Endogenous Government Policy and Welfare Caseloads

LUIS AYALA[a]
Universidad Rey Juan Carlos
ANGELA TRIGUERO[b]
Universidad de Castilla-La Mancha

Abstract

Governments can soften the impact of the business cycles on welfare caseloads introducing changes in benefit levels or in the proportion of claimants that enter in the program. This paper is motivated by this concern and takes as its starting point both the intensive literature on the determinants of welfare caseloads and the fundamentals of public choice theory applied to the design of welfare programs. The paper is based on data from the minimum income program of Catalonia's Government (PIRMI). We use time-series analysis to find that unemployment has strong and significant lagged effects on the caseload. Second, the generosity of the program is clearly predictive of receipt of benefit even in a context of high and growing unemployment rates. We also found, however, a fairly strong correlation between unemployment growth and the proportion of rejected applications. This later parameter might have been the chosen tool to moderate the increase in the number of recipients.

Keywords: welfare caseloads, endogenous policy, PIRMI, ADL models.

JEL: I30, I38, C22

[a] *Facultad de Ciencias Jurídicas y Sociales, Universidad Rey Juan Carlos, Paseo Artilleros s/n, 28032 Madrid, SPAIN, luis.ayala@urjc.es*
[b] *Facultad de Ciencias Económicas y Empresariales, Plaza de la Universidad 1, 02071 Albacete, SPAIN, angela.triguero@uclm.es*

INTRODUCTION[1]

The magnitude of the welfare caseload has been a subject of increasing concern to voters and policy-makers. When it comes to public policy discussions of welfare programs, there is no doubt that this issue is a major topic. Interest in the analysis of the determining factors of the changes in the number of recipients has heightened recently, fed by concerns about the increasing costs due to what has been called the Great Recession. Previous work has provided evidence that unemployment and policy changes play a key role in caseloads changes. Researchers have consistently documented that policy designs have a substantial impact on the number of recipients and macroeconomy may reinforce and support the direction of legislative changes. An intensive literature has examined the relative importance of the different factors in explaining caseload changes (CEA, 1997; Figlio and Ziliak, 1999; Moffitt, 1999a; MaCurdy, *et al.*, 2000; Blank, 2001; Wallace and Blank, 1999; Ziliak et al., 2000; Grogger *et al.*, 2003; Grogger, 2004; Page *et al.*, 2004; Haider *et al.*, 2004; Ayala and Pérez, 2005; Looney, 2005; Danielson and Klerman, 2008). Most of this research concludes that lower unemployment rates are important determinants of the caseloads declines but changes in welfare programs and other policies are also relevant.

Governments can soften the impact of the business cycles on welfare caseloads. Limited financial incentives that allow workers to keep less of their earnings while retaining benefits, lower benefit levels, compulsory work-related activities, time limits, or sanctions in case of non-compliance are some examples among a variety of options to reduce caseloads. There is, on one hand, a sizable body of research on the specific effects of each option on the aggregate welfare caseloads (Danielson and Klerman, 2008; Chaudary and Gathmann, 2009). Beyond the specific policies there is even evidence of the strong influence of the implementation of policy on caseloads (Mead, 2001; Loprest, 2012). On the other hand, public choice theory provides a comprehensive and consistent explanation of the possible effects of each of those options on the possible patterns of caseloads expansion and contraction. As shown by Moffitt (1999b), voters might react negatively to increases in welfare expenditures by seeking retrenchments in the system to limit the growth of caseloads. Lower levels of

[1] Financial support for this research was provided by the Ministry of Science and Technology (ECO2010-21668-C03-01) and Ivalúa.

benefits or stricter requirements to reduce take-up rates would become endogenous variables that policy-makers might use to that end.

The likelihood of governments limiting the responsiveness of welfare caseloads to macroeconomic conditions is especially high when the economy grows slowly and unemployment rates increase steadily. Financial constraints might foster the introduction of more restrictive conditions in the abovementioned parameters of the programs. There is a variety of possibilities since the political costs the government would face differ among the different options. These costs are clearly higher when benefit levels are lowered than when governments decide to reduce take-up rates.

Beginning in 2007, in many OECD countries economy underwent the deepest recession since the Great Depression. It stands to reason that a growing demand of benefits should have driven welfare caseloads to considerably higher levels than those registered before the economic downturn began. Recent evidence for the US shows, however, that welfare caseloads remained relatively flat (Zedlewski, 2008; Loprest, 2012). Bitler and Hoynes (2010) showed that since 2000 the trend in welfare caseloads bears little relationship to the national business cycle. The reason why this happens is that the welfare reform introduced in the mid-nineties gave rise to a decrease in the cyclicality of cash welfare. The available evidence suggests that the lack of increase in the post–welfare reform recession is explained almost completely by declines in take-up rather than declines in eligibility (Zedlewski, 2008; Purtell and Gershoff, 2012).

Governments therefore might use take-up rates in periods of economic downturns to avoid a dramatic growth of caseloads. This evidence raises important questions about the forces that shape government policy when the economy grows slowly. Depending on the political costs and the level of unemployment, governments might decide to modify some key programs' parameters –benefit levels– but using others –the proportion of claimants that enter in the program– to prevent the increase in the number of welfare recipients. Ignoring the existence of these relationships can result in unreliable estimates of the determinants of welfare caseloads.

This paper is motivated by this concern and takes as its starting point both the intensive literature on the determinants of welfare caseloads and some of the fundamentals of public choice theory applied to the design of welfare programs. In this article, we aim to narrow the gap in the literature waiving together these two strands. The paper is based on data of the minimum income program of Catalonia's Government. This is an interesting case of welfare design in a framework of economic recession. Spain is one of the countries where unemployment has grown the most during the great recession. Regarding the institutional design of the system, a relevant fact is that each regional government in Spain must finance the program with its own resources. There is no extra funding from the central government in case of economic downturns and in absence of changes in the design of the program increasing caseloads will give rise to noticeable growth of public expenditure. In Catalonia, while some of the implemented changes have tended to promote greater coverage among the potential claimants the government has also increased the proportion of rejected applications.

We use long time-series data to find that unemployment has strong and significant lagged effects on the caseload. Second, our results provide some insights for understanding the nature of endogenous government policy in the design of these programs in periods of economic downturn. The generosity of the program –average size of benefits– was clearly predictive of receipt of benefit even in a context of high and growing unemployment rates. We also found, however, a fairly strong correlation between unemployment growth and the proportion of rejected applications. This later parameter might have been the chosen tool for avoiding an unsustainable increase of the caseloads.

The structure of the paper is as follows. The following section reviews some of the pathways through which macroeconomic conditions may affect welfare caseloads in alternative frameworks of public choice decisions. Section two introduces the program and the variables used in the empirical analysis. Section three presents the empirical strategy. Results are discussed in the fourth section. The paper ends with a brief list of conclusions.

1. CONCEPTUAL FRAMEWORK

In the most basic approach, welfare caseloads can be considered a simple function of eligible households for the program and the corresponding take-up rate. Given that the decision of entering the program will be determined by household decisions and the utility they derive from receiving benefits, the main alternatives of governments to control the caseload will be reducing the level of benefits or increasing the proportion of rejections.

Under the assumption of constant take-up rates, welfare caseloads are a function of a bundle of measures representing macroeconomic conditions and the parameters of the program. Numerous studies have addressed the relative importance of each one of these factors in explaining variations in the caseloads. The most common result is the key role unemployment and macroeconomic conditions have on the number of recipients. However, there is recent evidence showing that caseloads seem less responsive to unemployment changes than they were some years ago. By interacting unemployment rates and measures of welfare reform Bitler and Hoynes (2010) found that the substantial changes implemented in welfare programs in the US during the nineties caused a decrease in the cyclicality of cash welfare.

This fact opens the door to a deeper understanding of the factors affecting the design of the programs that might cause a lower sensitivity of the number of recipients to unemployment changes. As shown by Zedlewski (2008), the available evidence suggests that the lack of increase in caseloads in the post–welfare reform recession was explained almost completely by declines in take-up rather than declines in eligibility. Declining real benefits, work requirements, sanctions for failure to meet particular rules, time limits, and state strategies that divert families from enrolling all played a part. More recent data from Loprest (2012) shows that the national caseload declined by 50 percent between 1997 and 2011, but specific state caseload reductions ranged from 25 to 80 percent. Factors such as the economy and the earned income tax credit played a key role in the caseload decline, but welfare policy had a substantial impact. The caseload decline could be attributed both to more families leaving the program and to fewer eligible families participating.

A key question therefore is which the political strategies that may produce a countervailing effect on caseloads when unemployment grows are. In the US case, Danielson and Klerman (2008) used difference-in-difference models of the determinants of the aggregate welfare caseload to find that while they could attribute about a quarter of the caseload decline to time limits and sanctions and about a fifth to the economy a residual policy bundle explained a third of the changes. After many years of research, we still have relatively little insight into which are the political channels through which governments develop endogenous strategies to maintain the number of welfare recipients around a sustainable level of expenditure.

Until relatively recently economic theory was silent on how policy-makers simultaneously modify some parameters of the program in different directions to prevent high pressures on government's fiscal situation. The major economic rationale for these endogenous strategies revolves around assertions of public choice theory. Governments have the ability to choose both the extent of welfare eligibility as the intensity of benefits provided through the programs. Moffitt (1999) provided a comprehensive explanation of the reasons for particular patterns of expansion or contraction in welfare expenditure within a public-choice framework. While primacy was assigned to voters and their preferences, the model works well also to identify the incentives of government to consider the recipiency rate as a policy goal.

Consider a conventional function of voter (V) preferences with a utility function like

$$U=f(C_V,C_P) \tag{1}$$

where C_V is the consumption of the voter and C_P is the consumption of the poor, $f_1>0$, $f_2\geq 0$. Two constraints can be added:

$$C_P = Y_P + B \tag{2}$$

$$C_V = Y_V - \mathrm{T} \tag{3}$$

being Y_P and Y_V the non-transfer income and before-tax income of the poor and non-poor, respectively; B the benefit level per welfare recipient; and T the tax payment per person to finance the welfare benefits. If this takes a per capita form:

$$T = BN_W / N_{np} = BR \tag{4}$$

where N_w is the number of units receiving welfare benefits and P is the size of the non-poor population. This makes R the per capita recipiency rate –over the entire non-poor population– and it can be considered a general measure of the caseload size. Government should decide the level of B that maximizes utility. The marginal condition for optimal B is:

$$\frac{U_2(C_V,C_P)}{U_1(C_V,C_P)} = R \tag{5}$$

This result implies that the price of increasing benefits is the recipiency rate. As posed by Moffit (1999), a central question in terms of our analysis is that R and B are endogenous. R is positively affected by benefits and negatively affected by the potential income of eligible units:

$$R = f(B,Y_P) \tag{6}$$

Considering the recipiency function an additional constraint, optimal benefits should meet the condition:

$$\frac{U_2(C_V,C_P)}{U_1(C_V,C_p)} = R(1+\eta) \tag{7}$$

where $R(1+\eta)$ is the elasticity of the recipiency rate with regard to the benefit. Therefore, the only exogenous variable determining the caseload is $Y_{P.}$ It seems reasonable that contractionary policies will receive support with declining real incomes and employment rates. The central issue, however, is that governments can change the level of benefits or the recipiency rate to control changes in welfare expenditure.

Earlier evidence summarized by Ribar and Wilhelm (1999) showed that estimated price effects range from negative and elastic results to positive results, with the majority of studies reporting small and negative results. Income estimates also range from strongly negative to strongly positive. Their own results reexamining the specification assumptions used in these analyses and treating the price variable as exogenous placed the range of price elasticities between -0.14 and 0.02. For income, the overlapping confidence bounds are wider, with the estimated elasticity ranging from 0.11 to 0.82. These results seem to indicate that welfare generosity might be much less sensitive to economic changes than the usual assumptions.

Baicker (2005) proposed a more general model than that of the previous analysis. Governments may determine eligibility standards, including asset tests and other requirements. The number of recipients should thus be a function of both eligibility parameter choices and the preferences and characteristics of the potential recipient pool. In her model, the first order condition is that the marginal rate of substitution between expanding eligibility and increasing benefits is just equal to the marginal cost of adding one recipient over the marginal cost of adding one dollar to the benefit amount.

These fundamentals introduce a possible relationship between the level of benefits and the recipiency rate and gives place to the analysis of different government strategies for preventing an unsustainable growth of the caseload. Shifts in the recipiency function are possible including among them possible actions focused on reducing the number of households entering into the program.

The extent to which governments make use of more restrictive strategies will depend on different issues. There might be institutional factors acting as potential incentives to reduce the number of recipients. In the US, for instance, before the welfare reform was enacted a matching financing formula protected states from the full economic costs of serving more families when the economy weakened, since the federal government shared the costs of increased caseloads with the states. The new system operates very differently because states generally do not get more federal funding when caseloads increase in hard economic times. Since financing is a block grant, decisions on whether or how to reallocate funds to address greater economic hardship rest solely with the state. As stated by Pavetti *et al.* (2011), there are some features of the new system that create a disincentive to serve more families during periods of greater need: i) the block grant structure means that if a state uses more funding for cash assistance, it will have less for other measures included in the welfare-funded programs; ii) since the primary performance measure of the welfare program is the work participation rate, the system rewards states for reducing their welfare caseloads, even if the economy is weak; iii) when the economy weakens and fewer jobs are available, it becomes more difficult for states to meet their prescribed work participation rates unless they keep caseloads down.

The incentives to reduce caseloads will depend therefore on the intensity of potential unemployment shocks and the specific institutional details of the program. It might be the case that there could be an expenditure threshold from which the government should try to reduce the caseloads through a higher proportion of rejections. It will depend on the possible trade-off between lower benefit levels or lower recipiency rates if unemployment reaches a sizable level. Estimates for the US show that a 10 percent increase in the cost of benefits causes a 3.8 percent decrease in benefit amounts, while a 10 percent increase in the cost of recipients causes a 2.8 percent decrease in the number of recipients (Baicker, 2005).

2. THE PIRMI PROGRAM AND ITS CONTEXT

The data used in this study are the administrative records of the Catalonian Minimum Income Program (PIRMI). Like other regional programs in Spain, the PIRMI Program was designed at the beginning of the nineties following the pattern of the French Revenue Minimum d'Insertion. In Southern European countries new welfare schemes were created some years before reforms were implemented in other OECD countries. By the later 1980s France and other countries had put into practice a new social tool trying to reconcile two different objectives: providing a basic level of economic protection and developing measures to improve social and labor participation of low-income households.

In the PIRMI program different activities were established aimed at achieving these two goals. First, there is a cash benefit which is set taking into account the household size. The monthly level of benefits for single-person households were 414 euros in 2010. Additional adjustments for each child or other adults are less than 100 euros. Second, the program comprises a variety of measures developed both to guarantee the basic preconditions of social participation and to improve recipients' employment opportunities.

Potential claimants can apply for benefits only if they have used up entitlement to other income maintenance programs. Like other European systems, the main difference from U.S. programs is that welfare covers all households. PIRMI access is not only allowed to female lone-parent households, but also to couples without children, single individuals or male-headed families. Eligibility conditions are restricted to an upper age limit (65 years of age, at which age claimants can benefit from the national non-contributory pension scheme) and a lower age limit (25 years of age, except for claimants with dependent children). Along with these, in order to prevent the formation of fictitious family units solely aimed at receiving the benefit, households must have been formed for a defined period before claiming that benefit. Another legal requirement is that of being officially registered in Catalonia as a resident. This requirement is compatible with people of other nationalities claiming the benefit.

Welfare policies in Spain are completely decentralised. The lack of initiative by the central government in the late 1980s encouraged regional governments to begin establishing their own welfare programs. The result of this development was a mosaic of highly varied schemes, with a striking disparity of regulations and benefit levels across the different regions. As a result, each regional government sets the level of benefits and any other aspect of the programs' design with total autonomy. In this sense, changes in welfare caseloads will raise needs for additional funding that can only come from the regions own resources.

[FIGURE 1]

Monitoring the flow of entries into and exits from the program is possible because of a wide base of administrative records. Our sample period –monthly data– runs from 1998 to the first quarter of 2011. This period is affected by the marked change in the business cycle that took place in 2007. Figure 1 shows how the total number of recipients has changed over the last and a half decade. The number of households receiving benefits remained roughly constant between the last third of the 1990s and the first years of the next decade. The average number of recipients was around 10,000. The number of recipients began to slightly increase in the next years through 2006 pushing that number above 12,000 households. In 2007 economy underwent the deepest recession since the seventies. As a result, the number of recipients rose to an historical high of nearly 30,000 households at the moment of data gathering (May 2011).

[FIGURE 2]

There might be different reasons why caseloads increased. A natural focus is what has happened in the labor market. The number of employees paying Social Security contributions fall from an historical high of nearly 3.5 million in 2007 to 3 million in 2011 (Figure 2). Before the economic crisis broke out there had been a strong increase in these numbers in clear contrast with the much more stable caseloads trend. Changes in unemployment have been more drastic with an unprecedented growth in the number of individuals registered as unemployed. Registered unemployment tripled in three years moving from 125,000 unemployed in 2007 to more than 600,000 four years later. The trend is very similar to the one observed for the caseloads. During the second half of the nineties unemployment declined noticeably, followed by a period of stability during the next seven years, but it began to creep up again in 2007, and continued upward at rather increasing pace.

These administrative data only provide a partial picture of the changes in macroeconomic conditions and unemployment. The Labour Force Survey (EPA) records quarterly data on unemployment at territorial level. The unemployed as a percent of the labor force is a standard measure for macroeconomic conditions in the analysis of welfare caseloads. This is not however the most direct measure of how changes in the labor market might affect the demand of welfare. Recent evidence for the Spanish economy shows that the intra-household distribution of unemployment can be more relevant than aggregate unemployment in order to explain poverty changes (Ayala *et al.*, 2011). The proportion of workless households or the unemployment rate of households heads can be key factors to explain the impact of recessions on poverty.

[FIGURE 3]

Figure 3 illustrates the changes in alternative rates in Catalonia taking into account this intra-household distribution of unemployment. The unemployment rate rose from a level slightly higher than a 6 percent in 2007 to an historical high of nearly a 20 percent three years later. The rate for households heads doubled from 2007 to 2010 while the proportion of households where all active members are unemployed rose from its lowest value –1.5 percent in 2005– to more than a six percent. The lack of employment has introduced, inexorably, a remarkable pressure on the demand for benefits. This can be corroborated looking at data on the proportion of 'disconnected' households or households who do not earn any income from labor and neither benefit from any Social Security transfers (i.e. pensions or other benefits) nor from unemployment insurance or assistance payments. The EPA provides quarterly information on this variable that can serve as a proxy for the demand of welfare benefits. With the natural caveats resulting from the limited sample size of the survey, it seems that this potential demand registered an extraordinary increase through the recession period (Figure 4). The rate rose from a proportion of affected households of 1.5 percent in 2007 to a 3 percent three years later.

[FIGURE 4]

Therefore, macroeconomic conditions have changed significantly over the last decade and a half. The deep recession that began in 2007 gave rise to an unparalleled growth of situations preluding considerably higher levels of demand for PIRMI benefits. These changes could introduce a strong pressure on the designers of the program as the increasing number of eligible households could be translated into a rapid growth in caseloads. In keeping with the theoretical background summarized in previous section, the government could have modified some of the parameters of the program to maintain the caseloads around a predefined threshold.

[FIGURE 5]

An indirect approach for testing the possible effect of unemployment changes in the number of recipients is looking differently at entry and exit flows in the program. Figure 5 shows how these monthly flows have changed over a time span of more than thirteen years. Both flows registered similar trends before the recession began. When the economic expansion came to a halt, entries grew at a faster pace but exits did not decline. This last fact contrasts with the standard assumption of lower exits from welfare programs in periods of declining employment opportunities. As stated above, it could also be an indirect proof of governmental reaction to prevent unsustainable growth of welfare caseloads. In addition to promoting exits, as mentioned before, governments can also affect the caseloads trough changes in benefits and the proportion of rejected applications. Average benefits, however, must not always be interpreted as policy decisions. In addition to legal changes mirroring government's preferences these amounts also represent changes in the economic needs of households entering into the programs. While in periods of lower unemployment rates households applying for benefits might be unable to find a job –having therefore very limited economic resources– an opposite situation might be the case in economic downturns. In this later context, it is possible a more varied mix of recipients including households who transitorily enter into the program to sum more resources to an unexpected low income.

[FIGURE 6]

Figure 6 plots the path followed by both variables. The data show that until 2002 average benefits grew slowly as a result of annual price indexation. From that year and up to 2007 there were few changes in the level of benefits. In 2007, however, benefits rose again with no remarkable changes in the years after. The proportion of rejected applications shows a much more erratic behavior. Despite this volatility, it is possible to appreciate a declining trend at the beginning of our sample period, a somewhat upward profile from then and up to the beginning of the economic crisis, and a sizable growth in this last period. As mentioned above, this last result might be associated with an endogenous process of decision-making. To prevent an unsustainable growth in the number of recipients the government might have chosen to increase rejections instead of reducing benefits.

Other institutional issues relevant to understand possible changes in caseloads are a set of partial reforms that were enacted during our sample period. While some reforms have promoted greater coverage among the poor others have made the program more restrictive.

3. EMPIRICAL IMPLEMENTATION

Over the past two decades, a variety of methods have been developed for modeling the dynamics of welfare caseloads. While most of the 1990s studies used panel data or time-series models more recent approaches have suggested alternative techniques. Grogger (2007), for instance, used Markov chains exploiting the inertia of caseloads to base forecasts of the future caseloads on current exits and entries. Zolotoy and Sherman (2009) implemented a two-step latent factor approach to model welfare caseloads.

Since we have data for one program and a long time-span –monthly data that run from January 1998 to the first quarter of 2011– estimation was by standard time-series analysis since more sophisticated techniques did not seem to be called for. The basic statistical equation that we estimate is:

$$C_t = \alpha_1 + \alpha_2 U_t + \alpha_3 B_t + \alpha_4 R_t + \alpha_5 \Pi + \varepsilon_t \qquad (8)$$

where C_t is the number of registered caseloads at the monthly level (the ratio of recipients to the population over 25 years of age), U_t is the unemployment rate, B_t is the average benefit –reflecting the program's generosity–, R_t is the proportion of rejected applications –reflecting the program's restrictiveness– and Π are dummies capturing the effects of specific reforms. The variables have been considered in logarithms to avoid the problem of a lack of stationarity in the variance. In addition, this allows the coefficients to be interpreted as elasticities. This approach enables to control the effects of macroeconomic conditions –unemployment rate– and the effects of the different strategies the government might undertake.

Before proceeding with the empirical analysis it is necessary to study the order of integration of all the variables considered –including entries (EN_t) and exits (Ex_t)– by performing unit roots tests for the full sample. The null hypothesis of non-stationary cannot be rejected with several formal stationarity tests. According to the results of the augmented Dickey–Fuller unit root test, as well as of the Phillips–Perron test, most of the variables included in equation (8) are I(1) and, therefore, non-stationary at levels but stationary at their first difference (Table 1). Only the proportion of rejected applications and the flow of exits seem to be I(0).

[TABLE 1]

Once the properties of the series have been confirmed it is necessary to specify an adequate form for the relationship introduced in (8). The approach chosen for this paper is an autoregressive distributed lag (ADL) model. We include as regressors lagged values of the caseloads and current and lagged values of unemployment rates:

$$C_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i\, C_{t-1} + \sum_{k=1}^{m} \sum_{i=0}^{n} C_{ki}\, X_{kt-i} + u_t \tag{9}$$

As stated by Grogger (2007) today's caseload depends in part on yesterday's caseload and the current levels of recipients exhibit inertia. Some authors have challenged, however, the introduction of lagged values of economic conditions in the specification of caseloads models. McKinnish (2005), for instance, suggests that estimates on lagged unemployment rates may merely reflect the presence of omitted variable or measurement error bias. Nevertheless, another large literature has found as necessary the lags of the measures of the economy to capture the dynamics of caseload change (Bartik and Eberts, 1999; Figlio and Ziliak, 1999; Wallace and Blank, 1999; Ziliak *et al.*, 2000; Mueser et al., 2000; Blank, 2001; Haider *et al.*, 2001; Grogger, 2007; Danielson and Klerman, 2008; and Bitler and Hoynes, 2010). An intensive literature has also examined the inertia component in the persistence of unemployment. Blanchard and Summers (1986) explained, for instance, the high dependence of current unemployment on past unemployment. They argued that physical capital, human capital, and insider-outsider theories are not enough to explain why shocks that cause unemployment upturns in a single period might have long-term effects. They concluded that hysteresis –unemployment inertia– is a feature of the business cycle rather than a consequence of a particular structure of the labor market. Such effects continue being an important source of persistence of European unemployment rates.

Most single-equation econometric models can be thought of as special cases of the ADL model. Alternative specifications of this model can be obtained by restricting various parameters (leading indicator, growth rate model, partial adjustment, common factor model, equilibrium correction mechanisms or dead-start model).[2] In this paper, our starting point is a basic ADL specified considering restrictions on a general error correction model (ECM). The reason of considering the later model is that welfare caseloads and unemployment time series can move together in a long-run equilibrium relationship. This possible long-run relationship between C_t and U_t can be anticipated using cointegration techniques. This is a central issue in this type of analysis. When the series are cointegrated by a common factor –cointegrating vector– it is not possible to

[2] See Hendry (1995) and Banerjee *et al.* (1993).

use a standard VAR-approach. Then, we have to account for this relationship and use an error-correction model to get consistent results.

A necessary condition to conduct cointegration tests is that the variables under study must be integrated of the same order. As stated before, the main variables are integrated of order 1 and therefore the appropriate cointegration tests can be determined. As usual in VAR models, the Akaike Information Criteria and the Schwarz Criteria have been used to define the optimal lag structure[3]. We test the presence of a cointegration relationship between the welfare caseloads and unemployment calculating the trace and maximum eigenvalue statistics (Johansen, 1995).

If the long run condition between caseloads and unemployment is confirmed, the equilibrium relationship can be transformed into a new equation through an Error Correction Mechanism (ECM). The ECM associates changes in one of the series (or both) to past equilibrium error, as well as to past changes in both. The long-run relationship is expressed as:

$$C_t = \varphi U_{t-1} + u_t \tag{10}$$

The error correction equations with one lag can be estimated as:

$$\begin{aligned} \Delta C_t &= \alpha_C + \beta_C Z_{t-1} + \gamma_{CC,i} \sum_{i=1}^{p} \Delta C_{t-i} + \gamma_{CU,j} \sum_{j=1}^{q} \Delta U_{t-j} + u_{C,t} \\ \Delta U_t &= \alpha_U + \beta_U Z_{t-1} + \gamma_{UC,i} \sum_{i=1}^{p} \Delta C_{t-i} + \gamma_{UU,j} \sum_{j=1}^{q} \Delta U_{t-j} + u_{U,t} \end{aligned} \tag{11}$$

considering

$$\begin{aligned} \Delta C_t &= \alpha_C + \beta_C Z_{t-1} + \gamma_{CC,1} \Delta C_{t-1} + \gamma_{CU,1} \Delta U_{t-1} + u_{C,t} \\ \Delta U_t &= \alpha_U + \beta_U Z_{t-1} + \gamma_{UC,1} \Delta C_{t-1} + \gamma_{UU,1} \Delta U_{t-1} + u_{U,t} \end{aligned} \tag{12}$$

where

[3] The AIC and SC Criteria are commonly used to determine lag lengths in VAR models.

$$Z_t = C_{t-1} - \varphi U_{t-1} \tag{13}$$

is the cointegration relationship and β_C and β_U are the speeds of adjustment to long run equilibrium of welfare caseloads and the unemployment rate.

4. RESULTS

a) *Determinants of Welfare Caseloads*

As stated above, we estimate a dynamic model that includes lagged terms of the caseloads among the explanatory variables. All the specifications include this dependent variable with one and two period lags among the determinants. Although the coefficients of the dynamic models are smaller than those of static models, the coefficients for the effects of unemployment and the program's parameters appear with the expected signs (Table 2). Several points are worth mentioning. Of all our findings, one unequivocal message is that economy matters. As expected, unemployment rates have sizable and significant effects on the program's caseloads. The higher unemployment rate is, the higher welfare caseloads are. A one-point rise in the unemployment rate increases caseloads about a 5 per cent.

[TABLE 2]

It seems, however, that the lagged effects of economic conditions on PIRMI participation are important. Columns (5)-(10) of Table 2 give general support to the notion that the optimal forecasting horizon for the model involves lagged effects of the economy. The parameter estimates for the lagged unemployment rates are consistent with the previous statement that including lags of the measures of the economy are needed to capture the dynamics of caseload change. The effects of changes in unemployment on caseloads are more modest when the rates are included in their current values. We also consider a moving average of unemployment ($U^S{}_t$) using 2 lagged terms, 3 forward terms, and the current observation in the filter (uniformly weighted) (Column 11). The estimated coefficient for this variable does not drastically change the picture presented in columns (3) and (4).

Among all the variables included in the specification –with the exception of the lagged caseloads–, the most important turns out to be the generosity of the program. We find that, to a high degree of statistical confidence, the estimated effects of the impact of changing the benefit levels are large. The estimated elasticities are higher than those of the unemployment rate (5.6 percent). In keeping with the public choice fundamentals previously reviewed, the ability of the government to choose the intensity of benefits can have substantial effects on welfare caseloads. The sizable coefficients are consistent with the hypothesis that the higher the benefits are, the greater the number of households receiving benefits is.

Compared to the estimated effects for unemployment and the average level of benefits, the coefficients for the variable reflecting the program's restrictiveness –proportion of rejected applications– are relative small. Nevertheless, the most striking result is the negative sign found for this variable. It seems that there is a kind of reverse causality suggesting that lowering the recipiency rate might have been chosen as a strategy to prevent increases in the program's expenditure. As we will see below, this kind of endogeneity might be related to changes in the unemployment rate. Decisions to impose more restrictions to reduce the flow of entries might be a response to unemployment shocks.

In general terms, the estimates are quite robust to a number of minor changes in the initial specification. In addition to the inclusion of the two previous parameters reflecting welfare designs our models also include controls for specific reforms. In general terms, these controls do not change the picture presented in the first columns of Table 2. The 2006 reform affected negatively to the caseloads (around one point) while the 2008 reform seems to have produced a positive influence (coefficients between 0.09 and 1.5). The first one of these reforms introduced some incentives to promote higher levels of labor participation among the recipients. The second one moderated some of the strictest rules of the previous reform including a reduction in the number of working hours required to access to complementary benefits.

b) *Determinants of the flows of exit and entry in the program*

An alternative approach to analyze the determinants of changes in the caseloads is to estimate specific models for the flows of entries and exits. As stated by Grogger (2007), in the simplest terms, today's caseload depends on yesterday's caseload plus entries and exits. The observed increase in the caseload could have resulted from an increase in entries, a decrease in exits, or some combination of the two. The preliminary results shown in section showed, however, that when the recession began entries grew at a faster pace but exits did not decline. As abovementioned, this uncharacteristic behavior is not in keeping with the standard assumptions of welfare participation and could thereby hide a governmental reaction to moderate the growth of welfare caseloads. According to standard theory the components of the exit and entry functions should be similar but the expected signs should differ. Under a linear specification of the relationship between unemployment and both flows, it should be expected that increases in unemployment reduce exits and boost entries with a similar effect for the generosity of the program.

[TABLE 3]

Our estimates yield, however, dissimilar results for each flow. Concerning entries, all the specifications included in Table 3 show a strong and significant effect of macroeconomic conditions. Again, it is necessary to include a structure of lags for better capturing the dynamic effect of unemployment on entries. A positive effect on entries is also found for the average level of benefits. The generosity of the program has led to increased use of benefits. Rejections, however, present the expected negative effect in this case.

[TABLE 4]

The fit is rather worse for the exits model. An amazing result is the positive effect of the unemployment rate on the number of recipients leaving the program. In contrast to the natural assumption that lower employment opportunities should reduce the probability of leaving the program there seems to be an opposite influence of macroeconomic conditions on exits. On the other side, the estimates for the two parameters reflecting generosity and restrictiveness are imprecise. It appears that these factors do not play a key role as determinants of exits from the program.

It seems therefore that there could be omitted variables that should be considered for an adequate modeling of the flow of exits. A key factor might be that the government could have applied stricter rules on the households staying in the program. As Danielson and Klerman (2008) found for the U.S., a residual policy bundle could explain the main changes in the number of exits. More control of compulsory work-related activities or harder sanctions in case of non-compliance are some examples of actions leading to lower numbers of households staying in the program. The shifts in the recipiency function would come then from the increase in entries resulting from higher unemployment rates and higher benefit levels and the increase in exits derived from policy actions focused on increasing the number of households leaving the program.

c) *The endogeneity of rejections*

Previous results suggest that the policy options under study –generosity and restrictiveness – do not have a clear countervailing effect on the number of caseloads. While the effect of the average levels of benefits on welfare caseloads is strong and positive, according to the estimated coefficients the proportion of rejected applications also might be pushing up the number of recipients. This contradictory result could be related to the previous discussion on the potential use of rejections as a policy strategy to reduce the number of caseloads. A plausible case can be made that those estimates could be hiding the relationship between unemployment and rejections. In times of severe recession governments might choose between an increase in the proportion of rejected applications, a decrease in the level of benefits, or some combination of the two. The political costs of reducing the program's generosity may be higher, at least in the short-term, than those of increasing rejections of welfare applications.

[TABLE 5]

Table 5 gives general support to the notion that the proportion of rejected applications might be linked to changes in the labor market over the economic cycle. The coefficients for unemployment appear in line with the previous hypothesis. The higher unemployment rate is, the higher rejections are. Coefficient estimates on lagged unemployment rates also reveal that there is a delay in the effect of changes in macroeconomic conditions on policy decisions. These results at least suggest that unemployment might be important to understand how the program's designers try to avoid large increases of the caseloads through a higher proportion of rejected applications.

A second relevant question is the extent to which there is a possible trade-off between generosity and restrictiveness in the PIRMI program. As stated before, both strategies could take place simultaneously. Despite the estimates seem sensitive to the different specifications, the most important factual finding is that results provide a rough indication of statistical association between changes in the average level of benefits and the proportion of rejected applications. In the most basic specification (Column 1 of Table 5), the generosity of the program seems to have a sizeable and significant effect on its restrictiveness. Therefore, the changes in one of the parameters of the program might in some sense matter more on the decisions on new recipients than changes in the unemployment rate. Rejections would be the response to increases in the average level of benefits to partially offsetting the effects on the caseloads numbers. This inference, however, is subject to some caveats as these effects seem dwarfed when controls for specific reforms and lagged unemployment rates are considered.

d) *Cointegration and ECM models*

A last empirical issue has to do with the possibility of testing whether the relationships found also hold in the long run. We carried out different test finding that the results are free of spurious results in both the short and the long run. The usual statistics of Johansen (1995) tests –maximun eigenvalues and a trace statistics– confirm that there exist cointegration relationships. Given that a cointegrating vector exists between the main variables of our estimates, we proceeded to estimate alternative error correction equations using data for the entire period.

[TABLE 6]

Table 6 illustrates how welfare caseloads have a stable long run relationship with the unemployment rate. It holds in all the specifications considering from one to four lags. According to the estimated parameter in the first model for the caseloads equation (-0.079) the adjustment in the long run of the number of caseloads to unemployment is confirmed. When the economy is working well (low unemployment rates) and the number of caseloads is low, they will increase. In periods of economic downturn (high unemployment rates) and higher numbers of caseloads, they will fall back to their equilibrium level .

[TABLE 7]

Table 7 presents estimates of alternative ECM models considering the other variables (C_t,R_t,Π_{2006},Π_{2008}). Results with these models also show that welfare caseloads have a stable long run relationship with the unemployment rate in most of the estimated models. The average number of caseloads adjusts to unemployment levels in the long run in all the specifications considering one-period lag. In the short run, changes in the unemployment rate also affect caseloads variations. The slope coefficient of -0.06 implies that if the number of caseloads in the previous month was higher than what the long-equilibrium relationship predicts then there will be and adjustment to reduce this number. About a 6.5 percent of the disequilibrium is corrected each month by changes in unemployment. Results of the ECM models also confirm the previous effects of the other covariates –generosity, restrictiveness and specific reforms.

5. CONCLUSION

Among the different issues that need to be addressed in the design of welfare programs one outstanding question is how to prevent an unsustainable growth of the caseloads in contexts of limited budgetary resources. According to standard economic theory unemployment upturns can cause a drastic increase in the number of eligible households. This natural effect might be reinforced of softened by the designers of the programs. Public choice theory has shown that different strategies might give rise to very different effects. Depending on the political costs and the extent of unemployment, governments might choose between an increase in the proportion of rejected applications, a decrease in the level of benefits, or some combination of the two.

In this paper we have estimated the simultaneous effects on caseloads of higher levels of generosity –changes in the average level of benefits– and higher doses of restrictiveness –a higher proportion of rejected applications– in a framework of increasing unemployment. Using data of the minimum income program of Catalonia's Government and autoregressive distributed lag models we have tested the extent to which macroeconomic conditions might change welfare caseloads not only through increasing the proportion of eligible households but also affecting the key parameters of the program.

As expected, economy matters. Changes in unemployment rates have sizable and significant effects on the program's caseloads. Our estimates show that the impact of this variable is especially strong when some lags are taken into account. In any case, the most important effect on the caseloads seems to be that caused by the generosity of the program. The estimated elasticities are higher for the level of benefits than for the unemployment rate. The ability of the government, therefore, to choose the intensity of benefits can have substantial effects on welfare caseloads. This effect holds even when unemployment rates move from relatively low to much higher levels.

The explicitness of this political strategy should not hide however that the apparent generosity of the program might be partially offset by other decisions. On the one hand, while entries in the program seem to be motivated by changes in unemployment or the average levels of benefits –in keeping with standard assumptions– our estimates have shown that the worsening of macroeconomic conditions has been associated with a higher number of exits instead of lowering the probabilities of leaving the program. Since the natural event should have been a decrease in exit rates, this is a possible indication of endogenous actions aimed at compensating the increasing number of caseloads.

On the other hand, a striking result of our estimates is the positive effect on the caseloads found for the variable reflecting the program's restrictiveness. This might also be a signal that the lowering of the proportion of accepted applications might be part of the strategy to prevent increases in the program's expenditure. In fact, our estimates have confirmed that decisions to impose more restrictions to reduce the flow of entries might have been used as a response to unemployment shocks.

It can be said, in short, that the effects of endogenous government policy might be as important, or even more so, than the economy on welfare caseloads. It is necessary therefore to modeling the changes themselves in the level of benefits or in the proportion of rejected applications as a response to changes in macroeconomic conditions. The choice of one or other alternative will depend on both the own level of unemployment and the political costs of each option.

References

Ayala, L.; Cantó, O. and J.G. Rodríguez (2011). Poverty and the business cycle: The role of the intra-household distribution of unemployment. ECINE Working Paper nº222.

Baicker, K. (2005). Extensive or intensive generosity? The price and income effects of federal grants. *Review of Economics and Statistics* 87, 371-384.

Banerjee, A., Dolado, J.J,; Galbraith, J.W. and D. Hendry (1993). *Co-integration, Error Correction, and the Econometric Analysis of Non-Stationary Data*. Oxford: Oxford University Press.

Bartik, T.J. and R.W. Eberts (1999). Examining the Effect of Industry Trends and Structure on Welfare Caseloads. In Sheldon Danziger (ed.), *Welfare Reform and the Economy: What Will Happen When a Recession Comes?* Kalamazoo, MI: Upjohn Institute for Employment Research.

Blanchard, O.J. and L. H. Summers (1986). 'Hysteresis and the European unemployment problem', in S. Fischer (ed.), *NBER Macroeconomics Annual* 1, 15–78, MIT Press, Cambridge, MA.

Blank, R. (2001). What Causes Public Assistance Caseloads to Grow? *Journal of Human Resources* 36, 85-118.

Bitler. M.P. and H.W. Hoynes (2010). The State of the Social Safety Net in the Post–Welfare Reform Era. *Brookings Papers on Economic Activity* 41, 71-147.

Chaudhary, L. and C. Gathmann (2009). Evaluating the US Welfare Reform: Endogeneity and Multidimensionality of Welfare Policy. IZA/CEPR 11th European Summer Symposium in Labour Economics.

Council of Economic Advisors (1997). *Technical Report: Explaining the Decline in Welfare Receipt, 1993-1996.* Washington, DC: Council of Economic Advisors.

Danielson, C., and J.A. Klerman (2008). Did Welfare Reform Cause the Caseload Decline?, *Social Service Review* 82, 703–30.

Engle, R.E. and C.W.J.Granger (1987). Cointegration and error-correction: Representation, estimation and testing. *Econometrica* 55, 251-76.

Figlio, D.N. and J.P. Ziliak. (1999). Welfare Reform, the Business Cycle, and the Decline in AFDC Caseloads. In S. Danziger (ed.), *Economic Conditions and Welfare Reform.* Kalamazoo, MI: Upjohn Institute for Employment Research.

Grogger, J., Haider, S.J. and Klerman, J. (2003). Why Did the Welfare Rolls Fall During the 1990's? The Importance of Entry. *American Economic Review* 93, 288-292.

Grogger, J. (2004). Welfare Transitions in the 1990s: The Economy, Welfare Policy, and the EITC. *Journal of Policy Analysis and Management* 23, 671-95.

Grogger, J. (2007). Markov forecasting methods for welfare caseloads. *Children and Youth Services Review* 29, 900-911.

Haider, S.J., Schoeni, R.F., Bao, Y. and C. Danielson (2004). Immigrants, welfare reform, and the economy. *Journal of Policy Analysis and Management* 23, 745-64.

Hansen B. and B. Seo (2002). Testing for two-regime threshold cointegration in vector error-correction models. *Journal of Econometrics* 110, 293 – 318.

Hendry, D.F. (1995). *Dynamic Econometrics*. Oxford: Oxford University Press.

Johansen, S. (1995). Identifying restrictions of linear equations with applications to simultaneous equations and cointegration. *Journal of Econometrics* 69, 111-132.

Johansen, S and K. Juselius (1994). Identification of the long-run and the short-run structure an application to the ISLM model. *Journal of Econometrics* 63, 7-36.

Looney, A. (2005). The Effects of Welfare Reform and Related Policies on Single Mothers' Welfare Use and Employment. Federal Reserve Board of Governors, Finance and Economics Discussion Series 2004-45. Washington, D.C.: Federal Reserve Board.

Loprest, P.J. (2012). How Has the TANF Caseload Changed over Time?. Temporary Assistance for Needy Families Program - B08.

MaCurdy, T, Mancuso, D. and M. O'Brien-Strain (2001). How Much Does California's Welfare Policy Explain the Slower Decline of Its Caseload. San Francisco, CA: Public Policy Institute of California.

McKinnish, T.G. (2005). Lagged Dependent Variables and Specification Bias. *Economics Letters* 88, 55-59.

Mead, L.M. (2001). Governmental Quality and Welfare Reform. Institute for Research on Poverty, Discussion Paper nº 1230-01.

Moffitt, R. (1999a). The Effect of Pre-PRWORA Waivers on AFDC Caseloads and Female Earnings, Income, and Labor Force Behavior. In S. Danziger (ed.), *Economic Conditions and Welfare Reform.* Kalamazoo MI: W.E. Upjohn Institute for Employment Research.

Moffitt, R. (1999b). Explaining Welfare Reform: Public Choice and the Labor Market. *International Tax and Public Finance* 6, 289-315.

Page, M.E., Spetz, J. and J. Millar (2004). Does the Minimum Wage Affect Welfare Caseloads? *Journal of Policy Analysis and Management* 24, 273-95.

Pavetti, L.D., Trisi, D. and Schott, L. (2011): TANF responded unevenly to increase in need during downturn. Center on Budget and Policy Priorities.

Purtell, K.M. and Gershoff, E.T. (2012). Low Income Families' Utilization of the Federal "Safety Net": Individual and State-Level Predictors of TANF and Food Stamp Receipt. National Poverty Center Working Paper Series 12-04.

Ribar, D.C. and M.O. Wilhelm (1999). The Demand for Welfare Generosity. *The Review of Economics and Statistics* 81, 96-108.

Stigler, M. (2012).Threshold cointegration: overview and implementation in R (*mimeo)*.

Wallace, G, and R. Blank (1999). What Goes Up Must Come Down? Explaining Recent Changes in Public Assistance Caseloads. In S. Danziger (ed.), *Economic Conditions and Welfare Reform*. Kalamazoo MI: W.E. Upjohn Institute for Employment Research.

Zedlewski, S. (2008). The Role of Welfare During a Recession. Urban Institute Recession and Recovery Report no. 3. Washington: Urban Institute.

Ziliak, J.P., Figlio, D.N., Davis, E.E. and L.S. Connolly (2000). Accounting for the Decline in AFDC Caseloads: Welfare Reform or Economic Growth? *Journal of Human Resources* 35, 570-586.

Zolotoy, L. and Sherman, A. (2009). Modeling the Dynamics of Welfare Caseload: a New Approach. Melbourne Business School (*mimeo*).

Figure 1. Changes in the number of recipients, 1998-2011

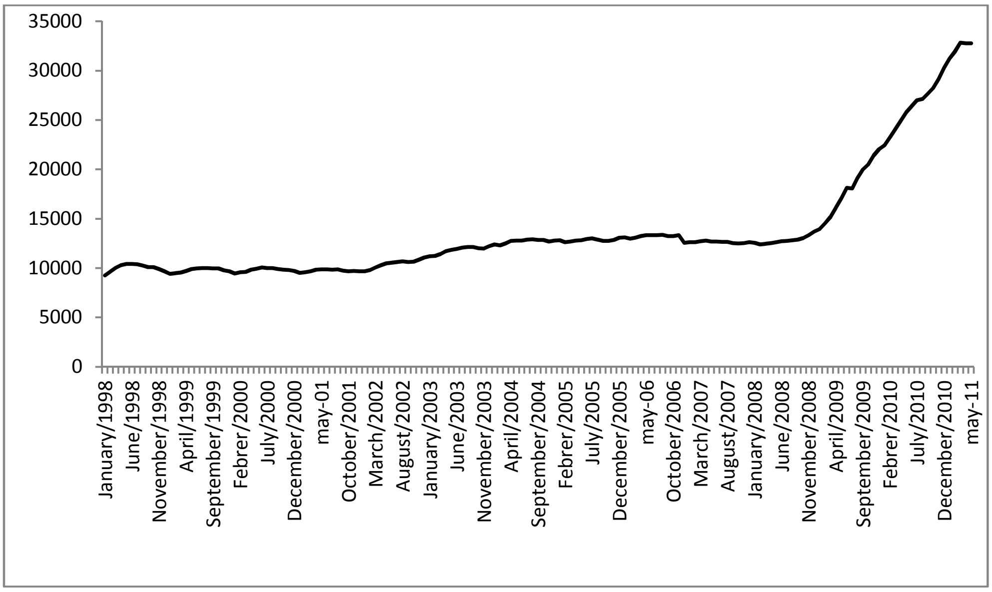

Figure 2. Changes in the number of employees paying Social Security contributions and registered unemployment, 1996-2011

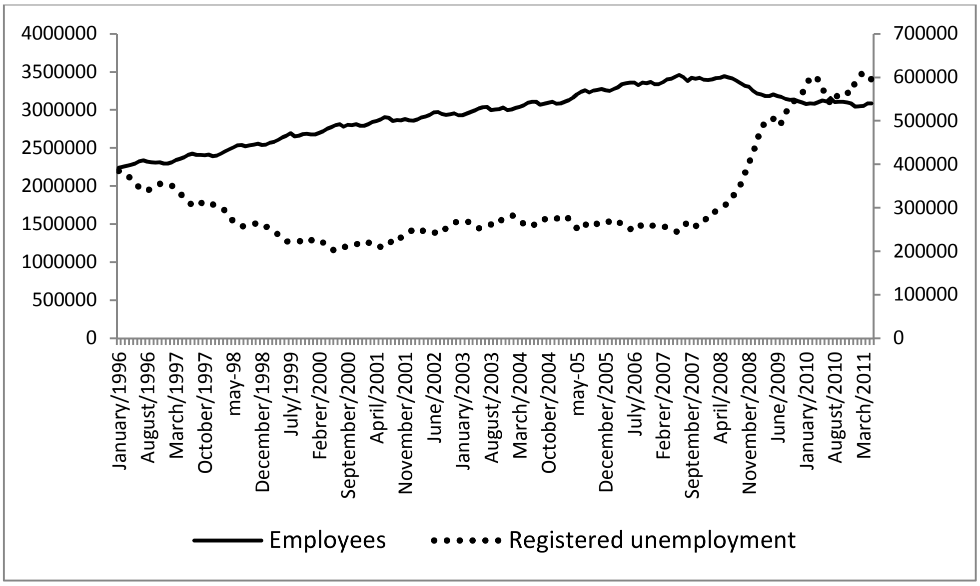

Figure 3. Quarterly alternative unemployment rates, 1998-2010

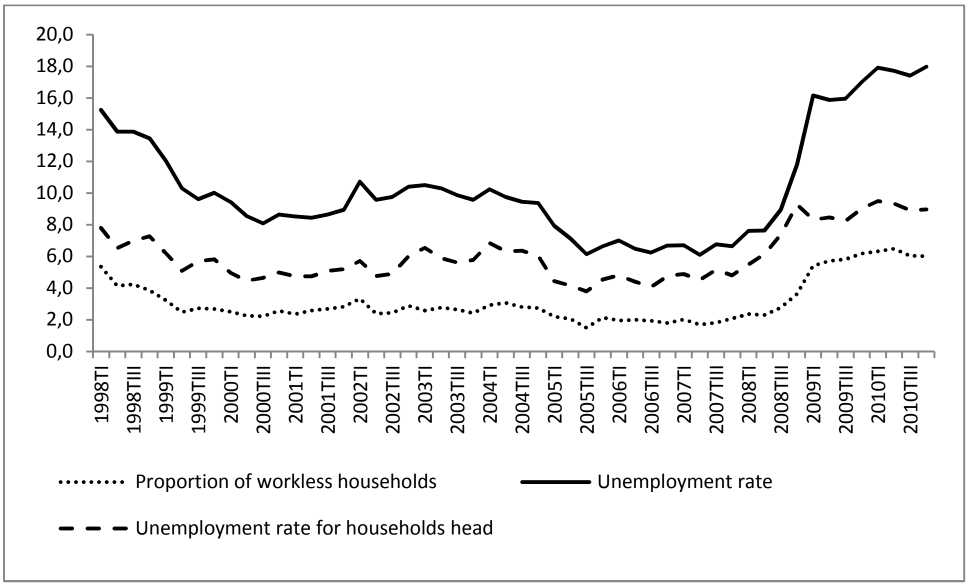

Figure 4. Proportion of households without income from the labor market and Social Security benefits, 1998-2010

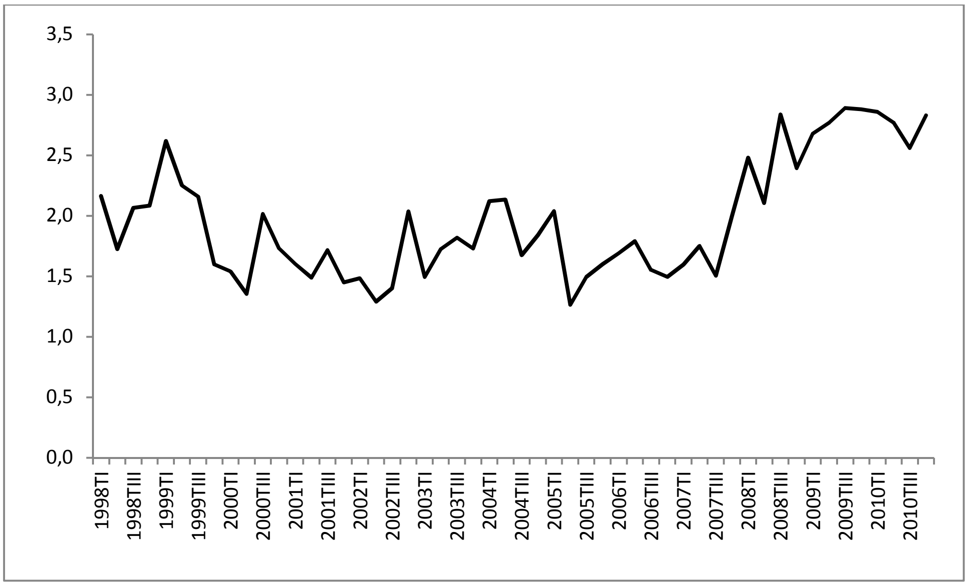

Figure 5. Flows of exit and entry in the PIRMI program

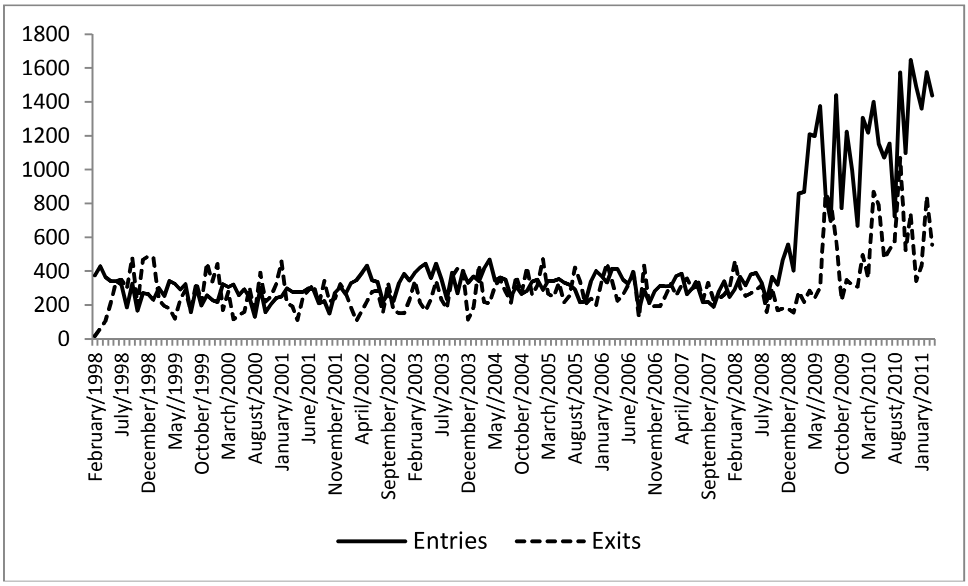

Figure 6. Average benefits and proportion of rejected applications

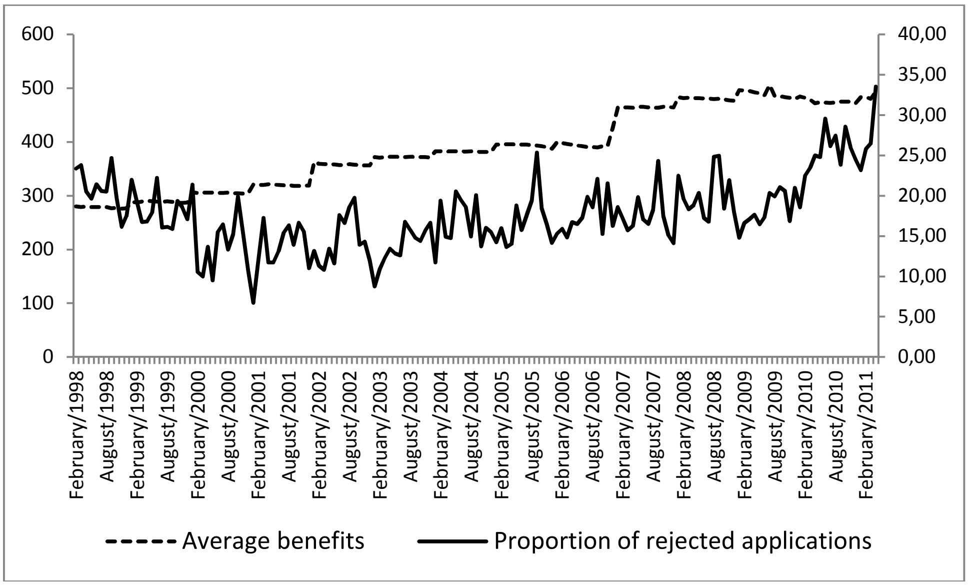

Table 1. Unit root and stationarity tests

	ADF			PP		
	τ	τ_{μ}	τ_{τ}	$Z(t_{\alpha})$	$Z(t_{\alpha^*})$	$Z(\bar{t}_{\alpha})$
C_t	-1.23	3.59	0.11	-1.84*	3.10	1.01
$D.C_t$	-3.48***	-11.90***	-4.56***	-11.8***	-12.3***	-13.1***
U_t	0.12	-0.76	-1.40	0.06	-0.89	-1.26
$D.U_t$	-4.71***	-12.5***	-5.03***	-12.6***	-12.6***	-13.0***
B_t	2.40	-0.73	-2.62	2.41	-0.72	-2.81
$D.B_t$	-6.16***	-12.2***	-6.78***	-11.8***	-12.2***	-12.2***
R_t	-0.56	-5.31***	-3.56**	-0.60	-5.14***	-6.20***
$D.R_t$	-8.72***	-17.3***	-8.79***	-20.1***	-20.0***	-20.2***
EN_t	-0.83	-2.98	-2.07	-0.84	-2.09	-3.78***
$D. EN_t$	-7.54***	-23.1***	-7.80***	-24.3***	-24.4***	-25.0***
EX_t	-0.96	-8.19***	-4.29***	-1.60	-8.26***	-8.65***
$D.EX_t$	-9.37***	-18.6***	-9.31***	-20.6***	-20.6***	-20.5***

*, **, *** Denote significance at the 10%, 5% and 1% levels, respectively.
τ , τ_{μ} and τ_{τ} correspond to the Augmented Dickey–Fuller statistics without a constant, with a constant, and with a constant and trend, respectively.
$Z(t_{\alpha})$, $Z(t_{\alpha^*})$ and $Z(\bar{t}_{\alpha})$correspond to the Phillips-Perron statistics without a constant, with a constant, and with a constant and trend, respectively.

TABLE 2. DETERMINANTS OF WELFARE CASELOADS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
C_{t-1}	0.217***	0.198***	0.122	0.135*	0.107	0.074	0.080	0.134	0.160*	0.146*	0.133*
	(0.076)	(0.076)	(0.078)	(0.078)	(0.076)	(0.079)	(0.081)	(0.082)	(0.082)	(0.083)	(0.077)
C_{t-2}	0.388***	0.401***	0.336***	0.316***	0.274***	0.276***	0.242***	0.283***	0.283***	0.279***	0.310***
	(0.072)	(0.072)	(0.074)	(0.074)	(0.073)	(0.074)	(0.079)	(0.086)	(0.080)	(0.081)	(0.074)
U_t	0.486***	0.538***	0.353***	0.329**							
	(0.103)	(0.105)	(0.126)	(0.126)							
B_t	0.562***	0.636***	0.529**	0.561**	0.761***	0.796***	0.796***	0.557**	0.513**	0.587**	0.594***
	(0.131)	(0.135)	(0.220)	(0.221)	(0.220)	(0.232)	(0.244)	(0.264)	(0.255)	(0.259)	(0.221)
R_t		-0.174**	-0.165*								
		(0.087)	(0.090)								
Π_{2006}			-0.089	-0.134*	-0.147*	-0.141*	-0.145*	-0.129	-0.104	-0.102	-0.143*
			(0.082)	(0.079)	(0.076)	(0.076)	(0.078)	(0.082)	(0.082)	(0.083)	(0.079)
Π_{2008}			0.426***	0.427***	0.350***	0.373***	0.443***	0.575***	0.546***	0.556***	0.409***
			(0.136)	(0.137)	(0.132)	(0.131)	(0.129)	(0.131)	(0.128)	(0.125)	(0.137)
U_{t-1}					0.507***						
					(0.127)						
U_{t-2}						0.517***					
						(0.137)					
U_{t-3}							0.481***				
							(0.144)				
U_{t-6}								0.212			
								(0.141)			
U_{t-9}									0.234*		
									(0.119)		
U_{t-12}										0.277**	
										(0.113)	
U^S_t											0.366***
											(0.128)
Constant	-6.371***	-7.270***	-6.931***	-6.787***	-8.711***	-9.097***	-9.165***	-6.692***	-6.351***	-6.982***	-7.100***
	(1.225	(1.295)	(1.695)	(1.707)	(1.726)	(1.865)	(2.012)	(2.153)	(1.986)	(1.98)	(1.706)
N	157	157	157	157	157	157	156	153	150	147	157
R^2	0.807	0.812	0.824	0.820	0.830	0.828	0.825	0.816	0.823	0.825	0.822
Log likelihood	380.5	382.7	388.9	388.4	389.7	390.2	389.0	379.7	370.3	363.2	388.9
F	5632	4601	3513	4101	4170	4192	4257	4143	4012	3985	4126

*, **, *** Denote significance at the 10%, 5% and 1% levels, respectively.

TABLE 3. DETERMINANTS OF ENTRIES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
U_t	1.131^{***}	1.177^{***}	0.621^{***}	0.615^{***}							
	(0.068)	(0.074)	(0.126)	(0.122)							
B_t	1.178^{***}	1.238^{***}	0.951^{***}	0.967^{***}	1.143^{***}	1.197^{***}	1.212^{***}	1.134^{***}	1.079^{***}	1.114^{***}	0.989^{***}
	(0.117)	(0.123)	(0.223)	(0.222)	(0.212)	(0.214)	(0.212)	(0.226)	(0.235)	(0.241)	(0.221)
R_t		-0.172*	-0.107								
		(0.102)	(0.096)								
Π_{2006}			-0.239^{***}	-0.265^{***}	-0.253^{***}	-0.241^{***}	-0.232^{***}	-0.240^{***}	-0.232^{***}	-0.219^{***}	-0.275^{***}
			(0.084)	(0.080)	(0.076)	(0.075)	(0.075)	(0.080)	(0.081)	(0.083)	(0.079)
Π_{2008}			0.728^{***}	0.717^{***}	0.567^{***}	0.557^{***}	0.581^{***}	0.793^{***}	0.873^{***}	0.901^{***}	0.692^{***}
			(0.129)	(0.128)	(0.124)	(0.127)	(0.123)	(0.119)	(0.108)	(0.099)	(0.128)
U_{t-1}					0.775^{***}						
					(0.118)						
U_{t-2}						0.776^{***}					
						(0.122)					
U_{t-3}							0.757^{***}				
							(0.118)				
U_{t-6}								0.542^{***}			
								(0.117)			
U_{t-9}									0.491^{***}		
									(0.110)		
U_{t-12}										0.508^{***}	
										(0.105)	
U^S_t											0.653^{***}
											(0.125)
Constant	-14.473^{***}	-15.239^{***}	-12.192^{***}	-12.068^{***}	-13.460^{***}	-13.789^{***}	-13.843^{***}	-12.920^{***}	-12.491^{***}	-12.746^{***}	-12.284^{***}
	(0.696)	(0.836)	(1.469)	(1.462)	(1.397)	(1.416)	(1.394)	(1.470)	(1.508)	(1.531)	(1.459)
Observations	159	158	158	159	158	157	156	153	150	147	159
R-squared	0.729	0.734	0.786	0.784	0.806	0.809	0.812	0.797	0.798	0.802	0.786
Log likelihood	-21.55	-20.45	-3.285	-3.673	4.364	5.144	6.058	-1.427	-1.264	-0.765	-2.745
F	209.9	141.6	111.6	139.5	158.6	160.5	163.1	145.3	142.9	143.7	141.5

*, **, *** Denote significance at the 10%, 5% and 1% levels, respectively.

TABLE 4. DETERMINANTS OF EXITS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
U_t	0.350***	0.377***	-0.072	-0.245							
	(0.120)	(0.117)	(0.217)	(0.235)							
B_t	0.512**	0.282	-0.062	-0.072	0.028	0.046	0.171	0.424	0.532	0.883**	-0.043
	(0.207)	(0.196)	(0.385)	(0.426)	(0.387)	(0.379)	(0.368)	(0.368)	(0.380)	(0.379)	(0.427)
R_t		0.212	0.241								
		(0.161)	(0.166)								
Π_{2006}			-0.125	-0.097	-0.066	-0.030	0.005	0.030	0.013	-0.039	-0.096
			(0.144)	(0.153)	(0.138)	(0.133)	(0.131)	(0.130)	(0.131)	(0.130)	(0.153)
Π_{2008}			0.572**	0.753***	0.454**	0.303	0.099	-0.041	0.029	0.061	0.728***
			(0.223)	(0.246)	(0.226)	(0.225)	(0.213)	(0.194)	(0.175)	(0.155)	(0.247)
U_{t-1}					0.106						
					(0.216)						
U_{t-2}						0.281					
						(0.215)					
U_{t-3}							0.520**				
							(0.205)				
U_{t-6}								0.712***			
								(0.190)			
U_{t-9}									0.685***		
									(0.178)		
U_{t-12}										0.696***	
										(0.165)	
U^S_t											-0.220
											(0.241)
Constant	-9.027***	-7.330***	-4.263*	-4.288	-5.629**	-6.118**	-7.376***	-9.304***	-9.889***	-12.005***	-4.515
	(1.230)	(1.324)	(2.538)	(2.805)	(2.549)	(2.508)	(2.422)	(2.388)	(2.443)	(2.408)	(2.819)
Observations	159	158	158	159	158	157	156	153	150	147	159
R-squared	0.095	0.133	0.171	0.148	0.161	0.175	0.203	0.242	0.251	0.282	0.146
Log likelihood	-112.1	-93.16	-89.64	-107.3	-90.61	-84.62	-80.10	-75.64	-73.56	-67.40	-107.5
F	8.206	7.890	6.269	6.677	7.326	8.056	9.613	11.83	12.12	13.94	6.603

*, **, *** Denote significance at the 10%, 5% and 1% levels, respectively.

TABLE 5. DETERMINANTS OF THE PROGRAM'S RESTRICTIVENESS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U_t	0.277***	0.196*							
	(0.054)	(0.105)							
B_t	0.378***	-0.147	-0.140	-0.070	-0.052	0.196	0.407**	0.438**	-0.119
	(0.094)	(0.189)	(0.189)	(0.190)	(0.189)	(0.184)	(0.183)	(0.190)	(0.188)
Π_{2006}		0.258***	0.264***	0.263***	0.259***	0.262***	0.237***	0.232***	0.253***
		(0.068)	(0.067)	(0.067)	(0.067)	(0.065)	(0.063)	(0.065)	(0.068)
Π_{2008}		0.008	0.001	-0.035	-0.014	-0.148	-0.161*	-0.106	-0.018
		(0.110)	(0.111)	(0.113)	(0.109)	(0.097)	(0.084)	(0.078)	(0.110)
U_{t-1}			0.201*						
			(0.106)						
U_{t-2}				0.237**					
				(0.108)					
U_{t-3}					0.215**				
					(0.105)				
U_{t-6}						0.380***			
						(0.095)			
U_{t-9}							0.423***		
							(0.085)		
U_{t-12}								0.388***	
								(0.082)	
U^S_t									0.230**
									(0.107)
Constant	-4.652***	-1.437	-1.492	-1.983	-2.040	-3.873***	-5.223***	-5.335***	-1.675
	(0.552)	(1.241)	(1.247)	(1.257)	(1.239)	(1.196)	(1.174)	(1.202)	(1.241)
Observations	159	159	159	158	157	154	151	148	159
R-squared	0.241	0.307	0.308	0.318	0.321	0.379	0.430	0.431	0.312
Log likelihood	14.95	22.23	22.32	23.58	24.17	29.95	35.98	34.16	22.79
F	24.71	17.06	17.12	17.82	17.97	22.75	27.54	27.12	17.45

*, **, *** Denote significance at the 10%, 5% and 1% levels, respectively.

TABLE 6. ERROR CORRECTION MODEL

	Model 1		Model 2		Model 3		Model 4	
C_{t-1}	1.000		1.000		1.000		1.000	
U_{t-1}	-0.770***		-0.794***		-0.751***		-0.810***	
	(0.093)		(0.090)		(0.073)		(0.077)	
Trend	-0.006***		-0.006***		-0.006***		-0.006***	
	(0.001)		(0.001)		(0.001)		(0.001)	
Constant	3.604		3.668		3.565		3.713	
Error Correction:	DC_t	DU_t	DC_t	DU_t	DC_t	DU_t	DC_t	DU_t
CointEq1	-0.079***	-0.032	-0.075***	-0.029	-0.079***	-0.073***	-0.069***	-0.053
	(0.015)	(0.037)	(0.013)	(0.032)	(0.012)	(0.029)	(0.009)	(0.022)
DC_{t-1}	-0.207***	-0.084	-0.210***	-0.077	-0.192***	-0.138	-0.189***	-0.144
	(0.078)	(0.189)	(0.077)	(0.186)	(0.076	(0.188)	(0.074)	(0.187)
DC_{t-2}	0.014	0.012	0.013	0.027	0.023	-0.044		
	(0.080)	(0.192)	(0.078)	(0.190)	(0.076)	(0.189)		
DC_{t-3}	0.057	-0.051	0.052	-0.051				
	(0.079)	(0.191)	(0.077)	(0.185)				
DC_{t-4}	0.023	0.072						
	(0.077)	(0.187)						
DU_{t-1}	-0.062**	-0.035	-0.065**	-0.041	-0.068**	-0.104	-0.059**	-0.079
	(0.038)	(0.091)	(0.037)	(0.089)	(0.036)	(0.089)	(0.034)	(0.086)
DU_{t-2}	-0.050	-0.044	-0.047	-0.038	-0.049	-0.098		
	(0.038)	(0.091)	(0.036)	(0.088)	(0.035)	(0.087)		
DU_{t-3}	-0.012	0.283	-0.010	0.286				
	(0.037)	(0.090)	(0.036)	(0.086)				
DU_{t-4}	-0.016	-0.029						
	(0.037)	(0.090)						
Constant	0.007***	0.002	0.007***	0.002	0.007***	0.003	0.007***	0.002
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
N	155		156		157		158	
R^2	0.265	0.060	0.275	0.071	0.277	0.016	0.278	0.017
Sum sq. resids	0.071	0.413	0.071	0.415	0.072	0.445	0.073	0.459
S.E. equation	0.022	0.053	0.022	0.053	0.022	0.054	0.022	0.055
F-statistic	7.175	2.099	9.401	2.688	12.924	1.500	21.144	1.899
Log likelihood	376.2	239.4	379.1	241.2	381.1	237.8	382.9	237.2
Akaike AIC	-4.725	-2.960	-4.757	-2.990	-4.778	-2.951	-4.796	-2.952
Schwarz SC	-4.529	-2.764	-4.601	-2.834	-4.661	-2.835	-4.719	-2.874

*, **, *** Denote significance at the 10%, 5% and 1% levels, respectively.

TABLE 7. ALTERNATIVE ERROR CORRECTION MODELS

	Model 1		Model 2		Model 3		Model 4	
C_{t-1}	1.000		1.000		1.000		1.000	
U_{t-1}	-0.951***		-1.051***		-1.060***		-0.449***	
	(0.095)		(0.108)		(0.105)		(0.174)	
Trend	-0.007***		-0.007***		-0.007***		-0.003***	
	(0.001)		(0.003)		(0.003)		(0.003)	
Constant	4.109		4.356		4.373		2.584	
Error Correction:	DC_t	DU_t	DC_t	DU_t	DC_t	DU_t	DC_t	DU_t
CointEq1	-0.062***	-0.035**	-0.058***	-0.004	-0.061***	0.007	-0.064***	-0.064**
	(0.008)	(0.020)	(0.008)	(0.021)	(0.009)	(0.022)	(0.016)	(0.041)
DC_{t-1}	-0.219***	-0.129	-0.228***	-0.115	-0.234***	-0.097	-0.249***	-0.096
	(0.074)	(0.191)	(0.075)	(0.191)	(0.075)	(0.190)	(0.075)	(0.192)
DU_{t-1}	-0.062**	-0.061	-0.058**	-0.056	-0.055**	-0.065	-0.031	-0.112
	(0.034)	(0.086)	(0.033)	(0.085)	(0.033)	(0.085)	(0.033)	(0.085)
R_t	-0.017***	0.007	-0.018***	0.004	-0.014**	-0.008	-0.007	0.006
	(0.007)	(0.019)	(0.008)	(0.019)	(0.008)	(0.020)	(0.009)	(0.022)
B_t			-0.003	0.062**	0.015	0.013	0.042***	0.028
			(0.012)	(0.032)	(0.017)	(0.042)	(0.017)	(0.042)
Π_{2006}					-0.011	0.032	-0.016***	0.025
					(0.007)	(0.018)	(0.007)	(0.019)
Π_{2008}							0.044***	-0.005
							(0.006)	(0.017)
Constant	-0.022**	0.014	-0.009	-0.360**	-0.105	-0.101	-0.260***	-0.164
	(0.013)	(0.034)	(0.077)	(0.196)	(0.096)	(0.244)	(0.095)	(0.243)
N	155		156		157		158	
R^2	0.298	0.005	0.319	0.048	0.329	0.067	0.351	0.084
Sum sq. Resids	0.070	0.462	0.0695	0.453	0.068	0.4441	0.066	0.437
S.E. equation	0.021	0.055	0.021	0.054	0.021	0.054	0.021	0.054
F-statistic	17.6	1.19	14.261	1.555	12.377	1.823	11.590	1.953
Log likelihood	385.6	236.7	386.054	238.259	387.264	239.843	389.820	241.210
Akaike AIC	-4.818	-2.933	-4.811	-2.939	-4.813	-2.947	-4.833	-2.952
Schwarz SC	-4.721	-2.836	-4.694	-2.823	-4.677	-2.811	-4.678	-2.796