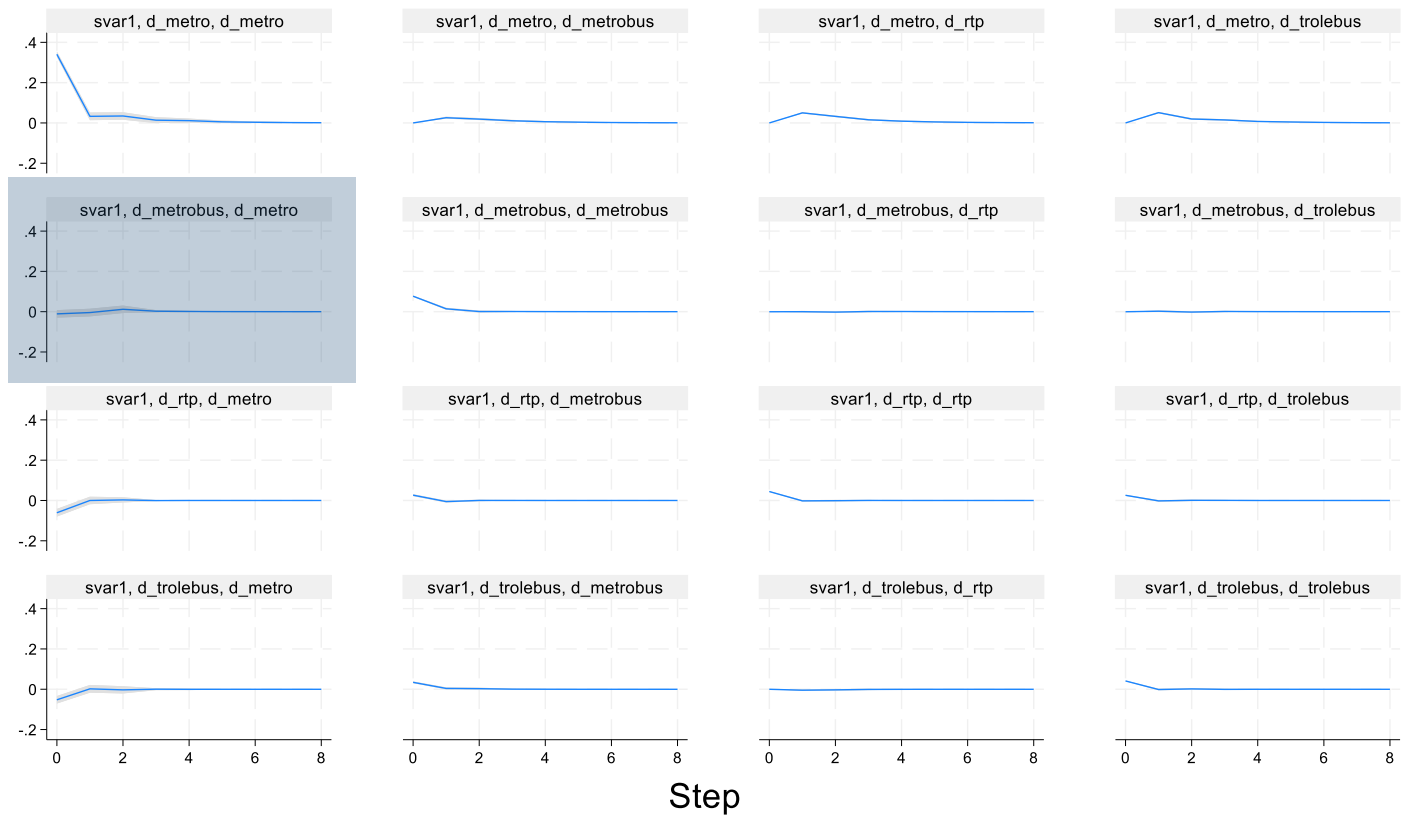
```
. irf graph oirf
```





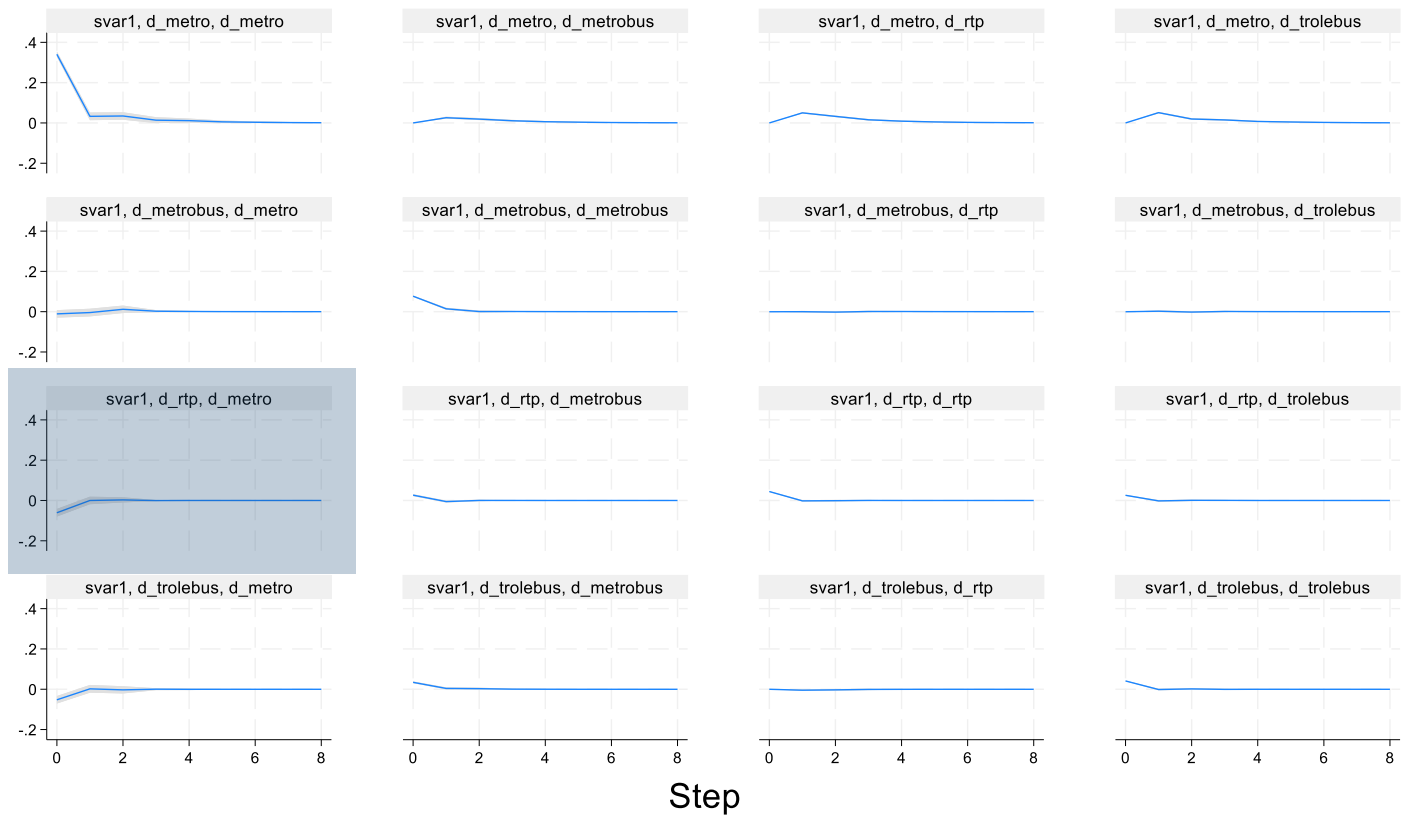
95% CI — Orthogonalized IRF

Graphs by irfname, impulse variable, and response variable



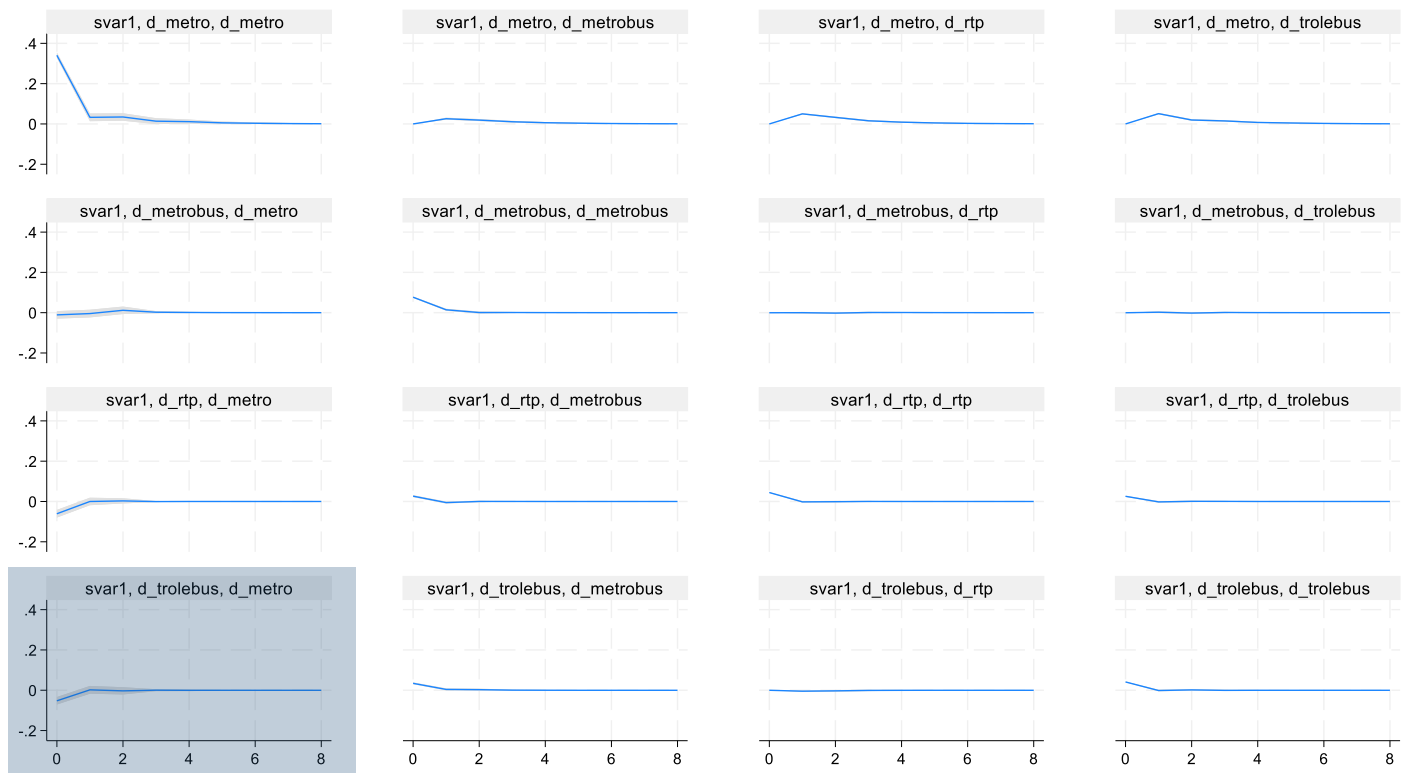
95% CI — Orthogonalized IRF

Graphs by irfname, impulse variable, and response variable



95% CI — Orthogonalized IRF

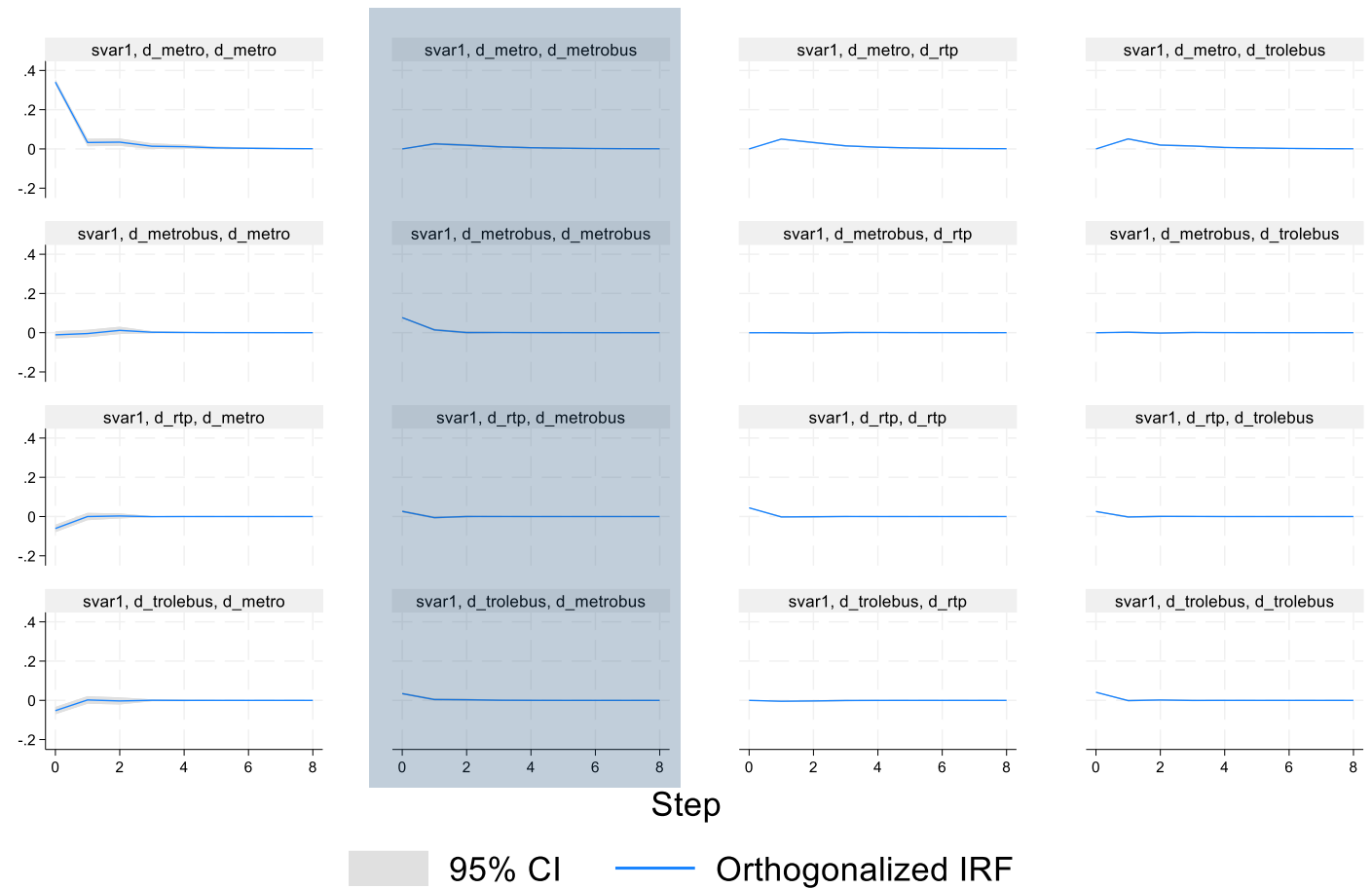
Graphs by irfname, impulse variable, and response variable



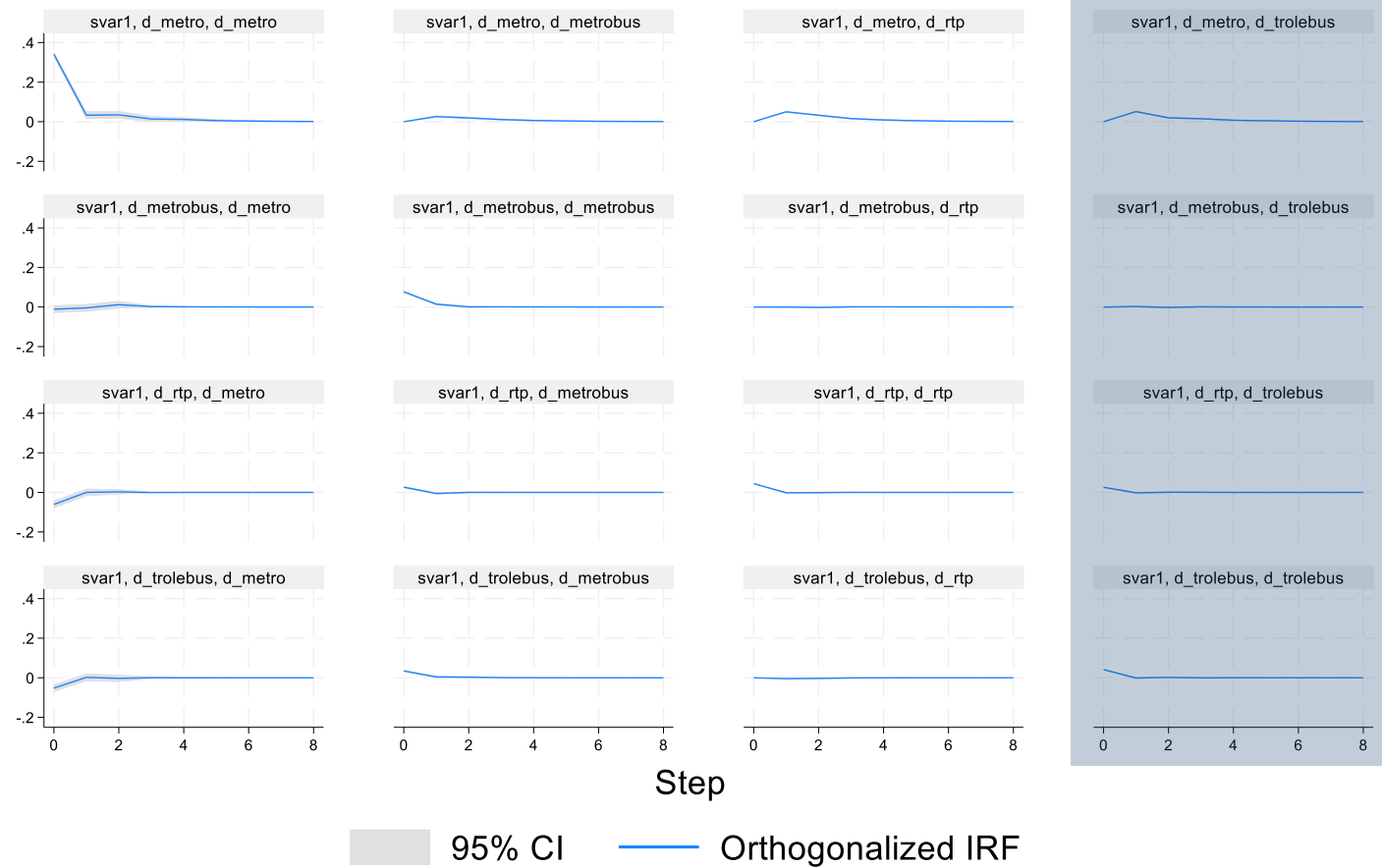
Step

95% CI Orthogonalized IRF

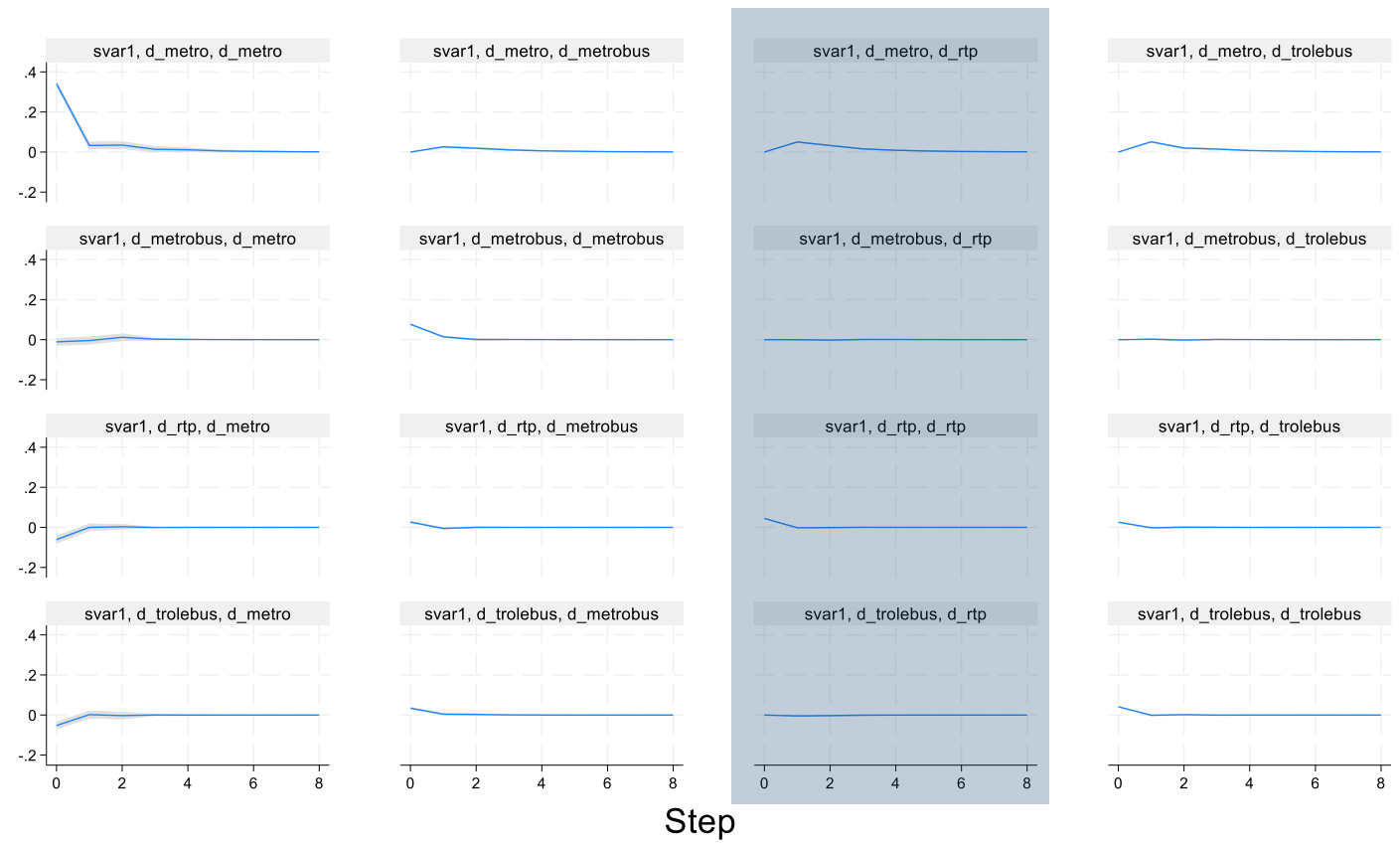
Graphs by irfname, impulse variable, and response variable



Graphs by irfname, impulse variable, and response variable



Graphs by irfname, impulse variable, and response variable



95% CI    Orthogonalized IRF

Graphs by irfname, impulse variable, and response variable



**Gracias por acompañarnos!**

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