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2012

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Documentos de Trabajo
N.º 1210

BANCO DE ESPAÑA
Eurosistema

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Documentos de Trabajo. N.º 1210
2012

ISSN: 1579-8666 (on line)

Abstract

In this paper we present the estimation results of a dynamic panel data model that explains the dynamic behaviour of default ratios in Spain for loans extended to the household sector. We estimate the models for two alternative definitions of default and for two different loan categories. The dataset consists of a panel of 50 provinces and covers the period 1984-2009. The results of the models show that the dynamic behaviour of the default ratios of loans extended to Spanish households can be reasonably well characterised with the lagged LHS variable, and the contemporaneous and the lagged values of credit growth, the unemployment rate and the interest debt burden. We find that the increase in the unemployment rate was the main driver of the sharp rise in default ratios between 2007 and 2009 in Spain and that the fall in interest rates since the end of 2008 contributed to moderating the upward path of default ratios in 2009. We also find that there is strong evidence of asymmetrical effects of unemployment ratios on default ratios, and differences between banks and savings banks in their sensitivity to the cycle.

Keywords: Default ratios, non-performing loans, household finances, financial pressure.

JEL Classification: D14, C23, G21.

Resumen

En este artículo se presentan los resultados de estimar modelos dinámicos de datos de panel, que explican la evolución dinámica de los ratios de morosidad de los créditos a los hogares en España. Estimamos modelos separados para dos definiciones distintas de morosidad y para dos segmentos de créditos diferentes. La muestra está constituida por un panel de las 50 provincias a lo largo del período 1984-2009. Los resultados de estos modelos muestran que el comportamiento dinámico de los ratios de morosidad se puede describir a partir de esa misma variable desfasada, y los valores contemporáneos y retardados del crecimiento del crédito, de la tasa de paro y de la carga financiera por intereses. Encontramos que los incrementos del desempleo han sido los principales responsables del fuerte aumento de las ratios de morosidad entre 2007 y 2009 en España y que la caída de los tipos de interés desde finales de 2008 ha contribuido a moderar en 2009 esa tendencia creciente. También encontramos fuerte evidencia de los efectos asimétricos de la tasa de paro sobre la morosidad, así como diferencias en la sensibilidad al ciclo entre los créditos concedidos por bancos y cajas de ahorros.

Palabras claves: Ratios de morosidad, créditos dudosos, posición financiera de las familias, presión financiera.

Códigos JEL: D14, C23, G21.

1 Introduction

The monitoring of the ability of the private sector to repay its debts is important for both macroeconomic and financial stability. In particular, from the macroeconomic perspective, a rise in the proportion of households or companies who cannot repay their debts is a sign of an increase in financial pressure for these agents, which might ultimately have an adverse impact on their expenditure decisions. The same developments will have a negative effect on financial institutions' profits due to the increase in non-performing loans, which may adversely impact financial stability. This, in turn, can have a second-round effect on macroeconomic developments if the ability of banks to lend is affected by this shock.

Naturally, macroeconomic developments are an important driver of the ability of agents to repay their debts. In particular, during economic expansions income tends to increase at a high rate, improving the ability of borrowers to afford debt service payments. On the contrary, during recessions the ability to repay debt deteriorates due to the low increase in income and, in the case of households, due to the rise in unemployment. The recent sharp increase in non-performing loans in Spain and other countries clearly illustrates the impact of the cycle on this variable. In fact, the relevance of the global rise in default ratios has recently attracted fresh attention to this issue (see Demyanyk and Hemert, 2009, or Mayer et al., 2009).

Against this background, in this paper we analyse the macroeconomic determinants of the ability of Spanish households to repay their debts. We focus on two different measures of default: i) the ratio of the outstanding amount of defaulted loans (i.e. those that are doubtful or in arrears) to total loans to the household sector, and ii) the percentage of borrowers with defaulted loans. The first measure is more important for financial stability analyses, whereas from the macroeconomic perspective the second measure is perhaps more relevant. As a matter of fact, the latter measure tends to show a higher correlation with macroeconomic variables such as consumption and real-estate investment. For both measures, we split the loans into two different categories: i) loans with real guarantees (*secured*) and ii) loans without real guarantees (*unsecured*). This distinction makes sense given the different level and dynamics of the two ratios analysed in the paper.

For each default variable and loan category, we estimate a model using panel data of 50 Spanish provinces for the period 1984 to 2009. The use of regional data, which is uncommon in the literature, allows us to exploit the regional variability of these data, alleviating the problem of the relatively short time period for which data are available. The methodology used is a dynamic panel data (DPD) estimation. Default ratios are obtained from the Central Credit Register (CCR) of the Banco de España. This database collects individual information on all loans over 6,000 Euros granted to resident borrowers by the credit institutions domiciled in Spain. Since this threshold is very low, we can safely assume that we have data on virtually every loan granted in Spain (Jiménez and Mencía, 2009). This database includes different characteristics of each loan and each borrower, such as type of risk, economic activity of the borrower, guarantees, location, holder's nature, period of payments and time (see Jiménez and Saurina, 2004, and Jiménez et al., 2006, for a thorough description).

Previous empirical studies on the determinants of household non-performing loans in Spain and other countries have found that the cycle, proxied by the GDP and/or the unemployment rate, and interest rates or the ratio of debt service to income are the main drivers of this variable. Others have also found that a high level of indebtedness is associated with a high level of non-performing loans (Rinaldi and Sanchis-Arellano, 2006; Figueira et al., 2005). Some papers based on UK data have also found that the loan-to-value ratio and/or the percentage of undrawn mortgage equity are negatively correlated with the percentage of mortgages in arrears (Figueira et al., 2005; Whitley et al., 2004). Various papers also found that a high growth of credit is associated with an increase in the non-performing loan ratio several years later (Delgado and Saurina (2004), and Martínez-Peón and Saurina (2000) for the private sector's non-performing loans).

The empirical studies have used a variety of different methodologies. Most papers estimate an Error Correction Model using macro data (Delgado and Saurina (2004), using Spanish data; Rinaldi and Sanchis-Arellano (2006), using data for various euro area countries; Whitley et al. (2004) and Figueira et al., (2005), using UK data). A further group of papers uses micro data and estimates a dynamic probit (May and Tudela (2005) using UK data; and Gross and Souleles (2002) using US data). Finally, other papers (Martínez-Peón and Saurina, 2000; Salas and Saurina, 2002) have used a dynamic panel data methodology.

To the best of our knowledge, this is the first paper to use Spanish regional data to estimate default ratios for households and the first paper to use a definition of default based on the number of borrowers with defaulted loans in Spain.

The rest of the paper is organised as follows. After this introduction, Section 2 describes developments in the variables analysed in the paper, Section 3 presents the empirical model and the data, Section 4 summarises the main results and Section 5 presents alternative models distinguishing between banks and savings banks, and models with asymmetrical effects of changes in the unemployment ratio. Finally, Section 6 concludes.

2 Changes in household default ratios in Spain

In this paper we use two alternative definitions of default. The first is the standard definition of the non-performing loan ratio, which we will refer to as the *default ratio based on the size of the loans* (*DRSL*)[1]:

$$DRSL = \frac{Outstanding\ loans\ classified\ as\ doubtful\ or\ in\ arrears}{Total\ Outstanding\ loans} \tag{1}$$

This is one of the key standard variables used to assess the quality of the assets of the banking system and it is especially relevant for financial stability purposes. However, since this variable is measured in terms of the size of loans rather than the number of loans or borrowers involved, it does not offer a good measure of how widespread defaults are among households. Therefore, in this paper we also use an alternative measure: the *default ratio based on the number of borrowers* (*DRNB*):

$$DRNB = \frac{Borrowers\ with\ loans\ classified\ as\ doubtful\ or\ in\ arrears}{Total\ number\ of\ borrowers} \tag{2}$$

which is possibly a better proxy for the financial pressure on the household sector. In fact, *DRNB* has a stronger relationship with macroeconomic variables than the *DRSL* (the correlation with consumption is.59 vs. .57, and with real-estate investment it is .73 vs. .69).

For both default measures (*DRSL* and *DRNB*) we consider separately the loans in two different categories: i) secured loans and ii) unsecured loans. Jiménez and Mencía (2009) identify those types of loans with mortgages and consumption purposes, respectively. House purchases usually entail big outlays that require loans of a bigger size and longer maturity, and, therefore, they are generally collateralised by the house purchased (mortgages) in order to reduce the payment of interests. By contrast, consumption is usually financed by loans without collateral, entailing a lower amount and a shorter repayment period. The differences in loan characteristics, too, on the consequences in the event of default could mean very different default dynamics for both types of debt.

Figure 1 displays the two alternative default measures for the two debt classes (*DRSL* in the left-hand panel and *DRNB* in the right-hand one) together with the unemployment rate during the sample period used in this paper (1984-2009). The figure clearly illustrates the cyclical pattern of both the non-performing household loans rate and the percentage of households with loans in arrears. In particular, both variables tend to rise when the unemployment rate increases and tend to fall when the unemployment rate falls. The first variable (*DRSL*) seems to show a higher variability with the cycle compared to the second one (*DRNB*). This is likely to reflect the fact that the probability of default is more sensitive to shocks for relatively new loans, which tend to be of higher amount, as compared to older loans.

As regards debt classes, Figure 1 shows that both *DRSL* and *DRNB* tend to show both a higher level and a much higher variability with the cycle for unsecured loans than for those related to secured loans. The lower probability of default of secured loans reflects the

1. Doubtful loans and loans in arrears are defined in annex 1. Note that this measure excludes write-offs, which remain on the CCR database as long as the debt continues to be neither reimbursed nor extinguished.

lower incentives to default on this class of debt, since in the event of default borrowers can lose their guarantee, which is normally their dwelling (mortgage loans). Also, contrary to other countries, like the US, lenders in Spain are allowed to use both the future earnings and other assets of the debtor to repay past debts, meaning that borrowers have fewer incentives to default on their debts.

Recent developments in default ratios show a sharp increase since 2007, which has coincided with the recession of the Spanish economy, after a long period in which these variables had decreased and stabilised at very low levels. At the end of the sample, they stood below their peaks during the two previous crises (at the beginning of the 80's and in 1992-93).

Figures 2 and 3 show that default ratios display a relatively high dispersion by province both in levels and in terms of changes. The dispersion in levels is higher when default ratios are high. One possible source of the heterogeneity in the regional data could be the developments in macroeconomic data. In this regard, Figure 4 shows that there is also some dispersion in the change in the unemployment rate. This heterogeneity suggests that there might be value in exploiting regional data to estimate the main macroeconomic determinants of default ratios, and their dynamics.

3 Empirical model

In the empirical model, we use logit transformations of the default ratio variables defined in the previous section. More precisely, we define y^{DRSL} and y^{DRNB} as follows:

$$\begin{aligned} y^{DRSL} &= \ln\left(\frac{DRSL}{1-DRSL}\right) \\ y^{DRNB} &= \ln\left(\frac{DRNB}{1-DRNB}\right) \end{aligned} \quad . \qquad (3)$$

This transformation, which is standard in the literature[2], implies that the LHS variables are defined for all real numbers. It also implies a non-linear effect of the changes in the explanatory variables, the effect being greater the higher these variables, a feature which is normally observed in the data.

Given the different levels and dynamics of default ratios depending on debt classes that we have shown in the previous section, we estimate different models for secured loans ($y^{DRSL,s}$ and $y^{DRNB,s}$) and for unsecured loans ($y^{DRSL,u}$ and $y^{DRNB,u}$). For each of these four variables we specify a dynamic panel data model (DPD).

$$y_{i,t}^{j,l} = \alpha \cdot y_{i,t-1}^{j,l} + \sum_{s=0}^{3} \beta_s{}' x_{i,t-s} + \eta_i + \varepsilon_{i,t} \qquad j = DRSL, DRNB, \qquad l = s, u \quad (4)$$

$$y_{i,t}^{j,l} = \alpha \cdot y_{i,t-1}^{j,l} + \sum_{s=0}^{3} \beta_s{}' x_{i,t-s} + u_{i,t}$$

In equation 4, the logit transformation of the ratio ($y^{j,l}$) in a given province (i) and year (t) depends on the previous year's value for the same variable (to account for the possibility of inertia in the changes in this variable), as well as other contemporaneous and lagged variables (vector $x_{i,t-j}$), non-observable provincial characteristics (η_i) and an error term ($\varepsilon_{i,t}$).

The lagged $y^{j,l}$ is introduced to capture the inertia in the dynamics of these variables. The coefficient α ($0 \le \alpha \le 1$) measures the degree of inertia. We expect default measures to exhibit a strong inertia since, once a loan has fallen into the non-performing category, it is likely to remain there for subsequent periods. In fact, it can only leave this category either by the borrower catching up with overdue payments when his/her financial position improves or when the credit institution writes off the loan completely. In either case, most of the portfolio of non-performing loans in one year would remain in this category the following year.

The choice of explanatory variables $x_{k,i,t-j}$ is based on both theory and previous empirical papers. The first one is the *Increase in the unemployment rate* (ΔUR_{it}). The unemployment rate (UR), which is defined as the number of unemployed workers divided by

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2. Salas and Saurina (2002) and Jiménez and Saurina (2006) use this transformation, while Jiménez and Mencía (2009) use the similar alternative Probit transformation.

the number of active people, is taken from the Labour Force Survey (*Encuesta de Población Activa*, EPA) of the Spanish National Institute of Statistics (INE). We expect a positive sign for the parameter of this variable since workers becoming unemployed, given the derived income drop, will experience greater difficulties in meeting their debt obligations. We have included the changes rather than the levels in *UR*, a specification which is in line with Brookes at al. (1994) and Figueira et al. (2005). By using this specification, we are implicitly assuming that what matters for the default ratios are the changes in unemployment rather than the level of unemployment. This assumption is based on the following. Loans are extended to those borrowers with a sound financial position and/or steady flows of income, and, therefore, it is unlikely that banks will lend to unemployed people. But once a loan has been extended, borrowers can become unemployed and, as a result, their ability to repay the loan can be affected. Therefore, the relevant magnitude is not the level of unemployment, but the inflows of unemployed. Some authors focus on broader measures of default that incorporate loans to non-financial firms, replacing the unemployment rate with GDP growth (Salas and Saurina, 2002; Delgado and Saurina, 2004; Jiménez and Saurina, 2006; Jiménez and Mencía, 2009), an approach that is equivalent to some extent.

The second explanatory variable considered is the *Increase in the interest debt burden* (ΔIDB_{it}). Variable *IDB* is defined as

$$IDB_{it} = \frac{\frac{C_{it}^{s}}{B_{it}^{s}} \cdot r_t^s + \frac{C_{it}^{u}}{B_{it}^{u}} \cdot r_t^u}{DI_{it}} \tag{5}$$

where C_{it}^{s} and C_{it}^{u} are the total outstanding amount of loans secured and unsecured, respectively, for each province and for each year; B_{it}^{s} and B_{it}^{u} are the number of people with loans both secured and unsecured in that province; DI_{it} is the per capita nominal disposable income in the same province[3]; and r_t^s and r_t^u are the interest rates applied to the outstanding loans of each type of loan[4]. We have used a single measure of *IDB,* which captures the overall interest burden for all debts, for all models and not specific measures of interest debt burden for each type of loan (loans with and without guarantees), since the ability to repay a specific loan is not necessarily only affected by the interest burden of that loan. Ideally, debt burden should include not only interest payments but also principal repayments, yet unfortunately, the latter are neither directly observable nor easy to estimate.

The *IDB* ratio, as we have defined it, summarises in one variable the impact of three variables: interest rates, indebtedness and household disposable income. We expect a positive sign for the coefficient of this variable since an increase in the relative debt burden would worsen the ability of households to meet their debt payments. Most papers use interest rates as a proxy for the interest debt burden. The advantage of our specification is that the impact on default ratios of changes in interest rates depends on the level of indebtedness (i.e. it is higher the higher the level of indebtedness), as well as on household

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3. Nominal disposable gross income is measured in base 1995. This information is from the Spanish National Institute of Statistics. Population data used for transforming it in per capita terms are also obtained from the same institutions historical series of population (there is an interpolation of 1997 and 1999 because there was no information for this series in 1998).

4. Although the CCR does not provide information on the interest rates applied to each loan, since 2003, the Banco de España's Statistics Bulletin (Table 19.12 http://www.bde.es/infoest/a1912e.pdf) provides monthly data on the mean interest rate applied in Spain to outstanding loans for house purchase (that we use as a proxy of loans with guarantee) and loans for consume and other purposes (proxy of loans without guarantee), for maturities: less than a year, from 1 year to 5 years, and more than 5 years. For earlier periods we have used a 1 year moving average of the interest rates applied to new loans.

disposable income. In fact, negative shocks to disposable income (i.e. an economic recession) would increase the interest debt burden, and eventually the pressure on the default ratios. The inclusion of *IDB* in differences rather than in levels can be justified along the same lines as in the case of the unemployment rate.

The third explanatory variable is the *Credit growth rate* (*CGR_{it}*), which is computed using CCR data. This variable is included to capture the various channels through which credit growth can have an impact on default ratios. First, increases in outstanding credit will have a contemporaneous effect on both *DRSL* and *DRNB*, simply by raising the denominator of both ratios. However, this effect will fade with the inherent credit life cycle since some time is needed between the moment money is lent (where all the loans are standard) and the moment a borrowers' payment is declared in arrears (usually, the proportion of loans going into arrears grows for the first two years, peaks, and then starts falling). Additionally, a strong increase in credit approvals might signal a deterioration of credit standards and, therefore, a future increase in both default measures (Gross and Souleles, 2002; Salas and Saurina, 2002).

For the estimation of equation 4, Arellano and Bond (1991) suggest using the first difference of the regression to remove each specific non-observable effect in respect of the provinces (η_i). However, this process of taking out the individual effect introduces a correlation between the new error term ($\Delta\varepsilon_{i,t}$) and the lagged dependent variable ($y_{i,t-1}^{j,l}$). Hence, the lags of the explanatory variables in levels are used as instruments, to address both correlation and endogeneity. Moreover, when applying first differences, the stationarity of regressors is ensured. GMM estimator consistency depends on two assumptions: i) the random error ($\varepsilon_{i,t}$) does not present serial correlation of second order and ii) the validity of the instruments (see Arrellano and Bond, 1991). Both assumptions are tested using a serial correlation test and a Sargan test, respectively. We also assume that $E\left[\Delta y_{i,t-2}^{j,l} u_{it}\right] = 0$, allowing us to exploit the additional moment conditions for the equations in levels, which provides an improvement in efficiency and a reduction in finite sample bias, particularly if default measures are persistent. We use an incremental Sargan test to test for these additional overindentifying conditions. In this way, we obtain consistent and efficient estimates and control for endogeneity in all the regressors.

4 Results

Estimation results (two-step system GMM estimations) for equation (4) are shown in Table 1 for the *DRSL* and in Table 2 for the *DRNB*. In all cases, non-statistically significant lags have been removed from the final model. As can be seen, for all models Sargan tests support the validity of the instruments used, while serial correlation tests also accept the correlation for the first lag and reject the correlation for the second lag, as we would expect in a properly specified DPD.

Although the model has been estimated using panel data for the 50 Spanish provinces, the results are valid for the whole country. Indeed, we can use the estimated coefficients to recover the expected default ratios for Spain. In order to do this, we use the information on each province to obtain provincial estimators of the corresponding default ratios and, from these, the Spanish default ratio is obtained by computing a mean weighted by credit size or number of borrowers, depending on the default definition used. As can be seen in Figure 5, this weighted mean, when compared with the observed level of default ratios, shows that the models are able to capture the cyclical behaviour of the different definitions of default.

In all the models considered, the results are similar in terms of both the signs and the statistical significance of the coefficients. The signs of the coefficients are in line with those that we were expecting. In particular, the coefficient of the lagged LHS variable is positive and statistically significant. The coefficient is relatively high, reflecting the strong inertia in these variables. In the case of the *DRSL* variable, the high inertia could be partly explained by the *carryover effect* of the former regulation in place up to 2004[5]. However, this is not the only source of inertia, since it also appears, although to a lesser extent, for the *DRNB* variable, which is not affected by this effect.

Regarding the variable *CGR*, the contemporaneous coefficient is negative and statistically significant (i.e. an increase in credit is associated with a fall in default ratios). This effect captures the impact of the expansion of the credit pool to new loans that are initially classified as *standard*. But the lagged *CGR* variables are positive and statistically significant up to the third lag, implying that the initial drop subsides in subsequent periods when a proportion of the new loans granted move into the default categories.

The variable ΔUR affects both *DRSL* and *DRNB* with a positive sign both contemporaneously and with some lags. The existence of lags can be justified by the existence of unemployment benefits, personal savings and financial support from other members of the family, elements that can in the short term support the ability of unemployed borrowers to repay their loans. Therefore, it could take some time before loans extended to borrowers who became unemployed are classified as doubtful or in arrears.

Finally, as expected, the coefficients of the contemporaneous and/or lagged Δ *IDB* variable are positive and significant (except the third lag in the *DRSL* and *DRNB* models for secured loans). This variable also has lagged effects on default ratios, but to a lesser extent than the case of the *UR*. This latter feature can be justified by the non-existence, in the case of the *IDB*, of a transitory complementary shock equivalent to the unemployment benefits in the case of the *UR*.

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5. See more details in Annex 1.

The size of the estimated coefficients is not a good proxy of the impact of each variable on the dependent variable. In order to do this, we need to compute some form of impulse-response function that allows us to take into account not only the contemporaneous effects of the RHS variables, but also their lags. Given the non-linear nature of the logit transformations used in the model (equation 3), these effects differ in size depending on the actual level of the LHS variable. Hence, in order to produce impulse-response functions or any sensitivity analysis, the selection of the initial position has a non-negligible effect.

To illustrate these effects we have used a base case where all the variables (*y, CGR,* ΔUR and ΔIDB) take as starting values the levels they had in 2006 for the whole country, the final year on a series of stable default ratios. For subsequent periods, we have assumed that the *UR* and *IDB* would remain unchanged. In the latter, increases equal to zero would be attained by considering that interest rates would not change, and credit increased at the same speed as nominal disposable income. Therefore, *CGR* has been set to the long-term average growth of nominal gross disposable income.

This base case is then compared with alternative scenarios in which the RHS variables are increased by 1 pp in year 0, remaining unchanged for the rest of the horizon. That implies a permanent increase in the original variables since the RHS variables are expressed in differences. Differences between these two scenarios (the base case and that with the shock) allow us to perform something similar to an impulse-response analysis for the estimated models. The results of these exercises are shown in Figure 6a and 6b (where the cumulative effects on the LHS variables are presented).

As can be seen in all panels of Figures 6a and 6b, the shocks analysed produce a transitory effect on default ratios, a feature that is a consequence of the specification used in which variables enter in differences and not in levels. These transitory effects are consistent with the fact that being in default is a transitory situation in that loans classified as in arrears or doubtful ultimately become either standard (if the borrower repays the amount of debt owed), are amortised (if the borrower repays in full the loans) or removed from the balance sheets (write-offs). The maximum effect in the level is reached between one and three years after the shock, depending on the variable.

Another interesting feature of the results is that, under the two definitions of default, the default ratio for secured loans appears to be less sensitive to changes in the RHS variables, especially in the case of the unemployment rate. This result is consistent with the less marked cyclical pattern of default ratios for this type of loan that was reported in section 2, a feature that reflects the lower incentives to default that the holders of these loans normally have when they face adverse shocks that impact their ability to repay their loans.

The comparison between the two definitions of default shows that *DRSL* is generally more sensitive to shocks, especially in the case of the *UR*, again a feature which is consistent with the findings in Section 2. As explained in Section 2, this pattern probably reflects the fact that the probability of default tends to be more sensitive to shocks for relatively new loans, which tend to be of a higher amount compared with older ones.

The increase in the level of credit entails in all cases a contemporaneous fall in both definitions of default. But during the following periods the default ratios tend to increase and, two or three years after the shock these ratios stand above the value of the base case scenario. This reflects the dynamic behaviour of the probability of default for a vintage of loans. Initially, the probability of default is very low since banks only extend loans to clients with a sound financial position. But later the probability of default tends to increase since adverse shocks impact a proportion of these borrowers. After some time (normally after the third year), the probability of default starts to decline since the outstanding amount of the debt tends to decrease and also, as a consequence, the debt burden falls. Conversely, a fall in credit growth would produce a similar effect but in the opposite direction.

A 1pp increase in the unemployment rate produces a significant impact on default ratios. As commented above, the effect is higher in the case of the DRNB than in the DRSL and, among debt classes, it is more marked for unsecured loans. The contemporaneous effect shows the greater magnitude, although the ratio continues to increase in subsequent years, reaching a maximum difference over the base case in the third year after the shock. Afterwards, the reduction in the default measures takes a considerable period of time.

The increase in the *IDB* produces a faster response in the default measures compared to the impact associated with the rise in *UR*, with the cumulated effect peaking between one and two years after the shock. Reversion to the long-term value is also faster than that found in the case of a shock to the *UR*.

Another way of looking at the effect of the three independent variables on the default measure is by analysing the contribution of each to the recent upward trend in household financial distress[6]. Figure 7 presents the results of this exercise. As can be seen, all three variables contributed in 2007 and 2008 to the increase in default ratios. The surge in the unemployment rate is the main driver of the upward trend in the default measures, followed by sharp deceleration of credit. In 2009, unemployment continued to be the main variable pushing default ratios upwards, but the reduction in interest rates observed since the end of 2008 has somewhat eased the increase in these ratios, especially in the case of secured loans.

The model underestimates the increase in 2007 and 2008 and overestimates that in 2009. These errors in timing might partly be a consequence of the change in the regulation in 2004 that has meant an earlier recognition of doubtful loans as compared to the previous regulation in place for most of the sample period analysed. However, other factors apart from this must account for these errors, since they are also observed in the case of the definition based on the number of borrowers in default (albeit to a lesser extent), for which this effect is not present.

6. See annex 2 for a detailed explanation of how this contribution has been computed.

5 Alternative specifications

5.1 Banks vs. savings banks

In order to check whether there are significant differences among credit institutions we have split our sample into two sub-samples, comprising, respectively, the loans granted by banks and savings banks. Both types of credit institutions represent more than 80% of all unsecured debt in the period analysed and more than 90% of secured debt (see figure 8). In the latter case, savings banks are the main players, accounting for a market share that has never fallen below 50%, while banks' market share has ranged from 25% to 40%. The gap between them was wider during the crisis in the early 90s, but has narrowed significantly in the second half of the decade and the opening years of the new century, remaining relatively stable until the end of the sample. In the case of unsecured loans, banks had a higher market share at the beginning of the sample period, although this has been smoothly declining since then. By contrast, savings banks started with a lower market share (especially if we measure the market by the size of the loans), but have been gaining market share throughout the sample period, surpassing banks in the second half of the 90s. In terms of numbers of borrowers, differences are not so clear, so gains in terms of size of unsecured loans seem to have come via increases in the quantity of the individual loans granted by savings banks.

Regarding the dynamics of the default measures, as can be seen in Figure 8, the cyclical pattern of the default we showed for the aggregate sample in previous sections is also present for both sub-samples. Additionally, the portfolio of unsecured loans has a more volatile pattern in both sub-samples, as it is also the case for the default specification based on the size of the loans. Nevertheless, we can also see some differences between banks' and savings banks' default ratios. Banks' default ratios are, in general, more sensitive to the cycle than savings banks' equivalent measures (default ratios peak at higher levels). This is especially the case for unsecured debt, where the heterogeneity of the portfolio could lead to differences in the type of loans granted by both types of institutions. By contrast, in the last cycle of increasing default ratios, the default ratios for savings banks' secured loans have increased somewhat more than the corresponding variables for banks, a pattern that has not been observed for unsecured loans.

Given these differences in the dynamics of the default measures, we have estimated separately models for the two types of institutions to see to what extent we can improve in this way the results obtained from the aggregated models estimated in the previous section. In table 3, we present the results for the same models we specified in the previous section, but with separate estimations for the loan portfolios of banks and savings banks. As can be seen, all the models show the same features we found for the sample that included all types of credit institutions. Both signs and level of significance are similar, as are the dynamics. Nevertheless, the values are different, although the exact consequences of these differences are difficult to discern from the estimated parameters. In order to do this, we have computed the same impulse-response exercises as in the previous sections. The results of this exercise are shown in Figures 9a and 9b.

As can be seen, the results of the impulse-response exercise show features similar to those we found for the previous models, both in terms of the direction of the effects and the size. However, we also observe divergences in the dynamic effects when we compare banks and savings banks. In the case of the models for the DRSL for secured debt (Figure 9a, left-hand panels), differences between credit institutions are small, with a lower persistence of the effects for the banks sub-sample. For the unsecured loans (Figure 9a, right-hand panels), DRSL measures are considerably more sensitive to unemployment and interest debt burden shocks for loans granted by banks than those granted by savings banks. They are also quite persistent, not tailing off completely at the end of the exercise horizon. The shock to credit growth is somehow different for banks, where there are two periods of default reductions after the shock, reducing the subsequent positive effect compared to the saving banks sub-sample.

When we use the DRNB alternative measure (Figure 9b), the results are similar to those of the DRSL, although the effects tend to be higher for the banks' loans sub-sample. In the case of unsecured debt (Figure 9b, right-hand panels), the degree of persistence is much lower than that we find for the DRSL measure, and more in line with that of the whole sample. Nevertheless, in the case of the credit growth rate shock, the negative initial effect continues for an extra period, in contrast to the other samples and default measures, as a consequence of the negative coefficient of the first lag of the variable (see Table 3).

As can be seen in Figure 10, both for banks and savings banks we find a positive fitting error for 2008 and a negative one for 2009, in line with the results based on the whole sample. Compared with the models estimated for the whole sample, the fitting errors in 2009 are much lower for both sub-samples. However, for 2008 the fitting errors of the sub-samples are similar or somewhat higher than is the case for the whole sample.

5.2 Asymmetric effect of the unemployment ratio

As mentioned in the previous section, the increase in the default ratios after the outbreak of the crisis in 2008 was faster than expected by the estimated models (see figures 7 and 10). One possible explanation for this puzzle could be the asymmetric effect that unemployment may have on default ratios. Our sample of indebted people only comprises people who were employed at the time of obtaining the loan (in Spain, it is seldom the case that loans are granted to people that has presented no documentation). Therefore, an increase in unemployment may affect the whole group of indebted people whereas a reduction would positively affect only a fraction of borrowers (those who have lost their job after taking out the loan). As a result, we would expect an increase in the unemployment ratio to have a greater impact on default ratios than a decrease in the same unemployment ratio, since the number of people potentially affected is higher in the former case.

To test this hypothesis, we have included an additional RHS variable, ΔUR (+), which is equal to ΔUR when there is an increase in the unemployment ratio and zero otherwise. If the effects of ΔUR on defaults are symmetric, we would expect ΔUR (+) not to be significant. The results of the estimation of this model are presented in Table 4.

The estimated models, when compared with the models with a symmetric effect of ΔUR (Table 1 and 2), present very similar coefficients for the variables that have not changed (Default, *CGR* and *IDB*). In the case of ΔUR (+), the contemporaneous coefficient is positive and statistically significant for all the specified models, implying that the previous hypothesis holds. An increase in the unemployment ratio (ΔUR + ΔUR (+)) has a positive effect on *the default ratios* that is much larger than the negative effect of a reduction in the unemployment ratio. In fact, the sum of the contemporaneous coefficients of ΔUR and ΔUR (+) is higher than that observed for ΔUR in the symmetric models (Table 1 and 2). By contrast, for the lagged variable there is no significant difference between positive and negative movements of *UR*, but the estimated values, in most cases, tend to be lower than those we had for the symmetric specification.

In this context, these models are able to explain the surge in the default ratios observed in 2008, derived from the increase in unemployment experienced by the Spanish economy since the beginning of the financial crisis, reflecting the greater impact on the contemporaneous default ratios and a lower persistence in the subsequent periods. As we did in the previous section, we present in Figure 11 the fitting errors for the 2007-2009 period. As can be seen, the errors are close to zero for 2008, and the size of the negative errors in 2009 is of a smaller magnitude than those we have for the symmetric models of Tables 1 and 2. In order words, this evidence suggests that the inclusion of asymmetries helps to improve significantly the performance of the model.

6 Concluding remarks

In this paper we have presented the estimation results of models that explain the dynamic behaviour of default ratios in Spain for loans extended to the household sector. More specifically, we have used two alternative definitions of default: the proportion of the outstanding amount of loans in default and the proportion of borrowers with defaulted loans. For each definition we have estimated two models: one for secured loans and another for unsecured loans. The dataset used to estimate the models consists of a panel of 50 provinces, and covers the period 1984-2009, including the last two crises of the Spanish economy. The models have been estimated using two-step system GMM.

The results of the models show that the dynamic behaviour of the default ratios of loans extended to Spanish households can be reasonably well characterised with the following variables: the lagged LHS variable, and the contemporaneous and the lagged values of credit growth, the unemployment rate and the interest debt burden. The coefficients of these variables are all significant and present the expected sign in all the estimated equations. However, there are some differences in the sensitivity of default to shocks to the independent variables depending on the definition of default and the type of loan. In particular, the definition of default based on size of loans tends to be more sensitive to shocks than that based on the number of borrowers in default. This is probably related to the fact that relatively new loans, for which the probability of default is normally more sensitive to shocks, tend to be of a higher amount. By loan classes, we have found that the sensitivity to shocks is higher for unsecured loans, a feature that probably reflects the comparatively higher incentives to default for this type of loan.

The impulse-response functions show that shocks to independent variables have a transitory effect on default. This feature, which is a consequence of the specification in differences of the RHS variables of the model, captures the fact that being in default is a transitory situation. However, the effects are relatively persistent.

According to the estimated results, the increase in the unemployment rate was the main driver of the sharp rise in default ratios between 2007 and 2009. The fall in interest rates since the end of 2008 contributed to moderating the upward path of default ratios in 2009. However, the model underestimates the increase in 2007 and 2008 and overestimates the increase in 2009. These errors in timing might partly be a consequence of the change in regulations in 2004, which involved an earlier recognition of doubtful loans as compared with the regulations in place for most of the sample period analysed. However, other factors apart from this should account for these errors, since they are also observed in the case of the definition based on the number of borrowers in default, for which this effect is not present.

We have also estimated the same models for two separate sub-samples of loans granted by banks and savings banks, respectively. Although the models are qualitatively similar, they differ quantitatively, showing differing sensitivity to the economic cycle.

We have also found strong evidence of asymmetric effects of unemployment on the default measures. In particular, we find that an increase in the unemployment ratio has a sharper impact on default ratios than a reduction in unemployment. The introduction of this feature into the model helps to improve its performance. More specifically, we show that a model that includes asymmetric effects can better explain the recent developments in default ratios.

Annex 1: Definitions

Spanish CCR classifies all loans in four different categories[7]: standard, doubtful due to customer arrears (*arrears*), doubtful for reasons other than customer arrears (*doubtful*) and *write-offs*. Standard loans are those loans that, according to the rules of the Banco de España, are not classified in any of the other three previous categories (CBE 4/2004, Annex IX, page 4).

The total amount of a loan must be considered to be in *arrears* by a bank if any portion of the loan (principal, interest or contractually agreed expenses) is past-due by more than three months. This category will also include the amounts of all the transactions of a customer if the balances classified as doubtful due to arrears exceed 25% of the total outstanding debt with the bank (CBE 4/2004, Annex IX, page 6). Previous legislation (CBE 4/1991) restricted the so-called transaction *carryover effect*, since it established that one of the following two conditions had to apply for this to occur: the accumulated past-due amounts classified as doubtful due to arrears had to exceed 25% of the amount payable; or there had to be amounts past-due by more than 12 months (6 months in the cases of mortgages and consumer credit). For instance, consider a mortgage of €100,000 and that by January a payment of €3,000 is missed. Under CBE 4/1991, by April, €3,000 would have been classified as in arrears while the remaining €97,000 would still be standard. By July, the entire amount would have been considered in arrears. Under new legislation (CBE 4/2004), the €100,000 would be in arrears since April. This change implies that, in the current cycle (after the legislative change), doubtful credit will grow faster than expected by previous cycle observations.

The category of *other doubtful loans* includes those loans which, although they are not classifiable as doubtful due to customer arrears, pose reasonable doubts regarding their full repayment under the contractual terms (CBE 4/2004, Annex IX, page 7). This includes those cases where borrowers moves into a situation where there is a significant deterioration in their solvency, such as general delays in payment, insufficient income to meet debts or the impossibility of obtaining further financing.

Finally, *Write-offs* include the amount of debt instruments for which the bank, after analysing them individually, considers the possibility of recovery to be remote and proceeds to derecognise them (CBE 4/2004, Annex IX, page 7). Once a loan has been classified as doubtful due to arrears for more than four years, it must be classified as a write-off. This is also the case for all debits from customers that are declared subject to bankruptcy proceedings for which there is notice that the liquidation phase has been or is to be declared, or whose solvency has undergone a notable and irreversible deterioration. Given the long period that a loan must be in arrears to be classified as a write-off, they are more likely to represent financial problems that households had in the past rather than actual financial stress. In fact, they are usually excluded from the definition of default.

The pace of write-offs would depend on the provisioning calendar. Banks could provision loans in arrears faster under CBE 4/2004 (Annex IX, page 13); but the floor is given by the following table:

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7. Banco de España (2004), Circular 4/2004, Annex IX (Boletín Oficial del Estado, no. 314, 30 December 2004).

Unsecured debt		Secured debt (loans secured by completed houses)	
Up to 6 months	4.5%	Over 3 years and up to 4 years	25%
Over 6 months and up to 12	27.4%	Over 4 years and up to 5 years	50%
Over 12 months and up to 18	60.5%	Over 5 years and up to 6 years	75%
Over 18 months and up to 24	93.3%	Over 6 years	100%
Over 24 months	100%		

Therefore, loans without guarantee may move from the *in arrears* category to *write-off* in two years, while mortgages would take longer. This calendar is similar to that previously established by CBE 4/1991, the main difference being with regard to the time at which provisions reach 100% of the loan, which in the case of unsecured loans was reduced to 21 months.

Nevertheless, new CBE 3/2010 establishes a single provisions calendar for both secured and unsecured debt, reducing considerably the maximum time to fully provision a loan. Nevertheless, in the case of secured loans, CBE 3/2010 established that provisions should not be necessary for the portion of the loan that could be recovered by repossession of the guarantee (establishing maximum amounts depending on the type of guarantee, first-residence houses, other finished houses or other real estate).

All debt	
Up to 6 months	25%
Over 6 months and up to 9	50%
Over 9 months and up to 12	75%
Over 12 months	100%

Annex 2: Computation of the individual contribution of each variable to the changes in the default ratio.

The computation of the contribution of the individual effects is not a straightforward task. To illustrate this we are going to consider the case of the effect of changes in the *CGR* on the *DRSL*. Firstly, the default ratios have been transformed to estimate the *DPD* models, and this logit transformation must be reversed. Therefore, the contemporaneous impact of the *CGR* on DRSL is computed following equation A1.

$$\frac{\partial DRSL_t}{\partial CGR_t}=\frac{\partial DRSL_t}{\partial y_t}\cdot\frac{\partial y_t}{\partial CGR_t}=\frac{e^{y_t^{DRSL}}}{1+e^{y_t^{DRSL}}}\cdot\frac{1}{1+e^{y_t^{DRSL}}}\cdot\beta_{CGR,t} \qquad \text{(A1)}$$

As can be seen in equation A.1, the influence of the *CGR*, will be magnified by the level of the *DRSL*, increasing the impact of the variable for higher *DRSL*.

Secondly, past movements of the *CGR* are also affecting the present movements of *DRSL* through two different channels. One is the direct channel estimated in the model by the lagged variables (lagged 1, 2 and 3 years). But there is a second channel, since lagged default rates are also present in the DPD model. Therefore, previous changes in *CGR* will influence the actual movements of the *DRSL,* according to equations A2, A3 and A4.

$$\begin{aligned}\frac{\partial DRSL_t}{\partial CGR_{t-1}}&=\frac{\partial DRSL_t}{\partial y_t}\cdot\left(\frac{\partial y_t}{\partial CGR_{t-1}}+\frac{\partial y_t}{\partial y_{t-1}}\cdot\frac{\partial y_{t-1}}{\partial CGR_{t-1}}\right)=\\&=\frac{e^{y_t^{DRSL}}}{1+e^{y_t^{DRSL}}}\cdot\frac{1}{1+e^{y_t^{DRSL}}}\cdot\left(\beta_{CGR,t-1}+\alpha\cdot\beta_{CGR,t}\right)\end{aligned} \qquad \text{(A2)}$$

$$\begin{aligned}\frac{\partial DRSL_t}{\partial CGR_{t-2}}&=\frac{\partial DRSL_t}{\partial y_t}\cdot\left(\frac{\partial y_t}{\partial CGR_{t-2}}+\frac{\partial y_t}{\partial y_{t-1}}\cdot\frac{\partial y_{t-1}}{\partial CGR_{t-2}}+\frac{\partial y_t}{\partial y_{t-1}}\cdot\frac{\partial y_{t-1}}{\partial y_{t-2}}\cdot\frac{\partial y_{t-2}}{\partial CGR_{t-2}}\right)=\\&=\frac{e^{y_t^{DRSL}}}{1+e^{y_t^{DRSL}}}\cdot\frac{1}{1+e^{y_t^{DRSL}}}\cdot\left(\beta_{CGR,t-2}+\alpha\cdot\beta_{CGR,t-1}+\alpha^2\cdot\beta_{CGR,t}\right)\end{aligned} \qquad \text{(A3)}$$

$$\begin{aligned}\frac{\partial DRSL_t}{\partial CGR_{t-3}}&=\frac{\partial DRSL_t}{\partial y_t}\cdot\left(\frac{\partial y_t}{\partial CGR_{t-3}}+\frac{\partial y_t}{\partial y_{t-1}}\cdot\frac{\partial y_{t-1}}{\partial CGR_{t-3}}+\frac{\partial y_t}{\partial y_{t-1}}\cdot\frac{\partial y_{t-1}}{\partial y_{t-2}}\cdot\frac{\partial y_{t-2}}{\partial CGR_{t-3}}+\frac{\partial y_t}{\partial y_{t-1}}\cdot\frac{\partial y_{t-1}}{\partial y_{t-2}}\cdot\frac{\partial y_{t-2}}{\partial y_{t-3}}\cdot\frac{\partial y_{t-3}}{\partial CGR_{t-3}}\right)=\\&=\frac{e^{y_t^{DRSL}}}{1+e^{y_t^{DRSL}}}\cdot\frac{1}{1+e^{y_t^{DRSL}}}\cdot\left(\beta_{CGR,t-3}+\alpha\cdot\beta_{CGR,t-2}+\alpha^2\cdot\beta_{CGR,t-1}+\alpha^3\cdot\beta_{CGR,t}\right)\end{aligned} \qquad \text{(A4)}$$

For higher order of lags, the variable is not present in the model, but the influence is derived from the lagged *y* of the model.

$$\begin{aligned}\frac{\partial DRSL_t}{\partial CGR_{t-h}}&=\frac{\partial DRSL_t}{\partial y_{t-h+3}}\cdot\left(\frac{\partial y_{t-h+3}}{\partial CGR_{t-h}}+\frac{\partial y_{t-h+3}}{\partial y_{t-h+2}}\cdot\frac{\partial y_{t-h+2}}{\partial CGR_{t-h}}+\frac{\partial y_{t-h+3}}{\partial y_{t-h+2}}\cdot\frac{\partial y_{t-h+2}}{\partial y_{t-h+1}}\cdot\frac{\partial y_{t-h+1}}{\partial CGR_{t-h}}+\frac{\partial y_{t-h+3}}{\partial y_{t-h+2}}\cdot\frac{\partial y_{t-h+2}}{\partial y_{t-h+1}}\cdot\frac{\partial y_{t-h+1}}{\partial y_{t-h}}\cdot\frac{\partial y_{t-h}}{\partial CGR_{t-h}}\right)=\\&=\frac{e^{y_t^{DRSL}}}{1+e^{y_t^{DRSL}}}\cdot\frac{1}{1+e^{y_t^{DRSL}}}\cdot\alpha^h\cdot\left(\beta_{CGR,t-3}+\alpha\cdot\beta_{CGR,t-2}+\alpha^2\cdot\beta_{CGR,t-1}+\alpha^3\cdot\beta_{CGR,t}\right)\end{aligned}$$

(A5)

Finally, the overall effect of *CGR* over *DRSL* (E_{CGR}) will be the sum of all the individual effects:

$$E_{CGR}=\sum_{h=0}^{\infty}\Delta CGR_{t-h}\cdot\frac{\partial DRSL_t}{\partial CGR_{t-h}} \qquad \text{(A6)}$$

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FIGURE 1: Default ratios and unemployment rate in Spain between 1984 and 2009.

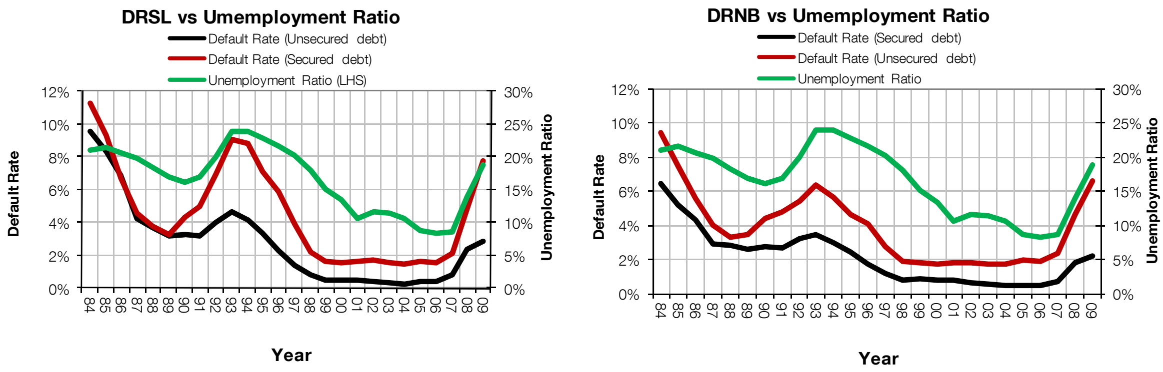


FIGURE 2: Default ratios between 1984 and 2009 (distribution by province).

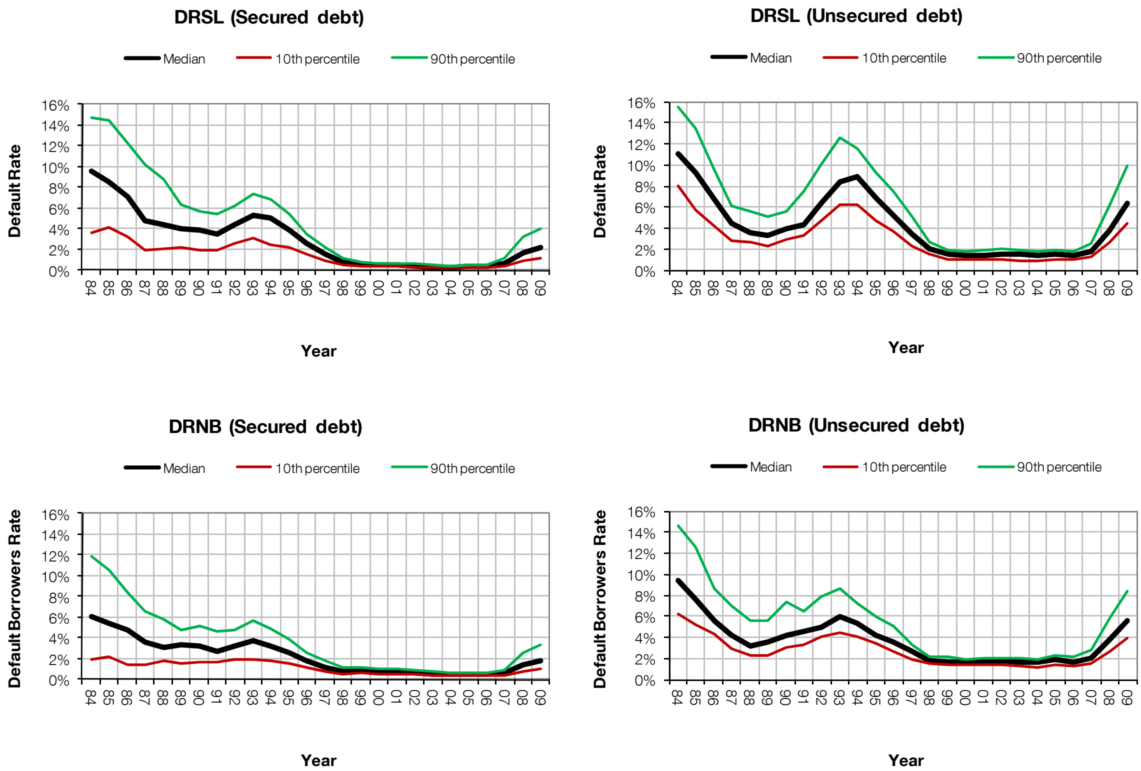


FIGURE 3: Default ratios (annual variation) between 1985 and 2009 (distribution by province).

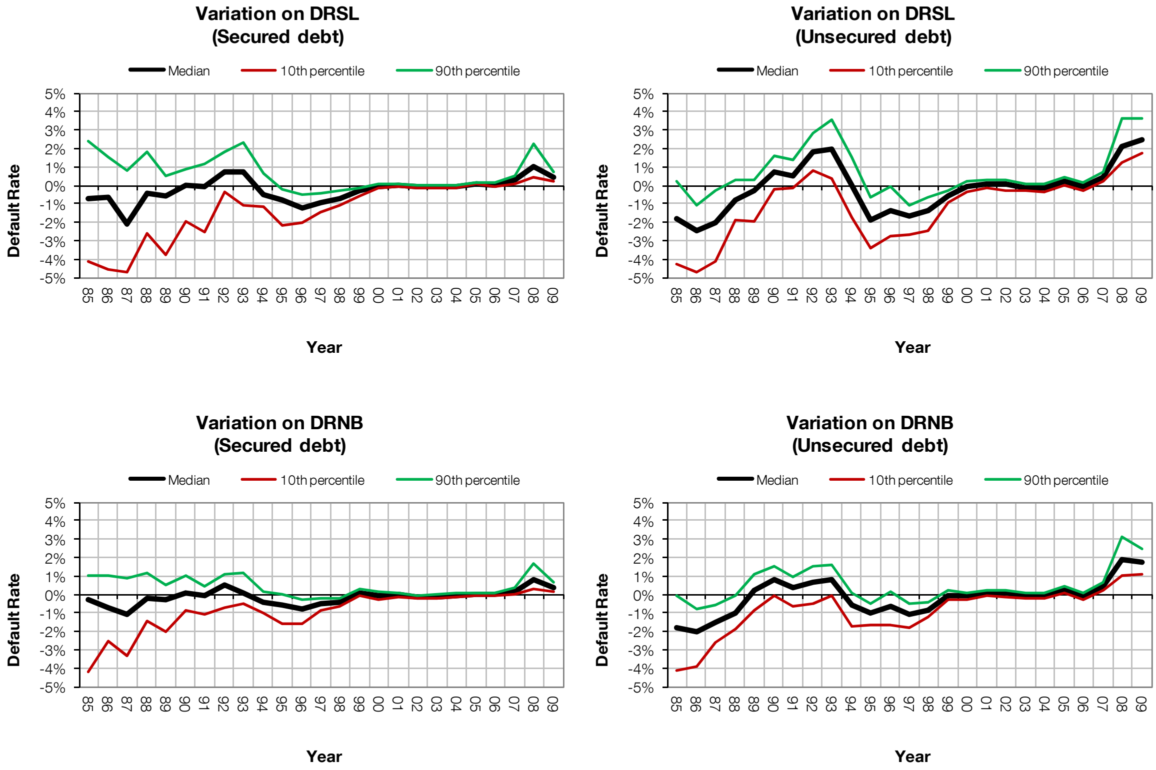


FIGURE 4: Change in the unemployment rate (distribution by province).

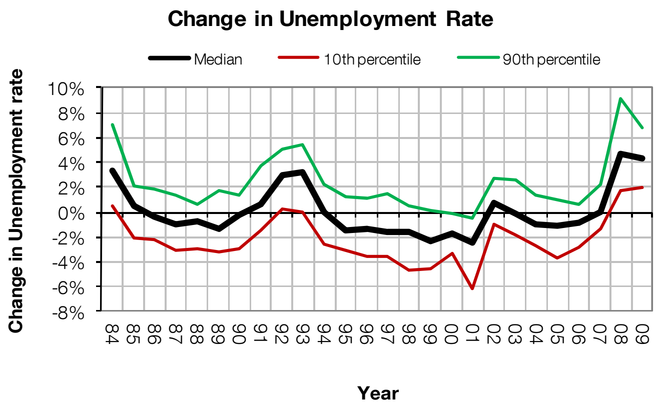


**FIGURE 5: Default ratios in Spain between 1984 and 2009.
Model estimates vs. observed data.**

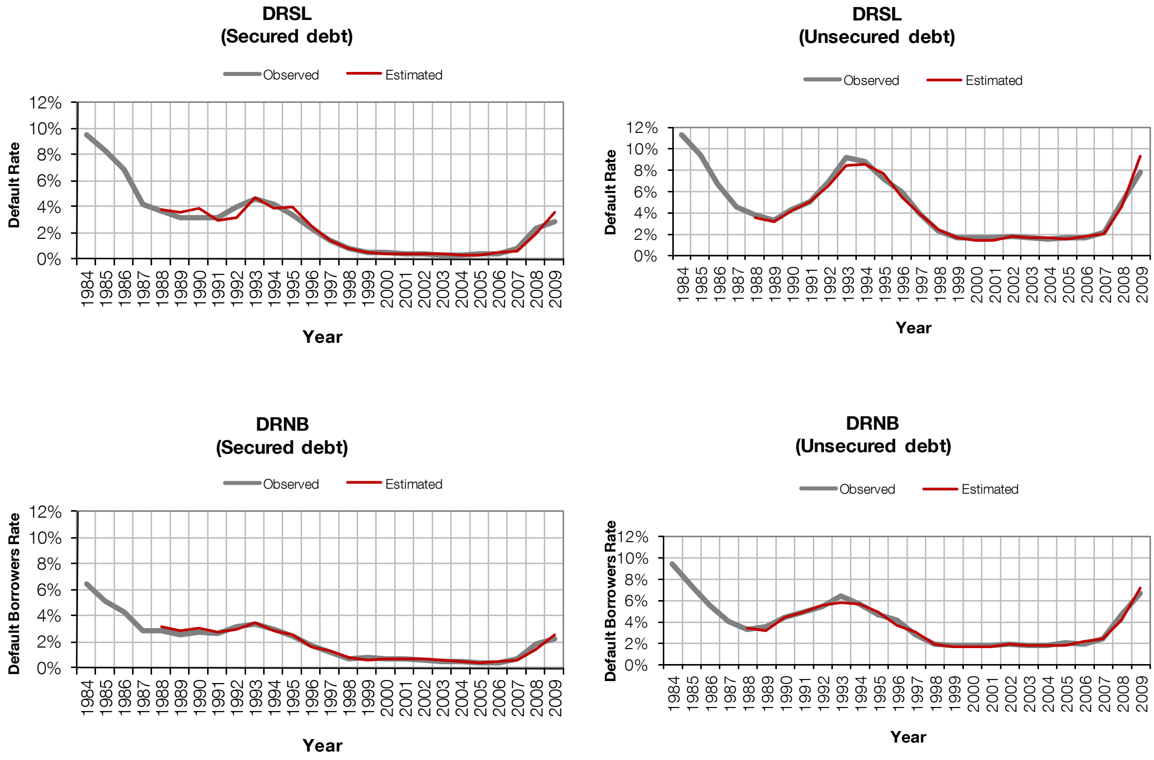
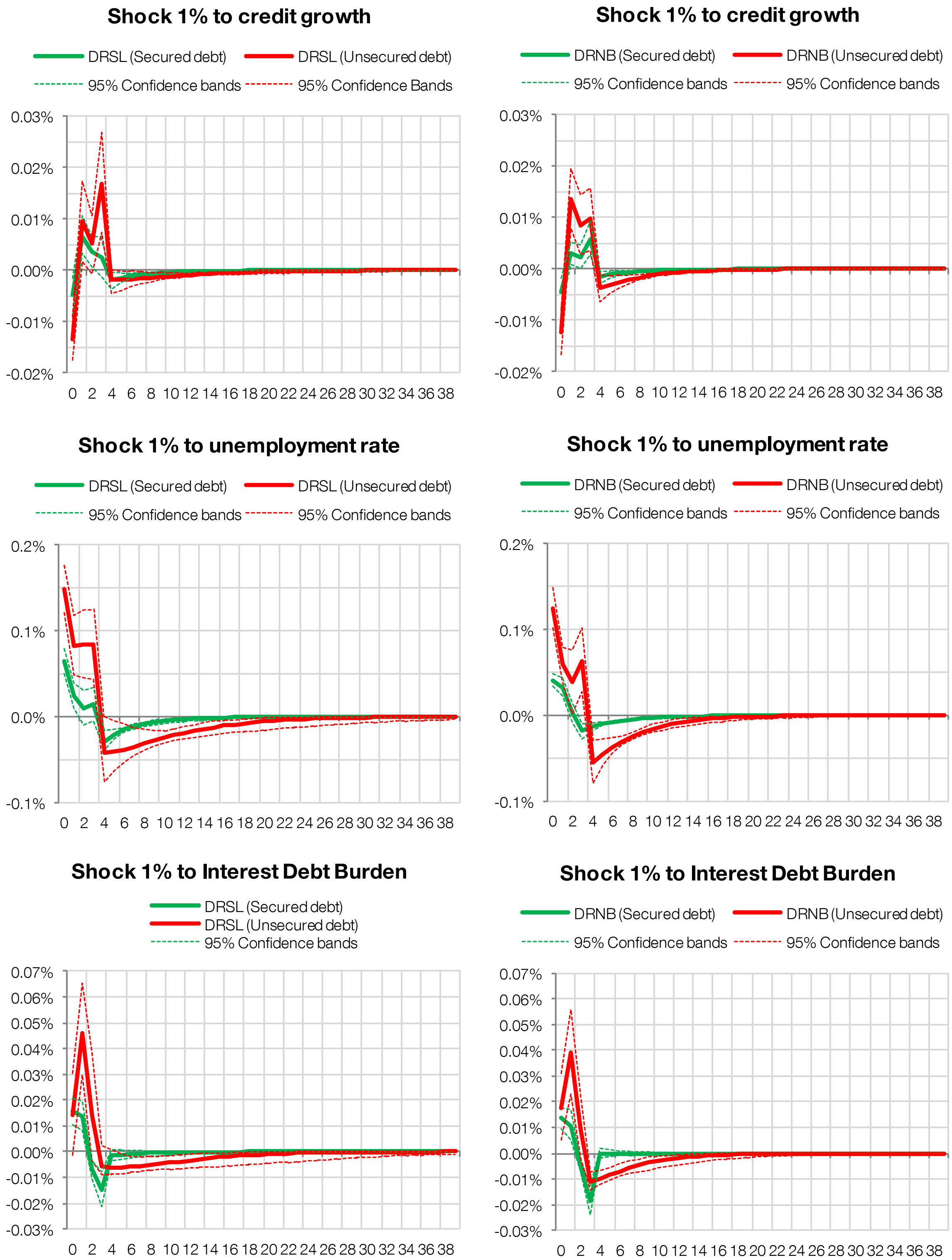
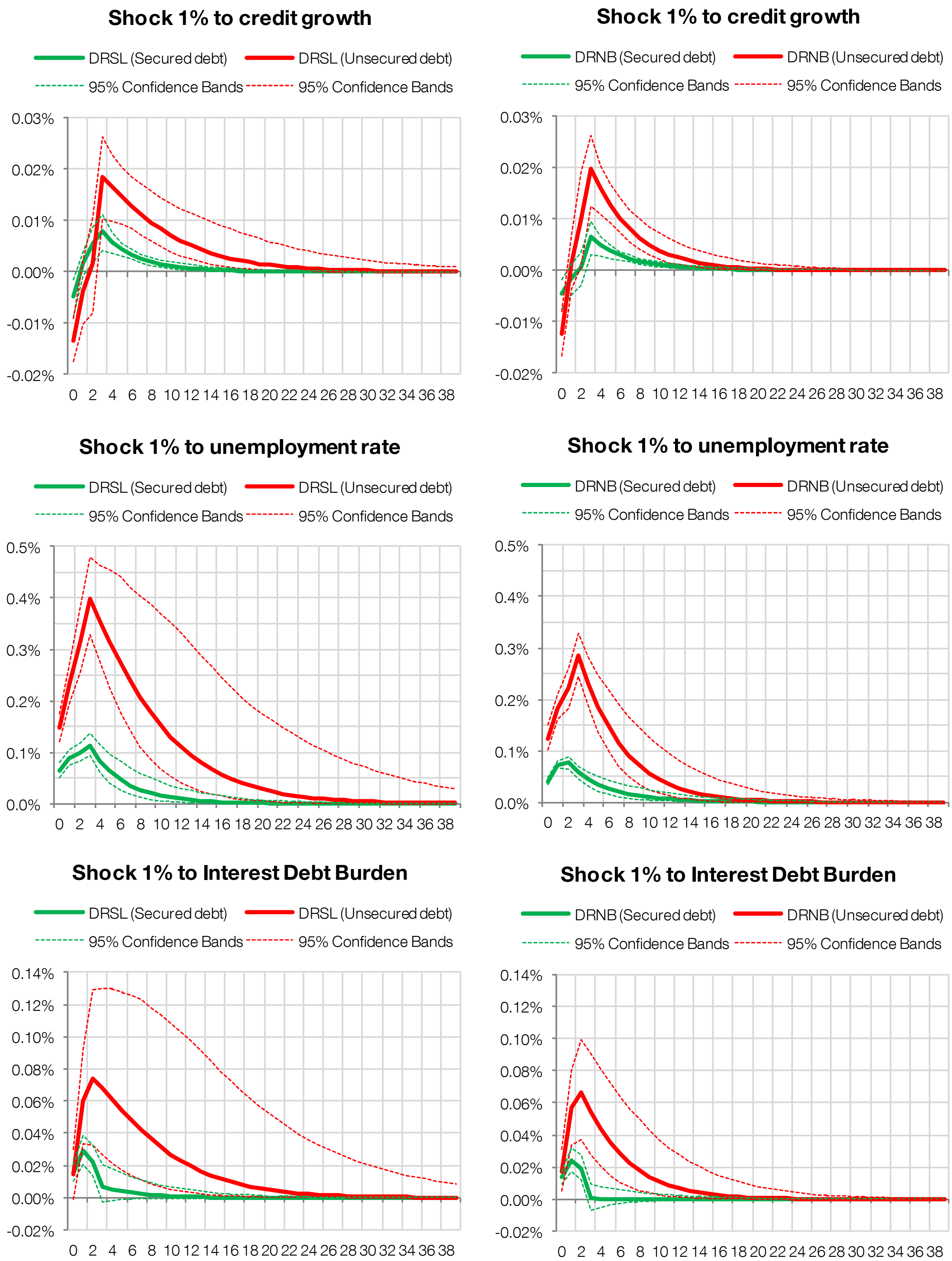


FIGURE 6a: Impact on default ratios of shocks in independent variables (credit growth rate, change in the unemployment rate and change in the interest debt burden).



95% confidence bands have been added (dotted lines), by performing a Montecarlo Simulation of the parameters in the DPD models, using normal multivariate distribution with the mean and the variance-covariance matrix obtained from the estimated system GMM.

FIGURE 6b: Cumulative impact on default ratios of shocks in independent variables (credit growth rate, change in the unemployment rate and change in the interest debt burden).



95% confidence bands have been added (dotted lines), by performing a Montecarlo Simulation of the parameters in the DPD models, using normal multivariate distribution with the mean and the variance-covariance matrix obtained from the estimated system GMM.

FIGURE 7: Factors accounting for the recent increase in default ratios.

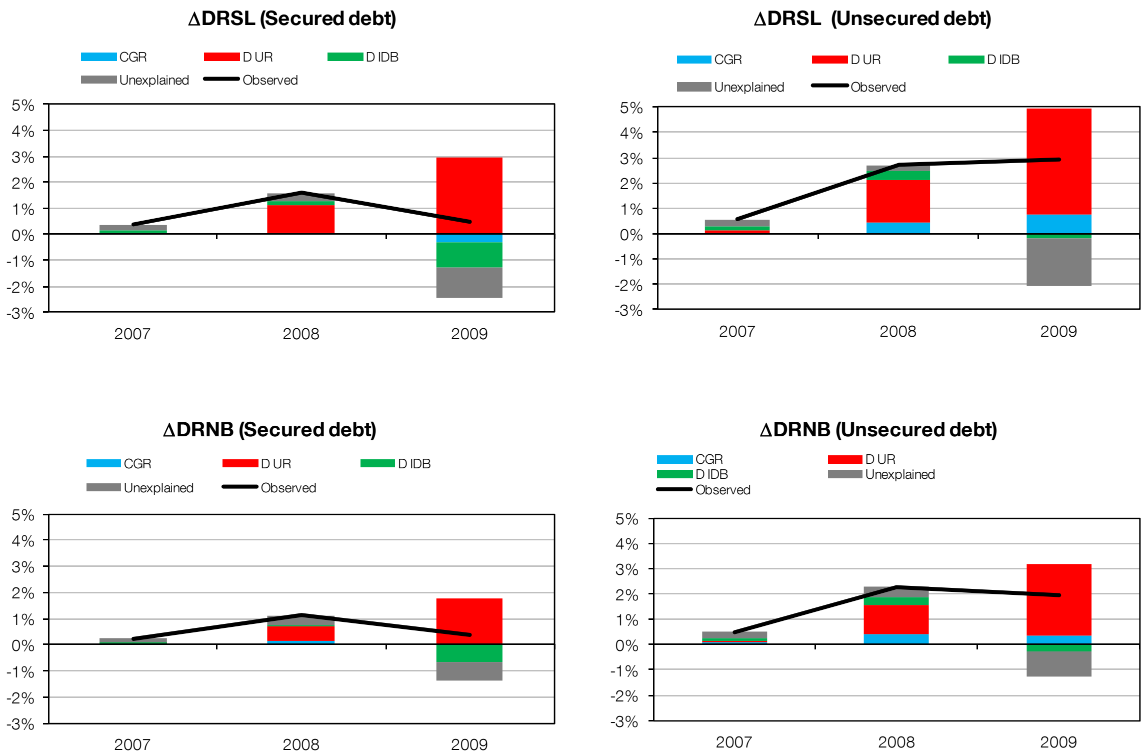


FIGURE 8: Default ratios and market share between 1984 and 2009. Banks vs. Saving Banks

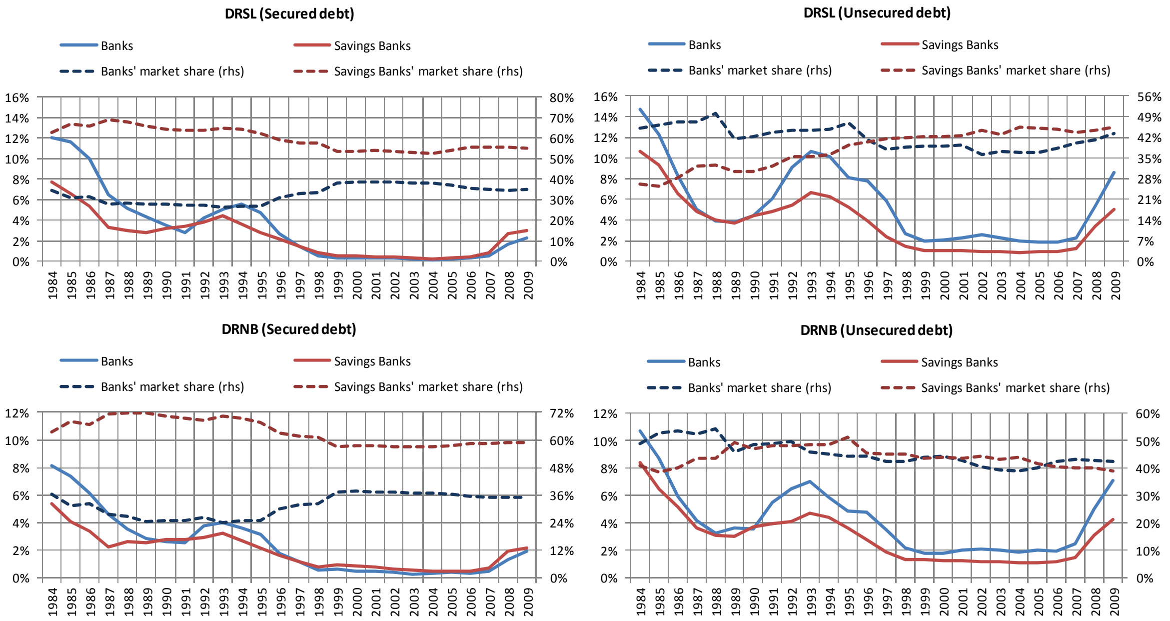
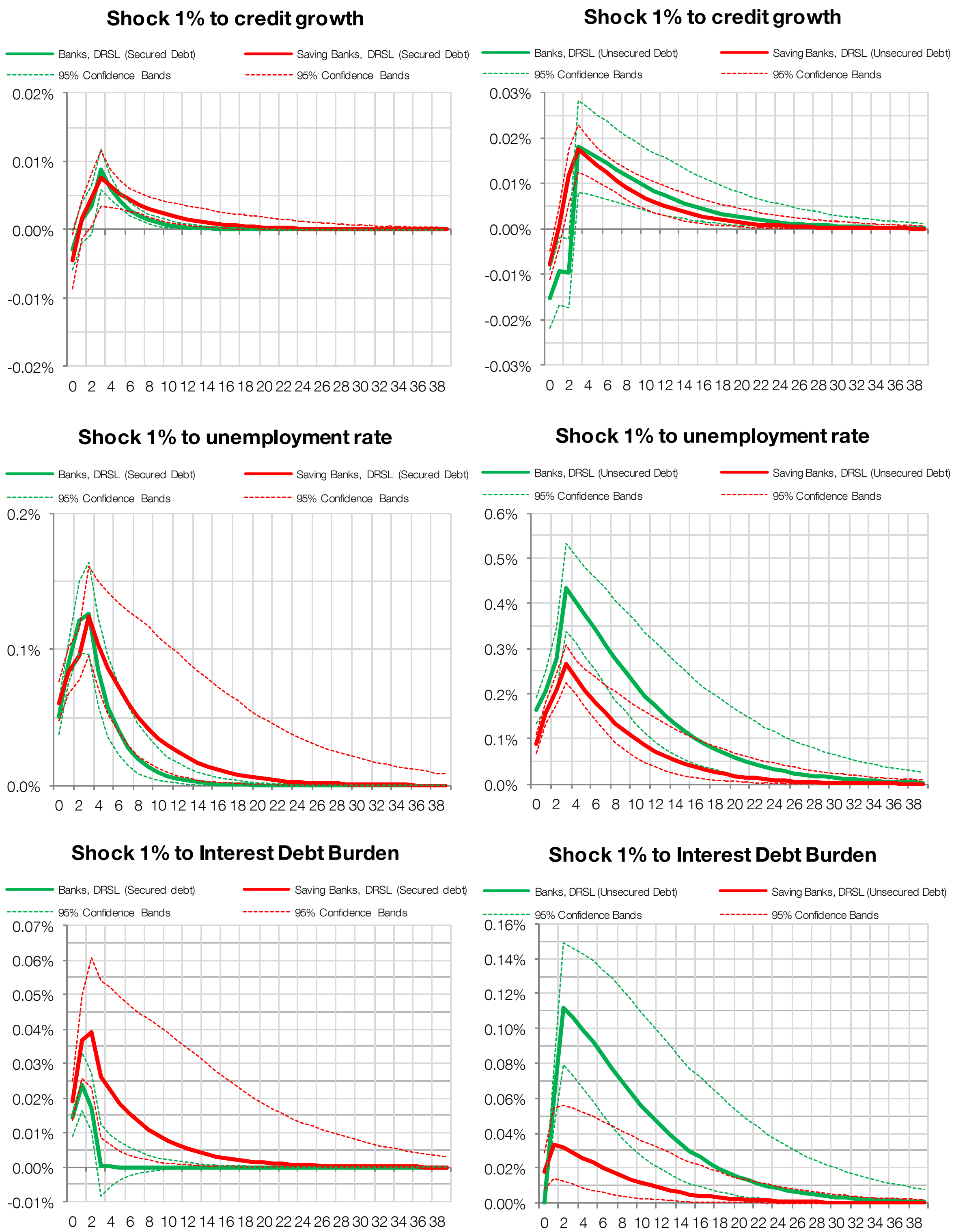
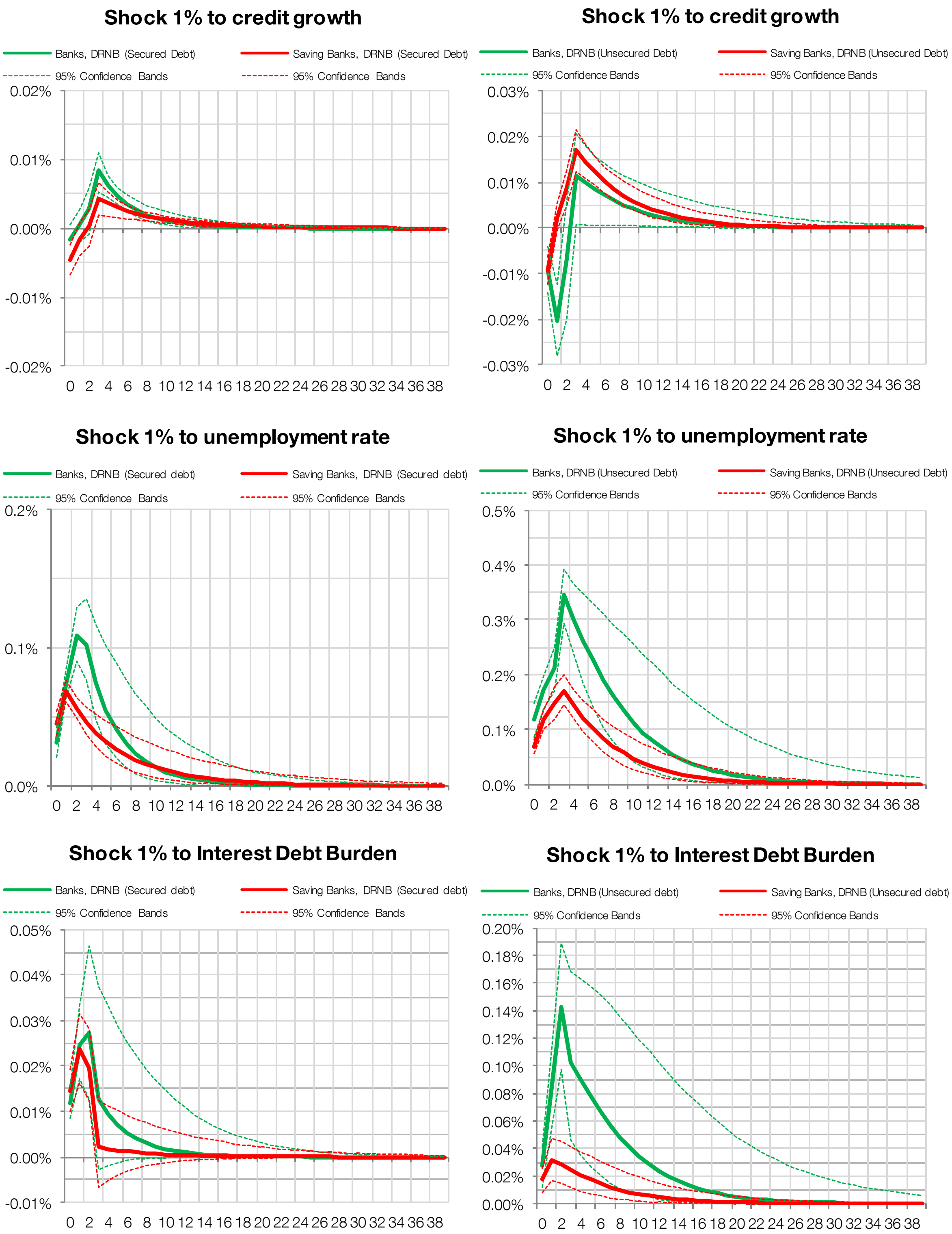


FIGURE 9a: Cumulative impact on the DRSL of banks and savings banks of shocks in independent variables (credit growth rate, change in the unemployment rate and change in the interest debt burden).



95% confidence bands have been added (dotted lines), by performing a Montecarlo Simulation of the parameters in the DPD models, using normal multivariate distribution with the mean and the variance-covariance matrix obtained from the estimated system GMM.

FIGURE 9b: Cumulative impact on the DRNB of banks and savings banks of shocks in independent variables (credit growth rate, change in the unemployment rate and change in the interest debt burden).



95% confidence bands have been added (dotted lines), by performing a Montecarlo Simulation of the parameters in the DPD models, using normal multivariate distribution with the mean and the variance-covariance matrix obtained from the estimated system GMM.

FIGURE 10: Fitting error in the recent increase in default ratios. Differences between models estimated for the whole sample and sub-samples with the portfolios of banks and savings banks, respectively.

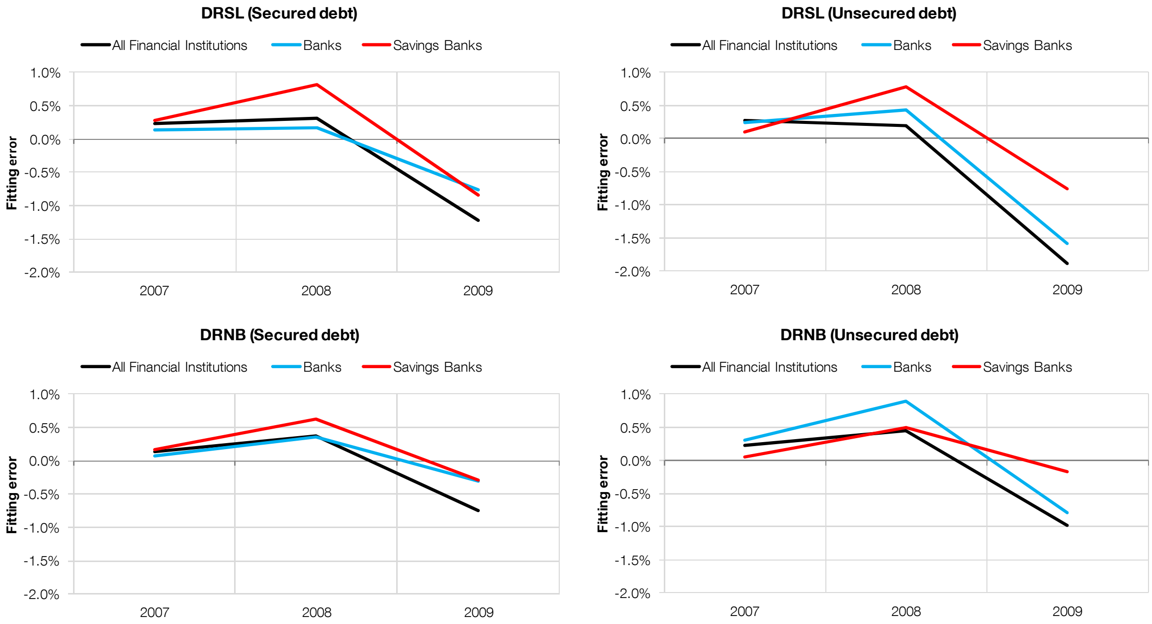
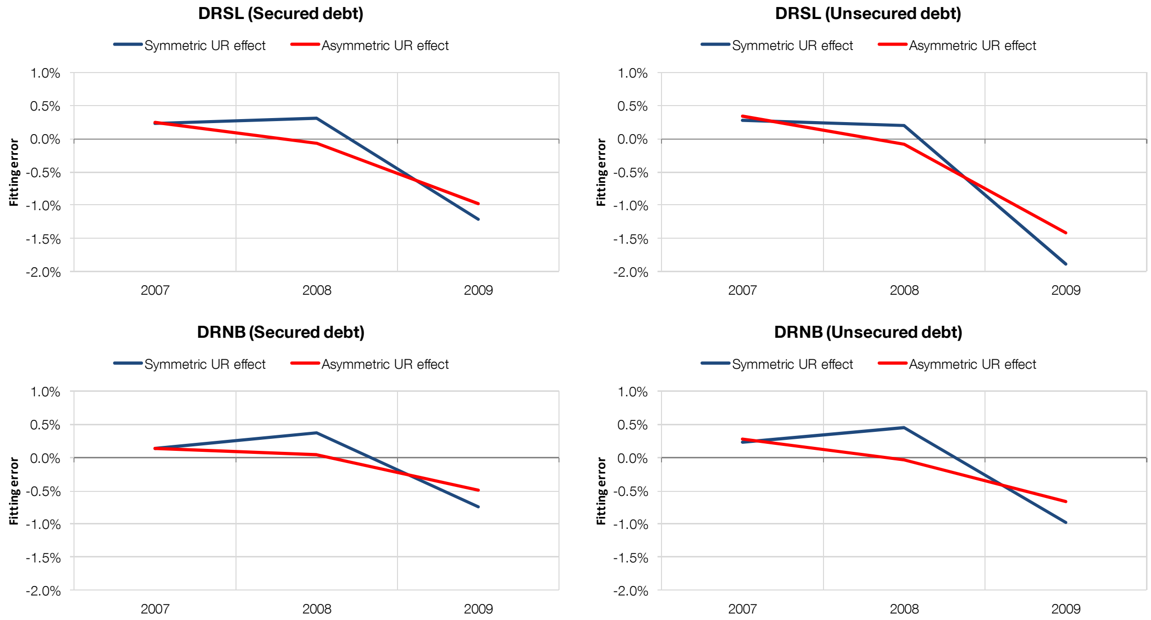


FIGURE 11: Fitting error in the recent increase in the default ratios. Differences between models estimated with a symmetric and asymmetric effect of changes in the unemployment ratio on default measures.



	DRSL (Secured Debt)			DRSL (Unsecured Debt)		
	β	z	P>|z|	β	z	P>|z|
y_j						
L1.	0.764	19.6	0.000	0.836	27.8	0.000
CGR	-0.857	-2.9	0.004	-0.679	-6.5	0.000
L1.	0.923	4.7	0.000	0.409	2.8	0.006
L2.	0.659	2.3	0.019	0.190	1.9	0.059
L3.	0.632	2.1	0.034	0.555	3.9	0.000
$\Delta\ UR$	10.569	10.3	0.000	7.336	11.5	0.000
L1.	5.313	6.7	0.000	3.401	6.5	0.000
L2.	4.674	6.5	0.000	2.894	5.4	0.000
L3.	5.743	5.5	0.000	3.335	4.2	0.000
$\Delta\ IDB$	2.688	6.0	0.000	0.738	1.8	0.069
L1.	2.564	6.0	0.000	1.954	6.2	0.000
L2.				0.519	1.9	0.065
L3.	-1.574	-3.2	0.001			
Intercept	-1.317	-5.2	0.000	-0.547	-3.9	0.000
Number of observations	1100			1100		
Number of groups	50			50		
Wald χ^2	10054.3	0.000		8360.17	0.000	
Serial correlation test						
M1	-4.6	0.000		-5.2	0.000	
M2	-0.8	0.443		-0.5	0.593	
Sargan test	47.3	1.000		48.6	1.000	
Incremental Sargan Test	0.4	1.000		1.2	1.000	

Table 1. Estimated DPD models for DRSL logit transformations.

All regressions are system GMM estimated with Stata v.11 (using xtdpd function); estimation and *z* stats are obtained from two step robust standard errors; individual observations are annual data of Spanish provinces from 1988 to 2009. In a system GMM both the level and difference equations are estimated, using a separate set of instruments. In the equation in differences, we have used as instruments for each year the second lag of *y*, *CGR*, ΔUR and ΔIDB. In the level equation, we have used as instruments for each year the variables in differences, lagged 2 periods for *y* and 4 periods for *CGR*, ΔUR and ΔIDB. Sargan test has the null hypothesis that the overidentification instruments for the GMM estimators are valid. We also perform an Incremental Sargan test for the validity of the instruments in the level equation (null hypothesis is that the instruments are valid). M1 and M2 are the test of first and second order serial correlation (a correct dpd specification should show correlation for the first lag but no correlation for the second one).

Table 2. Estimated DPD models for DRNB logit transformations.

	DRNB (Secured Debt)			DRNB (Unsecured Debt)		
	β	z	P>|z|	β	z	P>|z|
y^j						
L1.	0.800	23.2	0.000	0.779	21.9	0.000
CGR	-0.784	-3.4	0.001	-0.537	-5.6	0.000
L1.	0.392	2.9	0.004	0.469	4.9	0.000
L2.	0.287	1.8	0.076	0.302	2.8	0.005
L3.	0.904	4.2	0.000	0.369	4.7	0.000
Δ *UR*	6.727	10.7	0.000	5.331	11.0	0.000
L1.	4.811	9.1	0.000	2.678	9.0	0.000
L2.	2.544	4.3	0.000	2.034	4.0	0.000
L3.				3.142	4.8	0.000
Δ *IDB*	2.276	6.8	0.000	0.778	2.8	0.005
L1.	1.665	4.1	0.000	1.536	5.3	0.000
L2.				0.562	3.1	0.002
L3.	-2.131	-5.5	0.000			
Intercept	-1.098	-5.5	0.000	-0.782	-5.5	0.000
Number of observations	1100			1100		
Number of groups	50			50		
Wald χ^2	7565.2	0.000		12469.2	0.000	
Serial correlation test						
M1	-5.3	0.000		-5.6	0.000	
M2	1.0	0.315		-1.1	0.251	
Sargan test	48.7	1.000		48.6	1.000	
Incremental Sargan test	0.2	1.000		0.5	1.000	

All regressions are system GMM estimated with Stata v.11 (using xtdpd function); estimation and *z* stats are obtained from two step robust standard errors; individual observations are annual data of Spanish provinces from 1988 to 2009. In a system GMM both the level and difference equations are estimated, using a separate set of instruments. In the equation in differences, we have used as instruments for each year the second lag of *y*, *CGR*, Δ*UR* and Δ*IDB*. In the level equation, we have used as instruments for each year the variables in differences, lagged 2 periods for *y* and 4 periods for *CGR*, Δ*UR* and Δ*IDB*. Sargan test has the null hypothesis that the overidentification instruments for the GMM estimators are valid. We also perform an Incremental Sargan test for the validity of the instruments in the level equation (null hypothesis is that the instruments are valid). M1 and M2 are the test of first and second order serial correlation (a correct dpd specification should show correlation for the first lag but no correlation for the second one).

Table 3: Estimated DPD models for DRSL and DRNB logit transformations. Banks vs. Savings Banks

	DRSL												DRNB											
	Secured Debt						Unsecured Debt						Secured Debt						Unsecured Debt					
	Banks			Saving Banks			Banks			Saving Banks			Banks			Saving Banks			Banks			Saving Banks		
	β	z	P>|z|	β	z	P>|z|	β	z	P>|z|	β	z	P>|z|	β	z	P>|z|	β	z	P>|z|	β	z	P>|z|	β	z	P>|z|
y^j																								
L1.	0.710	20.4	0.000	0.832	21.8	0.000	0.862	40.6	0.000	0.839	30.4	0.000	0.760	16.3	0.000	0.845	28.7	0.000	0.822	18.7	0.000	0.82	31.4	0.000
CGR	-0.701	-2.1	0.036	-0.735	-2.4	0.018	-0.679	-4.8	0.000	-0.673	-5.3	0.000	-0.367	-1.5	0.123	-0.781	-4.4	0.000	-0.391	-3.7	0.000	-0.67	-6.4	0.000
L1.	0.789	2.8	0.005	0.838	4.0	0.000	0.242	1.8	0.071	0.617	5.1	0.000	0.348	1.7	0.082	0.422	2.9	0.004	-0.380	-2.6	0.010	0.69	6.8	0.000
L2.	0.503	1.9	0.063	0.452	1.8	0.074				0.692	4.5	0.000	0.413	2.0	0.051	0.249	2.0	0.051	0.364	3.0	0.003	0.36	4.4	0.000
L3.	1.326	3.4	0.001	0.520	1.8	0.068	0.740	5.4	0.000	0.393	3.0	0.003	1.040	3.2	0.001	0.645	3.4	0.001	0.485	3.6	0.000	0.52	5.2	0.000
$\Delta\ UR$	11.231	8.5	0.000	9.507	9.1	0.000	6.938	11.1	0.000	7.313	8.6	0.000	6.472	6.2	0.000	7.380	10.6	0.000	4.890	6.9	0.000	4.77	10.8	0.000
L1.	8.921	9.4	0.000	3.700	3.7	0.000	1.284	1.7	0.086	4.775	6.9	0.000	7.111	9.3	0.000	3.648	7.2	0.000	1.739	4.0	0.000	3.29	8.2	0.000
L2.	9.658	10.1	0.000	2.847	3.3	0.001	1.732	2.8	0.005	3.264	4.8	0.000	7.211	8.6	0.000				1.508	2.4	0.015	2.13	3.4	0.001
L3.	7.909	4.9	0.000	5.398	4.4	0.000	4.227	6.9	0.000	3.833	3.6	0.000	3.459	3.2	0.001				4.003	5.2	0.000	2.33	3.3	0.001
$\Delta\ IDB$	3.331	5.2	0.000	3.081	6.5	0.000				1.500	3.3	0.001	2.514	6.3	0.000	2.483	5.9	0.000	1.199	3.3	0.001	1.25	3.8	0.000
L1.	2.407	5.2	0.000	2.674	6.3	0.000	2.165	7.6	0.000	1.122	2.3	0.023	2.237	5.2	0.000	1.425	4.1	0.000	1.888	6.8	0.000	0.97	2.8	0.006
L2.				0.942	2.4	0.016	1.446	4.5	0.000				1.170	1.8	0.074				1.855	6.9	0.000			
L3.	-2.417	-3.5	0.000	-0.896	-1.7	0.087							-1.217	-2.0	0.048	-2.203	-5.7	0.000	-0.661	-2.5	0.011			
Intercept	-1.720	-6.7	0.000	-0.908	-3.7	0.000	-0.401	-5.5	0.000	-0.671	-5.5	0.000	-1.367	-4.4	0.000	-0.844	-4.9	0.000	-0.539	-3.2	0.001	-0.76	-6.6	0.000
# of observations	1100			1100			1100			1100			1100			1100			1100			1100		
# of groups	50			50			50			50			50			50			50			50		
Wald χ^2	8591.2	0.000		12190	0.000		8203	0.000		5061	0.000		8302	0.000		8339	0.000		7504	0.000		8539	0.000	
Serial correlation test																								
M1	-5.4	0.000		-5.0	0.000		-5.1	0.000		-4.9	0.000		-4.9	0.000		-5.8	0.000		-5.4	0.000		-4.9	0.000	
M2	0.9	0.356		-1.1	0.277		-1.4	0.171		0.7	0.482		-0.1	0.914		0.3	0.743		-2.3	0.023		2.1	0.040	
Sargan test	47.8	1.000		48.0	1.000		48.8	1.000		44.7	1.000		48.9	1.000		48.5	1.000		49.0	1.000		47.5	1.000	
Incremental Sargan Test	0.5	1.000		0.4	1.000		0.7	1.000		0.0	1.000		0.6	1.000		0.2	1.000		0.8	1.000		1.2	1.000	

All regressions are system GMM estimated with Stata v.11 (using xtdpd function); estimation and *z* stats are obtained from two step robust standard errors; individual observations are annual data of Spanish provinces from 1988 to 2009. In a system GMM both the level and difference equations are estimated, using a separate set of instruments. In the equation in differences, we have used as instruments for each year the second lag of *y*, *CGR*, ΔUR and ΔIDB. In the level equation, we have used as instruments for each year the variables in differences, lagged 2 periods for *y* and 4 periods for *CGR*, ΔUR and ΔIDB. Sargan test has the null hypothesis that the overidentification instruments for the GMM estimators are valid. We also perform an Incremental Sargan test for the validity of the instruments in the level equation (null hypothesis is that the instruments are valid). M1 and M2 are the test of first and second order serial correlation (a correct dpd specification should show correlation for the first lag but no correlation for the second one).

Table 4: Estimated DPD models for DRSL and DRNB logit transformations. Symmetric vs. Asymmetric employment effects

	DRSL						DRNB					
	Secured Debt			Unsecured Debt			Secured Debt			Unsecured Debt		
	β	z	P>|z|	β	z	P>|z|	β	z	P>|z|	β	z	P>|z|
y^j												
L1.	0.744	22.5	0.000	0.839	26.8	0.000	0.776	27.7	0.000	0.803	24.5	0.000
CGR	-0.532	-2.2	0.029	-0.591	-5.6	0.000	-0.409	-2.0	0.045	-0.393	-4.0	0.000
L1.	0.948	5.3	0.000	0.379	3.3	0.001	0.476	3.1	0.002	0.427	4.0	0.000
L2.	0.645	2.5	0.012	0.203	2.4	0.019	0.344	2.6	0.010	0.289	3.4	0.001
L3.	0.779	2.8	0.005	0.529	4.9	0.000	0.898	4.9	0.000	0.355	4.5	0.000
$\Delta\ UR$	3.546	2.5	0.014	3.497	3.8	0.000						
L1.	4.986	5.8	0.000	3.388	8.8	0.000	4.146	7.4	0.000	2.530	9.0	0.000
L2.	4.822	6.6	0.000	2.989	6.0	0.000	2.356	4.0	0.000	2.124	4.9	0.000
L3.	6.100	6.3	0.000	3.150	4.4	0.003	0.993	1.7	0.096	2.963	5.1	0.000
$\Delta\ UR\ (+)$	11.320	4.6	0.000	5.698	3.8	0.000	12.204	11.8	0.000	8.081	12.7	0.000
L1.												
L2.												
L3.												
$\Delta\ IDB$	2.507	6.4	0.000	0.658	1.8	0.072	2.047	7.2	0.000	0.807	3.4	0.001
L1.	2.211	5.2	0.000	1.909	6.5	0.000	1.440	4.2	0.000	1.572	6.2	0.000
L2.				0.615	1.9	0.053				0.813	4.2	0.000
L3.	-0.929	-2.6	0.010				-1.545	-5.2	0.000			
Intercept	-1.627	-7.3	0.000	-0.603	-4.6	0.000	-1.435	-8.4	0.000	-0.784	-5.9	0.000
# of observations	1100			1100			1100			1100		
# of groups	50			50			50			50		
Wald χ^2	12337	0.000		13909	0.000		8609	0.000		12488	0.000	
Serial correlation test												
M1	-4.7	0.000		-5.2	0.000		-5.4	0.000		-5.8	0.000	
M2	-0.5	0.620		-0.8	0.451		0.3	0.775		-1.7	0.085	
Sargan test	48.7	1.000		47.8	1.000		47.6	1.000		48.9	1.000	
Incremental Sargan test	0.4	1.000		0.5	1.000		0.2	1.000		0.5	1.000	

All regressions are system GMM estimated with Stata v.11 (using xtdpd function); estimation and *z* stats are obtained from two step robust standard errors; individual observations are annual data of Spanish provinces from 1988 to 2009. In a system GMM both the level and difference equations are estimated, using a separate set of instruments. In the equation in differences, we have used as instruments for each year the second lag of *y*, *CGR*, ΔUR, $\Delta UR(+)$ and ΔIDB. In the level equation, we have used as instruments for each year the variables in differences, lagged 2 periods for *y* and 4 periods for *CGR*, ΔUR, $\Delta UR(+)$ and ΔIDB. Sargan test has the null hypothesis that the overidentification instruments for the GMM estimators are valid. We also perform an Incremental Sargan test for the validity of the instruments in the level equation (null hypothesis is that the instruments are valid). M1 and M2 are the test of first and second order serial correlation (a correct dpd specification should show correlation for the first lag but no correlation for the second one).

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