Report on panel model results

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Abstract

These note is to relate several models that can use panel data.

The objective of these note is to give a broad overview of the possible models that can use panel data. There are several usual features to consider in a model with panel data, for example, changes on parameters for time or individual. Also, specification on error term is relevant for interpretation.

The note is based on Hsiao (2014). It goes from the theory in the text, to the application.

1 Data plots

Here is a summary of the data available for the analysis.

Figure 1 presents the initial data points, these are used for the analysis.

I made a decision on which brands to include based on the number of observations on the period previous to the tax implementation, the tax started in january 2021, I made an exploratory analysis on the december 2020 data. This would ease the inclusion of brand explicitly in the analysis, brands with few observations, with difficulties to calculate most estimates could be analyzed after applying some criteria to make groups of brands out of the individual ones.

Figure 2 only considers the 7 most frequent brands. The graph provides some guidance on what to consider for the proposed descriptive model. In particular, there is clear trend over time and there are price adjustments in january.

Except for prices of other products, there are no other potential regressors to consider at the same level of the data.

2 Dummies for each level: city, brand, time

Estimations using areg, fixed effects are imposed. Using this method there is one category with parameters "absorbed", which are not estimated as a result of the procedure.

Specification with indicators for city, brand and trend for time. Same tax effect on all the brands.

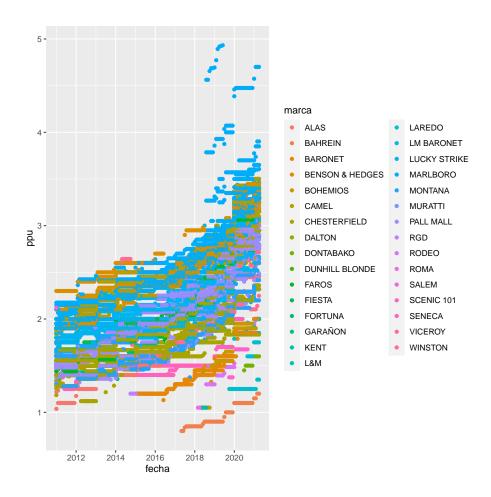


Figure 1: All brands average price per unit

Precios promedio por unidad

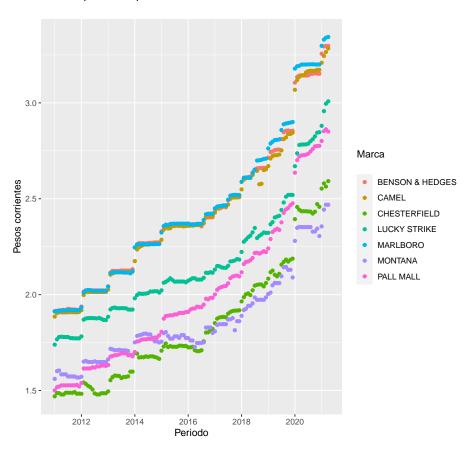


Figure 2: Seven brands average price per unit

$$y_{ctm} = \alpha_i^* + \gamma_m^* + \lambda * t + \beta_0' jan + \beta_1' tax 2020 + \beta_1' tax 2021 + u_{ctm}; \qquad (2.1)$$

$$c = 1, \dots, N; t = 1, \dots, T; m = 1, \dots, M.$$

Specification with indicators for city, brand and trend for time. Effect interacted for each brand.

$$y_{ctm} = \alpha_{i}^{*} + \gamma_{m}^{*} + \lambda * t + \beta_{0}^{'} jan + \beta_{1m}^{'} tax 2020 + \beta_{2m}^{'} tax 2021 + u_{itm}; \quad (2.2)$$

$$c=1,\dots,N; t=1,\dots,T; m=1,\dots,M.$$

Results with data for the 7 brands:

VARIABLES ppu ppu ppu 2.marca -0.012**** -0.011**** -0.006*** -0.006** (0.003) (0.003) (0.003) (0.003) 3.marca -0.595*** -0.592**** -0.591*** (0.004) (0.004) (0.003) (0.003) 4.marca -0.270*** -0.268*** -0.268** -0.268** 6.marca -0.51*** 0.010*** 0.011*** 0.010** 6.marca -0.524*** -0.521*** -0.521*** -0.521** 6.marca -0.435*** -0.435*** -0.411*** -0.401** 7.marca -0.435*** -0.435*** -0.411*** -0.410** 1.m1.20 (0.003) (0.002) (0.002) 1.m1.20#2.marca -0.007 -0.012 (0.024) 1.m1.20#3.marca -0.111** -0.112** 1.m1.20#4.marca -0.147*** -0.112** 1.m1.20#6.marca -0.052 (0.031) 1.m1.20#6.marca -0.023** -0.230***		(1)	(2)	(3)	(4)
3.marca	VARIABLES		` '		
3.marca	0				0.000**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	2.marca				
4.marca	3 marca			(0.003) 0.502***	
4.marca	J.marca				
5.marca	4.marca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$					
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	5.marca	0.011***			0.010***
7.marca		(0.003)		(0.002)	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	6.marca	-0.524***	-0.521***	-0.527***	-0.524***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$					
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	7.marca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.003)		(0.002)	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$1.m1_{-}20$				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 1 00 // 2				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.m1_20#2.marca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 m 1 20 4 2 man = -				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.1111_2U#3.marca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 m1 20#4 marca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.1111_20#4.111a1Ca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 m1 20#5 marca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.III1_20 // 0.IIIa1ca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.m1_20#6.marca				-0.235***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	"				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$1.m1_20\#7.marca$				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			(0.034)		(0.026)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$1.m1_{-}21$		0.285***		0.032*
$\begin{array}{cccccccccccccccccccccccccccccccccccc$					
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$1.\text{m}1_{-}21\#2.\text{marca}$				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$					
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$1.m1_{-}21#3.marca$				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 1 01 // 4				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.m1_21#4.marca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1 m1 91#5 marea				. ,
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.1111_21#9.IIIarca				
$\begin{array}{c} (0.063) & (0.048) \\ 1.\text{m1}_21\#7.\text{marca} & -0.036 & -0.031 \\ (0.034) & (0.026) \\ \text{m1} & -0.024^{***} & -0.024^{***} & -0.069^{**} \\ (0.004) & (0.004) & (0.004) \\ \text{ym} & 0.009^{***} & 0.009^{***} \\ & (0.000) & (0.000) \\ \text{m1}_20 & 0.209^{***} & 5 & -0.017^* \\ & (0.011) & 5 & (0.009) \\ \text{m1}_21 & 0.242^{***} & -0.011 \\ & (0.011) & (0.010) \\ \text{Constant} & -3.926^{***} \\ & & (0.018) \end{array}$	1 m1 21#6 marca				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.IIII_21TO.IIIaiCa				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.m1_21#7.marca		` /		. ,
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	- 11				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	m1	-0.024***			-0.069***
ym 0.009^{***} 0.009^{***} 0.009^{***} 0.009^{***} 0.000 0.209^{***} 0.017^{*} 0.011 0.242^{***} 0.011 0.011 0.011 0.010 Constant 0.018					
m1_20	ym				,
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.000)	(0.000)		
$\begin{array}{c} (0.011) & (0.009) \\ \text{m1_21} & 0.242^{***} & -0.011 \\ & (0.011) & (0.010) \\ \\ \text{Constant} & -3.926^{***} \\ & & (0.018) \end{array}$	$m1_{-}20$		5		
Constant (0.011) (0.010) (0.018)	1 01	(0.011)	0	,	
Constant -3.926*** (0.018)	$m1_21$				
(0.018)	O	(0.011)	2 000***	(0.010)	
` ,	Constant				
01 12 04.040 04.040 04.040			(0.018)		
Unservations 24 010 24 010 24 010 94 010	Observations	24,010	24,010	24,010	24,010
R-squared 0.897 0.897 0.940 0.940					

The columns 1 and 3 consider the same effect for each brand, the columns 2 and 4 estimate a different effect for each brand. The columns 1 and 2 consider a trend, columns 3 and 4 use a combination of dummy variables for year and month.

MANUAL: REMOVE THE CATEGORIES ZERO IN m1-20.marca

2.1 Comparisons by segment

Results for brand type: 1 is premium, 2 is medium, 3 is low.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ppu	ppu	ppu	ppu	ppu	ppu
9	0.000***	0.005***				
2.marca	-0.008*** (0.003)	-0.007*** (0.003)				
5.marca	0.003)	0.003)				
o.inarea	(0.002)	(0.002)				
$1.m1_{-}20$	()	0.198***		0.119***		0.225***
		(0.019)		(0.033)		(0.040)
$1.m1_20\#2.marca$		-0.009				
		(0.032)				
$1.\text{m}1_20\#5.\text{marca}$		0.051**				
1 1 01		(0.025)		0.100***		0.210***
1.m1 ₋ 21		0.235***		0.188*** (0.033)		0.310*** (0.042)
1.m1_21#2.marca		(0.019) -0.037		(0.033)		(0.042)
1.1111_{-21} $\pi^2.111$ α 1 α 4		(0.031)				
$1.m1_21#5.marca$		0.022				
,,		(0.025)				
m1	-0.018***	-0.018***	-0.040***	-0.040***	-0.013	-0.013
	(0.004)	(0.004)	(0.007)	(0.007)	(0.009)	(0.009)
ym	0.010***	0.010***	0.009***	0.009***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$m1_{-}20$	0.219***		0.182***		0.191***	
1 01	(0.012) $0.238***$		(0.021)		(0.034) $0.231***$	
$m1_21$			0.235***		(0.036)	
7.marca	(0.012)		(0.021) $-0.165***$	-0.166***	(0.030)	
7.IIIaiCa			(0.004)	(0.004)		
$1.\text{m}1_20\#7.\text{marca}$			(0.001)	0.102**		
				(0.041)		
$1.\text{m}1_21\#7.\text{marca}$				0.076*		
				(0.040)		
6.marca					0.101***	0.102***
					(0.007)	(0.007)
$1.\text{m}1_{-}20\#6.\text{marca}$						-0.119*
1 1 01 // 0						(0.072)
$1.\text{m}1_21\#6.\text{marca}$						-0.252***
Constant	-4.429***	-4.429***	-4.040***	-4.041***	-2.892***	(0.073) $-2.895***$
Constant	(0.019)	(0.019)	(0.037)	(0.037)	(0.051)	(0.051)
	(0.010)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	13,396	13,396	6,700	6,700	3,914	3,914
R-squared	0.917	0.918	0.846	0.846	0.760	0.761

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table with results to test for difference of coeficients in brands.

(1)	(2)	(3)	(4)	(5)	(9)	(7)	(8)	(6)
Edn	Equality of Intercept	ī	Equal	Equality of Tax 2020		Equal	Equality of Tax 2021	
Numerator	Denominator	뇐	Numerator	Denominator	ഥ	Numerator	Denominator	ഥ
9	23954	10163.44						
9	23942	10006.08	9	23942	8.15	9	23942	9.14
2	13344	19.05						
2	13340	16.81	2	13340	2.89	2	13340	1.88
1	6649	1604.66						
1	6647	1613.81	1	6647	60.9	1	6647	3.52
1	3867	187						
П	3865	193.13	1	3865	2.74	П	3865	11.8

All tests are significant at 1 percent level

3 Different parameters for each brand

Uses xtsur, user-defined, command. One estimate of each parameter for each brand. The intention was to make a unique model of Seemingly Unrelated Regressions to test the coefficients of the tax change for equality. Unfortunately, it is impossible (using the xtsur routine, in a 4th gen i7 with 16ram) to make the estimation based on the complete sample, with 7 brands. I present the test based on three groups of brands.

$$y_{itm} = \alpha_i^* + \lambda_1 * t + \beta_0' janDummy_m + \beta_1' taxDummy_m + u_{itm};$$

$$i = 1, \dots, N; t = 1, \dots, T.m = 1, 2, \dots, 7$$

3.1 Comparisons by segment

Results for premium brands

(1)	(2)	(3)
ppu1	ppu2	ppu5
0.156***	0.135***	0.151***
(0.018)	(0.018)	(0.012)
0.077	0.027	0.070
(0.000)	(0.000)	(0.000)
0.024***	0.000	0.003
(0.004)	(0.004)	(0.002)
0.009***	0.009***	0.009***
(0.000)	(0.000)	(0.000)
2,543	2,543	2,543
45	45	45
	ppu1 0.156*** (0.018) 0.077 (0.000) 0.024*** (0.004) 0.009*** (0.000) 2,543	ppu1 ppu2 0.156*** 0.135*** (0.018) (0.018) 0.077 0.027 (0.000) (0.000) 0.024*** 0.000 (0.004) (0.004) 0.009*** 0.009*** (0.000) (0.000) 2,543 2,543

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Results for lower segment brands

	(1)	(2)			
VARIABLES	ppu3	ppu6			
$m1_{-}20$	0.322***	0.204***			
	(0.047)	(0.030)			
$m1_{-}21$	0.364***	0.446***			
	(0.047)	(0.030)			
m1	0.009	-0.035***			
	(0.015)	(0.010)			
ym	0.007***	0.005***			
	(0.000)	(0.000)			
Observations	614	614			
Number of cve_ciudad	43	43			
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					
*** p<0.01. ** r	< 0.05. * p<	< 0.1			
Results for mid-range seg		ls			
Results for mid-range seg		(2)			
	gment branc	ls			
Results for mid-range seg VARIABLES	gment branc (1) ppu4	(2) ppu7			
Results for mid-range seg	gment branc (1) ppu4 0.150***	(2) ppu7 0.071***			
Results for mid-range seg VARIABLES m1_20	gment branc (1) ppu4 0.150*** (0.018)	(2) ppu7 0.071*** (0.018)			
Results for mid-range seg VARIABLES	(1) ppu4 0.150*** (0.018) 0.050***	(2) ppu7 0.071*** (0.018) 0.191***			
Results for mid-range seg VARIABLES m1_20	0.150*** (0.018) 0.050*** (0.018)	(2) ppu7 0.071*** (0.018) 0.191*** (0.018)			
Results for mid-range seg VARIABLES m1_20	0.150*** (0.018) 0.050*** (0.018) -0.013***	(2) ppu7 0.071*** (0.018) 0.191*** (0.018) -0.018***			
Results for mid-range seg VARIABLES m1_20 m1_21	0.150*** (0.018) 0.050*** (0.018) -0.013*** (0.005)	(2) ppu7 0.071*** (0.018) 0.191*** (0.018) -0.018*** (0.005)			
Results for mid-range seg VARIABLES m1_20 m1_21	0.150*** (0.018) 0.050*** (0.018) -0.013*** (0.005) 0.009***	0.071*** (0.018) 0.191*** (0.018) -0.018*** (0.005) 0.010***			
Results for mid-range seg VARIABLES m1_20 m1_21 m1	0.150*** (0.018) 0.050*** (0.018) -0.013*** (0.005)	(2) ppu7 0.071*** (0.018) 0.191*** (0.018) -0.018*** (0.005)			
Results for mid-range seg VARIABLES m1_20 m1_21 m1 ym	0.150*** (0.018) 0.050*** (0.018) -0.013*** (0.005) 0.009*** (0.000)	(2) ppu7 0.071*** (0.018) 0.191*** (0.018) -0.018*** (0.005) 0.010*** (0.000)			
Results for mid-range seg VARIABLES m1_20 m1_21 m1	0.150*** (0.018) 0.050*** (0.018) -0.013*** (0.005) 0.009***	0.071*** (0.018) 0.191*** (0.018) -0.018*** (0.005) 0.010***			
Results for mid-range seg VARIABLES m1_20 m1_21 m1 ym	0.150*** (0.018) 0.050*** (0.018) -0.013*** (0.005) 0.009*** (0.000)	(2) ppu7 0.071*** (0.018) 0.191*** (0.018) -0.018*** (0.005) 0.010*** (0.000)			

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4 Parameters are constant over time

Estimations using xtreg, first some static estimations, next the dynamic estimates. Separate regression for each brand.

The estimation routine has the possibility to distinguish between fixed or random individual coefficients.

Separate regression for each individual defined by city and brand.

$$y_{it} = \alpha_i^* + \beta_i' x_{it} + u_{it}; i = 1, \dots, N; t = 1, \dots, T.$$

Where i represents a combination of city and brand.

4.1 Static models

The proposed model only uses fixed regressors, the effect of the price change in every january, january 2020 and january 2021,

$$y_{it} = \alpha_i^* + \gamma_m^* + \lambda * t + \beta_0' jan + \beta_1' tax 2020 + \beta_1' tax 2021 + u_{it}; \tag{4.1}$$

$$c = 1, \dots, N; t = 1, \dots, T; m = 1, \dots, M.$$

It includes interactions, for the effect of the price change in january 2020 and january 2021, for different brand-types.

$$y_{it} = \alpha_i^* + \gamma_m^* + \lambda * t + \beta_0' jan + \beta_{1m}' tax 2020 + \beta_{2m}' tax 2021 + u_{it}; \qquad (4.2)$$

$$i = 1, \dots, N; t = 1, \dots, T; m = 1, \dots, M.$$

Because there are many omitted variables captured in the individual effects, there is the question of the relevance of them as fixed or random.

The result of the Hausman test for fixed effects does not rule out the non systematic difference in coefficients, this is in favour of the random effects model: $\text{Chi2}(4) = 0.60, Prob \ge chi2 = 0.9628$

The test of unit root, using the Fischer type estimation from Choi (2001): Inverse chi-squared (500) = 1112.8056, $Prob \ge chi2 = 0.0000$, does not rule out the presence of unit root for any panel (defined as a combination of city and brand), except for the model that includes a drift. The result suggests to consider different trends for each brand or city, there is an estimation by brand to test for unit roots by specifications of the panel.

The next table presents the static results by brand.

	(1)	(2)	(3)	(4)	(5)	(9)	(-)
VARIABLES	ndd	ndd	ndd	ndd	ndd	ndd	ndd
m1_20	0.193***	0.219***	0.192***	0.169***	0.232***	0.182***	0.177***
	(0.018)	(0.027)	(0.040)	(0.030)	(0.018)	(0.048)	(0.024)
$m1_{-}21$	0.231***	0.224***	0.270***	0.238***	0.237***	0.113**	0.218***
	(0.018)	(0.025)	(0.043)	(0.030)	(0.018)	(0.048)	(0.024)
m1	-0.013**	-0.031***	-0.007	-0.033***	-0.013**	-0.023**	-0.045***
	(0.006)	(0.007)	(0.011)	(0.000)	(0.006)	(0.012)	(0.009)
ym	0.010***	0.010***	0.007***	0.008	0.010***	0.006***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,650	3,207	2,700	3,213	5,539	1,210	3,407
R-squared	0.921	0.896	0.717	0.792	0.922	0.752	0.874
Number of gr_marca_ciudad	44	36	35	38	46	22	42

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The test of unit roots Testing difference in brands. Brand 1 () $F(43, 4466) = 33.51 \ Prob \ge F = 0.0000$

4.2 Dynamic models

An alternative model is to consider dynamics in the equation, for example the dependent variable with a lag or difference.

The second equation includes interactions, to consider the effect of the price change in every january and in january of 2020, when the tax was in place, different brand-types.

$$y_{it} = x'_{it}\beta_i + \alpha_i^* + \lambda_t + u_{it}; i = 1, \dots, N; t = 1, \dots, T.$$

Because there are many omitted variables captured in the individual effects, there is the question of the relevance of them as fixed or random.

The initial values become relevant. The way in which the T and N tend to infinity become relevant for asymptotic properties, like consistency.

	(1)	(2)
VARIABLES	ppu	ppu
$1.m1_{-}20$		0.504***
11 //01 1 00		(0.037)
$1b.tipo#0b.m1_20$		0.000
1h +in a // 1 a m 1 90		$(0.000) \\ 0.000$
$1b.tipo#1o.m1_20$		(0.000)
2o.tipo#0b.m1_20		0.000
20.t1p0#0b.H11_20		(0.000)
2.tipo#1.m1_20		-0.095*
2.61p0#1.1111_20		(0.056)
3o.tipo#0b.m1_20		0.000
30.πpo _π σσ.πτ-20		(0.000)
$3.\text{tipo}\#1.\text{m}1_20$		-0.109
5F = //		(0.080)
$1.m1_{-}21$		0.802***
		(0.034)
$1b.tipo#0b.m1_21$		0.000
		(0.000)
$1b.tipo#1o.m1_21$		0.000
		(0.000)
$2o.tipo#0b.m1_21$		0.000
		(0.000)
$2.\mathrm{tipo}\#1.\mathrm{m}1_21$		-0.104*
		(0.055)
$3o.tipo#0b.m1_21$		0.000
0.1. //4 4.04		(0.000)
$3.\mathrm{tipo}\#1.\mathrm{m}1_21$		-0.151*
1	0.116***	(0.083) -0.115***
m1	-0.116***	
m1_20	(0.009) $0.457***$	(0.009)
1111_20	(0.029)	
m1_21	0.751***	
1111_21	(0.026)	
	(0.020)	
Observations	23,616	23,616
R-squared	0.068	0.068
Number of gr_marca_ciudad	262	262
~		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3 Lag or trend

Separate regression for each brand We consider one lag of the dependent variable.

$$y_{it} = \alpha_i^* + \beta_i' y_{i,t-1} + \beta_i' x_{it} + u_{it}; i = 1, \dots, N; t = 1, \dots, T.$$

Results by brand

	(1)	(2)	(3)	(4)	(5)	(9)	(7)
VARIABLES	ndd	ndd	ndd	ndd	ndd	ndd	ndd
6)	÷	÷	÷)	÷)) ()
m1_20	0.193^{***}	0.201^{***}	0.166***	0.127^{+++}	0.223^{++}	$0.174^{\uparrow\uparrow\uparrow}$	0.150^{***}
	(0.005)	(0.008)	(0.011)	(0.000)	(0.005)	(0.017)	(0.007)
m1_21	0.069***	0.028***	0.061***	0.006	0.056***	0.044**	0.030***
	(0.005)	(0.007)	(0.012)	(0.000)	(0.005)	(0.017)	(0.007)
m1	0.037***	0.009***	0.023***	0.013***	0.036***	0.009**	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.005)	(0.003)
ym	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.ppu	0.964***	0.957***	0.971***	0.974***	0.960***	0.944***	0.959***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.011)	(0.005)
Observations	4,601	3,163	2,655	3,167	5,491	1,182	3,357
R-squared	0.994	0.991	0.979	0.983	0.994	0.968	0.989
Number of gr_marca_ciudad	44	35	35	38	46	22	42

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.4 Dynamic on differences

The dependent variable is the change of price in a given city.

$$\Delta y_{it} = \gamma \Delta y_{i,t-1} + u_{it}; i = 1, \dots, N; t = 1, \dots, T.$$

	(1)	(0)
VARIABLES	(1)	(2)
VARIABLES	D.ppu	D.ppu
1.m1_20		0.218***
1.1111_20		(0.004)
$1b.tipo#0b.m1_20$		0.000
1 //		(0.000)
$1b.tipo#1o.m1_20$		0.000
		(0.000)
$2o.tipo#0b.m1_20$		0.000
		(0.000)
$2.\mathrm{tipo}\#1.\mathrm{m}1_20$		-0.088***
		(0.006)
$3o.tipo#0b.m1_20$		0.000
		(0.000)
$3.\text{tipo}\#1.\text{m}1_20$		-0.051***
1 1 01		(0.008)
$1.m1_{-}21$		0.059***
1h tin a //Oh 201 91		$(0.004) \\ 0.000$
1b.tipo#0b.m1_21		(0.000)
1b.tipo#1o.m1_21		0.000
10.tip0#10.iii1_21		(0.000)
2o.tipo#0b.m1_21		0.000)
20.01po// 05.1111_21		(0.000)
$2.tipo#1.m1_21$		-0.055***
		(0.006)
3o.tipo#0b.m1_21		0.000
1 "		(0.000)
$3.\text{tipo}\#1.\text{m}1_21$		-0.009
		(0.009)
m1	0.025***	0.025***
	(0.001)	(0.001)
$m1_20$	0.183***	
	(0.003)	
$m1_{-}21$	0.040***	
	(0.003)	
Oh	00 000	00 000
Observations	23,308	23,308
R-squared Number of gr_marca_ciudad	$0.246 \\ 260$	$0.257 \\ 260$
Standard arrors in		

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

MANUAL: REMOVE THE ZEROS

With premium for the first label, it shows that the medium brands has lower impact on the tax, although, counterintuitively the lowest impact is estimated for the medium brands with a decrease of 8.9 cents while the lower brand only decreased 5 cents, both with respect to the premium brands average.

5 Consistent estimation for Variable Intercept

This models are based on Andrews, et al. (2006). The initial model comes from the transformation of:

$$y_{it} = x_{it}\beta_i + w_{j(i,t)t}\gamma + u_{it}\eta + q_{j(i,t)}\rho + \alpha_i + \phi_{j(i,t)} + \mu_t + \epsilon_{i,t};$$

 $i = 1, \dots, N; t = 1, \dots, T$

Given the interest only on the fixed independent variables, we can define an heterogeneity measure on brand and city (s), take the averages at that level, and make the transformation of variables, following:

$$y_{it} - \bar{y}_s = (x_{it} - \bar{x}_s)\beta_i + (w_{j(i,t)t} - \bar{w}_s)\gamma + (\epsilon_{i,t} - \bar{\epsilon}_s);$$

 $i = 1, \dots, N; t = 1, \dots, T$

Results in the left have the same estimate for the effect. Estimates in second column correspond to the first labeled brand, Benson.

	(1)	(2)
VARIABLES	dm_ppu_cm	dm_ppu_cm
$dm_m1_20_c$	0.202***	0.230***
	(0.010)	(0.021)
$dm_m1_21_cm$	0.232***	0.275***
	(0.010)	(0.021)
dm_m1_cm	-0.023***	-0.023***
	(0.003)	(0.003)
ym	0.009***	0.009***
	(0.000)	(0.000)
Observations	23,926	23,926
R-squared	0.865	0.866
Number of gr_marca_ciudad	263	263

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

RESULTADOS DE PRUEBAS DE DIFERENCIA DEL EFECTO POR MARCA FUERON NO SIGNIFICATIVOS.