# Misclassification of the Dependent Variable in a Debt-Repayment Behavior Context

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**Abstract**

This paper estimates a model of the household debt-repayment decision that accounts for the possibility of misclassification of self-reported debt-repayment status. It likewise estimates the extent of misclassification in a sample of data from different European countries. The evidence suggests that many households that are in arrears do not report this condition, so that the true level of arrears is, on average, 24 percent higher than that observed in our data. Furthermore, the effects on the incidence of arrears of adverse income and expense shocks are substantially greater than those predicted by estimators that ignore the possibility of misclassification.

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## 1. INTRODUCTION

For good reasons, many micro data studies of households' debt-repayment behavior rely on survey data, as, for example, Fay, Hurst, and White (2002), Bridges and Disney (2004), May and Tudela (2005), Lyons and Fisher (2006), or Duygan-Bump and Grant (2009). Like administrative (or lenders') data, survey data that incorporate a panel or retrospective dimension allow tracking households' debt-repayment decisions, but these data may better represent the population in studies of personal bankruptcy filings or broadly defined arrears. Moreover, surveys tend to gather a richer set of potentially relevant household characteristics for analyses of households' debt repayment behavior.

Debt-repayment survey data are not free of drawbacks, though. A concern is raised by their self-reported nature, as even the household's financially responsible person may not provide perfectly reliable answers.[1] For one thing, default seems a socially undesirable behavior, so that questions about debt-repayment might elicit underreporting of financial problems (i.e. false negatives). On the other hand, debt-repayment problems might leave a strong trace in memory, and there is some evidence that events' importance leads to over-reporting (i.e. false positives) on the part of the respondent (a phenomenon referred to in the literature as *telescoping*; see for example Chase and Harada, 1984). The significant underreporting of bankruptcy filings in the Panel Study of Income Dynamics (Fay et al., 2002) and of mortgage arrears in the British Household Panel Survey (May and Tudela, 2005) suggest that households are

[1] This is not the only concern with survey data. Typically, information on the temporal extension and/or magnitude of the repayment problem is not asked, so that the empirical proxy for "repayment problems" covers a wide range of default behaviors, ranging from bankruptcy to being a few days behind on repayment.

indeed misclassified as to debt-repayment status, as well as that the former type of misclassification is more prevalent than the latter.

Empirical studies of households' debt-repayment behavior typically run probit or logit regressions explaining whether households have experienced debt-repayment problems during certain periods of time. Hausman, Abrevaya, and Scott-Morton (1998), however, have shown that these traditional estimation techniques generally lead to inconsistent coefficient estimates when the dependent variable (in our case, the household debt-repayment status) is misclassified. While it is difficult to calculate the degree of inconsistency analytically, the simulation results in Hausman et al. (1998) and Hug (2010) indicate that relatively small amounts of misclassification (as little as 2 percent) can lead to significant amount of bias even in large samples. For this reason, traditional estimates are to be reexamined in order to obtain consistent, superior estimates.

In this paper, the modified maximum likelihood estimator proposed in Hausman et al. (1998) (referred hereafter as HAS 98) is applied to a standard model of debt-repayment behavior with a commonly used data set. This estimator, which is a natural extension of the parametric methods employed in the debt-repayment literature, allows correcting the bias caused by misclassification and estimating its extent, under the assumption that the extent of misclassification in the data is not too high. We are not the first applying the HAS 98 estimator or some generalization of it, which has been used in studies concerning job change (Hausman et al., 1998; Falaris 2011), smoking behavior (Brachet 2008), student cheating behavior (Caudill and Mixon, 2005), insurance fraud (Artís et al., 2002), language proficiency (Dustman and van Soest, 2001; Coulon and Wolff, 2007), or civil wars (Hug 2010).

Section 2 of the paper describes the data and the sample design. Our choice of data has been motivated by the contention that households that might eventually opt to default will take financial benefits and costs into account in making their debt-repayment decisions. Hence, and as in Duygan-Bump and Grant (2009), we have combined household-level information on being behind on repayment with country-level measures of default incentives. Although failure to do a monthly payment on time is generally not considered default, it may be viewed by lenders as a signal that credits could be at risk.

Section 3 presents the econometric specification and Section 4 discusses the results. The probabilities of false negatives that we have obtained range from essentially 0 in Ireland and the Netherlands to approximately 0.64 in Denmark, and tend to be higher for households with income above the country median income. Probabilities of false positives are much lower, ranging from almost 0 in the Netherlands to 0.04 in Greece, and differ little by income group. When the possibility of misclassification is taken into account, the overall level of arrears in the data (8.9 percent) is 24 percent higher than the observed amount (7.2 percent). Furthermore, the effects on the incidence of arrears of adverse income and expense shocks to households, and of countries' judicial and financial institutions, are generally larger. For example, a 10 percent cut in household income would increase the number of households being behind on repayment by about 13 percent, instead of the 9 percent increase predicted by traditional estimates. Likewise, increasing the cost of judicial proceedings from 0.5 percent of the claimed debt (as was the case of the Netherlands during the observation period) to 10.7 percent (as was the case of Spain) would increase the incidence of arrears after a negative health shock by about 48 percent, instead of the 18 percent increase predicted by traditional estimates. Section 5 concludes.

## 2. DATA AND SAMPLE DESIGN

The European Community Household Panel (ECHP) is an annual survey that interviewed a representative sample of households and individuals in each of 14 European countries between 1994 and 2001.[2] In addition to data on income, employment, health, and marital status of all household adults, which we will use to construct indicators for income and expense shocks at the household level, the ECHP asked the household respondent information about missed scheduled payments: "Has your household been in arrears at any time during the past 12 months, that is, unable to pay as scheduled any of the following?" The respondent then answered "Yes" or "No" to each of the following: Rent for accommodation, mortgage payments, utility bills, and hire purchase installments or other loan repayments. We consider any "Yes" answer to be indicative of arrears, whereby virtually any household may be in arrears. More restricted definitions could raise statistical concerns. Suppose, for example, that we wanted to analyze mortgage arrears only. If a sample of mortgagors were used, it would be probably selected in terms of repayment propensity. If, on the other hand, any household were considered a mortgage applicant and the whole sample of households were used, non-mortgagors would have to be arbitrarily assigned the status of "not in arrears", thus stirring up more misclassification.

The Doing Business (DB) project, launched by the World Bank in 2002, gathers quantitative indicators on the regulations that apply to local firms in 185 economies. The indicators cover a wide range of dimensions of the regulatory environment, including the complexity and cost of starting a business and the number of procedures,

[2] See http://epp.eurostat.ec.europa.eu/portal/page/portal/microdata/echp for detailed information on ECHP.

time, and cost needed to resolve a commercial dispute. More than 18,000 professionals assist in providing the data that inform the indicators, including legal professionals and credit bureaus officials. See www.doingbusiness.org for further details. To represent cross-country differences in the cost of default, and following Duygan-Bump and Grant (2009), we take advantage of three contract enforcement indicators and a measure of coverage by credit bureaus gathered by the DB project: The average number of calendar days it takes for dispute resolution; the cost, as a percentage of the debt, of judicial proceedings; the number of legal procedures mandated by law that must be followed to legally recover a debt; and the percentage of the adult population who has information on their repayment history, unpaid debts, or outstanding credit recorded in public or private registries.[3] The purpose of the first three indicators is to measure the efficiency of the judicial or administrative system in the collection of overdue debt, whereas the last one is intended to quantify the extent of information sharing among lenders. Borrowers are expected to be more willing to default when court action is less efficient or when information sharing among lenders is less prevalent. Although the DB project measures vary by country, they are nevertheless constant over the entire observation period.

The countries included in the ECHP are the 12 European Union Member States in 1994 (Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, and United Kingdom) plus Austria and Finland, which

[3] The DB project data were accessed in May 2006. As to the coverage measure, Jappelli and Pagano (2002) have found that the impact on defaults of private arrangements to share credit information is similar to that of public credit registries.

joined the survey in 1995 and 1996, respectively.[4] We excluded from the sample Germany, Luxembourg, and the UK, where information on arrears was not asked or asked incompletely. Finland and the 1996 wave of Greece were also removed due to what look like measurement problems in households' arrears status.[5] Within each country, we excluded households whose head is below 30 or above 60 years old,[6] whose adults are unrelated, whose income is below the 1st percentile or above the 99th percentile of the income sampling distribution,[7] or whose data on the explanatory variables listed in Section 3 are missing or inconsistent. Moreover, we took advantage of the panel dimension of the ECHP in constructing our sample: As falling into arrears is correlated with future adverse outcomes (Duygan-Bump and Grant, 2009), the possible endogeneity of income or expense shocks occurring between interviews $t-1$

[4] Data for Sweden are available since 1997. These data pertain to the Swedish Living Conditions Survey, but were transformed into ECHP format. Unfortunately, the Swedish survey did not collect information on arrears.

[5] In Finland, 43 percent (respectively, 38 percent) of the observations contain no valid answer to the question on mortgage arrears (arrears in other loans). In the 1996 wave of Greece, the percentage of households declaring to be in arrears is much higher (56%) than in any of the other waves (22-30%).

[6] The concept of head of household was dropped from the ECHP since the 1995 wave. By head of a household we mean the household's reference person, who generally coincides with the person responsible for the household's accommodation.

[7] Household income, a total after-tax yearly rate, has been expressed in 2005 prices using national consumer price indices, and normalized across countries using purchasing power standards.

and $t$ is reduced by assessing their effect on the probability of falling into arrears between $t$ and $t+1$. The main sample contains 106,626 observations (household-years), pertaining to 21,537 households. The number of observations by country is listed in Table 1.

Table 1 also presents the country-specific proportions of households holding any debt[8] and declaring to be in arrears, as well as statistics on contract enforcement and information sharing among lenders. The data show a negative correlation between having debts and being in arrears (-0.39) that is mediated by a geographical pattern: While being in debt is more prevalent in Northern European countries, the highest levels of arrears are generally observed in Mediterranean countries. As expected, the proportion of households in arrears is positively correlated with the cost of judicial procedures, as many lenders may prefer not to pursue repayment when that cost is high, and negatively correlated with the extent of credit bureaus. However, the negative correlations with the time for dispute resolution and the number of legal procedures to recover a debt are rather unexpected. Note, however, that if underreporting/overreporting of arrears varied across countries, these patterns would be to some extent an artifact of misclassification.

## 3. SPECIFICATION

[8] The ECHP questions on debt are: "Do you still have to repay money from an outstanding loan or mortgage for this accommodation?" and "Do you or anyone in your household presently have to repay debts from hire purchases or loans etc. other than any mortgage or loan connected with the house?" As our definition of arrears covers these debts but also rents and utility bills, it is possible that the proportion of households in arrears be larger than the proportion in debt.

We run modified probit regressions explaining whether household $i$ residing in country $c$ was in arrears between interviews $t$ and $t+1$. Let $y^*_{ict+1}$, a continuous random variable representing an unobserved propensity of the household to fall into arrears, be given by

$$y^*_{ict+1} = x'_{ict}\beta + \varepsilon_{ict+1}, \tag{1}$$

where $x_{ict}$ is a vector of covariates generally observed at $t$, $\beta$ is an unknown parameter vector, and $\varepsilon_{ict+1}$ denotes a standard normally distributed error term assumed independent of $x_{ict}$.[9] Without misclassification, the true binary response

$$\tilde{y}_{ict+1} = 1\left(y^*_{ict+1} > 0\right), \tag{2}$$

where the function $1(\cdot)$ equals one if its argument is true and zero otherwise, would be observed. When the true response may be misclassified, however, the observed response, $y_{ict+1}$, is to be distinguished from $\tilde{y}_{ict+1}$. For example, a household declaring not having been in arrears between $t$ and $t+1$ has $y=0$, although $\tilde{y}$ can be either 0 or 1.

As in Hausman et al. (1998), the probability of misclassification is made dependent on $\tilde{y}$. Furthermore, different levels of misclassification are allowed by

[9] Duygan-Bump and Grant (2009) estimate random effects probit models. Our statistical formulation, a pooled probit model for the arrears decision, has the advantage that can be naturally extended by the HAS 98 estimator. In any case, under traditional random effects assumptions, the pooled probit marginal effects are those of the random effects model averaged over the distribution of the unobserved effects in the population (Wooldridge, 2002, p. 486).

country. Gross and Souleles (2002) and Lopes (2008) have found an important role for the utility cost of default (a feeling of embarrassment or even disgrace) in the evolution of default rates over time. If that cost varied across countries too, misclassification would not be the same everywhere: The utility cost of default may increase the salience of arrears episodes in survey respondents' memory (see e.g. Hamann 2001), reducing the extent of misclassification by facilitating the retrieval of information from memory, or, as discussed in the introduction, leading to over-reporting on the part of the respondent. We also hypothesize that a feeling of embarrassment may come up *at the moment of reporting* repayment problems, whereby arrears are underreported, and whose extent may vary across countries as well. The misclassification probabilities are defined as:

$$\alpha_0^c = \Pr\left( y_{ict+1} = 1 \middle| \tilde{y}_{ict+1} = 0 \right) \tag{3}$$

$$\alpha_1^c = \Pr\left( y_{ict+1} = 0 \middle| \tilde{y}_{ict+1} = 1 \right) \tag{4}$$

In country $c$, the probability that a zero is misclassified as a one is given by the parameter $\alpha_0^c$, whereas the probability that a one is misclassified as a zero is given by the parameter $\alpha_1^c$.

The Total Probability Theorem is used to derive the expected value of the observed binary dependent variable:

$$E\left( y_{ict+1} \middle| x_{ict} \right) = \Pr\left( y_{ict+1} = 1 \middle| x_{ict} \right) = \alpha_0^c + \left( 1 - \alpha_0^c - \alpha_1^c \right) \Phi\left( x_{ict}' \beta \right), \tag{5}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. Clearly, expression (5) collapses to the usual one, $\Phi\left( x_{ict}' \beta \right)$, when there is no misclassification ($\alpha_0^c = \alpha_1^c = 0 \ \forall c$). Hausman et al. (1998) showed that if an ordinary probit model is estimated without allowing for misclassification when this exists, the resulting estimate

of $\beta$ will generally be inconsistent.[10] This result also applies if misclassification is improperly modeled, because then $E\left(y_{ict+1}\middle|x_{ict}\right)$ would be incorrectly specified (Wooldridge, 2002, p. 402). Although the direction and degree of asymptotic bias depend on the distributions of the index $x'\beta$ and the covariate vector $x$, the estimated beta coefficients appeared as downward biased in the Monte Carlo analyses carried out by Hausman et al. (1998) and Hug (2010). Moreover, relatively small amounts of misclassification (as little as 2 percent) can lead to significant bias even in large samples, and even if misclassification is unrelated to any of the independent variables. On the other hand, misclassification may imply a large loss of efficiency if it is allowed to depend on too many covariates or if one allows for misclassification when it is absent. These statistical properties suggest comparing the different estimates of $\beta$ using a Hausman (1978) specification test.

Identification of $\left(\left(\alpha_0^c,\alpha_1^c\right)_{c=1}^{C},\beta\right)$, where $C$ is the total number of countries in the sample, stems from the nonlinearity of $\Phi$ and the so-called monotonicity condition: It is assumed that $\alpha_0^c+\alpha_1^c<1$ holds in each country. In the above-mentioned article, Hausman et al. also obtained estimated alpha parameters without relying on an assumed error distribution. But the similarity of the maximum likelihood and semiparametric estimates led Hausman (2001) to conclude that the maximum likelihood approach to probit allowing for misclassification may give reasonable results in many actual empirical settings. Regarding the monotonicity condition, we find it plausible in the present context, as we expect *a priori* a small probability that a zero be misclassified as a one.

[10] The asymptotic analysis is as the number of sample households tends to infinity.

To estimate $\left(\left(\alpha_0^c, \alpha_1^c\right)_{c=1}^C, \beta\right)$, the (partial) log likelihood function

$$\left(\sum_{i=1}^N T_i\right)^{-1} \sum_{i=1}^N \sum_{t=1}^{T_i} \left( \begin{array}{c} y_{ict+1} \ln\left(a_0^c + \left(1 - a_0^c - a_1^c\right)\Phi\left(x_{ict}' b\right)\right) + \\ \left(1 - y_{ict+1}\right) \ln\left(1 - a_0^c - \left(1 - a_0^c - a_1^c\right)\Phi\left(x_{ict}' b\right)\right) \end{array} \right) \tag{6}$$

is maximized over $\left(\left(a_0^c, a_1^c\right)_{c=1}^C, b\right)$, where $N$ is the number of sample households, $T_i$ is household's $i$ number of periods in the panel, and $\left(\left(a_0^c, a_1^c\right)_{c=1}^C, b\right)$ is a generic element of the parameter space.[11] Function (6) is not globally concave, and since estimators corresponding to local maxima may have no useful properties, a series of steps were taken to increase the chance that the obtained maximum is global. A wide range of initial alpha parameter values were fed into the optimization routine, including those that, for each country, maximized (6) for values of $\left(\alpha_0^c, \alpha_1^c\right)$ chosen along a grid (as suggested in Lange et al., 1989). Initial values for the beta coefficients were alternatively set 0 and 50 percent larger than ordinary probit estimates. Maximizations were carried out using the Broyden-Fletcher-Goldfarb-Shanno algorithm, and convergence was accepted if the Hessian was negative definite and the scaled gradient was lower than $10^{-5}$.[12]

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[11] The non-negativity and monotonicity constraints on $\left(\alpha_0^c, \alpha_1^c\right)$ were set on the maximization process using the inverse multinomial logit transformation: $\alpha_0^c = \dfrac{\exp(\eta_0^c)}{1 + \exp(\eta_0^c) + \exp(\eta_1^c)}$ and $\alpha_1^c = \dfrac{\exp(\eta_1^c)}{1 + \exp(\eta_0^c) + \exp(\eta_1^c)}$. Maximization then proceeded over generic elements for $\eta_0^c$ and $\eta_1^c$.

[12] See Train (2003) for a good treatment of numerical maximization.

The independent variable of interest measures households' increase in the probability of arrears between $t$ and $t+1$ when an adverse shock occurred between $t-1$ and $t$. The adverse shock will be alternatively represented by: the percentage reduction in household income if income fell or else zero; an indicator for unemployment spells of the household head or spouse; an indicator for divorce of the head; and an indicator for health problems of the head or spouse. The construction of the reduction in income variable (taken from Fay et al., 2002) assumes that paying for debts is a priority for the household: The likelihood of falling into arrears increases as households experience larger decreases in income, but that likelihood do not decrease as the income increase has been larger. A health problem is defined as the change from very good, good, or fair to bad or very bad in self-reported health. In some specifications, the adverse shock variable will be interacted with institutional variables in order to see whether households' reaction to adverse shocks is affected by countries' financial and judicial institutions.

The other variables included in $x$ are standard in models of debt-repayment behavior: age (divided by 10) and age squared of the head, the head's educational category, whether the head is married or permanently cohabiting, whether the head is self-employed, family size, whether the household owns its home, household income in year $t-1$ and this income squared,[13] a country-specific three-month money market

[13] Fay et al. (2002) include income in $x$, Lyons and Fisher (2006) income (per person) and income squared, and Duygan-Bump and Grant (2009) the natural log of income. We employed a Wald test to choose between a linear and a quadratic specification for income, resulting in a clear rejection of the linearity assumption (*p*-value .00). Then, the *P* test described in Davidson and MacKinnon (1993, p. 528) was employed to choose

interest rate,[14] complete sets of country and year dummies, and an intercept. The reason to measure household income at $t-1$ rather than at $t$ is because the latter is highly correlated with the adverse shocks. Table 2 presents descriptive statistics for the main variables used in this study.

**4. RESULTS**

Country-level misclassification probabilities estimates, $(\hat{\alpha}_0^c, \hat{\alpha}_1^c)$, are presented in columns (1) and (2) of Table 3 with associated standard errors computed using the delta method. This table also presents the predicted level of arrears implied by these estimates as well as the observed level of arrears for comparison purposes. The predicted level of arrears in each country was obtained as follows. By the Total Probability Theorem,

$$\Pr(y_c = 1) = \Pr(y_c = 1 | \tilde{y}_c = 0)\Pr(\tilde{y}_c = 0) + \Pr(y_c = 1 | \tilde{y}_c = 1)\Pr(\tilde{y}_c = 1); \qquad (7)$$

as $\Pr(\tilde{y}_c = 0) = 1 - \Pr(\tilde{y}_c = 1)$,

$$\Pr(\tilde{y}_c = 1) = \frac{\Pr(y_c = 1) - \Pr(y_c = 1 | \tilde{y}_c = 0)}{\Pr(y_c = 1 | \tilde{y}_c = 1) - \Pr(y_c = 1 | \tilde{y}_c = 0)} = \frac{\Pr(y_c = 1) - \alpha_0^c}{1 - \alpha_1^c - \alpha_0^c}, \qquad (8)$$

where the second equality uses the definitions in expressions (3) and (4). Estimates of $(\alpha_0^c, \alpha_1^c)$ are taken from the first and second columns of Table 3, whereas the estimated $\Pr(y_c = 1)$ is obtained from the fourth column. The $(\hat{\alpha}_0^c, \hat{\alpha}_1^c)$ in Table 3 pertain to the regression (shown in column (2) of Table 5) in which the adverse shock is represented

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between the quadratic specification and a model having the log of income among the regressors. At standard significance levels, the quadratic specification is not rejected against the log income model (*p*-value .27), although the latter is strongly rejected against the former (*p*-value .00).

[14] Rates of interest were obtained from OECD.Stat on 2 November 2011.

by the percentage reduction in household income, but replacing this variable with a direct adverse shock indicator leaves them largely unchanged.

For households that are not in arrears, misclassification is low in all countries, ranging from 0.44 percent in the Netherlands to 4.04 percent in Greece. Estimates are precise and their confidence intervals do not contain zero.[15] Misclassification for households in arrears is generally much larger, but presents important differences across countries: From essentially 0 percent in Ireland and the Netherlands to approximately 64 percent in Denmark. The $\hat{\alpha}_1^c$s are less precisely measured (precision appears as directly related to the incidence of arrears), but for many of them the confidence interval does not contain zero.[16] In most countries the predicted level of arrears is higher than the observed amount. Comparing the weighted averages of the countries' level of arrears before and after the adjustment reveals that the true level is underestimated by 1.7 percentage points (8.9 vs. 7.2 percent). The correlation between predicted and observed arrears is very high (0.95). The correlation of predicted arrears with the percentage of households in debt increases to -0.48, but correlations with DB project measures experience little change.

The next-to-last two rows of Table 3 present the results of robust Wald tests (Wooldridge, 2002, p. 407) for the hypotheses $\alpha_0^1 = \ldots = \alpha_0^C$ and $\alpha_1^1 = \ldots = \alpha_1^C$, respectively. Each null is strongly rejected (*p*-values 0.00), what provides evidence in

[15] As probabilities are nonnegative, standard test procedures on $\alpha_0^c = 0$ or $\alpha_1^c = 0$ are inappropriate (Shapiro, 1985).

[16] The grid search probabilities that maximize (6) for each country are generally contained in the confidence intervals of the estimated misclassification probabilities.

favor of the country-specific misclassification probabilities assumption. As to the reasons behind these country differences, note that the negative cross-country correlation between $\hat{\alpha}_0^c$ and $\hat{\alpha}_1^c$ (-0.11) would be consistent with the cost of default argument if a feeling of embarrassment came up at the moment of reporting repayment problems ($\alpha_1^c$ would be directly related to utility costs), and if higher utility costs facilitated the retrieval of information from memory ($\alpha_0^c$ would be inversely related to utility costs). However, a positive correlation would be consistent too, if higher utility costs led to over-reporting of repayment problems. It is also possible that other dimensions of culture were playing a role, as suggested by the negative correlation of $\hat{\alpha}_0^c$ (-0.51) and $\hat{\alpha}_1^c$ (-0.14) with the country level of trust (as taken from the last row of Table I in Guiso et al., 2009). In any case, the country differences in misclassification are neither proxying for country effects on arrears, since a complete set of country dummies is included in $x$, nor resulting from differences in the definition of the variable measuring arrears, as this is essentially comparable across the countries and waves included in our sample.

A referee suggested that the utility cost of default could be also dependent on household income. Hence, we have allowed for different levels of misclassification by income group. Specifically, for households in country $c$ whose income at $t$ is below (respectively, not lower than) the country's median income, the probability that a zero is misclassified as a one is given by the parameter $\alpha_{0L}^c$ ($\alpha_{0H}^c$), whereas the probability that a one is misclassified as a zero is given by the parameter $\alpha_{1L}^c$ ($\alpha_{1H}^c$).[17] The monotonicity

[17] We have not divided households according to income at $t+1$ because this income could be correlated with arrears between $t$ and $t+1$. When households were divided

condition becomes $\alpha_{0L}^c + \alpha_{1L}^c < 1$ and $\alpha_{0H}^c + \alpha_{1H}^c < 1 \ \forall c$. Columns (1) and (2) of Table 4 list, respectively, $\left(\hat{\alpha}_{0L}^c, \hat{\alpha}_{1L}^c\right)$ and $\left(\hat{\alpha}_{0H}^c, \hat{\alpha}_{1H}^c\right)$ with associated standard errors computed using the delta method, whereas its third column presents the results of robust Wald tests for the hypotheses $\alpha_{0L}^c = \alpha_{0H}^c$ and $\alpha_{1L}^c = \alpha_{1H}^c$. The tests indicate that income plays a minor role in generating false positives: Only the increase in $\alpha_0$ with income observed in Ireland is statistically significant around the 0.05 level. False negatives, however, increase with income in almost all countries, although the increase achieves statistical significance at or around the 0.05 level in Ireland, Spain, France, and Belgium only. In Ireland, for instance, misclassification for low income households that are in arrears is 0.1 percent (*S.E.* = 0.9), but it increases to 40.5 percent (*S.E.* = 9.9) in the case of high income households. That these households underreport arrears more commonly is consistent with the utility cost argument if the associated feeling of embarrassment

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according to income at $t-1$, misclassification appeared as essentially unrelated to income. In principle, it is possible to obtain country-level estimates from $\alpha_{0L}^c$, $\alpha_{0H}^c$, $\alpha_{1L}^c$, and $\alpha_{1H}^c$, given that $\alpha_0^c = \alpha_{0L}^c \kappa_0^c + \alpha_{0H}^c (1-\kappa_0^c)$ and $\alpha_1^c = \alpha_{1L}^c \kappa_1^c + \alpha_{1H}^c (1-\kappa_1^c)$, where $\kappa_0^c$ (respectively, $\kappa_1^c$) denotes the probability that a household in country $c$ with $\tilde{y} = 0$ ($\tilde{y} = 1$) has income below the country median income. To estimate the kappas, we computed for each $i$ the predicted probability that $\tilde{y}_{ict+1} = 1$ given $x_{ict}$. If $\Phi\left(x_{ict}'\hat{\beta}\right) > .5$ we predicted $\tilde{y}_{ict+1}$ to be unity; if $\Phi\left(x_{ict}'\hat{\beta}\right) \leq .5$ $\tilde{y}_{ict+1}$ was predicted to be zero. The problem with this method was that in some countries all households had $\Phi\left(x_{ict}'\hat{\beta}\right) \leq .5$, what precluded identifying $\kappa_1$ for these countries.

varied directly with income. As to the estimated $\beta$ yielded by this income-dependent misclassification model, it is quite similar to that produced by the income-independent one. Indeed, a Hausman (1978) specification test does not reject the null that both beta parameter estimates have the same probability limit (*p*-value 0.103).[18] Hence, and in order to save some efficiency, the following results pertaining to the modified probit model were obtained under the income independent misclassification assumption.

Columns (1) and (2) of Table 5 present, respectively, ordinary and modified probit regressions explaining whether households fall into arrears between interviews $t$ and $t+1$. In both regressions the adverse shock is the percentage reduction in household income between $t-1$ and $t$. Table 5 presents estimated coefficients, standard errors clustered at the household level, and an adjustment factor that allows the marginal effect of continuous variables, and an approximation to the marginal effect of discrete variables, to be computed. The marginal effect on the true response is

$$\frac{\partial \Pr\left(\tilde{y}=1|x\right)}{\partial x_j} = \phi\left(x'\beta\right)\beta_j, \tag{9}$$

[18] Let $\hat{\beta}$ and $\hat{\hat{\beta}}$ denote modified probit estimates of $\beta$ obtained respectively under the income-independent and income-dependent misclassification models, and let $V$ represent an estimated asymptotic variance matrix. The test statistic, $\left(\hat{\beta}-\hat{\hat{\beta}}\right)'\left(V\left(\hat{\hat{\beta}}\right)-V\left(\hat{\beta}\right)\right)^{-1}\left(\hat{\beta}-\hat{\hat{\beta}}\right)$, is asymptotically distributed as $\chi^2$ with degrees of freedom equal to the number of parameters in $\beta$ (27 in this case).

where $\phi$ is the pdf of the standard normal distribution. The adjustment factor $\phi(x'\beta)$ and the overall expression (9) are estimated by plugging in an estimate $\hat{\beta}$ and then averaging across observations.[19]

The coefficients estimated by the ordinary and modified probit models present identical signs, but modified probit estimates are substantially larger (in absolute value) than ordinary probit counterparts. This same pattern is expected among marginal effects, as the ordinary probit adjustment factor is smaller. Modified probit standard errors are also larger, a result that is partly due to the fact that, in the presence of misclassification of the dependent variable, ordinary probit overstates the precision of the estimates (Hausman et al., 1998). The likelihood values show that accounting for misclassification substantially improves the fit of the model. Moreover, the null that the ordinary and modified probit estimates of $\beta$ have the same probability limit is strongly rejected (*p*-value 0.00). For these reasons, the following discussion will stress the results obtained under the modified probit specification.

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[19] Let $x_s$ and $\beta_s$ represent the adverse shock components of $x$ and $\beta$, and let $x_{-s}$ and $\beta_{-s}$ denote the vectors $x$ and $\beta$ with the adverse shock component excluded. For the percentage reduction in household income variable $x_s = x_{s,1}x_{s,2}$, where $x_{s,1} = 1(\Delta\text{income} < 0)$ and $x_{s,2} = -\Delta\text{income in }\%$. Following Ai and Norton (2003) and Greene (2010), the marginal effect of $x_{s,1}x_{s,2}$ on the incidence of arrears is $\frac{\partial\left(\Delta\Pr\left(\tilde{y}=1 \middle| x_{s,1}, x_{s,2}, x_{-s}\right)/\Delta x_{s,1}\right)}{\partial x_{s,2}} = \phi\left(\beta_s x_{s,2} + x_{-s}\beta_{-s}\right)\beta_s$. Therefore, for the percentage reduction in household income the adjustment factor has $x_{s,2}$ in the place of $x_s$.

The percentage reduction in household income is positively associated to the probability of being in arrears and statistically significant at 0.05 level. A 10 percent reduction in income increases the level of that probability by about 0.012, whereas the predicted increase in the ordinary probit case is 0.008. Since the predicted average probability of arrears is 0.089, a 10 percent reduction in income would thus increase the number of households in arrears by about 13 percent. In Spain, average after-tax annual household income decreased from €23,931 in 2008 to €21,215 in 2011 (both quantities expressed in euros of 2005), an 11.3 percent cut. Thus, as a result of this change the incidence of arrears in Spain would have increased by 0.014, a figure that amounts to 30 percent of the increase in Spanish banks' rate of doubtful loans between 2008 (2.1 percent) and 2011 (6.8 percent).[20] For some households, part of that income cut was due to the 5 percent reduction (on average) in the monthly earnings of government employees implemented by the Spanish government between June and December 2010. This reduction was equivalent to a 2.9 percent cut over the whole year, and since the Spanish average inflation rate in 2010 was 1.8 percent, for many affected households the reduction in real earnings was probably around 4.7 percent. If earnings were the only source of income, these households' resulting change in the incidence of arrears

[20] Data on household income were taken from the Living Conditions Survey conducted by the Spanish National Statistics Institute. Statistics on total and doubtful loans were taken from the Bank of Spain. Both sorts of data were accessed on 10 December 2012. Doubtful loans are loans in relation to which there is reasonable doubt regarding full repayment. They include non-performing loans, which are those in respect of which some amount of principal, interest or contractually agreed expense is more than three months past-due.

would have been 0.006, i.e. 43 percent of the income effect on arrears during the period 2008-2011.

The incidence of arrears is also affected by other household characteristics and macroeconomic conditions. For given household income (and other regressors), family size is directly related to the probability of falling into arrears: An extra household member increases that probability by approximately 0.030. Significant effects are also associated to the head's education. Heads with less than a high school diploma, for example, are about 0.052 more likely to fall into arrears than heads with more than high school.[21] Once misclassification is accounted for, the head's age is a strong predictor for falling into arrears, whose likelihood increases with age up until 41 years old and decreases from that moment on. Increases in the interest rate are directly related to the probability of falling into arrears, but the effect is imprecisely measured and attains no statistical significance.

The models in columns (1) and (2) of Table 5 were re-estimated having a direct indicator of an adverse shock (unemployment of the head/spouse; divorce of the head; health problems of the head/spouse) in place of the reduction in household income variable (one indicator at a time).[22] Table 6 presents the marginal effect associated to

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[21] This effect was computed with the finite-difference method, i.e. $\Phi\left(x'\beta \middle| x_j = 1\right) - \Phi\left(x'\beta \middle| x_j = 0\right)$, where $x_j$ is the less than a high school diploma indicator.

[22] For these additional estimations, we employed the same initial parameter values used to start the optimization algorithm leading to the results in column (2) of Table 5. The only exception was, of course, the beta parameter value associated to the shock itself,

each indicator, as well as that associated to a 10 percent reduction in income for comparison purposes. The marginal effect of each direct indicator was computed with the finite-difference method, and standard errors were calculated using the delta method.

Very significant effects on the incidence of arrears are associated to the adverse shocks: Incidence increases by about 0.045 when the head or the spouse becomes unemployed, by 0.066 when the head divorces, and by 0.064 when the health condition of the head or the spouse deteriorates. The corresponding increases predicted by the ordinary probit model are substantially lower: 0.035, 0.054, and 0.047, respectively. To investigate the channels through which adverse shocks alter the incidence of arrears, we have calculated the reduction in household income associated to each of the shocks. The income decrease is around 10 percent in the case of an unemployment or negative health shock, and around 24 percent in the case of a divorce. Hence, for example, we would expect that, as a consequence of the reduction in income only, the increase in the incidence of arrears caused by a divorce were about 0.030, which is less than half of the estimated response. Thus, the incidence of arrears seems to be also altered by changes in households' preferences or expenses induced by the shock.

In Spain, the unemployment rate surged from (an average of) 11.3 percent in 2008 to 18.0 percent in 2009. As a consequence, the probability that a Spanish single-earner household experienced an unemployment shock became 0.067 higher. Assuming that spouses' employment status are independent, this probability increased by about 0.114 in two-earner couples. Overall, experiencing an unemployment shock became

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which was alternatively set 0 and 50 percent larger than the corresponding ordinary probit estimate.

about 0.08 more likely between 2008 and 2009. With the help of expression (9) we have calculated the implied increase in the incidence of arrears for the whole population: 0.003 (*S.E.* = 0.001). As the predicted average probability of arrears in Spain is 0.099, the number of Spanish households in arrears would have increased by 3.0 percent as a consequence of the unemployment surge. The increase predicted by ordinary probit is 2.4 percent.

Duygan-Bump and Grant (2009) have found that households' degree of reaction to adverse events depends on country-specific characteristics such as the efficiency of the judicial system and the extent of information sharing among lenders. To investigate whether this result still holds after misclassification has been accounted for, we take advantage of the DB project indicators. We have recast our model by adding interaction terms between each adverse shock and the DB project indicators (one shock at a time). This allows the effects of adverse shocks to depend on country-specific regulatory environments, and is a way of probing the contention that households take financial benefits and costs into account in making their debt-repayment decisions. As the correlations between the four indicators are small, the four resulting interaction terms have been jointly included in $x$. The indicators themselves, however, have not been included in $x$ because they are constant over the observation period and are thus indistinguishable from country-specific effects. Table 7 presents the results from this exercise. For simplicity, the table lists only the estimated coefficients associated to the interaction terms (the adverse shocks are specified by the column names), as well as an adjustment factor that allows marginal effects to be computed.[23]

[23] Let $DB_j$, $j = 1, \ldots, 4$, denote the DB project measures. When $x_s$ represents a direct indicator of an adverse shock, the marginal effect of $x_s DB_j$ is

Although a few modified probit estimated coefficients are smaller (in absolute value) than the ordinary probit counterparts (see, for example, the interaction term between the percentage reduction in income and the cost of judicial proceedings), and there is one sign reversal (the interaction term between the unemployment shock and the cost of judicial proceedings), modified probit estimates tend to be, once again, larger. As to marginal effects, they tend to be also larger in the modified probit case. Suppose, for example, that the percentage of adult population registered in credit bureaus increased from 1.8 (the case of France) to 100 (as in Ireland). As a result, the incidence of arrears after an unemployment spell would be 0.068 lower, a 76 percent decrease with respect to the average rate, instead of the 0.050 reduction predicted by the ordinary probit model. As a rule, we find that information sharing among lenders mitigates arrears, which is in line with the negative association between information sharing and non-performing loans found in Jappelli and Pagano (2002). As an additional example, suppose that the cost of judicial proceedings as a percentage of the debt rose from 0.5 (as in the Netherlands) to 10.7 (the case of Spain). Then, the incidence of arrears after a negative health shock would increase by about 0.043 (48 percent), instead of the 0.016

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$$\frac{\partial\left(\Delta \Pr\left(\tilde{y}=1 \middle| x_s, x_{-s}\right)/\Delta x_s\right)}{\partial DB_j} = \phi\left(\beta_s + \beta_{s,1}DB_1 + \beta_{s,2}DB_2 + \beta_{s,3}DB_3 + \beta_{s,4}DB_4 + x_{-s}\beta_{-s}\right)\beta_{s,j},$$

where $\beta_{s,j}$ is the coefficient associated to $x_s DB_j$ and $\phi(\cdot)$ is the adjustment factor. When $x_s$ represents the percentage reduction in household income, the marginal effect of $x_{s,1}x_{s,2}DB_j$ is $\frac{\partial^2\left(\Delta \Pr\left(\tilde{y}=1 \middle| x_{s,1}, x_{s,2}, x_{-s}\right)/\Delta x_{s,1}\right)}{\partial x_{s,2}\partial DB_j} = \phi(A)\left(1 - A\left(A - x_{-s}\beta_{-s}\right)\right)\beta_{s,j}$,

where $A = \beta_s x_{s,2} + \beta_{s,1}x_{s,2}DB_1 + \beta_{s,2}x_{s,2}DB_2 + \beta_{s,3}x_{s,2}DB_3 + \beta_{s,4}x_{s,2}DB_4 + x_{-s}\beta_{-s}$ and $\phi(A)\left(1 - A\left(A - x_{-s}\beta_{-s}\right)\right)$ is the adjustment factor.

increase predicted by ordinary probit.[24] This response of arrears to the cost of judicial proceedings is in agreement with the higher rate of default caused by a larger backlog of pending trials found by Jappelli et al. (2005).

## 5. CONCLUSIONS

In this paper we have estimated two models of the household debt-repayment decision using survey data: A standard model and a model allowing for misclassification of self-reported debt-repayment status. In order to minimize sample selection issues, the payments considered pertain to a wide variety of household debts, but also to contractual obligations for which there is no an underlying credit contract.

We have found strong evidence of misclassification of households' debt-repayment status, particularly of households that are behind on repayment. For these households, misclassification (i.e. false negatives) tends to be higher among households with income above the median. The prevalence of false negatives in some countries is quite consistent with the underreporting of bankruptcy filings in the Panel Study of Income Dynamics and of mortgage arrears in the British Household Panel Survey. For households that are not in arrears, misclassification (i.e. false positives) is generally low but different from zero. After correcting for misclassification, the overall level of arrears in the data has been revised upwards from 7.2 to 8.9 percent.

The impacts on the incidence of arrears of shocks that reduce households' ability to repay become substantially larger once the possibility of misclassification has been allowed for. In the case of an adverse shock to household income (respectively, of an

[24] Although in these two examples the estimated sign of the response is consistent with theoretical predictions and the available evidence, some estimated coefficients present unexpected signs. Note also that coefficient estimates tend to be imprecisely measured.

unemployment spell of the household head or spouse), the estimated impact is revised upwards by about 50 (29) percent. Results also suggest that the impact on households' willingness to repay of certain country-specific institutions (the efficiency of the judicial system and the extent of information sharing among lenders) may be larger than those previously estimated. The households' debt-repayment behavior documented in this paper and, in general, the line of research developed here, seem relevant for the design of more effective social insurance policies and credit market institutions.

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Table 1. Statistics on debt and institutions: 1994-2001

| Country | (1) Observations | (2) Debt[a] | (3) Arrears[a] | (4) Time | (5) Cost | (6) Procedures | (7) Coverage |
|---|---|---|---|---|---|---|---|
| Denmark | 6,644 | 89.3 | 3.3 | 83 | 3.8 | 15 | 7.7 |
| Netherlands | 12,341 | 75.9 | 2.2 | 48 | 0.5 | 22 | 68.9 |
| Belgium | 7,775 | 64.2 | 7.8 | 112 | 9.1 | 27 | 55.3 |
| France | 15,655 | 70.8 | 9.2 | 75 | 3.8 | 21 | 1.8 |
| Ireland | 7,382 | 68.5 | 9.4 | 217 | 7.2 | 16 | 100 |
| Italy | 16,607 | 27.7 | 6.3 | 1,390 | 3.9 | 18 | 59.9 |
| Greece | 8,900 | 25.0 | 23.4 | 151 | 8.2 | 14 | 17.7 |
| Spain | 13,808 | 44.8 | 5.3 | 169 | 10.7 | 23 | 42.1 |
| Portugal | 11,256 | 35.2 | 3.7 | 320 | 4.9 | 24 | 64.3 |
| Austria | 6,258 | 44.4 | 2.1 | 374 | 1.0 | 20 | 45.4 |
| *Total* | *106,626* | *52.3* | *7.2* | | | | |
| Correlation with Debt | | | -0.39 | | | | |
| Correlation with Arrears | | | | -0.10 | 0.49 | -0.45 | -0.26 |

Notes: Authors' calculations based on data from the European Community Household Panel and the Doing Business project. [a] Weighted figures. *Debt*: Percentage of households holding any kind of debt (housing and non-housing). *Arrears*: Percentage of households having missed a scheduled rent, mortgage, utility, hire-purchase or other loan payment in the last 12 months. *Time*: Total number of calendar days it takes, on average, for dispute resolution. *Cost*: The cost (as a percentage of the debt) of judicial proceedings. *Procedures*: Total number of legal procedures mandated by law that must be followed in order to legally recover a debt. *Coverage*: Percentage of the adult population who has information on their repayment history, unpaid debts, or outstanding credit recorded in public or private credit registries.

Table 2. Descriptive statistics: 1994-2001 European Community Household Panel

| *Variable* | Mean | Std dev | Minimum | Maximum |
|---|---|---|---|---|
| Age of household head | 44.8 | 7.9 | 30 | 60 |
| Family size | 3.5 | 1.4 | 1 | 16 |
| Household income (1,000)[a] | 29.1 | 15.5 | 0.7 | 117.7 |
| Percentage reduction in income[b] | 7.3 | 15.4 | 0 | 100.1 |
| Interest rate | 5.6 | 2.8 | 3.0 | 14.0 |

| *Variable (%)* | Mean | *Variable (%)* | Mean |
|---|---|---|---|
| Arrears[c] (unweighted) | 7.4 | Unemployment of head/spouse[b] | 4.2 |
| Less than a high school diploma | 50.3 | Health problems of head/spouse[b] | 4.1 |
| High school graduate | 31.1 | Year 1995 | 16.4 |
| More than a high school diploma | 18.6 | Year 1996 | 18.7 |
| Married | 81.8 | Year 1997 | 17.3 |
| Self-employed | 18.2 | Year 1998 | 16.5 |
| Owner | 74.5 | Year 1999 | 15.8 |
| Head divorced[b] | 0.5 | Year 2000 | 15.3 |

Notes: Data relate to 21,537 households observed at $t$, where $t = 1995,\ldots,2000$. [a] Observed at $t-1$. [b] Between $t-1$ and $t$. [c] Between $t$ and $t+1$. Household income is a total after-tax yearly rate expressed in 2005 prices using national consumer price indices and normalized across countries using purchasing power standards. The interest rate is either the three-month interbank offer rate or the rate associated with Treasury bills, Certificates of Deposit, or comparable instruments, each of three month maturity. It is expressed as percent per annum.

Table 3. Misclassification probabilities estimates and predicted level of arrears by country

| | (1) $\alpha_0^c$ | | (2) $\alpha_1^c$ | | (3) Predicted arrears | (4) Observed arrears |
|---|---|---|---|---|---|---|
| Country | Coefficient | Std. error | Coefficient | Std. error | % | % |
| Denmark | .0092 | .0038 | .6397 | .1954 | 6.8 | 3.3 |
| Netherlands | .0044 | .0012 | .0196 | .4400 | 1.8 | 2.2 |
| Belgium | .0171 | .0068 | .3765 | .1606 | 10.0 | 7.8 |
| France | .0154 | .0039 | .1024 | .1397 | 8.7 | 9.2 |
| Ireland | .0231 | .0050 | .0008 | .0040 | 7.3 | 9.4 |
| Italy | .0177 | .0031 | .3756 | .1543 | 7.5 | 6.3 |
| Greece | .0404 | .0204 | .4046 | .0689 | 34.9 | 23.4 |
| Spain | .0091 | .0026 | .5493 | .0940 | 9.9 | 5.3 |
| Portugal | .0085 | .0027 | .6017 | .1439 | 7.3 | 3.7 |
| Austria | .0062 | .0025 | .3651 | .5186 | 2.4 | 2.1 |
| Wald test of: | | | | | | |
| $\alpha_0^1 = \ldots = \alpha_0^C$ | .00 | | | | | |
| $\alpha_1^1 = \ldots = \alpha_1^C$ | | | .00 | | | |
| Correlation: | | | | | .95 | |

Notes: Parameter estimates pertain to the regression presented in column (2) of Table 5. Standard errors are computed using the delta method. The Wald test results are probability values.

Table 4: Misclassification probabilities estimates by country and income group

| | (1) | | (2) | | (3) Wald test of: | |
|---|---|---|---|---|---|---|
| Country | $\alpha_{0L}^{c}$ | $\alpha_{1L}^{c}$ | $\alpha_{0H}^{c}$ | $\alpha_{1H}^{c}$ | $\alpha_{0L}^{c} = \alpha_{0H}^{c}$ | $\alpha_{1L}^{c} = \alpha_{1H}^{c}$ |
| Denmark | .0132 | .5376 | .0084 | .5422 | .47 | .97 |
| | (.0070) | (.2900) | (.0036) | (.3424) | | |
| Netherlands | .0061 | .0010 | .0040 | .2432 | .45 | .34 |
| | (.0028) | (.0022) | (.0012) | (.2534) | | |
| Belgium | .0176 | .3588 | .0180 | .5313 | .97 | .08 |
| | (.0134) | (.1731) | (.0073) | (.1519) | | |
| France | .0192 | .0103 | .0156 | .1980 | .63 | .06 |
| | (.0086) | (.1647) | (.0040) | (.1425) | | |
| Ireland | .0101 | .0010 | .0260 | .4052 | .06 | .00 |
| | (.0087) | (.0090) | (.0055) | (.0991) | | |
| Italy | .0101 | .3624 | .0177 | .4397 | .13 | .33 |
| | (.0059) | (.1575) | (.0035) | (.1595) | | |
| Greece | .0864 | .3644 | .0450 | .3377 | .12 | .68 |
| | (.0356) | (.0832) | (.0206) | (.1174) | | |
| Spain | .0087 | .5257 | .0095 | .6510 | .88 | .03 |
| | (.0066) | (.1041) | (.0028) | (.0941) | | |
| Portugal | .0105 | .5576 | .0076 | .5266 | .50 | .76 |
| | (.0045) | (.1609) | (.0026) | (.2012) | | |
| Austria | .0048 | .4699 | .0061 | .6722 | .85 | .32 |
| | (.0075) | (.5311) | (.0026) | (.4118) | | |

Notes: Standard errors computed using the delta method are shown in parentheses. The Wald test results are probability values.

Table 5. Results explaining whether households fall into arrears

| | (1) Ordinary Probit | | (2) Modified Probit | |
|---|---|---|---|---|
| Independent variable | Coefficient | Std. error | Coefficient | Std. error |
| Pct. reduction in income | .0074* | .0004 | .0114* | .0012 |
| Age ( ÷10 ) | .2371 | .1285 | .4187* | .1953 |
| $Age^2$ ( ÷100 ) | -.0292* | .0143 | -.0515* | .0217 |
| Exactly high school graduate | .0953* | .0298 | .2076* | .0563 |
| Less than high school | .2653* | .0303 | .4322* | .0599 |
| Married | -.2452* | .0263 | -.3301* | .0441 |
| Self-employed | -.1157* | .0241 | -.2074* | .0448 |
| Family size | .1548* | .0072 | .2302* | .0189 |
| Owner | -.4036* | .0198 | -.5543* | .0424 |
| Income | -.0339* | .0018 | -.0517* | .0047 |
| $Income^2$ | .0002* | .0000 | .0003* | .0000 |
| Interest rate | .0042 | .0052 | .0072 | .0084 |
| Intercept | -1.584* | .284 | -1.808* | .465 |
| Log-likelihood | -23518.8 | | -23442.2 | |
| Adjustment factor for marginal effects[a] | .1186 (.1039) | | .1287 (.1091) | |

Notes: The number of observations is 106,626 in both columns, of which 7,921 report to be in arrears. Estimations include country and year dummies, and standard errors are clustered at the household level. Unreported category: more than a high school diploma. [a] The adjustment factor for the percentage reduction in income variable, computed as shown in note 19, is in parentheses. * Significant at 5%.

Table 6. Increases in the probability of falling into arrears

| | (1) Ordinary Probit | | (2) Modified Probit | |
|---|---|---|---|---|
| Adverse shock | Marginal effect | Std. error | Marginal effect | Std. error |
| 10% reduction in income | .008* | .000 | .012* | .002 |
| Head/spouse unemployed | .035* | .004 | .045* | .009 |
| Head divorced | .054* | .014 | .066* | .021 |
| Head/spouse in worse health | .047* | .005 | .064* | .013 |

Notes: The marginal effect is the average increase in the probability of falling into arrears under the hypothesized shock, holding constant all other household characteristics and macroeconomic conditions. Standard errors are computed using the delta method. * Significant at 5%.

Table 7. Institutions and arrears

| | Pct reduction in income | | Head/spouse unemployed | | Head divorced | | Head/spouse in worse health | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Ordinary Probit | Modified Probit | Ordinary Probit | Modified Probit | Ordinary Probit | Modified Probit | Ordinary Probit | Modified Probit |
| Shock*Time | $-1.52\times10^{-6}$* | $-2.95\times10^{-6}$* | .00019** | .00020* | -.00013 | -.00023 | -.00001 | -.00003 |
| | ($8.35\times10^{-7}$) | ($1.69\times10^{-6}$) | (.00007) | (.00011) | (.00022) | (.00031) | (.00007) | (.00012) |
| Shock*Cost | -.00049** | -.00045* | -.00030 | .0088 | -.0075 | -.0017 | .0093 | .0237 |
| | (.00012) | (.00027) | (.0084) | (.0122) | (.0282) | (.0408) | (.0099) | (.0153) |
| Shock*Procedures | .00030** | .00029 | .0149* | .0168 | -.0068 | -.0099 | -.0153* | -.0273* |
| | (.00010) | (.00019) | (.0078) | (.0127) | (.0213) | (.0335) | (.0083) | (.0150) |
| Shock*Coverage | -.00004** | -.00005* | -.0032** | -.0043** | .0030 | .0031 | -.00059 | -.00055 |
| | (.00002) | (.00003) | (.0012) | (.0016) | (.0026) | (.0033) | (.0012) | (.0018) |
| Adjustment factor for marginal effects | .1028 | .1079 | .1579 | .1619 | .1804 | .1759 | .1686 | .1766 |

Notes: All estimations include country and year dummies as well as the regressors listed in Table 5. Standard errors clustered at the household level are in parentheses. The adjustment factors are computed as shown in note 23. * Significant at 10%. ** Significant at 5%.