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The behavior of social transfers over the business cycle: empirical evidence of Uruguay

Ronald Miranda*
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Abstract

This paper analyzes the cycle fluctuations of the social transfers in Uruguay over the period 1988.Q1 to 2016.Q3. The unobservable cyclical components are extracted from the observable time series following different empirical strategies. The results show that social transfers behave procyclical and lag the macroeconomics fluctuations. In this way, social transfers instead of contributing to stabilize the Uruguayan economy have aggravated the business cycle, and through various items of expenditure, expose the vulnerable groups of society to more adverse economic conditions.

Keywords: social transfers; business cycle; detrending; Uruguay.

JEL Classification: C10; E32; H50; H55.

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El comportamiento de las transferencias sociales a lo largo del ciclo económico: evidencia empírica de Uruguay

Ronald Miranda
Leonel Muinelo

Resumen

En este trabajo se analizan las fluctuaciones cíclicas de las transferencias sociales en Uruguay durante el período 1988.1er trimestre a 2016.3er trimestre. Los componentes cíclicos no observables se extraen de las series temporales observables siguiendo diferentes estrategias empíricas. Los resultados muestran que las transferencias sociales se comportan de forma procíclica y a la zaga de las fluctuaciones macroeconómicas. De esta manera, las transferencias sociales, en lugar de contribuir a estabilizar la economía uruguaya, han agravado el ciclo económico y, a través de diversos rubros de gasto, exponen a los grupos vulnerables de la sociedad a condiciones económicas más adversas.

Palabras clave: transferencias sociales; ciclo económico; Uruguay.

Código JEL: C10; E32; H50; H55.

1. Introduction

Fiscal policy has traditionally been considered an effective instrument for affecting aggregate demand, the distribution of income and wealth, and the economy's capacity to produce goods and services (Musgrave 1959). Therefore, the correct selection of the composition and combination of these policies has become of crucial importance for achieving a broad-based stable path of economic evolution (Goñi et al 2011).

When analyzing the cyclical performance of the fiscal policy, government spending has a crucial role, reducing the duration and intensity of recessions (Vegh and Vuletin 2014). A vast literature has analyzed the cycle fluctuations of the overall government expenditure over the business cycle; however, just a few studies examined the cyclical movements of the social government expenditure. In this paper we focus on social components of public spending for three main reasons. First, social transfers represent an important proportion of the government expenditure; accordingly, their design is relevant for the role of the fiscal policy as a stabilization tool for the business cycle. Second, these transfers respond from very specific government policy objectives focused on income maintenance, income and wealth inequalities reduction, and poverty fall. Finally, our analysis focuses on the case of Uruguay because we have a complete and disaggregated base of social transfers, with a quarterly frequency and for a sufficiently long period.

We explore the cycle movements of social transfers' components over the business cycle for the Uruguayan economy from 1988.Q1 to 2016.Q3. In this sense, we first made seasonality detection in unadjusted macroeconomics time series; then we estimated the unobservable cyclical components of the series using different detrending procedures, and finally, we revised the most relevant cycle properties of the social transfers components obtained with alternatives detrending methods. This last point is extended to examine the nonlinear causal relationships.

We found empirical evidence that social transfers behave procyclical and lag the business cycle in the Uruguayan economy during the sample period. In this address, we show that this pattern is drive by old age benefits and survivors' pension's components. In addition, we identified high-degree of variability and persistence of social transfers and its components. In this sense, our results implicate that these transfers have aggravated the business cycles, and exposed more the most economically vulnerable groups of Uruguayan society to macroeconomics adverse episodes.

The remainder of the paper proceeds as follows. Section 2 presents a detailed review of the related literature. Data and variables are present in Section 3. The empirical strategy is present in Section 4 while Section 5 presents the main findings. Concluding remarks can be found in Section 6.

2. Backgroud

The macroeconomic analysis of fiscal policy is concerned with the collection and expense of the government revenues in order to reach an optimal outcome (efficiency criteria), but also with the level of the social welfare in the economy (equity criteria). Thus, is relevant to know how and why the government makes alternatives policy decisions, and how its policies affect the macroeconomic performance and, therefore, the economic status of the different groups that compose the society (Hindricks and Myles 2013).

Scholars have identified different patterns through which public expenditure may affect output fluctuations (Veght et al. 2017):

- countercyclical, the government expenditures drive in an opposite direction of the output fluctuations, this action tends to stabilize the business cycle;
- procyclical, which is associated with government spending following the same output movements, which reinforces the business cycle;
- a-cyclical, which involves keeping the cycle component of government expenditures constant over the output cycle, it does not stabilize or reinforces the business cycle.

Fiscal policy has been typically a-cyclical or countercyclical in developed countries and procyclical in developing countries, stabilizing and exacerbating the business cycle, respectively (Gavin and Perotti 1997, Talvi and Végh 2005, Klemm 2014).

The traditional economic literature gives three main arguments to explain why the fiscal policy would behave procyclicality. The first one refers to the lack of access to international financial markets during the bursts in developing countries, which leaves governments without the possibility to run a countercyclical policy (Caballero and Krishnamurthy 2004, and Kaminsky et al. 2004). The second argument is associated with political economy pressures of multiple groups in society (e.g. unions, industrial firms, patronage networks, local government, ministries) for appropriate the additional public spending in the economic windfall episodes (e.g. booms in commodities prices, foreign-aid transfers, and natural resources endowments), labeled as the "voracity effect". In this last case, there are socially and politically pressures that lead governments to spend too much in good times, even supported permanent expenditure by transitory additional revenues (Tornell and Lane 1999). Akitoby et al. (2006) provide empirical evidence for the case of 51 developing economies over the period 1970 – 2002 that support the voracity effects. On the other hand, Alesina et al. (2008) indicate that fiscal procyclicality emerges from political distortions due to corrupt democracies; the argument is that the corrupted context leads voters to increase the demand for government spending in order to avoid the government abuse of power, such as appropriation of excessive rents[1]. Finally, the global financial crisis has become an alternative interpretation of the procyclicality policy. Some scholars have become supportive of the arguments that procyclical fiscal behavior is a consequence of the over-optimism in the government´s output forecasts, particularly during economic expansion rather than in normal times (Frankel and Schreger 2013, Cimadomo 2012 and 2016).

There have been much fewer studies that examine the cycle properties of the government social subsidies and transfers components of the public spending. Arreaza et al. (1999) investigating a sample of the EU and OECD countries between 1971 and 1993, observe that government transfers tend to behave more countercyclical over the economic cycle than the other components of the public expenditure. In this sense, Prasad and Gerecke (2010) argue that although the few studies of social public spending, several of them find a countercyclical or a-cyclical fluctuation over the economic cycle in OECD countries. Recently, Michaud and Rothert (2018) analyzed the government spending and its components conducted over the business cycle in a sample of 30 countries in the period 1980 – 2015. They found that the cyclical patterns of the government spending are explained by the cyclicality of the social transfers component, which behaves procyclical in emerging economies and countercyclical in developed economies. However, none of these few studies has investigated the cyclical behavior of social transfers for LAC countries.

[1] For more details about this argument, see Frankel et al. (2013), Vegh and Vuletin (2014), Avellan and Vuletin (2015), and Vegh et al. (2017).

3. Data

The sample used consist on quarterly data of public spending variables of the Uruguayan economy for the period 1988.Q1 to 2016.Q3[2]. It is important to point out that with this information we cover 100 percent of the social transfers implemented in Uruguay. All fiscal data are administrative information obtained from the Banco de Previsión Social (BPS) expressed in millions of Uruguayan pesos, and they were converted into constant prices using the Consumer Prices Index (CPI) (base 2010=100) from the Instituto Nacional de Estadística (INE – Uruguay). Meanwhile Gross Domestic Product (GDP) comes from the Uruguayan Central Bank. Social transfers expenditure corresponds to Central Government level (including the BPS), which is structured based on a set of benefits that cover the needs of differentiated groups of the population, in terms of demographics and income.

We define social transfers as the cash amount of social public benefits from the government to population associated with social and economic risks. This is compound by the sum of passive social benefits (benefits to retiree's workers of the economic activity) and active social benefits (benefits to active workers of the economic activity).

The first category, passive social benefits, includes old age, survivors' pensions, and pensions to old age and disability plus temporary subsidies, being the last one the only non-contributive program. Old age refers to cash transfers to formal workers that have reached the retirement age; survivors' pensions are related with the cash transfers to widows of formal workers and family members meeting specific requirements (such as incapacity); pensions to old age and disability are cash transfers to people 65 and older

[2] See table A.1 in the Appendix for definitions and sources of all variables.

with insufficient income; and temporary subsidies are associated with cash transfer to disabilities.

The active social benefits include illness subsidies, employment injury, unemployment subsidies, maternity and family allowances, all of them being contributive programs. Illness subsidies refers to cash transfers to formal workers with transitory illness; employment injury benefits are cash transfer to formal workers with total and permanent incapacity; unemployment subsidies are cash transfer to unemployed workers; maternity allowances refer to maternity and parental leaves allowances and care for the parent; while family allowances (*Asignaciones Familiares*, AFAM) are cash benefits to the family based on the level of income and also includes medical care for children and mother[3].

Table 1 provides a statistical overview of public spending and social transfers in Uruguay over the period 1998.Q1 to 2016.Q3. While government size was below 23% of the GDP over the period 1988 – 1994 then increased reaching a 28% at the end of the sample period being the passive benefits the most important social transfer over the period.

[3] Family allowances initially was a contributive program, and then some benefits extension was adding in the subsequent periods. Now, the major contribution for this program is the *Plan de Equidad*, a non-contributive program creates in 2008 (Amarante et al. 2008).

Table 1 – Government spending and social transfers in Uruguay, period 1988 – 2016 (averages, percentage of GDP)

	1988/1989	1990/1994	1995/1999	2000/2004	2005/2009	2010/2014	2015	2016
Expense of Central Government	**17.80**	**22.82**	**25.80**	**25.94**	**25.42**	**28.08**	**28.79**	**28.59**
Current expenditure	**15.48**	**20.49**	**23.04**	**23.27**	**22.51**	**24.94**	**26.48**	**26.07**
Compensation of employees	3.10	4.06	4.61	4.75	4.67	4.93	4.99	4.75
Non-personal expenditure	2.32	3.05	3.50	3.53	3.97	3.59	3.75	3.70
Social passive benefits	6.96	9.31	10.39	10.52	8.71	8.88	9.38	9.71
Transfers (*)	3.10	4.06	4.54	4.47	5.16	7.54	8.35	8.19
Investment	**2.32**	**2.49**	**2.77**	**2.67**	**2.91**	**3.13**	**2.31**	**2.24**
	Social transfers							
A) Social Transfers	**7.67**	**9.91**	**11.02**	**11.28**	**9.43**	**9.90**	**10.64**	**9.71**
A.1) *Social passive benefits*	**6.96**	**9.31**	**10.39**	**10.52**	**8.71**	**8.88**	**9.38**	**9.71**
Contributive								
a. Old age	5.31	7.18	7.86	7.70	6.14	6.25	6.68	6.93
b. Survivor pensions (**)	1.23	1.62	1.99	2.27	2.05	2.04	2.09	2.16
No contributive								
c. Pensions to Old Age and Disability	0.42	0.51	0.54	0.55	0.52	0.58	0.61	0.63
A.2) *Active social benefits*	**0.71**	**0.60**	**0.64**	**0.76**	**0.72**	**1.02**	**1.25**	-----
Contributive								
d. Illness subsidies	0.11	0.10	0.08	0.08	0.09	0.20	0.27	-----
e. Unemployment	0.14	0.20	0.26	0.34	0.20	0.33	0.49	-----
f. Maternity allowances	0.05	0.04	0.05	0.05	0.05	0.07	0.13	-----
No contributive								
g. Family allowances (***)	0.40	0.25	0.24	0.29	0.38	0.42	0.37	-----

Notes: The sample period covers average data from 1988 to the third quarter of 2016, which are selected according to the government administrations and at the sample end.
(*) Include: Banco de Previsión Social transfers (active social benefits), transfers to public entities and other public institutions, debt services and affected rents.
(**) Include: Transitory subsidies.
(***) Include: Law-Decree 15.084 – AFAM (contributory), Law 16.697 – AFAM (contributory), Law 17.139 – AFAM (non-contributory), Law 17.758 – *Plan Nacional de Emergencia Social* (PANES) (non-contributory), Law 18.227 – *Plan de Equidad* (non-contributory).
Source: Own elaboration based on data from Ministerio de Economía y Finanzas and Banco de Previsión Social (Uruguay).

Table 1 also shows the composition of the passive and active social benefits into subcategories. On the one hand, old age benefits constituted the largest items of passive social benefits (6% of the GDP), followed by survivors' pensions (2% of the GDP). On the other hand, family allowances and unemployment subsidies are the most important components of the active social benefits. Although, the sum of them does not reach the 1% of the GDP. In fact, we observe a very small size of active social benefits in terms of GDP.

4. Empirical strategy

This section explains the procedure we use to analyze the cycle fluctuations of the social transfers and its components over the business cycle. First, we revise the seasonal adjustment techniques of the time series due to quarterly data is used. Second, we describe the detrending procedures we use to extract the unobservable cyclical component of the observable economic time series. Finally, we explain the properties of the cycle fluctuations, and explore the nonlinear causal relationships between series.

The methodological procedure allows us to decomposing the observed series Y_t into four unobservable components (Espasa and Cancelo 1993):

- T_t is the trend, representing the long-term evolution of Y_t .
- C_t is the cycle, corresponding to the systematic deviations of Y_t with respect to the trend, displaying succession of phases of expansion and recession.
- S_t is the seasonal movement, including the regular and systematic oscillations of Y_t intra-year, such as quarterly, repeated year by year.
- I_t is an irregular component, referring to non-systematic oscillations or idiosyncratic shock.

In this sense, a well-known formulation of the observable time series Y_t composing as the sum of the four unobserved components as follows:

$$Y_t = T_t + C_t + S_t + I_t \qquad t = 1,\ldots,T \qquad (1)$$

meanwhile, the multiplicative decomposition of Y_t is:

$$Y_t = T_t.C_t.S_t.I_t \qquad t = 1,\ldots,T \qquad (2)$$

Let the natural logarithm of the previous expression, the observable time series Y_t be denoted by y_t, and the unobservable components $\{T_t, C_t, S_t, I_t\}$ by $\{t_t, c_t, s_t, e_t\}$, respectively:

$$y_t = t_t + c_t + s_t + e_t \qquad t = 1, \ldots, T \qquad (3)$$

Removing the seasonal and irregular components from the series could be possible to obtain the relevant features, the trend–cycle. The literature discussion falls upon two issues, the "seasonal adjustment", and given that seasonal adjustment does not distinguish between trend and cycle, the other discussion falls upon "cycle extraction" techniques (Canova 1998).

4.1 Seasonal adjustment

The main objective of seasonal adjustment process is to identify and subtract the seasonal components (fluctuations and calendar effects) of the unadjusted time series, which can impede a clear interpretation of the time series movements. As a result, the seasonally adjusted series obtained is compound of the trend, cycle and irregular components.

In this paper, we examine the signal extraction in a univariate time series context of an ARIMA data generating process. More specifically, we use both parametric and non-parametric methods. The non-parametric method is characterized by the analysis of the real series decomposition but do not refer explicitly to any type of theoretical model of data generation (Findley et al. 1998). In this case, the most recent implemented method is X–13ARIMA–SEATS (Census Bureau of Economics 2017). For its part, the parametric method, decompose the observable time series assuming that each unobservable component follows a theoretical econometric model, in this case, the reference procedure is TRAMO–SEATS (Gómez and Maravall 1996).

4.2 Cycle extraction

The investigation of the cycle of the fiscal transfers' components and business cycle require generating the cyclical components via detrending of the time series of interest. In the economic literature, there are controversial issues about which procedures adopt to extract the cyclical component of the times series, consequently, several researchers decided to implement alternative methods. In this sense, Canova (1998) remove the trend using different detrending techniques, and found that their results are sensitive to the selection of the procedure.

In light of prior discussion, and as robustness check of our results, we apply different trend–remove methods that involve: Linear Trend (LT), Segmented Linear Trend (SEGM), Quadratic Linear Trend (QT), First Order Differences (FOD), Beveridge–Nelson filter (BN), Hodrick–Prescott (HP), and Hamilton filter (Hf). Although these trend-remove methods are commonly used in the empirical analysis; to our knowledge, seldom study submit a wide range of them.

Behind these different detrending techniques underlying different assumptions. On the one hand, the LT, SEGM, and QT methods assume that the trend component is a deterministic process, which is uncorrelated with the cyclical component, that can be represented with a first-degree, first-degree with a structural break, and second-degree polynomial function of time, respectively (Canova 1998 and Mills 2003). On the other hand, the FOD, BN, HP, and Hf methods assume that the trend component is a stochastic process. The FOD technique is based on the assumption that the unobservable trend component behaves as a random walk process without drift, the cyclical component following a stationary process, and both are uncorrelated (Canova 1998). The Beveridge and Nelson´s (1981) decomposition assume that the trend component behaves as a unit root with drift and the cyclical component follow a stationary process, and both unobservable components are perfectly correlated. However, Kamber et al. (2017) show that it does not produce a reasonable accurate cycle component due to parameters estimated underlying an overrate of the trend contribution in the variance decomposition. Therefore, they introduce a modified version of the decomposition that improve the detrending procedure, called BN filter, that used a Bayesian framework (with a "Minnesota" shrinkage prior). For its part, Hodrick and Prescott (1980 and 1997) assume that the trend is smoothly stochastic process over the time, and it was uncorrelated with the cyclical component. Finally, Hamilton (2017) propose a linear regression of a non-stationary process based on the future value of the time series and the most recent four lags. Here, the residual estimated represent the cyclical component that follows a stationary process, and it is uncorrelated with the trend component.

4.3 Cycle properties

Once the cyclical component for each series is obtained, we first proceed to analyze the characteristics of the cyclical fluctuations of the series (c_{it}) itself and its relationship with the benchmark cycle series (c_t^*), in our case the GDP, through three kinds of analysis.

Firstly, we examine the error standard deviation and the first order autocorrelation coefficient of each series c_{it}. The error standard deviation is a measure of the absolute volatility (amplitude) of the cycle of each series from the trend. In addition, we consider the error standard deviation of the cyclical component of one series over the error standard deviation of a benchmark series, ($\sigma_{c_{it}} / \sigma_{c_{it}^*}$) which represents a measure of relative volatility (deviation from the reference cycle). While the first order autocorrelation coefficient of c_{it} measure the persistence (or degree of inertia) of the cyclical deviations from the trend.

Secondly, we estimate the co-movements through the cross–correlation coefficients, $\rho_i(k)$, between the cyclical fluctuation of one series c_{it}, and the cyclical benchmark series c_t^* at t. On the one hand, the value of $\rho_i(k)$ for $k=0$ shows the contemporaneous degree of co-movements of c_{it} and c_t^*. A positive (negative) value of $\rho_i(0)$ indicates that c_{it} is procyclicality (countercyclical). A value of $\rho_i(0)$ close to zero indicates a-cyclicality (uncorrelation) between both series[4]. On the other hand, the values of $\rho_i(k)$ for $k \neq 0$ depict the phases changes of the cycles of c_{it} and c_t^*. We say that, c_{it} is leading (or lagging) the c_t^* if $\rho_i(k)$ reaches the maximum value for $k<0$ ($k>0$). If the maximum value of $\rho_i(k)$ is reached for $k=0$, both series synchronize.

Finally, the existence of the correlation between variables does not necessarily implicate causality; for this reason, we also analyze the temporal dependence between variables. In fact, several studies analyses the linear dependence relations between time series based on the Granger (1969) causality test. However, Granger test is not useful to detect nonlinear causal relations so common in the economic variables; therefore, we use modified version of Hiemstra and Jones (1994) nonlinear Granger causality test developed by Diks and Panchenko (2006)[5].

[4] We follow Fiorito and Kollintzas (1994) that classify and denotes the degree of contemporaneous co-movements as: “strong”, for $0.5 \le \rho_i(0) < 1$; “weak” for $0.2 \le \rho_i(0) < 0.5$, and “uncorrelated” for $0 \le \rho_i(0) < 0.2$.

[5] Hiemstra and Jones (1994) test is nonparametric one based on probabilities distributions across time; Diks and Panchenko (2006) introduce an improvement for the over-reject of the null hypothesis.

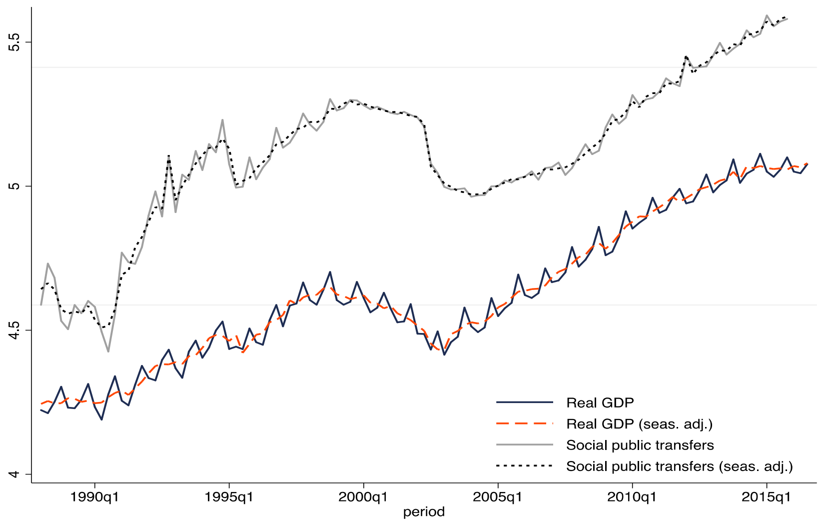
5. Results

First, we present the results of the seasonal adjustment, and then, the detrending methods used to extract the cyclical components of the economic time series. Second, we report the principal outcomes of the cyclical properties of the social transfers and its components. Finally, nonlinear causality tests are developed.

5.1 Seasonal adjustment

We use the X–13ARIMA–SEATS method for the seasonal and calendar adjustment of official statistics. Formal diagnostics of seasonality suggest that seasonality is present in the social transfers variables (see table A.3 in the appendix). For this reason, we used the seasonal adjustment time series of the social transfers variables[6].

Figure 1 – Real GDP and social transfers seasonal adjustment (in logarithms, 1988.Q1 – 2016.Q3)



Note: Seasonal adjustment (seas. adj.) was made using X–13ARIMA–SEATS.
Source: Central Bank and Banco de Previsión Social - Uruguay.

[6] Very similar results are obtained using TRAMO-SEATS method. These results are not reported for reasons of space, but they are available upon request.

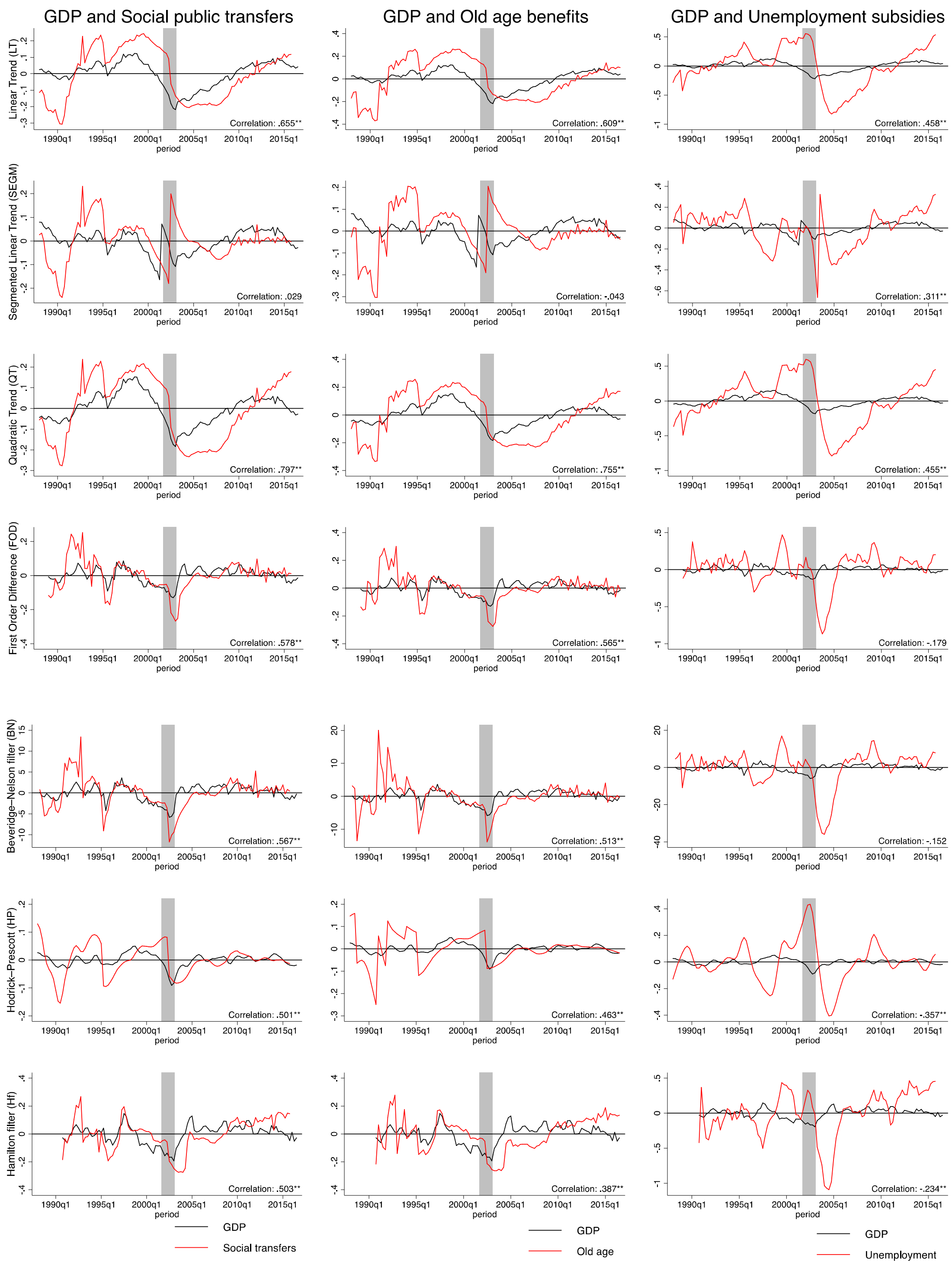
In general terms, this visual inspection of figure 1 shows that both the natural logarithm of real GDP and social public transfers' series presents systematic oscillations intra-year, i.e. seasonality, which are even more regular and pronounced in the case of real GDP. However, when the seasonal adjust is perform over the observed series, emerges that the estimated series remove the seasonality.

5.2 Detrending methods

Figure 2 displays the plots of the estimates of the cyclical components of real GDP, social transfers, old age benefits, and unemployment subsidies during the period 1988.Q1 – 2016.Q3, using the seven different detrending methods. The plot representation allows appreciate the co-movements of social transfers, old age benefits and unemployment subsidies with real GDP. The y-axis value equal to zero represents the trend, therefore, we visualize the fluctuations of the cyclical components around it. When the cycle takes a value above zero indicates an expansion, whereas a value below zero indicates a recession[7].

[7] The figures of the cyclical components of the other social transfers are not illustrates for reasons of space but are available upon request.

Figure 2 – Cyclical components



Note: Shaded area in the time series plots cover the year 2002, it illustrates the most important financial crisis in the Uruguayan economy. Real GDP (red line), passive social benefits (and its components) were estimated in the sample period 1988.Q1 – 2016.Q3; social transfers and active social benefits (and its components) were estimated in the sample period 1988.Q1 – 2015.Q4. The selected social transfers categories are represented by column (black line). Significance level: ** $\rho < 0.5$.

Source: Own estimations.

The visual inspection of figure 2 allows see that the patterns of the cyclical component of the series in terms of volatility (e.g. amplitude of the cycle peak from the trend), persistence (e.g. extension between downfall and recovery) and co-movements (e.g. dissimilarity in the number of lag periods). Firstly, all detrend methods identify adequately the crisis episode of 2002 with real GDP cycle below its trend[8]; the cyclical components are below zero. Secondly, independently of the trend-remove procedures, social fiscal transfers and its components synchronize or lags the business cycle, but in any case, lead; finally, the cyclical components patterns have not been reveal a low degree of a smooth path, as HP shown.

5.3 Cycle properties

5.3.1 Volatility and persistence

We focus on the properties of the cyclical components of the social transfers' variables analyzing first the volatility and persistence of each series itself; and then, the correlation with real GDP. Table 2 illustrates the results of the absolute and relative volatility; and persistence of the real GDP and the considered social transfers components.

[8] The most important financial crisis episode in Uruguay as reference period, shaded area in the plots in 2002.

Table 2 – Volatility and persistence of social transfers and real GDP cycles in Uruguay

Property\Variable	GDP	Social transfers	*Passive social benefits*	Old age	Survivors pensions	Pension to old age and disability	*Active social benefits*	Illness subsidies	Unemployment subsidies	Maternity allowances	Family allowances
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
Method: Linear Trend (LT)											
Absolute volatility	0.080	0.160	0.167	0.176	0.152	0.149	0.221	0.415	0.349	0.297	0.250
Relative volatility	---	2.000	2.088	2.200	1.900	1.863	2.763	5.188	4.363	3.713	3.125
Persistence	0.973	0.964	0.938	0.944	0.946	0.944	0.950	0.976	0.959	0.888	0.871
Method: Segmented Linear Trend (SEGM)											
Absolute volatility	0.047	0.085	0.098	0.102	0.105	0.086	0.196	0.391	0.179	0.242	0.240
Relative volatility	---	1.809	2.085	2.170	2.234	1.830	4.170	8.319	3.809	5.149	5.106
Persistence	0.800	0.811	0.783	0.792	0.873	0.792	0.923	0.966	0.749	0.813	0.845
Method: Quadratic Trend (QT)											
Absolute volatility	0.074	0.158	0.163	0.174	0.134	0.147	0.160	0.221	0.347	0.249	0.186
Relative volatility	---	2.000	2.088	2.200	1.900	1.863	2.763	5.188	4.363	3.713	3.125
Persistence	0.967	0.961	0.935	0.942	0.932	0.943	0.952	0.96	0.959	0.868	0.812
Method: First Order Differencing Detrending (FOD)											
Absolute volatility	0.044	0.09	0.099	0.099	0.097	0.093	0.13	0.15	0.232	0.172	0.166
Relative volatility	---	2.045	2.250	2.250	2.205	2.114	2.955	3.409	5.273	3.909	3.773
Persistence	0.816	0.791	0.738	0.754	0.763	0.751	0.846	0.879	0.88	0.57	0.679
Method: Beveridge-Nelson filter (BN)											
Absolute volatility	1.829	3.687	4.483	4.502	4.203	4.108	5.627	6.319	9.939	8.416	8.179
Relative volatility	---	2.016	2.451	2.461	2.298	2.246	3.077	3.455	5.434	4.601	4.472
Persistence	0.815	0.747	0.551	0.568	0.672	0.623	0.865	0.913	0.908	0.291	0.539
Method: Hodrick-Prescott (HP)											
Absolute volatility	0.023	0.054	0.052	0.066	0.052	0.048	0.076	0.091	0.156	0.108	0.099
Relative volatility	---	2.362	2.262	2.86	2.271	2.109	3.297	3.987	6.808	4.696	4.336
Persistence	0.919	0.874	0.767	0.699	0.782	0.847	0.915	0.933	0.948	0.375	0.808
Method: Hamilton (Hf)											
Absolute volatility	0.068	0.114	0.118	0.119	0.107	0.131	0.201	0.240	0.336	0.248	0.225
Relative volatility	---	1.689	1.751	1.764	1.584	1.944	2.973	3.550	4.975	3.677	3.330
Persistence	0.867	0.839	0.788	0.766	0.822	0.844	0.882	0.851	0.875	0.794	0.834

Note: Absolute volatility measures the cycle amplitude from the trend for each series; Relative volatility measures the cycle amplitude of the series w.r.t. the benchmark series; Persistence shows the degree of inertia of the cycle to reach the trend. Real GDP, social passive benefits (and its components) were estimated in the sample period 1988.Q1 – 2016.Q3; social transfers and active benefits (and its components) were estimated in the sample period 1988.Q1 – 2015.Q4.
Source: Own estimations.

We observe that the economic cycle (column 1) is less volatile than the social transfers series (column 2 to 11), both in absolute and relative terms across the trend-remove procedure. For instance, by Hf method, the absolute volatility of GDP cycle component is 6.8% (column 1) and the absolute volatility of social transfers cycle component is 11.4% (column 2). Meanwhile passive social benefits and its categories show a similar level of high volatility, active social benefits show lower volatility than its components. Among social transfers components, old age shows the highest relative volatility into social passive benefits categories; while, illness subsidies and unemployment subsidies present a high volatility into active social benefits categories. These results could be explained by the different characteristics of the social transfers analyzed. In the case of passive social benefits and its components are associated to stable phenomenon's in the long–run and more structural design of the fiscal policy; whereas the active social benefits are related with flexible phenomenon in the short-run, such as cycle fluctuations (unemployment subsidies) or policy priorities (family allowances).

From table 2 also we can see that the majority of the components of the fiscal transfers series present high persistence. For instance, social transfers present values of first order autocorrelation coefficient between 0.75 and 0.96 across the trend-removal methods. Therefore, these transfers have rigidities to recover the trend path in ups and downs, which could be a problem in an adverse macroeconomic episode because do not contribute to the economic revival. Particularly, notice that the cyclical components of the time series obtained by SEGM and QT methods are less volatility and persistence than the LT method; therefore, assess the inclusion of structural breaks and non-linear trend could play an important role in a deterministic time trend specification to estimates the cyclical component.

5.3.2 Co-movements and phases changes

Table 3 presents the co-movements and phases changes between the cyclical components of social transfers variables with real GDP cycle (benchmark).

The contemporaneous co-movements suggest strong procyclicality of social transfers (column 1). Passive social benefits show strong procyclicality from 0.44 to 0.77. Similarly, old age benefits vary from 0.39 to 0.76, survivors' pensions move from 0.43 to 0.76, and pension to old age and disability differ between 0.62 and 0.87.

However, active social benefits co-movements present more substantial divergences than passive social benefits. While the FOD, BN, HP and Hf trend-remove procedures indicate an a-cyclicality behave of active social benefits, the LT, SEGM, and QT methods involve a strong procyclicality (column 6). Similarly, active social benefits components (columns 7 to 10) co-movements are sensitive to the trend-remove procedures; however, we found some common facts. Illness subsidies vary from 0.51 to 0.84 and maternity allowances move between 0.29 and 0.76, both categories are procyclicality. In the case of unemployment subsidies, they behave weakly countercyclical by HP (-0.36) and Hf (-0.23) procedures and a-cyclical by FOD (-0.18) and BN (-0.15). Therefore, they present a limited performance as automatic stabilizer of the macroeconomic cycles.

To sum up, we have a systematic relationship between short-term fluctuations of the social transfers' components and the business cycle. Given the structural nature of passive social benefits and its components, we would expect that they conducted a-cyclical, but our empirical evidence shows that these transfers have been dominated by the procyclicality; consequently, instead of contributing to stabilize the Uruguayan economy, have aggravated the business cycle. Similarly, these procyclical patterns are followed by some active social benefits components, such as illness subsidies, maternity allowances, and to lesser extent, family allowances, in which we expected an a-cyclical behave. Moreover, the most important social transfers component to conduct a countercyclical fiscal policy, unemployment subsidies, present unclear results of their cyclical behave. In this sense, due to social transfers are generally associated with the government goals of income maintenance and poverty reduction, we can infer that the design of the social fiscal policy in Uruguay had not had the desired effect on the most economically vulnerable groups of them.

Table 3 – Co-movements and phases changes of social transfers in Uruguay

Property\Variable	**Social Transfers**	***Passive social benefits***	Old age	Survivors pensions	Pension to old age and disability	***Active social benefits***	Illness subsidies	Unemployment subsidies	Maternity allowances	Family allowances
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Method: Linear Trend (LT)										
Co-movements (k = 0)	0.655	0.601	0.609	0.431	0.851	0.607	0.744	0.458	0.761	0.226
Lead (-)/Lags (+) (k)	0.724 (k = 4)	0.659 (k = 5)	0.676 (k = 5)	0.485 (k = 5)	0.876 (k = 2)	0.768 (k = 5)	0.754 (k = 1)	0.870 (k = 8)	0.845 (k = 3)	0.267 (k = -6)
Method: Segmented Linear Trend (SEGM)										
Co-movements (k = 0)	0.029	-0.037	-0.043	-0.160	0.497	0.555	0.600	0.311	0.487	0.401
Lead (-)/Lags (+) (k)	0.192 (k = 4)	-0.174 (k = 8)	-0.162 (k = -7)	-0.395 (k = 8)	0.550 (k = 4)	0.588 (k = 3)	0.700 (k = 5)	0.713 (k = 8)	0.654 (k = 6)	0.401 (k = 0)
Method: Quadratic Trend (QT)										
Co-movements (k = 0)	0.797	0.767	0.755	0.762	0.866	0.503	0.841	0.455	0.708	-0.053
Lead (-)/Lags (+) (k)	0.853 (k = 3)	0.811 (k = 2)	0.802 (k = 2)	0.821 (k = 3)	0.886 (k = 2)	0.869 (k = 7)	0.889 (k = 3)	0.860 (k = 8)	0.849 (k = 5)	-0.056 (k = 1)
Method: First Order Differencing Detrending (FOD)										
Co-movements (k = 0)	0.578	0.565	0.565	0.533	0.655	-0.016	0.548	-0.179	0.344	0.065
Lead (-)/Lags (+) (k)	0.586 (k = 1)	0.570 (k = 1)	0.571 (k = 1)	0.545 (k = 1)	0.661 (k = 1)	0.599 (k = 5)	0.588 (k = 3)	0.616 (k = 6)	0.496 (k = 3)	0.197 (k = -6)
Method: Beveridge-Nelson filter (BN)										
Co-movements (k = 0)	0.567	0.514	0.513	0.506	0.623	0.059	0.518	-0.153	0.299	0.077
Lead (-)/Lags (+) (k)	0.576 (k = 1)	0.502 (k = 1)	0.503 (k = 1)	0.508 (k = 1)	0.613 (k = 1)	0.624 (k = 5)	0.648 (k = 3)	0.690 (k = 8)	0.443 (k = 3)	0.232 (k = -6)
Method: Hodrick-Prescott (HP)										
Co-movements (k = 0)	0.501	0.504	0.463	0.493	0.588	-0.029	0.512	-0.357	0.292	0.211
Lead (-)/Lags (+) (k)	0.528 (k =1)	0.531 (k = 1)	0.489 (k = 1)	0.521 (k = 1)	0.615 (k = 1)	0.654 (k = 6)	0.702 (k = 3)	0.713 (k = 7)	0.493 (k = 4)	0.211 (k = 0)
Method: Hamilton (Hf)										
Co-movements (k = 0)	0.503	0.436	0.386	0.508	0.638	0.062	0.614	-0.234	0.465	0.232
Lead (-)/Lags (+) (k)	0.564 (k = 2)	0.519 (k = 2)	0.469 (k = 2)	0.578 (k = 2)	0.671 (k = 1)	0.662 (k = 7)	0.671 (k = 3)	0.663 (k = 8)	0.673 (k = 4)	0.298 (k = -6)

Note: Real GDP benchmark series. k is the cross-correlation order in quarter frequency. Co-movements $\rho_i(0)$: (+) procyclicality, (-) countercyclicality, 0 a-cyclicality. Synchronize: if the maximum value of $\rho_i(k)$ involves $k<0$, $k=0$, $k>0$ the series lead, synchronize, and lags the reference series (respectively). Real GDP, social passive benefits (and its components) were estimated in the sample period 1988.Q1 – 2016.Q3; social transfers and active benefits (and its components) were estimated in the sample period 1988.Q1 – 2015.Q4.
Source: Own estimations.

Table 3 also documents different phases (lead/lags) of social transfers' series over the business cycle, where the *k* value represents the cross-correlation order in quarter's frequency. We observe that the aggregate of social transfers (column 1) lag the business cycle between 1 to 4 quarters, depending on the trend-remove method. For example, Hf shows that real GDP at *t* has a positive effect on the future level of social transfers, reaching the highest point at lag 2 (after six months). The economic intuition is expressed as follows, we first have a peak (or slump) in the cycle fluctuation of the business cycle, and then a peak (or slump) two quarters later in the cycle movements of social transfers. In addition, real GDP is positively cross-correlated with passive social benefits and its components, which lag the real GDP cycle from 1 to 3 quarters. Besides, active social benefits lag the business cycle among 3 to 7 quarters. In relation with active social benefits categories, unemployment subsidies programs are negatively correlated with the macroeconomic cycle and lag it from 6 to 8 quarters. In this sense, we first have a slump (or peak) in the business cycle, and then, among 6 to 8 quarters later a peak (or slump) in the cycle variations of unemployment subsidies.

5.3.3 Causality

The results of the nonlinear Granger causality test are shown in table 4. Given that social transfers and its components lag the business cycle, we are interested to report unidirectional causality from GDP to social transfers (or its components). This implicates reject the null hypothesis that GDP does not nonlinear Granger cause social transfers (or its components) and does not reject the null hypothesis that social transfers (or its components) nonlinear Granger cause GDP.

Table 4 – Results of nonlinear Granger causality test

Null hypothesis	LT	SEGM	QT	FOD	BN	HP	Hf
	T statistics	T statistics	T statistics	T statistics	T statistics	T statistics	T statistics
GDP does not cause social transfers	1.060 [0.1446]	1.432 [0.0761]	1.739 [0.0410]	1.485 [0.0688]	1.929 [0.0268]	0.894 [0.1856]	1.305 [0.0960]
Social transfers do not cause GDP	1.056 [0.1453]	1.378 [0.0841]	0.509 [0.3052]	1.559 [0.0594]	0.157 [0.4377]	1.679 [0.0465]	0.680 [0.2483]
GDP does not cause *passive social benefits*	0.633 [0.2634]	0.726 [0.2339]	1.365 [0.0861]	2.289 [0.0110]	2.253 [0.0121]	1.678 [0.0466]	0.162 [0.5641]
Passive social benefits do not cause GDP	1.499 [0.0669]	1.746 [0.0403]	0.197 [0.5782]	1.674 [0.0471]	0.919 [0.1790]	1.084 [0.1391]	0.565 [0.2859]
GDP does not cause old age benefits	1.028 [0.1520]	1.460 [0.0721]	1.902 [0.0286]	2.509 [0.0060]	1.816 [0.0346]	1.173 [0.1203]	0.156 [0.4379]
Old age benefits do not cause GDP	1.245 [0.1066]	1.600 [0.0547]	0.127 [0.5507]	1.621 [0.0525]	0.940 [0.1735]	1.025 [0.1526]	1.325 [0.0926]
GDP does not cause survivors´ pensions	1.039 [0.8506]	0.678 [0.2487]	1.563 [0.0590]	1.406 [0.0799]	2.031 [0.0211]	0.618 [0.2682]	0.800 [0.2117]
Survivors´ pensions do not cause GDP	2.028 [0.0212]	1.003 [0.1580]	0.194 [0.5770]	1.540 [0.0618]	1.067 [0.1429]	1.574 [0.0577]	1.355 [0.0877]
GDP does not cause pensions to old age and disabilities	1.027 [0.1522]	1.639 [0.0505]	1.797 [0.0362]	1.364 [0.0862]	2.670 [0.0037]	1.822 [0.0342]	0.833 [0.2024]
Pensions to old age and disabilities do not cause GDP	1.363 [0.0865]	1.835 [0.0332]	0.449 [0.3265]	2.174 [0.0148]	2.118 [0.0170]	1.400 [0.0807]	1.401 [0.0806]
GDP does not cause *active social benefits*	1.266 [0.1027]	1.330 [0.0917]	2.071 [0.0191]	1.128 [0.1296]	1.957 [0.0251]	1.760 [0.0391]	1.249 [0.1057]
Active social benefits do not cause GDP	0.265 [0.6044]	0.270 [0.3934]	1.399 [0.0809]	0.543 [0.7063]	(0.462) [0.6779]	1.512 [0.0652]	0.961 [0.1684]
GDP does not cause illness subsidies	1.291 [0.0984]	1.968 [0.0245]	2.634 [0.0042]	1.364 [0.0862]	1.770 [0.0383]	2.045 [0.0204]	1.975 [0.0241]
Illness subsidies do not cause GDP	0.155 [0.5615]	1.021 [0.1535]	1.518 [0.0645]	0.469 [0.3193]	0.297 [0.3833]	1.229 [0.1094]	0.578 [0.2816]
GDP does not cause unemployment subsidies	2.036 [0.0208]	2.277 [0.0113]	2.525 [0.0057]	1.735 [0.0413]	1.453 [0.0731]	1.588 [0.0560]	1.902 [0.0286]
Unemployment subsidies do not cause GDP	1.707 [0.0438]	(0.071) [0.5284]	1.487 [0.0685]	0.673 [0.2504]	0.577 [0.2818]	1.833 [0.0333]	0.845 [0.1991]
GDP does not cause maternity allowances	2.646 [0.0040]	1.670 [0.0474]	1.915 [0.0277]	1.583 [0.0566]	2.329 [0.0099]	0.608 [0.2714]	1.298 [0.0971]
Maternity allowances do not cause GDP	1.119 [0.8683]	0.763 [0.2227]	0.342 [0.6339]	0.522 [0.3010]	0.825 [0.2045]	1.016 [0.1547]	1.436 [0.0755]
GDP does not cause family allowances	0.280 [0.6102]	0.374 [0.3540]	1.234 [0.1085]	1.209 [0.1132]	0.444 [0.3285]	2.018 [0.0217]	0.906 [0.1824]
Family allowances do not cause GDP	1.293 [0.0979]	1.285 [0.0994]	0.115 [0.5458]	1.009 [0.1565]	0.736 [0.2307]	0.253 [0.3999]	0.736 [0.2307]

Note: The null hypothesis is that one series does not nonlinearly Granger cause the other series. T-statistics is illustrated in absolute value and p-value is reported in brackets. Following Kollias et al. (2017), the lag length used for the nonlinear causality test and the Bandwidth are set to one. In the case of the Bandwidth, values less (more) than 1 result in larger (smaller) p-values (Bekiros and Diks 2008).
Source: Own estimations.

Summarizing briefly the main findings, we obtained evidence of unidirectional nonlinear causality from real GDP to social transfers by {QT, BN}, from real GDP to passive social benefits by {FOD, BN, HP;}, from real GDP to old age benefits by {QT, FOD, BN}, from real GDP to active social benefits by {QT, BN, HP}, from real GDP to unemployment subsidies by {SEGM, QT, FOD, Hf}, from real GDP to maternity allowances by {LT, SEGM, QT, FOD, BN}, among others causality relationship. Thus, we have detected an impact of the macroeconomics cycle on social transfers and its components; consequently, there are certain fiscal policy responses on social transfers caused by the economic activity phases.

6. Conclusions

In this paper we investigate how have social transfers been conducted in Uruguay over the business cycle in the period 1988.Q1 – 2016.Q3. We could observe that social transfers behave procyclical and lagged the business cycle during the last decades, therefore, they perform exacerbate expansions and recessions of the business cycle. Particularly, we identified that the procyclicality behaves of social transfers have been led by old age benefits and survivors' pensions. Moreover, significant causality relationship was detected, such as from real GDP to old age benefits and from real GDP to unemployment subsidies. Additionally, we identified high variability and persistence of social transfers.

Some fiscal policy recommendations emerge from our analysis. First, an adequate design of the social transfers' components could be playing an important role for the fiscal policy targets as a stabilization tool for the business cycle and for a specific government policy objective focused on income maintenance, income and wealth inequalities reduction, and poverty fall. Specifically, the design of them would have to involve an a-cyclical behaviour of old age benefits, survivors' pensions, pensions to old age and disability, illness subsidies, and maternity allowances; and countercyclical behavior of unemployment subsidies and family allowances. Note that an a-cyclical or countercyclical behave of these social transfers components would be effective to smooth the macroeconomics downturns and mitigate the income reduction or poverty rise. Second, the establishment of national fiscal rules (e.g. structural balance budget targets, revenues, expenditure, and debt rules) would be helpful to stabilize the macroeconomic cycle. Third, given the small size of active social benefits in terms of GDP, these components might not be able to exercise any relevant impact on stabilizing the macroeconomic fluctuations and to prevent the cyclical increase of poverty during the economic busts. Thus, the improvement of active social benefits would be desirable.

7. References

Akitoby, B., Clements, B., Gupta, S. and Inchauste, G. (2006) 'Public Spending, Voracity, and Wagner's Law in Developing Countries', European Journal of Political Economy, 22, 908–924.

Alesina, A., Campante, F. and Tabellini, G. (2008) 'Why Is Fiscal Policy Often Procyclical?', Journal of the European Economic Association, 6, 1006–1036.

Amarante V., G. de Melo, A. Machado and A. Vigorito (2008), "Criterio de selección para ingresar al nuevo sistema de Asignaciones Familiares". Informe Final de convenio Udelar- Ministerio de Desarrollo Social.

Arreaza, A., Sgrensen, B. and Yosha, O. (1999) 'Consumption Smoothing through Fiscal Policy in OECD and EU Countries'. In Fiscal Institutions and Fiscal Performance, University of Chicago Press, 59–80.

Avellan, L. and Vuletin, G. (2015) 'Fiscal Procyclicality and Output Forecast Errors', Journal of International Money and Finance, 55, 193–204.

Bekiros, S. and Diks, C. (2008) 'The Nonlinear Dynamic Relationship of Exchange Rates: Parametric and Nonparametric Causality Testing', Journal of Macroeconomics, 30, 1641–1650.

Beveridge, S. and Nelson, C. (1981) 'A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurment of the Business Cycle', Journal of Monetary Economics, 7, 151–174.

Caballero, R., and Krishnamurthy, A. (2004). Fiscal Policy and Financial Depth. NBRE Working Paper 10532, 1-20.

Canova, F. (1998) 'Detrending and Business Cycle Facts', Journal of Monetary Economics, 41, 475–512.

Census Bureau US. (2017). X-13ARIMA-SEATS Reference Manual, Version 1.1. Washington DC. http://www.census.gov/srd/www/x13as/

Cimadomo, J. (2012). Fiscal Policy in Real Time. The Scandinavian Journal of Economics, 114(2), 440-465.

Cimadomo, J. (2016). Real-time data and fiscal policy analysis: A survey of the literature. Journal of Economic Surveys, 30(2), 302-326.

Diks, C. and Panchenko, V. (2006) 'A New Statistic and Practical Guidelines for Nonparametric Granger Causality Testing', Journal of Economic Dynamics and Control, 30, 1647–1669.

Findley, D., Monsell, B., Bell, W., Otto, M. and Chen, B.-C. (1998) 'New Capabilities and Methods of the X-12-ARIMA Seasonal-Adjustment Program', Journal of Business

& Economic Statistics, 16, 127–152.

Fiorito, R. and Kollintzas, T. (1994) 'Stylized Facts of Business Cycles in the G7 from a Real Business Cycles Perspective', European Economic Review, 38, 235–269.

Frankel, J. and Schreger, J. (2013) 'Over-Optimistic Official Forecasts and Fiscal Rules in the Eurozone', Review of World Economics, 149, 247–272.

Frankel, J., Vegh, C. and Vuletin, G. (2013) 'On Graduation from Fiscal Procyclicality', Journal of Development Economics, 100, 32–47.

Gavin, M. and Perotti, R. (1997) 'Fiscal Policy in Latin America', NBER Macroeconomics Annual, 12, 11–72.

Gómez, V., and Maravall, A. (1996). Programs TRAMO and SEATS. Banco de España, Documento de Trabajo 9628.

Goni, E., Lopez, J. H. and Serven, L. (2011), 'Fiscal Redistribution and Income Inequality in Latin America', World Development, 39,1558-1569.

Granger, C. (1969) 'Investigating Causal Relations by Econometric Models and Cross-Spectral Methods', Econometrica, 37, 424–438.

Hamilton, J. (2017) 'Why You Should Never Use the Hodrick-Prescott Filter', NBER Working Papers 23429, 1–45.

Hiemstra, C. and Jones, J. (1994) 'Testing for Linear and Nonlinear Granger Causality in the Stock Price- Volume Relation', The Journal of Finance, 49, 1639.

Hindricks, J. and Myles, G. (2013) Intermediate Public Economics, London, England, The MIT Press, Cambridge, Massachusetts.

Hodrick, R. and Prescott, E. (1980) 'Postwar U.S. Business Cycles: An Empirical Investigation', Carnegie Mellon University discussion paper 451.

Hodrick, R. and Prescott, E. (1997) 'Postwar U.S. Business Cycles: An Empirical Investigation', Journal of Money, Credit and Banking, 29, 1-16.

Kamber, G., Morley, J. and Wong, B. (2017) 'Intuitive and Reliable Estimates of the Output Gap from a Beveridge-Nelson Filter', The Review of Economics and Statistics, 100, 550–566.

Kaminsky, G., Reinharta, C., and Vegh, C. A. (2004). When It Rains, It Pours: Procyclical Capital Flows and Macroeconomic Policies. NBER Macroeconomics Annual, 19, 11-53.

Klemm, A. (2014) 'Fiscal Policy in Latin America over the Cycle', IMF Working Papers, 14, 1–32.

Kollias, C., Paleologou, S., Tzeremes, P. and Tzeremes, N. (2017) 'Defence Expenditure and Economic Growth in Latin American Countries: Evidence from Linear and Nonlinear Causality Tests', Latin American Economic Review, 26, 1–25.

Michaud, A. and Rothert, J. (2018) 'Redistributive Fiscal Policies and Business Cycles in

Emerging Economies', Journal of International Economics, 112, 123–133.

Mills, T. (2003) '"Classical" Techniques of Modelling Trends and Cycles'. In Modelling Trends and Cycles in Economic Time Series, London, Palgrave Macmillan UK, 13–38.

Muinelo-Gallo, L. and O. Roca-Sagalés (2013) 'Joint determinants of Economic Growth, Income Inequality, and Fiscal Policies', Economic Modelling, 30, 814-824.

Musgrave, R. (1959) The Theory of Public Finance, New York: McGraw-Hill.

Prasad, N. and Gerecke, M. (2010) 'Social Security Spending in Times of Crisis', Global Social Policy: An Interdisciplinary Journal of Public Policy and Social Development, 10, 218–247.

Talvi, E. and Végh, C. (2005) 'Tax Base Variability and Procyclical Fiscal Policy in Developing Countries', Journal of Development Economics, 78, 156–190.

Tornell, A., and Lane, P. (1999). The Voracity Effect. American Economic Review, 89(1), 22-46.

Vegh, C., Lederman, D. and Bennett, F. (2017) Leaning Against the Wind: Fiscal Policy in Latin America and the Caribbean in a Historical Perspective, World Bank.

Vegh, C. and Vuletin, G. (2014) 'The Road to Redemption: Policy Response to Crises in Latin America', IMF Economic Review, 62, 327–370.

Appendix

Table A.1 –Variables and sources

Variable	***Definition***	***Source***
Real Gross Domestic Product (GDP)	*Gross Domestic Product at constant prices (volume index 2005=100).*	*Central Bank of Uruguay. Data period covers 1988:Q1 – 2016:Q3.*
Social transfers (Social trf)	*Sum of passive social benefits and active social benefits.*	*Banco de Previsión Social (BPS). Data period covers 1988:Q1 – 2015:Q4.*
Passive social benefits (Passive sb)	*Sum of old age plus survivors' pensions plus pension to old age and disability plus temporary subsidies.*	*BPS. Data period covers 1988:Q1 – 2016:Q3.*
Old age (Old age)	*Monthly cash transfer to formal workers that have reached the retirement age.*	*BPS. Data period covers 1988:Q1 – 2016:Q3.*
Survivors' Pensions (Pensions)	*Monthly cash transfer to widows of formal workers and family members meeting specific requirements (incapacity, etc.).*	*BPS. Data period covers 1988:Q1 – 2016:Q3.*
Pensions to old age and disability (Pensions oldage disability)	*Monthly cash transfer to people 70 and older with insufficient income or people with disability.*	*BPS. Data period covers 1988:Q1 – 2016:Q3.*
Temporary Subsidies	*Disability subsidy.*	*BPS. Data period covers 1997:Q2 – 2016:Q3.*
Active social benefits (Active sb)	*Sum of illness subsidies plus employment injury plus unemployment subsidies plus maternity allowance and family allowance.*	*BPS. Data period covers 1988:Q1 – 2015:Q4.*
Illness subsidies (Illness)	*Monthly cash transfer to formal workers with transitorial illness.*	*BPS. Data period covers 1988:Q1 – 2015:Q4.*
Employment injury benefits	*Monthly cash transfer to formal workers with total and permanent incapacity.*	*BPS. Data period covers 1988:Q1 – 2015:Q4.*
Unemployment subsidies (Unempl)	*Monthly cash transfer to unemployed workers.*	*BPS. Data period covers 1988:Q1 – 2015:Q4.*
Maternity allowance (Maternity)	*Maternity leave and parental leave allowance and care for the parent.*	*BPS. Data period covers 1988:Q1 – 2015:Q4.*
Family allowance (Family)	*Bi-monthly payment to the family based on the level of income and includes medical care for children and mother.*	*BPS. Data period covers 1988:Q1 – 2015:Q4.*

Table A.2 – Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
RGDP	115	105.705	27.923	65.998	166.143
RGDP (tc)	115	105.983	27.687	69.806	160.441
RGDP (sa)	115	105.752	27.723	69.709	160.854
RGDP (s)	115	-0.047	3.500	-4.189	7.073
RGDP (i)	115	-0.231	1.076	-6.239	1.334
Social trf	115	173.535	43.555	83.616	268.464
Social trf (tc)	115	172.998	42.891	91.716	264.983
Social trf (sa)	115	173.522	43.320	90.919	271.827
Social trf (s)	115	0.013	4.063	-8.734	11.853
Social trf (i)	115	0.524	3.451	-3.290	25.371
Passive sb	112	171.905	42.955	83.616	268.464
Passive sb (tc)	112	171.541	42.642	91.709	267.575
Passive sb (sa)	112	171.925	42.775	90.914	267.562
Passive sb (s)	112	-0.020	4.069	-8.599	11.702
Passive sb_(i)	112	0.384	3.159	-3.282	25.492
Old age	115	117.156	26.677	59.038	170.730
Old age (tc)	115	117.112	26.305	61.691	168.999
Old age (sa)	115	117.182	26.479	61.451	170.456
Old age (s)	115	-0.026	3.473	-8.789	10.621
Old age (i)	115	0.070	1.527	-3.511	9.373
Pensions	115	33.550	10.114	12.674	52.544
Pensions (tc)	115	33.572	9.826	14.772	51.289
Pensions (sa)	115	33.555	10.075	12.622	53.007
Pensions (s)	115	-0.005	0.825	-2.308	2.488
Pensions (i)	115	-0.017	0.745	-3.498	3.617
Pension oldage disability	115	9.328	2.874	4.489	15.661
Pension oldage disability (tc)	115	9.328	2.800	5.286	15.349
Pension oldage disability (sa)	115	9.329	2.864	4.479	15.816
Pension oldage disability (s)	115	0.000	0.227	-0.581	0.661
Pension oldage disability (i)	115	0.001	0.237	-1.128	1.191
Active sb	112	13.529	6.514	6.358	33.128
Active sb (tc)	112	13.461	6.533	7.499	32.212
Active sb (sa)	112	13.522	6.500	7.369	32.098
Active sb (s)	112	0.007	0.431	-1.082	1.030
Active sb (i)	112	0.061	0.306	-0.423	2.062
Illness	112	2.151	1.660	0.781	7.091
Illness (tc)	112	2.149	1.645	0.834	6.811
Illness (sa)	112	2.149	1.646	0.827	6.933
Illness (s)	112	1.000	0.052	0.888	1.075
Illness (i)	112	1.000	0.017	0.965	1.041
Unempl	112	4.721	2.555	1.586	13.718
Unempl (tc)	112	4.745	2.501	1.696	13.297
Unempl (sa)	112	4.722	2.534	1.516	13.235
Unempl (s)	112	1.000	0.084	0.748	1.284
Unempl (i)	112	0.989	0.048	0.666	1.046
Maternity	112	0.992	0.604	0.349	3.269
Family	112	5.650	2.384	2.429	9.922
Family (tc)	112	5.639	2.393	2.417	9.751
Family (sa)	112	5.565	2.376	2.404	9.755
Family (s)	112	0.000	0.128	-0.317	0.287
Family (i)	112	0.011	0.454	-2.229	2.316

Note: Trend-Cycle component (tc), seasonal adjustment series (sa), seasonal component (s), irregular component (i).
Source: Own estimations.

Table A.3 – Results from seasonal adjustment

Method: X-13ARIMA-SEAT	**GDP**	**Social Transfers** (1)	***Passive social benefits*** (2)	Old age (3)	Pensions (4)	Pension oldage disability (5)	***Active social benefits*** (6)	Illness (7)	Unemp (8)	Maternity (9)	Family (10)
Observation	115	112	115	115	115	115	112	112	112	112	112
Seasonal	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log transformations	None	None	None	None	None	None	None	Yes	Yes	Yes	No
Mean correction	None	None	None	None	Yes	None	None	None	None	Yes	Yes
ARIMA model (P,D,Q)											
Seasonal	(0 1 0)	(0 1 0)	(0 1 2)	(0 1 2)	(0 1 1)	(0 1 1)	(0 1 0)	(2 1 0)	(0 1 0)	(1 1 0)	(1 0 0)
(BP,BD,BQ)	(0 1 1)	(1 0 0)	(0 1 1)	(0 1 1)	(1 0 0)	(1 0 0)	(0 1 1)	(0 1 1)	(1 0 0)	(1 0 0)	(1 0 0)
BIC	1.681	4.018	3.510	3.128	0.428	-1.961	-0.656	-5.650	-4.072	-4.712	-2.634
SE (res)	2.168	6.750	4.666	4.048	1.053	0.324	0.684	0.055	0.126	0.084	0.216
Q-val	5.199	20.773	10.889	10.515	11.971	13.371	11.382	8.296	16.215	16.826	23.722
Easter corrections	Yes	None	None	None	None	None	None	Yes	None	Yes	None
Outlier corrections	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Skewness	0.461	0.845	0.028	0.844	0.263	0.239	0.755	0.390	0.256	0.361	0.793
Kurtosis	0.081	0.000	0.552	0.000	0.029	0.374	0.702	0.460	0.091	0.704	0.730
Ljung-Box	0.990	0.144	0.620	0.651	0.609	0.498	0.725	0.824	0.368	0.266	0.050
LB. on Seas	0.980	0.991	0.473	0.864	0.330	0.562	0.871	0.509	1.000	0.278	1.000
LB on sq.	0.962	0.004	0.447	0.435	0.007	0.175	0.781	0.075	0.847	0.431	0.123
					Diagnostic						
Basic checks definition	Good	Good	Good	Good	Good	Good	Good	Good	Good	Good	Good
Residual seasonality:											
- test qs test on sa	Good	Good	Good	Good	Good	Good	Good	Good	Good	Bad	Good
- test qs test on i	Good	Good	Good	Good	Good	Good	Good	Good	Good	Bad	Good
Residual trading days tests f-test on sa	Good	Good	Good	Good	Good	Good	Good	Good	Good	Good	Good

Note: Significant at 5% (Good), significant at 10% (Uncertain), not significant (Bad).
Source: Own estimations.

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Instituto de Economía

Facultad de Ciencias Económicas y de Administración

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