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Abstract

Governments can soften the impact of the business cycle on welfare spending. Depending on the political costs and the extent of unemployment, they might choose between a decrease in the proportion of accepted applications, a decrease in the level of benefits, or some combination of the two. This paper is motivated by this concern, weaving together 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 autoregressive distributed lag models to find that the generosity of the program is clearly predictive of the receipt of benefits even in contexts of high and growing unemployment rates. We also find a fairly strong correlation between unemployment growth and the proportion of rejected applications and a trade-off between the level of benefits and rejections.

Keywords: welfare caseloads, endogenous policy, ADL models.

JEL: I30, I38, C22

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 the growing number of recipients and the consequent increase in spending are major topics. Interest in the analysis of the determining factors of the changes in the number of welfare recipients has heightened recently, fed by concerns about the increasing costs resulting from what has been called the Great Recession. Researchers have consistently documented that policy design has a substantial impact on the number of recipients and that macroeconomic conditions 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 caseload declines, but changes in the programs and other policies are also relevant.

Governments can soften the impact of the business cycle 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 a sizable body of research on the specific effects of each option on aggregate welfare caseloads (Danielson and Klerman, 2008; Chaudhary and Gathmann, 2009). Furthermore, there is evidence of the strong influence of the implementation of policy on caseloads (Mead, 2001; Loprest, 2012). Public choice theory also provides a comprehensive and consistent explanation of the possible effects of each of those options on the possible patterns of caseload expansions and contractions. As shown by Moffitt (1999b), voters might react negatively to increases in welfare spending by seeking retrenchments in the system. Lower levels of benefits or stricter requirements to reduce the number of recipients could become endogenous variables that policy-makers might use to that end.

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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 parameters of the programs. The political costs the government would face differ depending on the different options. These costs are clearly higher when benefit levels are lowered than when governments decide to reduce the proportion of accepted applications.

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

This evidence raises important questions about the forces that shape government policy when recessions begin. In periods of economic downturn, governments might decide to modify some parameters –benefit levels– but use others –the proportion of claimants that enter the program– to prevent the increase in the number of welfare recipients and, thus, increase in spending. 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. We aim to narrow the gap in the literature by weaving together these two strands. Our purpose is to analyze how changes in unemployment give rise to both increasing caseloads and changes in the programs' parameters. More precisely, we examine how governments might use simultaneously higher benefit levels and lower acceptance rates to prevent a dramatic increase in welfare spending avoiding political costs.

The paper is based on data from the minimum income program of Catalonia's government. This is an interesting case of welfare design in the framework of an economic recession. Spain was one of the countries where unemployment grew the most during the Great Recession. A second relevant fact is that in this country, each regional government must finance welfare programs with its own resources. There is no extra funding from the central government in case of economic downturns, and increasing caseloads will give rise to a noticeable growth in public spending. In the case of Catalonia, some of the implemented changes have tended to promote greater economic coverage among the potential claimants, but the government has also increased the proportion of rejected applications.

Using long time-series data, we find that unemployment has strong and significant lagged effects on caseloads. Our results, however, provide some insights for understanding the nature of endogenous government policy in the design of these programs in economic recessions. The generosity of the program –level of benefits– is clearly predictive of receipt of benefits even in the context of high and growing unemployment rates. We also find a fairly strong correlation between unemployment growth and the proportion of rejected applications. This later parameter and the number of exits may have been the chosen tools 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. The 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 a given program and the corresponding take-up rate. Given that the decision of entering the program will be determined by households' decisions and the utility they derive from receiving benefits, governments' main alternatives for controlling welfare spending will be to modify the eligibility parameters, reduce the level of benefits, or increase the proportion of rejected applications.

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 particular program. Numerous studies have addressed the relative importance of each one of these factors in explaining variations in caseloads. The most common result is the key role unemployment and macroeconomic conditions have on the number of recipients. However, as stated before, 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.

Some key questions, therefore, are how governments react to higher levels of unemployment and which political strategies may produce a countervailing effect on caseloads. 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. We still have relatively little insight into what the political channels are that governments use to develop endogenous strategies to maintain the number of welfare recipients around a sustainable level of spending.

The major economic rationale for these endogenous strategies revolves around assertions of public choice theory. Governments have the ability to choose both the number of accepted applications and the intensity of benefits provided through a number of programs. Depending on the political costs they face, the extent of unemployment, voters' preferences and financing formulas, they will choose one option or another.

A basic model of a government maximization function may clarify these relationships, providing a framework for our estimates. Consider an economy that consists of a continuum of households with mass normalized to unity. Households are heterogeneous with respect to exogenously given income y. Income is distributed according to some given income distribution with a strictly positive density function f on the support $[y,\breve{y}] \subset R_+$. According to the previous statements, the key parameters of this economy are (U, y_r, y_p), where U denotes unemployment and y_r, y_p are the mean income levels of taxpayers and poor households, respectively. Policy options are summarized by (E, C, B, R), where E is the number of eligible households, C is the number of caseloads, B is the level of benefits, and R is a variable representing the program's restrictiveness. These variables can be related to each other. Caseloads depend on –increasing in– B and –decreasing in– R, and there may be some key endogeneity that renders R to be a function of B or E.

Different policy strategies may be subject to different constraints such as reducing C, reducing B, increasing R or other possible combinations. Policy strategies can be defined as a function of the economy. As previously mentioned, the number of eligible households for the welfare program is increasing in U and decreasing in y_p, B is decreasing in U and increasing in y_p, and R is increasing in U and decreasing in y_p. The strategies can also be classified into budget balancing, expansive or contractive, or adding or not changes in elegibility. In our framework, the government's goal is to prevent the number of caseloads from reaching a given threshold when unemployment is high. The key question is how the government reacts to higher unemployment levels: limiting the growth of caseloads by reducing B and increasing R, increasing B and increasing R or reducing B and reducing R.

Different authors provide a comprehensive explanation of the reasons for particular patterns of expansion or contraction in welfare spending using these parameters within a public-choice framework [Moffitt (1999) and Baicker (2005)]. While primacy in these models is usually assigned to voters and their preferences, they also work well to identify the incentives of the government to consider benefits and a set of parameters representing the program's restrictiveness as policy goals. Consider that the government's goal is choosing the level of benefits and the number of recipients (P) that maximize a conventional function of voter (V) preferences with a utility function such as

$$U=f(c_V, c_p, B, P) \tag{1}$$

where c_V is the consumption of the voter (taxpayer) and c_p the consumption of the poor.

The standard budget constraint for the government is:

$$y = c + (P/N)\, sB \tag{2}$$

where y is per capita income, c is individual consumption, N is the size of the non-poor population (taxpayers), and s is the fraction of benefits paid by the local government, $s=S(B,y)$. We assume first that welfare benefits are decentralized and that central and local governments share these costs. As stated before, this constraint might be extended considering a maximum program's spending threshold (G) that depends on macroeconomic conditions $G^*(U)$, $BP \leq G^*$. One possible generalization of the maximization problem is that R might be a function of B. The government may react to increasing levels of eligible households for the program by imposing greater restrictions on potential claimants if B is unchanged or increased. Among the very different options, the most typical is increasing the proportion of rejected applications. Therefore, P might be a function of B and a set of eligibility parameters E, $P(B,E)$.

The first-order condition is[2]

$$\frac{\frac{\partial f}{\partial E}}{\frac{\partial f}{\partial B}} = \frac{\frac{\partial P}{\partial E} S(B,y)B}{P(B,E)\left(S(B,y) + \frac{\partial S}{\partial B} B\right) + \frac{\partial P}{\partial B} S(B,y)B} \tag{3}$$

This result implies that the marginal rate of substitution between expanding eligibility and increasing benefits is equal to the marginal cost of adding one recipient over the marginal cost of adding one unit to the level of benefits. Because the price of increasing benefits is the recipiency rate, governments can change the level of benefits or the recipiency rate to control welfare spending. In periods of limited budgetary resources, governments might combine both strategies to prevent unsustainable growth in welfare spending. Shifts in the recipiency function might be endogenous, including different actions focused on reducing the number of households entering into the program.

The extent to which governments make use of more restrictive strategies will also depend on other factors. The distribution of the costs of new recipients between the different levels of government stands out as the most important institutional characteristic. Welfare spending is the product of the level of benefits and caseloads. In some cases, regional governments do not receive more funding when caseloads increase. In the case of completely decentralized programs, all the costs resulting from increasing recipients will correspond to local governments (s=1). The incentives to reduce caseloads will therefore depend on the intensity of potential unemployment shocks and the institutional design of

[2] As in Baicker (2005), we make no assumptions about the form of the utility function. Other authors have considered Stone-Geary utility functions in the analysis of welfare programs [Hoynes (1996), Langørgen and Rønningen (2004)].

the program. The spending target will depend on the possible trade-off between benefit levels and recipiency rates.

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 Europe, new welfare schemes were created some years before reforms were implemented in other OECD countries. By the late 1980s, these countries had introduced a new social tool that attempted to reconcile two different objectives: providing a basic level of economic protection and developing measures to improve the social and labor participation of low-income households.

In the PIRMI program, different activities were established that aimed at achieving these two goals. First, there is a cash benefit, which is set based on household size. The monthly benefit levels for single-person households were 414 euros in 2010. Additional adjustments for each child or other adults were 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 between this and U.S. programs is that welfare covers all households. Access to PIRMI is available not only to female single-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 benefits, households must have been formed for a defined period before claiming benefits. Another legal requirement is 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 decentralized. The lack of initiative by the central government in the late 1980s encouraged regional governments to begin establishing their own welfare programs. The result is a mosaic of highly variable 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 a region's own resources.

[FIGURE 1]

Monitoring the flow of entries into and exits from the program is possible due to 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 decade and a half. The number of households receiving benefits remained roughly constant between the last third of the 1990s and the first years of the next decade, with an average number of 10,000 recipients. The number of recipients began to increase slightly in the following years through 2006, pushing that number above 12,000 households. In 2007, the 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 are several possible reasons for the increases in caseloads. A natural focus is what happened in the labor market. The Labor Force Survey (EPA) records quarterly data on unemployment at the territorial level. The unemployed as a percent of the labor force is a standard measure for macroeconomic conditions in the analysis of welfare caseloads. Figure 2 illustrates the changes in the unemployment rate in Catalonia, which rose from a level slightly higher than 6 percent in 2007 to a historical high of nearly 20 percent three years later. The lack of employment has introduced, inexorably, a remarkable pressure on the demand for benefits.

[FIGURE 3]

This can be corroborated by examining data on the proportion of 'disconnected' households or households that neither earn income from labor or benefit from any Social Security transfers (i.e., pensions or other benefits) nor benefit from unemployment insurance or assistance payments. The EPA provides quarterly information on this variable that can serve as a proxy for the demand for 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 3), rising from a proportion of affected households of 1.5 percent in 2007 to 3 percent three years later. 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 in situations preluding considerably higher levels of demand for PIRMI benefits. These changes could introduce strong pressure on the designers of the program as the increasing number of eligible households may be translated into a rapid growth in caseload.

[FIGURE 4]

An indirect approach for testing the possible effect of unemployment changes in the number of recipients is looking differently at program entry and exit flows. Figure 4 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. However, 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 be an indirect proof of governmental reaction to prevent unsustainable growth in welfare caseloads.

[FIGURE 5]

As mentioned above, in addition to promoting exits, governments can also affect the caseloads through 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 the government's preferences, average benefits also represent changes in the economic needs of households entering the program. Figure 5 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 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 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 to the beginning of the economic crisis, and a sizable growth in this last period. This last result might be associated with an endogenous decision-making process. To prevent an unsustainable growth in welfare spending, the government may have chosen to increase rejections instead of reducing benefits.

Other institutional issues relevant to understanding possible changes in caseloads are a set of partial reforms that were enacted during our sample period. While some reforms promoted greater coverage among the poor, others made the program more restrictive. Two outstanding reforms were those of 2006, which aimed at promoting higher levels of labor participation, and 2008, which introduced more flexible conditions to participate in labor-oriented activities.

3. EMPIRICAL IMPLEMENTATION

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

Because we have data for one program over a long time-span –monthly data that run from January 1998 to the first quarter of 2011– the estimation was performed using time-series analysis. The assumption is that caseload growth can be modelled as a function of variables thought to influence it such as economic conditions and the policy environment. As compared to panel data models to forecast caseloads, its disadvantage is that this approach does not take special account of the unobserved variables. Its advantage is that it can be applied relatively cheaply when the variables chosen are key policy parameters. Our assumption is that in this program the caseload growth can be modelled as a function of macroeconomic conditions, the generosity of the program and its restrictiveness. Given the sheer frequency and magnitude of the fluctuations, this kind of long-term forecast might be an important aid to managing the program handling a variety of policy decisions.

The basic statistical equation that we estimate is:

$$C_t = \alpha_1 + \alpha_2 U_t + \alpha_3 B_t + \alpha_4 R_t + \alpha_5 \Pi + \varepsilon_t \qquad (4)$$

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 benefit level –program's generosity–, R_t is the proportion of rejected applications –program's restrictiveness– and Π are dummies capturing the effects of specific reforms. The variable representing the program's generosity is the official benefit level adjusted with the regional Consumer Price Index. An alternative option might be to consider the average benefit level. The problem with the latter is that it is largely dependent on the caseload composition. In practice, this measure might change with the income deficit of the average household on welfare being more an outcome that measures the characteristics of applicants than a policy variable.

The logarithms of the variables have been considered to avoid the problem of a lack of stationarity in the variance. This also allows the coefficients to be interpreted as elasticities, which enables us to control the effects of macroeconomic conditions, such as the unemployment rate, and the effects of the different strategies the government might undertake.

In order to study the order of integration of all the variables considered, including entries (EN_t) and exits (Ex_t), we performed 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 (4) 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 (4). As stated by Grogger (2007), today's caseload depends in part on yesterday's caseload and the current levels of recipients exhibit inertia. The approach chosen to address this inertia component is an autoregressive distributed lag (ADL) model. We include as regressors lagged values of the caseloads and current and lagged values of unemployment rates:

$$C_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i \, C_{t-1} + \sum_{k=1}^{m} \sum_{i=0}^{n} \beta_{ki} \, X_{kt-i} + u_t \qquad (5)$$

Some authors, however, have challenged the introduction of lagged values of economic conditions in the specification of caseload models. McKinnish (2005), for instance, suggests that estimates on lagged unemployment rates may merely reflect the presence of omitted variables or measurement error bias. Nevertheless, another large body of literature has found the lags of the measures of the economy necessary 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 body of literature has also based the inertia component on the persistence of unemployment. Blanchard and Summers (1986) stated the high dependence of current unemployment on past unemployment. They concluded that hysteresis is a feature of the business cycle rather than a consequence of a particular structure of the labor market. Such effects continue to be an important source of the persistence of unemployment in European countries.

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).[3] In this paper, our starting point is a basic ADL, considering restrictions on a general error correction model (ECM). The reason for considering the latter is that welfare caseloads and unemployment time series can move together in a long-run equilibrium relationship. This potential long-run relationship between C_t and U_t can be anticipated using cointegration techniques. We test the presence of a cointegration relationship between the welfare caseloads and unemployment. The Akaike Information Criteria and the Schwarz Criteria have been used to define the optimal lag structure.

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 prior equilibrium error, as well as to past changes in both. The long-run relationship is expressed as:

$$C_t = \varphi U_{t-1} + u_t \tag{6}$$

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

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

$$\begin{aligned}\Delta C_t &= \alpha_C + \beta_C Z_{t-1} + \gamma_{CC,i}\sum_{i=1}^{p}\Delta C_{t-i} + \gamma_{CU,j}\sum_{j=1}^{q}\Delta U_{t-j} + u_{C,t}\\ \Delta U_t &= \alpha_U + \beta_U Z_{t-1} + \gamma_{UC,i}\sum_{i=1}^{p}\Delta C_{t-i} + \gamma_{UU,j}\sum_{j=1}^{q}\Delta U_{t-j} + u_{U,t}\end{aligned} \tag{7}$$

considering

$$\begin{aligned}\Delta C_t &= \alpha_C + \beta_C Z_{t-1} + \gamma_{CC,1}\Delta C_{t-1} + \gamma_{CU,1}\Delta U_{t-1} + u_{C,t}\\ \Delta U_t &= \alpha_U + \beta_U Z_{t-1} + \gamma_{UC,1}\Delta C_{t-1} + \gamma_{UU,1}\Delta U_{t-1} + u_{U,t}\end{aligned} \tag{8}$$

where $Z_t = C_{t-1} - \varphi U_{t-1}$ is the cointegration relationship and β_C and β_U are the speeds of adjustment to long-run equilibrium of the caseload 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. Table 2 shows that the coefficients for the effects of unemployment and the program's parameters appear with the expected signs. Several points are worth mentioning. As expected, unemployment rates have sizable and significant effects on the program's caseloads. The higher the unemployment rate is, the higher welfare caseloads are. A one-point rise in the unemployment rate increases caseloads by approximately 5 per cent.

[TABLE 2]

The lagged effects of economic conditions on PIRMI participation are important. Columns (5)-(8) of Table 2 give general support to the notion that lags of the measures of the economy are needed to capture the dynamics of caseload change. 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) to check the robustness of the results (Column 8). The estimated coefficient for this variable does not drastically change the picture presented in the other columns.

Among all the variables included in the specification, 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. 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.

Compared to the estimated effects for unemployment and the level of benefits, the coefficients for the variable reflecting the program's restrictiveness –proportion of rejected applications– are relative small. Nevertheless, the negative sign of this variable is in keeping with the expected effect. 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 spending. 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 representing the program's design, 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 negatively affected the caseloads, while the 2008 reform seems to have produced a positive influence. The first 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 reforms, including a reduction in the number of working hours required to access to complementary benefits.

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

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 described in section two, however, showed that when the recession began, entries grew at a faster pace but exits did not decline. As mentioned above, this uncharacteristic behavior is not in keeping with the standard assumptions of welfare participation theories and may thereby hide a governmental reaction to moderate the growth in caseloads. According to standard theory, the determinants 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 is expected that increases in unemployment reduce exits and boost entries, with a similar effect for the generosity of the program.

[TABLE 3]

Our estimates, however, yield dissimilar results for each flow. Concerning entries, all the specifications included in Table 3 show a strong and significant effect of macroeconomic conditions.[4] Again, it is necessary to include a structure of lags to better capture the dynamic effect of unemployment on entries. A positive effect on entries is also found for the level of benefits. The generosity of the program has led to increased use of benefits, while rejections present the expected negative effect.

[TABLE 4]

The fit is rather poor for the exit rates models.[5] One interesting result is the positive but not significant effect of the unemployment rate on the rates of recipients leaving the program. In contrast to the natural assumption that lower employment opportunities should reduce the probability of leaving the program, macroeconomic conditions seem to have the opposite influence on exits. However, 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 certain that there could be omitted variables that should be considered for an adequate modeling of the flow of exits. A key factor may be that the government is applying stricter rules to 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 caseloads. More control of compulsory work-related activities or stricter sanctions in the 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

[4] Entries are defined by dividing the number of new recipients by the population over 25 years of age.

[5] Exits are defined by dividing the number of households leaving the program by the total number of recipients.

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– might have a clear countervailing effect on the size of the caseload. While the effect of the level of benefits on welfare caseloads is positive, an increasing proportion of rejected applications may reduce the number of recipients. This result could be related to the previous discussion on the potential use of rejections as a policy strategy to reduce the caseload. A plausible case can be made that those estimates could be hiding the relationship between unemployment and rejections. In times of severe recession, governments may choose between an increase in the proportion of rejected applications, a decrease in the level of benefits, or some combination of the two. As stated above, 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 may be linked to changes in the labor market over the economic cycle. The coefficients for unemployment appear in line with the previous hypothesis. Coefficient estimates on lagged unemployment rates also reveal that there might be a delay in the effect of changes in macroeconomic conditions on policy decisions. These results at least suggest that unemployment is important to understand how program designers try to avoid large increases in caseload 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 above, both strategies could take place simultaneously. Although the estimates seem sensitive to the different specifications, the most important factual finding is that the 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. In some sense, the changes in one of the parameters of the program might matter more to the decisions on new recipients than changes in the unemployment rate.

Rejections would be the response to partially offset the effects on the caseloads of not reducing the level of benefits and growing unemployment. This inference, however, is subject to some caveats as these effects seem smaller when controls for specific reforms and lagged unemployment rates are considered.

d) *Cointegration and ECM models*

A final empirical issue has to do with whether these relationships also hold in the long run. We conducted different tests and found that the estimates are free of spurious results in both the short and the long run. The usual Johansen (1995) tests confirm that cointegration relationships exist. Given that a cointegrating vector exists between the main variables in our estimates, we proceeded to estimate alternative error correction equations using data for the entire period. Table 6 illustrates how welfare caseloads have a stable, long-run relationship with the unemployment rate, which holds in all the specifications considering one to four lags. All the reported ECM statistics in Table 6 are statistically significant at the 1% level (correction from 6.5 percent to 7.9 percent per month).

[TABLE 6]

Table 7 presents estimates of alternative ECM models including 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 the estimated models. The average number of caseloads adjusts to unemployment levels in the long run in all the specifications considering a one-period lag. In the short run, changes in the unemployment rate also affect caseload variations. The slope coefficient of -0.096 implies that if the number of caseloads in the previous month was higher than what the long-equilibrium relationship predicts, there will be an adjustment to reduce it. About 9.6 percent of the disequilibrium is corrected each month (Model 4 in Table 7).

[TABLE 7]

This adjustment is related to the idea of a threshold or predefined level of unemployment from which the government introduces more restrictive requirements. The presence of political interference in the natural relationship between unemployment and welfare caseloads is a signal that the government uses some parameters of the program to avoid higher spending in times of crisis or austerity.

5. CONCLUSION

Among the different issues that need to be addressed in the design of welfare programs, one outstanding question is how to prevent unsustainable growth in the caseloads in a context of limited budgetary resources. According to standard economic theory, upturns in unemployment can cause a drastic increase in the number of welfare-eligible households. This natural effect might be reinforced or softened by the designers of the programs. Public choice theory has shown that different strategies can 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 level of benefits– and higher doses of restrictiveness –a higher proportion of rejected applications– in a framework of increasing unemployment. Using data from Catalonia's minimum income program 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 by 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 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, however, should not hide that the apparent generosity of the program might be partially offset by other decisions. On the one hand, while entries into the program seem to be motivated by changes in unemployment or in the level of benefits –in keeping with standard assumptions– our estimates have shown that worsening macroeconomic conditions are associated with a higher number of exits rather than a decrease in the probability of participants leaving the program. Because the natural event should be a decrease in exit rates, this is a possible indication of endogenous actions aimed at compensating for the increasing number of caseloads.

On the other hand, a striking result of our estimates is the positive effect on the program's restrictiveness found for the level of benefits and the unemployment rate. This may also be a signal that lowering the proportion of accepted applications might be part of the strategy to prevent increases in the program's spending. In fact, our estimates confirm 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 model the changes themselves in the level of benefits or in the proportion of rejected applications as a response to changes in macroeconomic conditions.

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

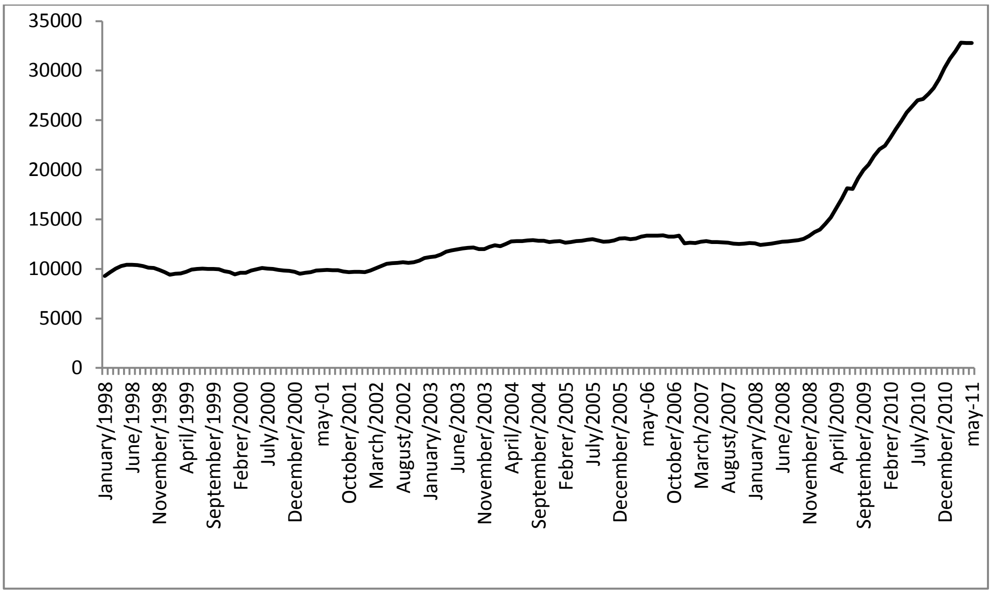

Figure 2. Unemployment rate, 1998-2010

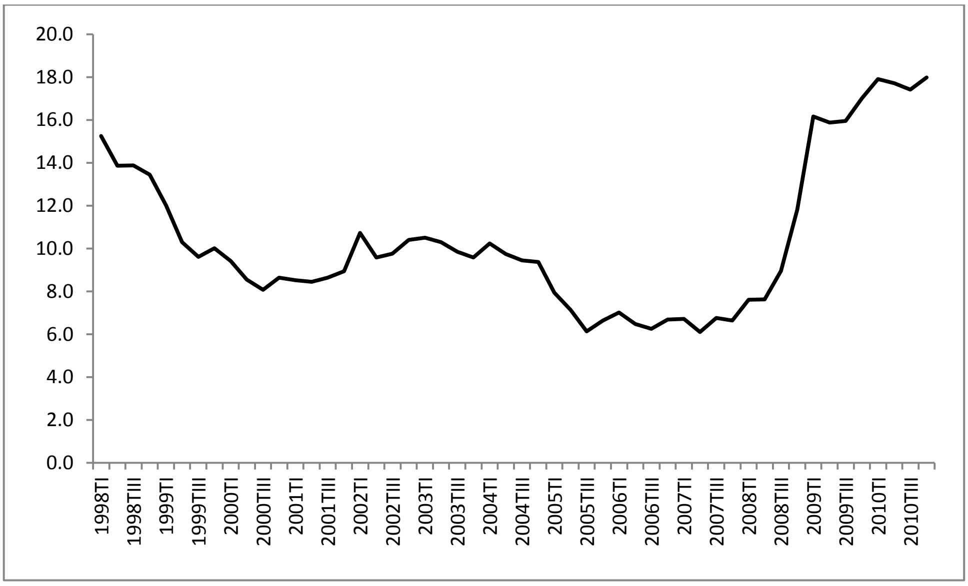

Figure 3. Proportion of households without income from the labor market and Social Security benefits, 1998-2010

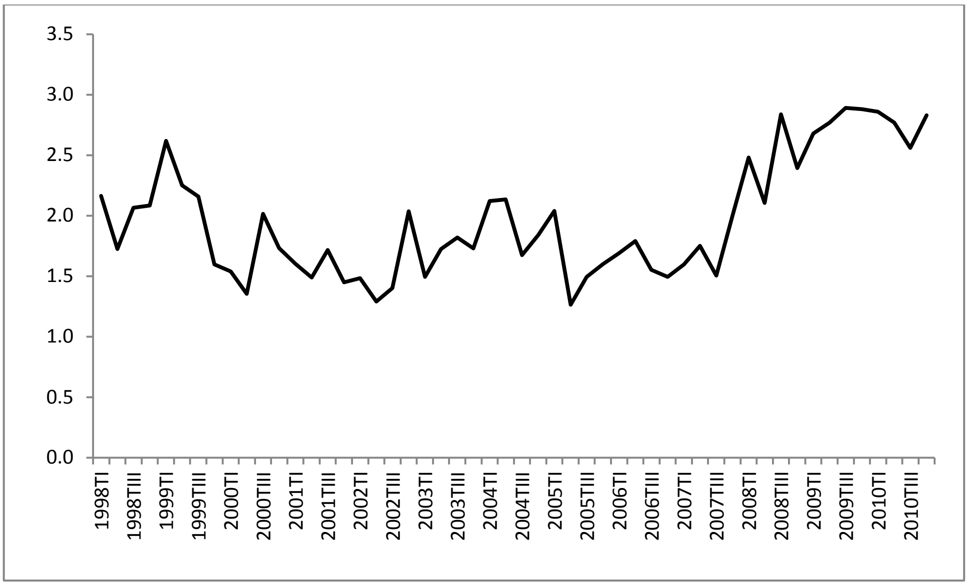

Figure 4. Flows of exit and entry in the PIRMI program

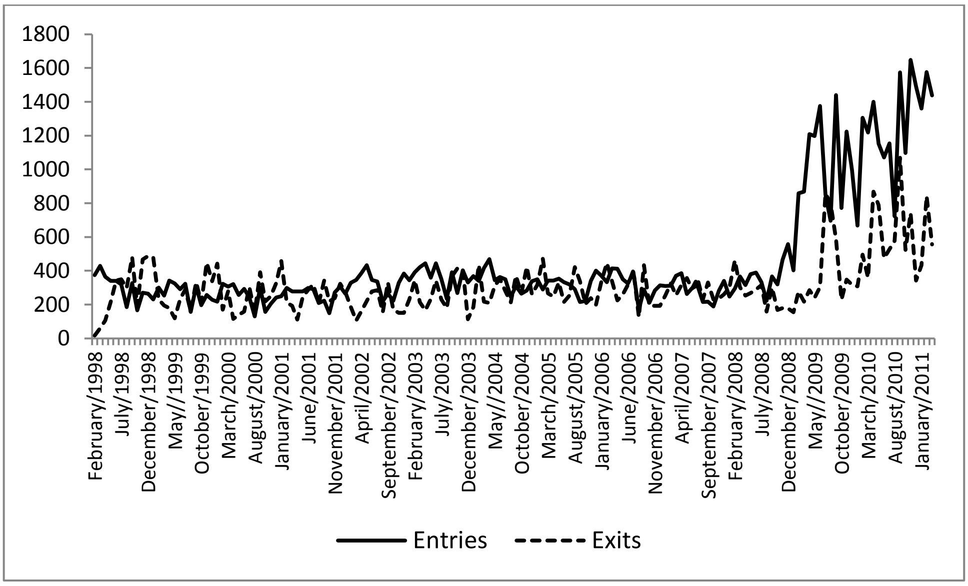

Figure 5. Average benefits and proportion of rejected applications

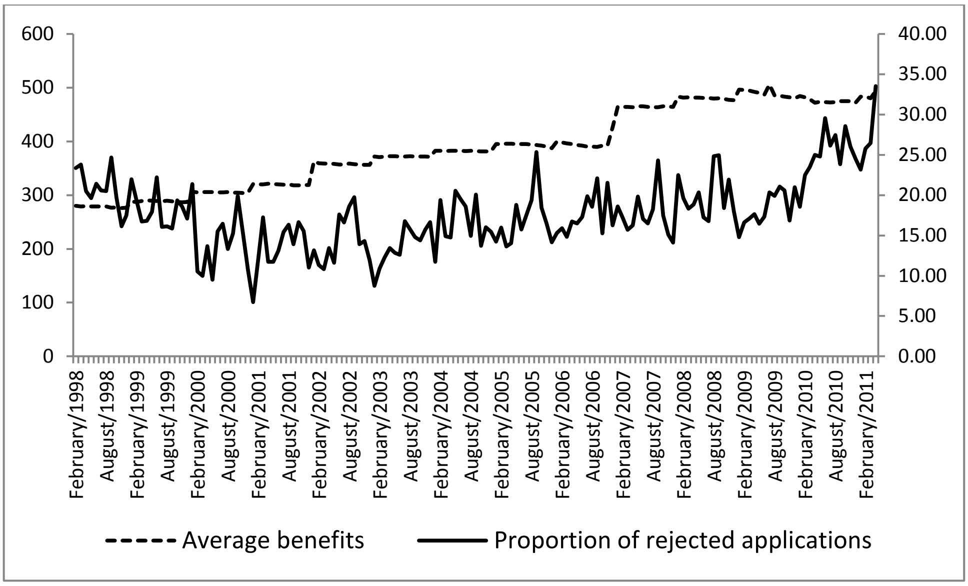

Table 1. Unit root and stationarity tests

	ADF			PP		
	τ	τ_{μ}	τ_{τ}	$Z(t_{\alpha})$	$Z(t_{\alpha*})$	$Z(t^{-}_{\alpha})$
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	3.411	-0.880	-3.148	3.581	0.777	-3.540**
$D.B_t$	-6.109***	-7.275***	-7.277***	-12.490***	-13.325***	-13.291***
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 $Z(t^{-}_{\alpha})$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)
$Caseloads_{t-1}$	0.775***	0.757***	0.703***	0.706***	0.694***	0.682***	0.660***	0.699***
	(0.078)	(0.078)	(0.078)	(0.078)	(0.077)	(0.077)	(0.077)	(0.077)
$Caseloads_{t-2}$	0.194**	0.220***	0.249***	0.240***	0.247***	0.255***	0.271***	0.247***
	(0.078)	(0.078)	(0.077)	(0.076)	(0.075)	(0.075)	(0.075)	(0.076)
$Unemployment_{t}$	0.044***	0.045***	0.030**	0.029**				
	(0.008)	(0.008)	(0.012)	(0.012)				
$Generosity_{t}$	0.080***	0.083***	0.100***	0.106***	0.124***	0.133***	0.145***	0.112***
	(0.018)	(0.017)	(0.034)	(0.034)	(0.034)	(0.036)	(0.036)	(0.034)
$Restrictiveness_{t}$		-0.017*	-0.008					
		(0.009)	(0.009)					
$Reform_{2006}$			-0.018**	-0.020**	-0.021***	-0.021***	-0.023***	-0.022***
			(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$Reform_{2008}$			0.036***	0.037***	0.032**	0.030**	0.034***	0.034**
			(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)
$Unemployment_{t-1}$					0.038***			
					(0.012)			
$Unemployment_{t-2}$						0.041***		
						(0.013)		
$Unemployment_{t-3}$							0.041***	
							(0.013)	
$Unemployment^{S}_{t}$								0.033***
								(0.012)
Constant	-0.747***	-0.743***	-0.942***	-0.992***	-1.150***	-1.236***	-1.338***	-1.043***
	(0.180)	(0.179)	(0.266)	(0.259)	(0.267)	(0.281)	(0.287)	(0.259)
N	157	157	157	157	157	157	156	157
R^2	0.993	0.993	0.993	0.993	0.993	0.993	0.994	0.993
Log likelihood	375.2	377.2	382.8	382.4	384.2	384.6	383.8	383.1
F	5064	4127	3125	3653	3737	3756	3832	3687

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

Table 3. Determinants of entries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Unemployment_t$	0.656***	0.747***	0.527***	0.467***			
	(0.06)	(0.06)	(0.123)	(0.126)			
$Generosity_t$	0.573***	0.784***	0.594*	0.604*	0.884***	0.875***	0.665**
	(0.129)	(0.131)	(0.318)	(0.334)	(0.327)	(0.334)	(0.332)
$Restrictiveness_t$		-0.387***	-0.355***				
		(0.085)	(0.086)				
$Reform_{2006}$		-0.087	-0.165**	-0.178**	-0.169**	-0.159*	-0.178**
		(0.082)	(0.083)	(0.080)	(0.080)	(0.081)	(0.083)
$Reform_{2008}$		0.291**	0.287**	0.152	0.194	0.280**	0.251*
		(0.131)	(0.137)	(0.135)	(0.139)	(0.135)	(0.137)
$Unemployment_{t-1}$				0.600***			
				(0.124)			
$Unemployment_{t-2}$					0.546***		
					(0.128)		
$Unemployment_{t-3}$						0.459***	
						(0.124)	
$Unemployment^S_t$							0.513***
							(0.129)
Constant	-8.369***	-10.494***	-8.852***	-8.113***	-10.017***	-9.856***	-8.562***
	(0.742)	(0.839)	(2.008)	(2.102)	(2.058)	(2.107)	(2.100)
N	159	158	158	158	157	156	159
R^2	0.507	0.565	0.583	0.536	0.565	0.559	0.542
Log likelihood	-55.5	-55.3	-55.3	-55.5	-55.3	-54.8	-55.5
F	80.25	66.72	42.58	44.45	49.68	48.09	45.51

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

Table 4. Determinants of exits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
$Unemployment_t$	-0.115	-0.032	-0.126	-0.292				
	(0.111)	(0.107)	(0.221)	(0.242)				
$Generosity_t$	-0.136	-0.362	-0.491	-0.272	-0.322	-0.423	-0.327	-0.211
	(0.241)	(0.231)	(0.574)	(0.638)	(0.577)	(0.564)	(0.544)	(0.641)
$Restrictiveness_t$		0.007	0.015					
		(0.149)	(0.155)					
$Reform_{2006}$			-0.016	-0.08	-0.03	0.013	0.041	-0.082
			(0.148)	(0.159)	(0.141)	(0.136)	(0.133)	(0.160)
$Reform_{2008}$			0.121	0.247	0.023	-0.065	-0.225	0.214
			(0.236)	(0.262)	(0.238)	(0.236)	(0.220)	(0.264)
$Unemployment_{t-1}$					-0.02			
					(0.220)			
$Unemployment_{t-2}$						0.092		
						(0.217)		
$Unemployment_{t-3}$							0.276	
							(0.203)	
$Unemployment^S_t$								-0.262
								(0.249)
Constant	-2.781**	-1.632	-0.667	-1.6	-1.897	-1.557	-2.512	-2.019
	(1.384)	(1.481)	(4.022)	(3.634)	(3.560)	(3.412)	(3.403)	(4.048)
N	159	158	158	159	158	157	156	159
R^2	0.01	0.019	0.021	0.018	0.019	0.034	0.057	0.016
Log likelihood	-99.1	-80.9	-80.9	-99.1	-80.9	-75.69	-73.79	-99.1
F	0.811	1.019	0.662	0.725	0.752	1.348	2.276	0.636

*, **, *** 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)
$Unemployment_t$	0.249***	0.214*					
	(0.054)	(0.114)					
$Generosity_t$	0.516***	-0.084	-0.062	0.072	0.097	0.538*	-0.027
	(0.117)	(0.299)	(0.301)	(0.303)	(0.297)	(0.285)	(0.299)
$Reform_{2006}$		0.237***	0.242***	0.233***	0.228***	0.207***	0.228***
		(0.074)	(0.074)	(0.073)	(0.072)	(0.071)	(0.075)
$Reform_{2008}$		-0.022	-0.035	-0.081	-0.057	-0.210**	-0.055
		(0.123)	(0.124)	(0.126)	(0.120)	(0.103)	(0.123)
$Unemployment_{t-1}$			0.224*				
			(0.115)				
$Unemployment_{t-2}$				0.266**			
				(0.116)			
$Unemployment_{t-3}$					0.239**		
					(0.111)		
$Unemployment_{t-6}$						0.411***	
						(0.097)	
$Unemployment^S_t$							0.252**
							(0.116)
Constant	-5.342***	-1.852	-1.88	-1.896	-1.91	-1.86	-7.730***
	(0.672)	(1.880)	(1.852)	(2.003)	(2.869)	(2.954)	(1.723)
N	158	158	158	157	156	153	158
R^2	0.242	0.29	0.29	0.292	0.302	0.305	0.429
Log likelihood	18.07	23.31	23.31	23.46	24.78	25.39	36.8
F	24.7	15.65	15.65	15.75	16.45	16.58	26.65

*, **, *** 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}	-0.742	***			-0.734	***			-0.820	***			-0.774	***	
	(0.101)				(0.109)				(0.059)				(0.080)		
Trend	-0.006	***			-0.006	***			-0.006	***			-0.006	***	
	(0.001)				(0.001)				(0.000)				(0.001)		
Constant	3.531				3.512				3.728				3.587		
Error Correction:	DC_t		DU_t		DC_t		DU_t		DC_t		DU_t		DC_t		DU_t
CointEq1	-0.065	***	-0.038		-0.057	***	-0.034		-0.105	***	-0.078	***	-0.079	***	-0.059***
	(0.014)		(0.041)		(0.013)		(0.038)		(0.010)		(0.026)		(0.010)		(0.024)
DC_{t-1}	-0.090		-0.046		-0.162	***	-0.088		-0.336	***	-0.230		-0.226	***	-0.143
	(0.080)		(0.241)		(0.064)		(0.190)		(0.068)		(0.179)		(0.074)		(0.174)
DC_{t-2}	-0.187	***	-0.101		-0.160	***	-0.087		-0.341	***	-0.234				
	(0.065)		(0.197)		(0.062)		(0.186)		(0.068)		(0.179)				
DC_{t-3}	0.419	***	0.130		0.441	***	0.140								
	(0.065)		(0.195)		(0.064)		(0.189)								
DC_{t-4}	-0.091		-0.049												
	(0.074)		(0.222)												
DU_{t-1}	-0.062	***	-0.036		-0.066	***	-0.040		-0.131	***	-0.098)		-0.092	***	-0.070
	(0.031)		(0.093)		(0.031)		(0.091)		(0.033)		(0.087)		(0.037)		(0.086)
DU_{t-2}	-0.076	***	-0.044		-0.068		-0.041		-0.131	***	-0.098				
	(0.031)		(0.094)		(0.030)		(0.091)		(0.033)		(0.087)				
DU_{t-3}	0.094	***	0.254	***	0.104		0.259								
	(0.031)		(0.093)		(0.030)		(0.091)								
DU_{t-4}	-0.047		-0.029												
	(0.033)		(0.098)												
Constant	0.005	***	0.002		0.005		0.002		0.009	***	0.004		0.007		0.002
	(0.002)		(0.005)		(0.002)		(0.005)		(0.002)		(0.005)		(0.002)		(0.005)
N	150				151				152				153		
R^2	0.594		0.118		0.586		0.118		0.438		0.057		0.280		0.038
Sum sq. resids	0.045		0.412		0.046		0.412		0.063		0.440		0.083		0.458
S.E. equation	0.018		0.054		0.018		0.054		0.021		0.055		0.024		0.055
F-statistic	22.761		2.083		28.87		2.724		22.765		1.778		19.346		1.951
Log likelihood	394.8		229.5		396.4		231.5		376.3		228.5		357.8		227.4
Akaike AIC	-5.131		-2.926		-5.144		-2.960		-4.873		-2.927		-4.625		-2.921
Schwarz SC	-4.930		-2.726		-4.984		-2.800		-4.754		-2.808		-4.546		-2.842

*, **, *** 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}	-0.742***		-0.734***		-0.820***		-0.774***	
	(0.101)		(0.109)		(0.059)		(0.080)	
Trend	-0.006***		-0.006***		-0.006***		-0.006***	
	(0.001)		(0.001)		(0.000)		(0.001)	
Constant	3.531		3.512		3.728		3.587	
Error Correction:	DC_t	DU_t	DC_t	DU_t	DC_t	DU_t	DC_t	DU_t
CointEq1	-0.073***	-0.045***	-0.078***	-0.011	-0.076***	0.000	-0.096***	-0.107***
	(0.010)	(0.023)	(0.012)	(0.027)	(0.011)	(0.026)	(0.023)	(0.053)
DC_{t-1}	-0.243***	-0.140	-0.248***	-0.145	-0.256***	-0.128	-0.248***	-0.091
	(0.075)	(0.176)	(0.075)	(0.175)	(0.075)	(0.175)	(0.076)	(0.177)
DU_{t-1}	-0.092***	-0.058	-0.092***	-0.058	-0.086***	-0.065	-0.069**	-0.123
	(0.037)	(0.086)	(0.036)	(0.086)	(0.036)	(0.085)	(0.037)	(0.087)
R_t	-0.011	0.009	-0.013	0.002	-0.008	-0.007	-0.003	0.006
	(0.008)	(0.020)	(0.009)	(0.020)	(0.009)	(0.021)	(0.009)	(0.022)
B_t			-0.096***	0.074	0.003	0.024	0.080**	-0.077
			(0.027)	(0.064)	(0.027)	(0.062)	(0.035)	(0.081)
Π_{2006}					-0.012	0.028	-0.012	0.020
					(0.009)	(0.020)	(0.009)	(0.020)
Π_{2008}							0.043***	-0.004
							(0.007)	(0.017)
Constant	-0.013**	0.018	0.539***	-0.422	-0.020	-0.159	-0.465***	0.454
	(0.015)	(0.035)	(0.159)	(0.372)	(0.152)	(0.355)	(0.201)	(0.470)
N	153		153		153		153	
R^2	0.290	0.035	0.297	0.059	0.304	0.071	0.320	0.097
Sum sq. Resids	0.082	0.459	0.081	0.448	0.081	0.442	0.079	0.430
S.E. equation	0.024	0.056	0.024	0.055	0.024	0.055	0.023	0.054
F-statistic	15.127	1.343	12.408	1.849	10.605	1.865	9.728	2.221
Log likelihood	358.9	227.2	359.7	229.2	360.3	230.1	362.1	232.3
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