The Repayment of Unsecured Debt by European Households*

Charles Grant†   Mario Padula‡

August, 2016

*The opinions expressed in this article are the authors own and do not reflect the view of Commissione di Vigilanza sui Fondi Pensione

†University of Brunel. E-mail address: charles.grant@brunel.ac.uk
‡Commissione di Vigilanza sui Fondi Pensione

Abstract

The existing literature that estimates the incidence of arrears relies on either household survey data or administrative data derived from the lender's records of their borrowers. But estimates based on these different sources will give different estimates of arrears. Moreover, the estimates are not useful for policy analysis or for the bank's lending decision, since they ignore the fact some households do not borrow. This paper discusses the selection issues involved in using either data source, and is the first paper to bound the estimate of the household's underlying propensity to repay. To demonstrate the methodology, it uses data from the EU-SILC survey for 2008 to estimate the factors that affect repayment among Eurozone households.

Keywords: Manski Bounds, Consumer Credit, Arrears.

JEL classification: D14, K42, O17.

1 Introduction

Understanding the drivers of household repayment behaviour is a central question to researchers and policy-makers. Several papers have investigated the determinants of repayment among households. For example, Berkowitz and Hynes (1999), Domowitz and Sartain (1999), Fay, Hurst and White (2002) look at bankruptcy filings among US households. Boheim and Taylor (2000), Bridges and Disney (2004) and Duygan and Grant (2009) instead look at household survey data on arrears from either the UK or from the EU. In these papers, whether the household defaults (or is in arrears) is regressed against a set of explanatory variables. In contrast, Gross and Souleles (2002) and Foote *et al.* (2010) both used the lender's own records on borrowers to estimate arrears among US households. An advantage of using administrative data provided by the lender is that it may well be a more reliable estimate of arrears since the lender has incentives to keep accurate records on default behaviour or arrears. However, using information on borrowers automatically excludes households who either were refused credit, or did not apply for credit, and hence the results will not, generally, be comparable to those obtained with survey data (e.g. a representative sample of the entire household population). Grant and Padula (2013) and Karlan and Zinman (2009) also use data from lender's records, and are particularly interesting from a methodological view. These two papers attempt to explore the fact that not all households will actually borrow. Karlan and Zinman (2009) report results where the interest rate is randomly varied between households, and show how default rates depend on the interest rate. Grant and Padula (2013) discuss the likely behaviour of those households refused credit. However, a major weakness of these two papers is that neither accounts for application behaviour. Dell'Arricia, Igan and Laeven (2012) also include information on rejected households to investigate the decision to accept the loan. They further noted that the characteristics of borrowers seems to have changed in the years prior to the financial crisis. However, they did not formally estimate a model of application behaviour, nor did they estimate how this changing composition affected arrears. A key aim of this paper is to explain how to estimate arrears in a way to properly account for both the borrowers decision to apply for credit, and the lenders decision to give credit. That is, we will make explicit the assumptions underlying existing estimates and how these assumptions affect the interpretation of the results. To the best of our knowledge, this is the first paper to address both issues in an empirical model with the aim of constructing an estimate of the underlying repayment behaviour of households.

Understanding repayment behaviour has important policy implications. Hitherto, there has been much more research on US rather the European households. In particular, the recent sub-prime mortgage crisis has revived the interest in household default behaviour and has demonstrated the inability of large segments of the households population to repay their debts. Demyanyk and Van Hemert (2011) show that the quality of sub-prime mortgage loans deteriorate in the six consecutive years before the US sub-prime crises and argue that the boom of house prices between 2003 and 2005 contributed to conceal these trends. Foote, Gerardi and Willen (2008) show that negative house-equity is a necessary but not sufficient condition to determine households mortgage default, an argument also made by Campbell and Cocco (2011). Guiso, Sapienza and Zingales (2013) use survey data to estimate the importance of strategic default on mortgages among US households during the crisis (e.g. a change in the underlying arrears behaviour of households), while Mayer, Pence and Sherland (2009), using data on the population of sub-prime loans, argue there was a deterioration in lending standards.

Much of the US policy debate has emphasised that an important role is likely to be played by the mortgage market institutions, for instance, see Campbell (2012). A related question is whether the system of public guarantees caused the financial intermediaries to extend credit to households otherwise deemed too risky households had the guarantees been absent. For example, Mian and

Sufi (2009) argue that mortgage supply increased sharply in the US between 2002 and 2005; this in itself is likely to cause an increase in the proportion of US households in arrears even if there had been no change in the underlying repayment behaviour of borrowers. The question raises a more general problem, relevant for secured as well as unsecured debt, that to understand arrears one has first analyze the household decision to apply for a loan, and the lender decision to accord the loan. This key problem is inadequately discussed throughout the existing literature, and is the object of this paper. If some households do not apply for credit, or have their credit application turned-down, then actual arrears will not capture the household's underlying propensity to default. Failing to account for this issue can cause both lenders and policy-makers to make flawed decisions (and indeed, a major cause of the recent sub-prime crisis seems to have been an under-estimate of the propensity to default of household types who previously did not have access to the credit market). The aim of this paper is to explore how we might construct an estimate of the household underlying propensity to default that accounts for the fact that not all households borrow. As we will find, there are significant differences between households in different EU countries in their underlying propensity to pay, and we believe this must have important implications for the design of public policy.

For us to actually observe a household in arrears, three things must have happened: (i) the household applies for a loan (or credit line); (ii) the loan is granted; (iii) the household fails to repay the loan. Changes in actual level of arrears can result from changes in any of these three processes. Existing studies of arrears that use household survey data to estimate changes in actual arrears conflate steps (i)-(iii). They thus provide little insight into reasons for recent changes in repayment behaviour, nor can such estimates be used to say anything about the underlying repayment behaviour of households. Studies which rely on lender's administrative data clearly can not account for the application process. The key contribution of this paper is to disentangle effects (i)-(iii) and to provide a policy relevant estimate of repayment behaviour. It will develop a methodology to help us understand the likely effect of policy interventions.

This paper focuses on the unsecured debt held by European households. Household debt in Europe is a much smaller proportion of income compared to the US. Unsecured debt is 28 percent of total household debt. The prevalence of arrears in the EU is lower than in the US, but there is great heterogeneity between European countries. In Nordic countries, such as Sweden, Denmark and the Netherlands the percentage of arrears is 3.5, 2.2 and 1.0, while in Mediterranean Europe it ranges from 14.2 in Greece to 2.9 in Italy.

The rest of the paper is organized as follows. Section 2 discusses the identification of three relevant notions of propensity to default. Section 3 presents the estimators used to bound the identification regions. Section 4 describes the data; Section 5 illustrates the results; and the conclusions are drawn in Section 6.

2 Identification

There is considerable confusion in the existing literature about what exactly is being estimated when reporting the rate of arrears among households. There are at least three different concepts of repayment that we may want to measure:

(i) The propensity to repay among those households given credit.

(ii) The propensity to repay among those households applying for credit.

(iii) The propensity to repay in the whole population of households.

The first of these items is the easiest and least controversial to estimate; it is simple to construct from bank lending data. However, while this variable is crucial when assessing the bank's capital requirements (as per the Basel accord), it is less informative about the underlying behaviour of households when policy changes. The bank would like to know about item (ii), which would enable it to understand which households can profitably be given credit and which households should be refused. To be clear, the lender wants to know the propensity to repay among applicant households and hence the likely repayment behaviour of an applicant household if that household is given the loan. Obviously the bank does not observe the repayment behaviour of those households that are refused. Nevertheless, given the lender's administrative records, an estimate of item (ii) can be constructed, and banks make considerable effort to estimate this item in order to make their lending decision.

The last item in this list (the propensity to repay in the whole population) is the key estimate if we are to understand how households react to changes in the policy environment. Most obviously, an estimate of this item can only be constructed from survey data (e.g. a survey of the entire household population), since it requires a random sample of the entire population which must include households currently without credit. Moreover, whereas item (ii) requires some assessment of the likely repayment behaviour of applicants who are refused credit, item (iii) additionally requires an assessment of the repayment behaviour of those households that do not apply for credit. Nevertheless, given survey data, an estimate of the propensity to default in the population is possible.

However, in practise almost all papers, hitherto, have instead estimated the actual rate of repayment (or default) in the population (and how this changes with the household's characteristics). We assert that the distinction between the propensity to repay and actual repayment is important, since changes in policies which influence the propensity to repay are likely also to affect the borrowing and lending decision. Reducing the punishment for default or arrears, for instance, will likely encourage lenders to refuse loan applications as well as encourage borrowers to apply for credit; making the effect on the actual rate of repayment observed in the population unclear.

To proceed, we need to formalize the insights above about what precisely is being estimated when arrears is analyzed. First define the variables R, C and A as binary, $\{0,1\}$, indicators for whether the loan is paid on schedule, whether the loan is given and whether the loan is applied for. That is we define:

$$R = \mathbb{1}\{\text{The loan is repaid on schedule}\}$$
$$C = \mathbb{1}\{\text{The loan is given}\}$$
$$A = \mathbb{1}\{\text{The loan is applied for}\}$$

The policy relevant variable of interest is R, which we want to model using a sample of $i = 1, \ldots, N$ households where for each household we observe some characteristics $X_i \in \mathcal{R}^q$. That is, we want to construct an estimate of $Pr(R = 1|X = x)$, and how it changes as the characteristics X change. As an aside, estimating arrears is equivalent to estimating repayment, since arrears arise when the household does not repay on schedule, and hence it equals $1 - R$.

2.1 Estimates Using Survey Data

There are a number of estimates of the repayment behaviour of households, currently available in the literature such as Berkowitz and Hynes (1999) or Duygan and Grant (2009). These estimates either use survey data (a representative sample of households from some underlying population, such as the EU or US population), or they use data that has been made available from a lender's credit records. Those studies that have used survey data have regressed the incidence of default (or arrears) against a variety of explanatory variables. Clearly, a household will only be observed to be in default or arrears, if the household is borrowing. That is, if it has both applied for credit, and the application for credit has been accepted. This reduced form estimate will clearly not capture the underlying propensity to repay of the household, since it ignores the decision to borrow, and ignores the decision to lend. Noting that those households that repay on schedule are those households not in arrears, we can write the underlying propensity to repay as made up of the propensity to repay if the households is borrowing, and the propensity to repay if it is not, where a household might not borrow either because its credit application has been refused (presumably because it has been judged a bad credit risk), or because it does not want to borrow. Formally, this can be written as:

$$\begin{aligned} Pr(R=1|X=x) = {} & Pr(R=1|C=1,A=1,X=x)\cdot Pr(C=1,A=1|X=x) \\ & + Pr(R=1|C=0,A=1,X=x)\cdot Pr(C=0,A=1|X=x) \\ & + Pr(R=1|A=0,X=x)\cdot Pr(A=0|X=x) \end{aligned} \tag{1}$$

Clearly a problem exists because neither $Pr(R=1|C=0,A=1,X=x)$ (the propensity to repay among households refused credit), nor $Pr(R=1|A=0,X=x)$ (the propensity to repay among those households who do not apply for credit), can be directly estimated from data.

Equation 1 also make clear an important point (for which it is easier to write the estimate for default rather than repayment). The naive estimate of default delivers the sample analog of $Pr(R=0,C=1,A=1|X=x)$ which equals $Pr(R=0|C=1,A=1,X=x)\cdot Pr(C=1,A=1|X=x)$. This will be informative of $Pr(R=0|X=x)$, the propensity to default, only in the special case in which $Pr(A=1|X=x)=Pr(C=1|A=1,X=x)=1$. Nevertheless it is the implicit assumption common to all papers which use an estimate of the incidence of actual default to make statements about the underlying propensity to default.

In other words, the existing literature estimates the observed incidence of default or arrears, where clearly only those households who are actually borrowing, for which both $C=1$ and $A=1$, can default. These estimates ignore the selection process and can not be interpreted as a structural parameter unless it is assumed that no household that is not currently borrowing would have defaulted (or been in arrears) should it have been borrowing. That is, the reduced form estimate will equal the structural estimate as long as we make the following assumption:

Assumption 1 *For each $X=x$, the probability of the loan being repaid on schedule, given that either no loan application is made, or the loan application is rejected, is* 1*, i.e.:*

$$Pr(R=1|A=0,X=x)=Pr(R=1|C=0,A=1,X=x)=1.$$

If this assumption is made then the underlying propensity to repay $Pr(R = 1|X = x)$ can be replaced by $\theta_n(x)$ where:

$$\theta_n(x) = Pr(R = 1|C = 1, A = 1, X = x)Pr(C = 1|A = 1, X = x)Pr(A = 1|X = x) + [1 - Pr(C = 1|A = 1, X = x)]\, Pr(A = 1|X = x) + [1 - Pr(A = 1|X = x)]$$

This estimate allows us to recover how the propensity to repay changes with household characteristics as long as the composition of borrowers does not change.

We believe that assumption 1 is implausible, and thus naive estimates of the propensity to repay that calculate $\theta_n(x)$ will be misleading if they are interpreted as structural parameters. That is, we do not believe estimates of $\theta_n(x)$ can be useful for policy analysis, since such estimates will not enable us to understand household arrears when there are changes in the composition of borrowers; and in particular if policy-variables change.

2.2 Estimates Using Lender Records

An alternate approach to investigating which factors affect repayment has used administrative data supplied by the lender (see, for example, Gross and Souleles, 2002). This approach estimates repayment using the sample of credit applicants. In this approach the decision by the household is either ignored (or viewed as unimportant) or the object of interest is the repayment behaviour of credit applicants. In the second case, the researcher typically wishes to recover:

$$Pr(R = 1|A = 1, X = x) = Pr(R = 1|C = 1, A = 1, X = x) \cdot Pr(C = 1|A = 1, X = x) + Pr(R = 1|C = 0, A = 1, X = x) \cdot Pr(C = 0|A = 1, X = x) \tag{2}$$

where the decision to grant credit to the applicant, and the repayment behaviour of households given credit is observed. However the repayment behaviour of refused applicants is not observed. Often attention is restricted to those applicants granted credit, and the propensity to default is estimated on this sample hence the object of interest (the probability of repayment among applicants) is replaced by

$$Pr(R = 1|C = 1, A = 1, X = x) \tag{3}$$

Estimates of 3 are sometimes used by banks to construct borrowers' credit scores. A more sophisticated credit scoring algorithm tries to estimate $Pr(R = 1|X = x, A = 1)$, which requires that some estimate of the behaviour of the rejected loan applications needs to be made. Many lenders solve this problem by giving a small sample of households the loan even though they are rejected by the credit scoring algorithm, enabling the lender can construct the sample analogue of $Pr(R = 1|C = 0, A = 1, X = x)$ (the probability of repayment among applicants denied credit). Lenders have sometimes made this 'experimental' data available for academic research (see Karlan and Zinman, 2009 for example).

Given that lending to candidates who would normally be rejected can be costly, as such households are usually worse credit risks, lenders do not want to estimate $Pr(R = 1|C = 0, A = 1, X = x)$ for more choices of x and for more observations than is strictly necessary. An alternative approach to the problem is to explicitly model the decision to grant the loan. For example, Boyes, Hoffman, and Low (1989) and Jacobson and Roszbach (2003) both obtained estimates of $Pr(R = 1|X = x, A = 1)$ in a fully parametric setting by constructing a bivariate Probit model where the probability of the household getting the loan and the probability of arears were jointly estimated. Identification in these models, however, requires imposing one-or-more exclusion restrictions: variables that affect whether the lender provides the loan, but not whether it is repaid. (The importance of exclusion restrictions was not fully recognized when these papers were published, as both Boyes, Hoffman, and Low (1989) and Jacobson and Roszbach (2003) obtained identification from the functional form of the probit equations.) However, non-parametric identification requires exclusion restrictions, for which there needs to be some economic rational. As argued by Grant and Padula (2013), a lender would only include a variable in the credit scoring decision (which decides whether the loan is granted) if it also explains arrears. Hence any choice of exclusion restriction is *ipso facto* incompatible with optimal behaviour by the lender.

Grant and Padula (2013) proposed using bounds to solve the identification problem. They noted that while $Pr(R = 1|C = 0, A = 1, X = x)$ is not observed, it must be bounded between zero and one, thus (following the approach described in Manski, 1989 and Manski, 1990) a lower bound and an upper bound can be placed on the true value of $Pr(R = 1|A = 1, X = x)$ (the repayment behaviour of credit applicants). The lower bound and upper bounds are defined as:

$$\theta_l^b(x) = Pr(R = 1|C = 1, A = 1, X = x) \cdot Pr(C = 1|A = 1, X = x)$$

$$\theta_u^b(x) = \theta_l^b(x) + [1 - Pr(C = 1|A = 1, X = x)]$$

These bounds can be tightened if we are prepared to make the following reasonable assumption.

Assumption 2 *For each $X = x$, the probability that the loan is repaid on schedule, given that the loan application is refused, is no better than the probability that the loan is repaid on schedule, given that the loan is granted, i.e.:*

$$Pr(R = 1|C = 0, A = 1, X = x) \leq Pr(R = 1|C = 1, A = 1, X = x).$$

This assumption (2) is made in Grant and Padula (2013), and gives an economic rationale for implementing the monotone treatment selection assumption discussed in Manski and Pepper (2000). By making this assumption, a tightened upper bound can be derived, where:

$$\theta_{tu}^b(x) = Pr(R = 1|C = 1, A = 1, X = x)$$

The true estimate of repayment among applicant households must lie somewhere between the lower and the tightened upper bound. Note, however, that neither the estimate from experimental data, nor the estimate using the bounds construct the policy relevant estimate of the propensity to default; the estimate which controls both for whether a credit application is made, and for whether credit is granted.

2.3 An estimate of the underlying propensity to repay

An important aim of this study is to construct an estimate of $Pr(R = 1|X = x)$, which no paper has hitherto estimated. The probability of the loan being repaid on schedule given $X = x$ can be written as:

$$
\begin{aligned}
Pr(R=1|X=x) = & \; Pr(R=1|C=1,A=1,X=x)\cdot Pr(C=1,A=1|X=x) \\
& + \; Pr(R=1|C=0,A=1,X=x)\cdot Pr(C=0,A=1|X=x) \\
& + \; Pr(R=1|A=0,X=x)\cdot Pr(A=0|X=x) \\
= & \; Pr(R=1|A=1,X=x)\cdot Pr(A=1|X=x) \\
& + \; Pr(R=1|A=0,X=x)\cdot Pr(A=0|X=x)
\end{aligned} \tag{4}
$$

We have shown in Section 2.2 how to bound $Pr(R = 1|A = 1, X = x)$. The sampling process does not disclose the sample analog of $Pr(R = 1|A = 0, X = x)$, but we know that it belongs to the interval $[0, 1]$. Therefore, we can construct a lower bound and an upper bound to $Pr(R = 1|X = x)$, and do not make assumption 2. These bounds are, respectively:

$$
\begin{aligned}
\theta_l(x) &= Pr(R=1|C=1,A=1,X=x)\; Pr(C=1|A=1,X=x)\; Pr(A=1|X=x) \\
\theta_u(x) &= Pr(R=1|C=1,A=1,X=x)\; Pr(C=1|A=1,X=x)\; Pr(A=1|X=x) \\
&\quad + [1 - Pr(C=1|A=1,X=x)]\;\; Pr(A=1|X=x) + [1 - Pr(A=1|X=x)]
\end{aligned}
$$

These bounds are wider than in the previous section, where we discussed what is estimated when using data provided by the lender and/or the estimate is restricted to using data only from those households who apply for credit. In practise these bounds can be rather too wide to be practically useful. Nevertheless, simple economic assumptions can be used to tighten these bounds. For example, by using assumption 2 the upper bound can be tightened to where

$$\theta_{tu}(x) = Pr(R = 1|A = 1, C = 1, X = x) \cdot Pr(A = 1|X = x) + [1 - Pr(A = 1|X = x)] \quad (5)$$

We would also like to tighten the lower bound. A simple and intuitive assumption that can do this is to assume that households who apply for loans are weakly less likely to repay than households who do not, i.e. $Pr(R = 1|A = 0, X = x) \geq Pr(R = 1|A = 1, X = x)$. In which case the lower bound will be the same as the lower bound used for the estimate using applicant data only. An alternative assumption, which can also be used to create a tightened lower bound, compares households who do not apply for a loan with those who are given a loan.

Assumption 3 *For each $X = x$, the propensity to repay the loan on schedule by households where no loan application is made, is at least as good as the propensity to repay the loan on schedule, given that an application is made and the household is given credit, i.e.:*

$$Pr(R = 1|A = 0, X = x) \geq Pr(R = 1|C = 1, A = 1, X = x).$$

In this case the new tightened lower bound becomes

$$\theta_{tl}(x) = Pr(R = 1|C = 1, A = 1, X = x) \cdot \{Pr(C = 1|A = 1, X = x)\ Pr(A = 1|X = x) + [1 - Pr(A = 1|X = x)]\} \quad (6)$$

These new bounds considerably tighten the between which the true value of $Pr(R = 1|X = x)$ can lie. Moreover, these bounds rely on simple and plausible economic assumptions about the behaviour of borrowers and lenders.

While restricting the borrowers and lenders behaviour in an arguably reasonable way, assumptions 2 and 3 involve quantities that are typically unobserved by the econometrician and therefore cannot be tested, whatever the data generating mechanism. The data typically do not disclose the propensity to repay among those who do not apply for credit or among those who apply for and are not granted credit. Furthermore, it is not obvious how experimental data can be used to obtain the sample analogs of $Pr(R = 1|C = 0, A = 1, X = x)$ and $Pr(R = 1|A = 0, X = x)$; generally, experiments do not allow us to observe the repayment behaviour of someone who is not granted credit or of someone who does not apply for credit.

However, it is worth emphasizing that virtually all papers estimating $Pr(R = 1|X = x)$ from either representative samples of the entire population or lender data make even stronger assumptions than assumptions 2 and 3. To estimate $Pr(R = 1|X = x)$ from data on actual repayment, one has to assume that the propensity to default is the same between those who are given credit and those who are not, and those who apply and those who do not. In most of the existing literature, these assumptions are made implicitly without being clearly stated. Moreover, while being useful in that they allow the econometrician to obtain a point estimate of $Pr(R = 1|X = x)$, these assumptions clearly neglect important aspects of the lending and the borrowing decisions; they are in many contexts implausible and are not tested. Our approach here is twofold. On the one hand, we make these assumptions transparent and clarify their role in identifying $Pr(R = 1|X = x)$ from observed actual arrears behaviour. On the other hand, by relaxing these assumptions we show how far our inferences on $Pr(R = 1|X = x)$ can go.

3 Estimation

The data comprises of a sample S of N i.i.d. observations. For each observation i we observe a set of explanatory variables X_i. The data also reports a set of binary variables: R_i (a dummy that takes the value one if the household repays the loan and zero if it defaults); C_i (a dummy that takes the value one if the household receives the loan and zero if it is refused); and A_i (a dummy that takes the value one if the household applies for a loan and zero if it does not). However, the value of these binary variables is not always observed by the econometrician. In particular while A_i is observed for all i's; C_i is observed only for those $i \in S_A \subset S$ such that $A_i = 1$; and R_i is observed only for those $i \in S_R \subset S_A$ such that $C_i = 1$ and $A_i = 1$.

Given what is observed we can construct the sample estimate of the probability of repaying on schedule among households given the loan $Pr\,(R = 1|C = 1, A = 1, X = x)$; the probability of receiving the loan $Pr\,(C = 1|A = 1, X = x)$; and the probability of applying for the loan $Pr\,(A = 1|X = x)$.

Given data from the lender the econometrician observes whether a household repays if it has been given a loan, and whether the household has received the loan. We can divide households into four groups: those household that repay (for which $R = 1$ and $C = 1$ and $A = 1$); those households that do not repay (for which $R = 0$ and $C = 1$ and $A = 1$); those households who are refused credit (where $C = 0$ and $A = 1$ but there is a missing value for R); and those households that do not apply for credit (where $A = 0$ and both R and C are missing).

The naive estimate $\theta_n(x)$ is found by assuming all household who are refused the loan would have repaid (households in the third and fourth group are put together with the households that repay and are given a value of one). That is we can construct

$$R_n = \begin{cases} 1 & \text{if} \quad R = 1 \text{ or } C = 0 \text{ or } A = 0 \\ 0 & \text{if} \quad R = 0 \text{ and } C = 1 \text{ and } A = 1 \end{cases}$$

which will be defined on the whole sample S. Using this sample, we can estimate $Pr\,(R_n = 1|X = x)$ to obtain the naive estimate of the probability of default.

The bank upper bound $\theta_u^b(x)$ and the bank lower bound $\theta_l^b(x)$ can also be found assuming all households refused the loan would have repaid (for the upper bound) or would have defaulted (for the lower bound). Equivalently, these two estimates are constructed by dropping the fourth group (keeping only those households that applied for credit) and placing all households in the third group with the first group (for the upper bound) or with the second group (for the lower bound):

$$R_u^b = \begin{cases} 1 & \text{if} \quad R = 1 \text{ or } C = 0 \\ 0 & \text{if} \quad R = 0 \text{ and } C = 1 \end{cases}$$

$$R_l^b = \begin{cases} 1 & \text{if} \quad R = 1 \text{ and } C = 1 \\ 0 & \text{if} \quad R = 0 \text{ or } C = 0 \end{cases}$$

which are only defined for the sample S_A. Using this sample, we can estimate $Pr\left(R_u^b = 1|X = x\right)$ and $Pr\left(R_l^b = 1|X = x\right)$ to obtain the estimates of $\theta_u^b(x)$, the bank upper bound, and $\theta_l^b(x)$, the bank lower bound of the probability of default. The bank tightened upper bound $\theta_{tu}^b(x)$ is found by estimating default among those who receive the loan for which we observe the actual arrears behaviour (the sample S_R).

The upper and the lower bounds $\theta_l(x)$ and $\theta_u(x)$ can be estimated by assuming all households in the third and the fourth group are placed with the first and the second group. That is, we create two new variables R_u and R_l where

$$R_u = \begin{cases} 1 & \text{if} \quad R = 1 \text{ or } C = 0 \text{ or } A = 0 \\ 0 & \text{if} \quad R = 0 \text{ and } C = 1 \text{ and } A = 1 \end{cases}$$

$$R_l = \begin{cases} 1 & \text{if} \quad R = 1 \text{ and } C = 1 \text{ and } A = 1 \\ 0 & \text{if} \quad R = 0 \text{ and } C = 0 \text{ or } A = 0 \end{cases}$$

Using the whole sample S (for which both R_u and R_l are defined), we can estimate $Pr\left(R_u = 1|X = x\right)$ and $Pr\left(R_l = 1|X = x\right)$ to obtain the estimates of the upper and the lower bound of the underlying propensity to default of households.

Overall, we have a number of objects we need to estimate. While the bounds can be estimated using a fully parametric estimator such as a Probit or Logit estimator, we instead follow the procedure of Blundell, Gosling, Ichimura, and Meghir (2007), and estimate the bounds non-parametrically using the Nadaraya-Watson kernel estimator. For illustrating the approach, let us focus on the naive estimate of default θ_n, for which we estimate $E(R_n|X = x)$ using the whole sample S (assume that X is continuous). The Nadaraya-Watson estimator is defined as:

$$\frac{\sum_{j\neq i} R_{nj} I(x_j \in X_n) K([x_i - x_j]/a_n)}{\sum_{j\neq i} I(x_j \in X_n) K([x_i - x_j]/a_n)}$$

where $I(\cdot)$ is the indicator function for whether the j^{th} observation is in the X_n neighbourhood, $K(\cdot)$ is the Gaussian kernel function, $X_n = \{x \text{ s.t. } ||x - x'|| \leq 2a_n \text{ for some } x' \in X\}$ and a_n is positive, tends to zero and is chosen through cross-validation (see Härdle, Hall, Marron, 1988). The other bounds (and all the other objects of interest) are estimated in a similar way. We can construct the variances of the kernel estimators using Bowman and Azzalini (1997) (see also Pagan and Ullah, 1999). We also provide 95 percent confidence regions around the bounds, using the variances of the kernel estimates.

Unfortunately, unlike the other objects to be estimated, no simple transformation of R exists to capture the tightened upper bound $\theta_{tu}(x)$, and the tightened lower bound $\theta_{tl}(x)$. Instead, it is necessary to construct these bounds from the estimate of $Pr\,(R = 1|C = 1, A = 1, X = x)$ using the sample S_R; the estimate of $Pr\,(C = 1|A = 1, X = x)$ using the sample S_A; and the estimate of $Pr\,(A = 1|X = x)$ using the whole sample S. Given these estimates we construct $\theta_{tu}(x)$ and $\theta_{tl}(x)$ using 5 and 6. The standard errors of these estimates are constructed by bootstrapping using 200 iterations.

4 Data

The data used in this paper is taken from the European Union Survey of Income and Living Conditions (EU-SILC). This dataset is a representative survey of households in each participating European household. The survey has been asked each year since 2004 and is designed to replace the European Community Household Survey (ECHP), which was discontinued in 2003. Each year the survey asks identical questions in each of the participating European countries, thus facilitating cross-country comparison of household behaviour. The survey asks a number of questions about the household's composition, housing, income and labour market participation, and living conditions (including a number of questions about poverty and social exclusion). The survey has both a cross-sectional component and a rotating panel component (with households included for four years before being replaced).

While the focus of the survey is on income, each year also includes an additional module of questions on an issue of contemporary interest. In 2008 the module of additional questions was titled *Module on over-indebtedness and financial exclusion* and focused on debts, arrears, repayments and those who do not have access to credit. This paper exploits these questions, asked only in 2008, to focus on the determinants of repayment behaviour of households in those European countries included in the 2008 survey. Note that the recent financial crisis began around this year; the results may have been very different if we had data for other years. While a small number of questions on debt and arrears are included in the main survey each year, those questions are far less detailed and focus only on arrears on housing and on utility payments, excluding all other types of loan, as well as questions on financial exclusion, which does not allow the analysis attempted in this paper.

In the 2008 wave of the questionnaire, the household was asked about debts on utility bills, rent, credit card, hire purchase and other bank loans (including overdrafts), and mortgages. For each kind of debt, the survey asked "*in the last 12 months, has it happened that your household was unable to make a repayment on this loan on time*". These arrears are self-reported and may thus be under-reported. Moreover, we do not observe the extent of the arrears, which may well cover a wide range of different behaviour. At one extreme these households may be entering bankruptcy; at the other the household may be only a few days late on a due payment and have subsequently remedied the situation. Our analysis is not able to distinguish between these two extremes, and this should be kept in mind throughout.

As well as asking about arrears, and whether the household has a loan, the 2008 wave of the survey asks households that do not currently have a loan about why they are not borrowing. Each non-borrowing household reports either that it did not want to borrow; or that it has made an application for credit which has been refused (although the question specified no time frame). Our methodology will exploit this piece of information to construct the bounds to the underlying propensity to default.

This paper concentrates on those countries that were in the Eurozone in 2008, eliminating all other households from the sample. It also restricts attention to households where the household head was between the ages of 30 and 60. Self-employed households are removed since we wish to concentrate on households borrowing to smooth consumption, rather than borrowing for other purposes. Only single households and those households headed by a couple (whether married or not) are included, hence excluding households with multiple unrelated adults (since in such households it is unclear who is responsible for any loan or its repayment). The sample also excluded those households with incomplete information. After making these selections, there are 47,880 households included in the analysis.

An important variable included in the analysis is income, measured as total household labour market income and transfers less taxes on income. Beyond information on income and arrears, the survey also measures a number of household and individual characteristics; our regression analysis will include whether the household is headed by a couple, whether the household head went to university, and whether the household self-reports that they suffered what they believed was a substantial fall in income over the last year. The panel component of the survey, which excludes the key questions used in our analysis, shows that on average incomes fell by 633 euros for those reporting a fall, but increased by 877 euros if they did not. Table 1 provides the mean and the standard deviation for our main variables of interest for the whole sample (which includes those households who do not borrow), as well as for the sub-samples of those borrowers who repay on schedule and those who report arrears The data shows there are some differences between the groups. Households who repay on schedule are richer than the average household in the sample; are more likely to have attended university, and are more likely to be a couple. Households in arrears, in contrast, have much lower income, are slightly younger, are less likely to be in a couple or to have attended university, and are much more likely to report that their income has fallen substantially. The regression analysis below will explore these differences in more detail.

The bottom panel of table 1 reports the percentage of households in the whole population who apply for a loan, who are given a loan, and who end up reporting they are in arrears. The table shows that 74.4 percent of households in the sample report that they apply for a loan, and that most (but not all) such households will end up borrowing. Given that 71.8 percent of households have a loan this means 96.4 percent of applicants have their loan accepted. The table also shows that 6.9 percent of households end up reporting arrears (this is 9.6 percent of households who borrow).

5 Results

The results are obtained through kernel regressions where the bandwidth has been chosen by cross-validation. Each of the regressions includes income, age, whether the household is in a couple, whether the household head graduated from university, and whether the household self-reports it suffered a significant fall in income over the last year as explanatory variables. Separate results have been estimated for the naive estimate (which assumes all non-borrowers would have repaid), the lender's estimate (which excludes non-borrowers), and the policy estimate (which accounts for whether the household applies for credit and for whether credit is given). The main text will report the results for three of the largest Eurozone countries (Germany, Spain and Italy) while a further nine Eurozone countries have their results discussed in the additional supporting material (although briefly summarised in the main text).

5.1 A Naive Estimate of Repayment

In this section we provide the naive estimate of repayment, which are obtained assuming that all non-borrowers would have repaid. The left-hand side of figure 1 presents the results for age for Germany, Spain and Italy. It plots age on the horizontal axis and the percentage of households that repay on the vertical axis. The estimates for age are obtained by holding income and the other variables at the median of their Eurozone distribution, and calculating the estimated rate of repayment for household heads between the ages of 30 and 60. For each estimate, a 95 percent coverage region (or confidence interval) was estimated, between which the true estimate must lie; the confidence interval has been plotted with dashed lines.

The results show that the rate of repayment typically increases with age. In Germany (the top-left panel), the oldest households are over 2 percent more likely to repay than middle-aged households, who are in turn nearly 3 percent more likely to repay than the youngest households (and these differences are statistically significant). The differences across age-groups in Spain (middle-left) are slightly larger: young Spanish households are over 3 percent less likely to repay than middle-aged households, and nearly 5 percent less likely to repay than the oldest households. In Italy, in contrast, there is no significant difference in the incidence of arrears between middle-aged households and the youngest households. However, those households aged 60 are over 1 percent more likely to repay than households aged 45. The results in the additional supporting material show that there are also differences in the repayment behaviour of households across age-groups in many other Eurozone countries.

The effect of income, shown on the right-hand side of figure 1, are calculated for a household aged 45 (with the other characteristics held at their Eurozone median), with the estimated level of repayment calculated at every 10th centile of the Eurozone income distribution from the 10th to the 90th decile, with additional estimates at the 5th and the 95th decile of the Eurozone income distribution (making 11 income points in the distribution). For each estimate, a 95 percent coverage region (or confidence interval) was estimated, between which the true estimate must lie, and plotted with dashed lines. Using the same income points in all Eurozone countries facilitates the easy comparison of these estimates across countries.

For the naive estimates, which assumes all non-borrowers would have repaid if they had had a loan, there are large and significant differences across all income groups. Middle income households in Germany are nearly 15 percent more likely to repay than those German households at the bottom of the Eurozone income distribution, but over 2 percent less likely to repay than households at the top of the distribution. The differences in Italy are smaller; the richest households are 9 percent less likely to experience arrears than the poorest households. In Spain, the poorest households are significantly different from both middle income households (which are 3 percent more likely to repay) and high income households (which are 4 percent more likely to repay), but middle income and high income households are not significantly different from each other. The results reported in the additional supporting material shows that, for all the other countries included in the analysis, older households are significantly more likely to repay their debts than younger households. Overall, these results show that there are dramatic differences in the effect of income across countries.

Table 2 reports the effect of couple, university, and the self-reported income shock for Germany, Italy and Spain. Couple is not significant any of these three countries, nor in most of the countries included in the additional supporting material. The exceptions, in which couple is significant, are Belgium, Finland, and Portugal. University, in contrast, is significant in each of the three countries included in table 2. University reduces repayment in Germany by nearly 2 percent, by over 1 percent in Italy, and by 1 percent in Spain. The results in the additional supporting material shows that university is also significant in most other Eurozone countries: only in Finland, Netherlands, Luxembourg and Austria is it not significant. The results reported there show that it raises repayment by 3 percent in Belgium, and Ireland, by nearly 7 percent in Greece, and by 2.5 percent on Slovenia. However, University educated households are 3 percent more likely to be in arrears in Portugal.

The self-reported income shock reduces repayment in every country included in the analysis, and the reported effects are often large. For example, table 2 shows that the income shock reduces repayment in Germany by over 5.5 percent and by nearly 7 percent in Spain. The smallest effect is in Italy, where it reduces repayment by 4 percent. The results are similar in the additional countries included supporting material where the largest effect is in Finland at over 16 percent, while the smallest effects are in Greece, Portugal and Slovenia, where the self-reported income shock reduces repayment by around 5 percent.

5.2 The Estimate of Repayment Among Borrowers

In this section, we estimate the drivers of repayment if credit is given by the lender (e.g. the sample of borrowers; the type of data which is typically available from lenders' administrative records). The results for age are reported on the left-hand-side in figure 2. The first thing to notice is that the rate of repayment among households given the loan is estimated to be lower than the naive estimate (which assumed all non-borrowers would have repaid their loan). For example, at age 30, the estimated repayment rate of German households is 91.7 percent in the naive estimate, but is 89.4 percent for the estimate that only includes current borrowers. The other countries (including those reported in the supporting material) show a similar pattern. However, although the estimates are lower than for the naive estimates, they nevertheless otherwise show a very similar pattern.

In Germany, the young are nearly 4 percent less likely to repay than middle-age households, which are over 3 percent less likely to repay than the oldest households in the survey. Austria is very similar to Germany whereby households aged 30 are 3 percent less likely to repay than 45-year-old households, who are over 2 percent less likely to repay than 60 year-old households. In Spain, the effect of age is larger between young and middle-aged households at nearly 3 percent, but smaller between middle-aged and older households, at under 2 percent. Finally, in Italy, there is no significant difference between age groups. The results for the countries reported in the additional supporting material show a similar range of effects. The largest effects are in Finland, where the difference between the oldest and youngest households is 9.5 percent, and in Slovenia, where the difference is nearly 7 percent. In contrast, there are no statistically significant differences across age-groups in Luxembourg, Ireland or Portugal.

The effect of income on repayment for the different Eurozone countries is shown in the right-hand side of figure 2. The results show that there are large differences across income groups, and again the differences are slightly larger when using borrower records compared to the naive estimates in figure 1. In all three countries in figure 2, high income households are significantly more likely to repay than middle-income households, who are, in turn, significantly more likely to repay than low-income households (those at the 10th Eurozone income centile). But while the differences in rates of repayment across income groups are significant, the size of the effect differs between countries. For example, in Germany, the rate of repayment among the lowest income households is 20 percent lower than middle-income households which are over 4 percent lower than among the highest income German households. While in Spain, the lowest income households are nearly 6 percent less likely to repay than middle income households, and 7 percent less likely to repay than the highest income households. The effect of income in Italy is much larger where the poorest are nearly 22 percent less likely to repay than middle income households, which are over 4 percent less likely to repay than the highest income households.

The countries included in the supplementary material also show similar income effects. The Netherlands, Belgium, Greece and Austria also show significant differences between high and middle-income groups and between middle-income and low income groups: the differences between the high and low income groups is between 17.5 percent and 21 percent. Differences across income groups are also significant in Finland, and at 31 percent, are considerably larger. In both Portugal and Slovenia, there are significant differences between the poorest and middle-income households, but these middle income households are not statistically different from higher income households (and the overall difference across income groups is smaller than for the other countries). Finally, in Luxembourg and Ireland, high income households are more likely to repay than middle and low income households, with the overall difference between high and low income households of 8.5 percent in Luxembourg, and 5 percent in Ireland.

The second column of table 2 shows the effect of couple is not significant in Germany, Spain or Italy, but that the effect of university, while small, is significant (it increases repayment by only 1.5 percent in Spain). The effect of the income shock on repayment among borrowers is significant in all three countries and the size of this effect is typically quite large. In Germany, Spain and Italy, experiencing an income shock significantly increase the incidence of arrears by around 7 percent. The supporting material shows the results are mostly similar in the other Eurozone countries. Except in Greece, the effect of university is small (and is not significant in Finland and Austria); while the effect of the income shock is typically larger, in Finland, Ireland, and the Benelux countries it increases by over 10 percent (again Greece is the exception, with the income shock having no effect). While couple has no effect in most countries, it is significant in Belgium, Finland, Greece and Portugal.

5.3 The Estimate of Repayment Among Applicants

The bank, when it makes its lending decision, wishes to understand the propensity to default among applicants. When deciding on whether to give a loan when an application has been made, the lender needs to know their likely repayment behaviour. This means that the estimate must account for the fact that some applicants are not given credit. Estimates of the bank upper bound, bank tightened upper bound, and the bank lower bound are reported in the third-fifth columns of table 2 and the results shown in figure 3. The upper bound assumes all refused credit applicants would have repaid while the lower bound assumes they would have been in arrears: the true estimate must lie somewhere between these two estimates. By assuming that those households whose credit application was rejected are weakly less likely to repay than those households whose application was accepted, we can construct the tightened bank upper bound $\theta^b_{tu}(x)$. If this assumption is satisfied then the true propensity to repay among credit applicants must instead lie between $\theta^b_{tu}(x)$ and $\theta^b_l(x)$. These bounds have been drawn with solid lines in the figures (the upper and tightened upper bounds are often close together). Since these bounds have been estimated, we have also drawn the 95 percent coverage region with a dashed line in these figures. For the upper bound and the tightened upper bound, the dashed line is above the solid line, while for the lower bound the dashed line is below the solid line, hence the 95 percent coverage region is wider than the point estimates of the bounds (the distance between the solid lines).

The effect of age on the propensity to repay among credit applicants is shown in the left-hand side of figure 3. In most countries the upper bound and the tightened upper bound are quite close together, which suggests that assumption 2 does not have much affect on the estimates (although in some cases it will cause the results to become significant). In Germany the estimates are only significantly different when comparing the very youngest households aged 30 with the oldest households aged 60. The size of the effect can calculated by looking at $\theta^b_{tu}(x) - \theta^b_l(x)$ at the different ages. The lower number is the smallest difference we can construct (taking the difference between $\theta^b_{tu}(x)$ at age 30 and $\theta^b_l(x)$ at age 60), while the higher number is the largest difference we can construct (taking the difference between $\theta^b_l(x)$ at age 30 and $\theta^b_{tu}(x)$ at age 60). For Germany, this exercise suggests that households aged 30 are between 4.6 and 8.3 percent less likely to repay than households aged 60. In Spain, young households are significantly different from middle-aged households, which are significantly different from the oldest households. In contrast, there are no significant differences between Italian households at different ages. But this is not surprising, since age was not significant when attention was restricted to borrowers only. The additional supporting material shows a similar range of results. The youngest Dutch households are less likely to repay than the oldest households in the Netherlands, but the difference is only just over 3 percent. In Belgium, while age is not significant when looking at the difference between the upper and the lower bound, since the 95 percent coverage regions overlap for the youngest and oldest households (even though the point estimates do not), the results are significant when looking at the tightened upper bound, with the youngest households between 4.5 percent and 9.5 percent more likely to be in arrears. Similarly, in both Finland and in Slovenia, the oldest households are more likely to repay than households aged 45 or younger. In contrast, there are no significant differences between Luxembourg, Irish, Greek or Portuguese households at different ages. But this is not surprising, since age was not significant when attention was restricted to borrowers only. There is also no significant difference between age-groups in Austria when looking at credit applicants; however, this result is more surprising since there was a difference across age-groups in Austria when attention was restricted to those granted credit. This shows that the selection issue is a non-trivial problem.

The comparison between income levels is shown on the right-hand side of figure 3, taking eleven points in the Eurozone income distribution. The effect of income is is typically larger than the effect of age. The figure shows that at low levels of income the bounds are usually very wide (because a large proportion of these households were refused credit), while at high levels of income the bounds are considerably closer together. For each country, the tightened bound is quite close to the upper bound, hence tightening the bounds in this way makes little difference to the results. In Germany and Italy there are large and significant differences across income groups, with the poorest households much less likely to repay. For example, in Germany, using the tightened bounds, the poorest households are between 23 and 33 percent less likely to repay than the highest income households while in Italy they are between 26 and 34 percent less likely to repay. In Spain, while nevertheless significant, the differences across income-groups are smaller (between 6.5 and 9.2 percent between the lowest and highest income households when looking at the tightened bounds). Moreover, at every income level, Spanish households are more likely to repay than either German or Italian households.

The additional supporting material shows that in the Netherlands, Austria and Finland, high income households are more likely to repay their debts than middle income households, who in turn are more likely to repay than low income households. (In the Netherlands the upper and lower bounds are very close together, meaning the effects are very tightly estimated: the 10th income centile are 18 percent more likely to be in arrears than the 90th Eurozone income centile). In Belgium, households at the 10th income centile are less likely to repay than households at the 50th or the 90th income centiles, and the very richest households more likely to repay than median households when looking at the tightened bounds. In Ireland and in Luxembourg, high income households are more likely to repay than middle and low income households (the difference, using the tightened bounds, between the 10th and 90th centile is between 8 and 16 percent in Luxembourg, and between 4 and 20 percent in Ireland). Greece shows low repayment rates at all income levels, but while high income households show higher repayment rates than middle or low income households, there is no statistically significant difference between households at lower income levels. In Portugal, there is never a difference across income groups in their repayment when looking at the wider bounds, but when looking at the tightened bounds, the 5th Eurozone income centile has higher arrears than middle or higher income households.

The results for couple, university and the income shock are reported in columns 3-5 of table 2. The table shows that couple is not significant in any of the three countries; this is not surprising since couple had not been significant among borrowers and obviously will remain insignificant when including rejected applicants. The effect of university remains significant in Italy and Spain, but including rejected households means the effect of university becomes insignificant Germany. Looking at the tightened bounds, university reduces repayment by between just under 2 percent and 5 percent in Italy; and by around 1.5 percent in Spain. The results of the income shock remain significant among credit applicants in all three countries reported in table 2. In Germany the income shock reduces repayment by 5.4-9.8 percent, in Italy by 3.9-9.0 percent, and in Spain by 7.2-7.9 percent. The results are similar in those countries whose results are reported in the additional supporting material. The effect of couple remains significant only in Finland, while the effect of university remains significant in Belgium (where it raises arrears by between 4.4 percent and 8.8 percent) and in Slovenia (where the estimated effect is between 3 and 4 percent). The effect of the income shock are significant in most countries; in Belgium, the Netherlands, Finland and Luxembourg the income shock increases arrears by over 10 percent, but is much smaller in Ireland, Austria and Slovenia. In Portugal and in Greece, the income shock does not have a significant effect on repayment (although the tightened upper and the lower bounds do not overlap in Portugal, the 95 percent coverage regions do overlap).

5.4 An Estimate of the Underlying Propensity to Repay

Arguably, the most important quantity to estimate is the underlying propensity to repay among all households, which includes those households that do not apply for credit. For example, in order to estimate the effect of changes in the policy environment on arrears we need some assessment of how the pool of applicants changes as policy changes. The policy relevant estimate thus requires an assessment of the underlying propensity to repay among all households regardless of whether the household made an application for credit, or if that application was accepted. An upper and a lower bound on the propensity to repay can be constructed by assuming all non-borrowers would have repaid (for the upper bound θ_u), or that they would all have experienced arrears (for the lower bound θ_l). Estimates for these bounds are shown using a dashed line in figure 4. The last four columns of table 2 also present the upper and the lower bounds for the estimates of arrears (and the associated bootstrapped 95 percent coverage regions). A problem, however, is that the bounds (and the associated coverage regions) are typically rather wide. This means the coverage regions invariably overlap when we compare the highest and lowest income households; when we compare the oldest and the youngest households; when we compare married to single households, whether the household is university educated, or if it suffers a negative income shock. Consequently, for all countries (including those for which results are only reported in the online supplementary material), the estimates of the effect of the five variables are never significant when using the upper and the lower bound.

To tighten these bounds we can assume that rejected households are weakly less likely to repay than households whose application was accepted, and that non-applicant households are weakly more likely to repay had they received a loan than those households who actually received credit. Note that using the alternative assumption, that credit applicants are weakly worse risks than non-applicants (e.g. using $\theta_l^b(x)$ rather than $\theta_{tl}(x)$ for the tightened lower bound) gives very similar results. Results for the tightened upper bound $\theta_{tu}(x)$ and the tightened lower bound $\theta_{tl}(x)$ are shown in table 2, and displayed in figure 4 as solid lines. Tightening the bounds (particularly tightening the lower bound) makes a substantial difference as they narrow the coverage regions and allow the effect of the variables to be significant. Hence we will concentrate on describing these results.

The tightened upper bound and tightened lower bound on the effect of age on the underlying propensity to default are shown with solid lines on the left-hand side of figure 4. In Spain the youngest households are significantly more likely to experience arrears than the oldest households, with the effect estimated to be between 4.7 and 5.5 percent. However, age is not significant in either Germany or Italy. The effect of income is shown on the right-hand side of figure 4. German households at the 10th centile of the Eurozone income distribution are significantly different from middle-income households, which (comparing the 40th to the 95th centile) are significantly different from high income households. In Italy, only the very richest households are less likely to be in arrears than the very poorest households. In Spain, while the point estimates of the tightened upper and tightened lower bounds do not overlap when comparing the high income and the low income households, the 95 percent coverage regions do overlap, and hence we can not confirm than income has a significant affect on arrears. The results in last four columns of table 2 show that neither couple nor university are significant for any of the three countries included in the table. However, the income shock significantly reduces repayment among Spanish households, where the size of the effect is estimated to be between 5.9 and 8.2 percent.

The results for those countries reported in the supplementary material are similar. The only country for which age is significant is Finland (where the youngest households are 7.4-12.2 percent more likely to be in arrears than the oldest households). In contrast, most countries show significant differences between different income groups. The exceptions are the Netherlands, Ireland and Portugal, since although the point estimates of the tightened upper and tightened lower bounds do not overlap when comparing the high income and the low income households, the 95 percent coverage regions do overlap, and hence we can not confirm than income has a significant affect on arrears in these countries. The income shock is only significant in the Netherland and Finland, where the size of the effect is between 6.5-14.3 percent in the Netherlands, and 13.4-20.5 percent in Finland. The results reported in this section contrast with the naive estimates (which implicitly assume that non-borrowers would have repaid), or with the estimates using only borrowers, showing the importance of the key assumptions contained in those estimates if they are to be interpreted as estimates of the underlying repayment behaviour of households.

5.5 Differences Across Eurozone Countries

Having estimated the underlying propensity to repay in different Eurozone countries, we can investigate whether there are differences in the propensity to repay between particular countries. If we concentrate on the tightened upper bound and the tightened lower bound, we find there is no difference in the propensity to repay of households in Germany and households in Italy at each age level and each income level. However, German households differ from Spanish households. Our estimates show that for middle-aged and older households, German households are more likely to experience arrears than Spanish households (the confidence region does not overlap for households between the ages of 45 and 57). There are also differences across income groups: Spanish households are more likely to repay on schedule than German households for those households between the 10th and the 70th centiles of the Eurozone income distribution. Similarly, German households are also more likely to repay than Greek households for households between the 30th and 80th centile of the income distribution and at all age-groups from age 33 to age 60. These results affirm that differences in behaviour between countries play an important role in explaining arrears.

6 Conclusion

Several papers have estimated the factors causing households to experience arrears. Many studies have used survey data on a random sample of the population; others have used administrative data provided by a lender. This paper discusses the different estimates that are current in the literature. We believe there is considerable confusion over the interpretation of these different estimates, because each makes important (and implausible) assumptions about households who do not receive a loan. Naive estimates of repayment are typically obtained with representative samples of the household population and make silent the assumption that households who do not receive credit would have repaid their debts had they had credit. Estimates relying on lenders administrative records typically ignore those households who are refused credit, and hence implicitly assume they behave exactly like those given credit. Because these estimates ignore the selection problem (as not all households currently borrow), both estimates are likely to seriously over-estimate the repayment of households. Just as seriously, because the implicit assumptions behind each of these estimates differs, the estimates will also differ, even when both purport to estimate the same underlying probability of arrears.

This paper discusses how to construct several different estimates of arrears, which have important, albeit different, economic interpretations. The simplest estimate is a calculation of the probability of arrears among existing borrowers, which is important when lenders want to manage the risk profile of their outstanding loans. A second useful estimate arises when the bank makes their lending decision and thus wants to construct an estimate of the likely arrears behaviour of credit applicants. Lastly, and a key contribution of this paper, the policy-maker wants to know how changes in the regulatory environment will change the underlying propensity to default of households. (As an example, the US policy debate on the role of lending criteria contained in Foote *et al.*, 2010, recognized that the lender's decision to foreclose was endogenous, but ignored the endogeneity of the original decision to lend). While there are several attempts in the literature to properly estimate the propensity to arrears among loan applicants (see Boyes, Hoffman, and Low 1989, Karlan and Zinman 2009, or Grant and Padula 2013), to the best of our knowledge, no previous paper has estimated the underlying propensity to repay using household survey data, which accounts for applicant and lender behaviour. The paper which comes nearest to capturing our concept of the propensity to default is Guiso *et al.* (2013), who try to capture this underlying propensity to default by asking hypothetical questions to a random sample of US households, and changing the household's hypothetical circumstances; but they restricted attention to existing homeowners, while our study explores the underlying arrears behaviour of the household regardless of whether the household has a loan.

This paper uses data from EU-SILC to construct estimates of each of the different quantities that have previously been reported in the literature on default, before it constructs bounds on the true incidence of arrears among credit applicants and among the whole population. Moreover, it discusses how simple, and plausible, assumptions about the behaviour of lenders and borrowers can narrow these bounds. When estimating the propensity to default, assuming rejected applicants are less likely to repay than accepted households tightens the upper bound, while assuming that households who received credit are weakly less likely to default than households who did not apply tightens the lower bound. An alternative, and easily implementable assumption that tightens the lower bound is to assume that credit applicants are weakly more likely to default than non-applicants. In this case, the tightened lower bound will be the same as the lower bound used for the estimate using applicant data only.

Our estimates focus on the effect of age, income, couple, a university education and an income shock on repayment. We show that the existing literature is likely to draw incorrect inference about default behaviour, and to over-estimate how likely households are to repay. The level of arrears is an important variable if, for example, lenders are deciding which households should receive credit; or government wants to know the likely costs of supporting debtor households when the regulatory environment changes. The paper also shows that the importance of explanatory variables is likely to be mis-understood: our results for the Eurozone countries, for example, showed that using the naive estimate (which assumes all non-borrowers would have repaid), university educated households are less likely to experience arrears, but the true estimate of the underlying propensity to repay showed that university was no longer significant. Our results also showed that there were differences in the underlying propensity to default between German and Spanish households (e.g. after accounting for the selection effects involved in the decision to apply and to lend). This suggests that policy may have to be different in the two countries to account for differences in underlying behaviour. It also suggests that future research could usefully try to explain these differences between countries.

Finally, we hope this paper motivates researchers and policy-makers to give considerably more thought to what exactly they are estimating, and to what they exactly want to estimate. In particular, our results suggest there should be more attention given to how the propensity to default is inferred from actual arrears. For example, the lender, when computing the value-at-risk (relevant to regulators under the Basel accord), wants to know arrears among current borrowers; but when making the lending decision, it wants to know the rate of arrears among applicants. Policy-makers want to know how policy affects default behaviour in the whole population (as well as how lenders will change their lending behaviour is response to changes in policy). Hence the key estimate of interest, when discussing policy changes, is to understand the underlying propensity to default (even if the other estimates are also potentially sensitive to these changes). We believe future research investigating arrears should, if it wants to be useful, be clear about which of these problems the estimate is attempting to address.

References

Berkowitz, J., and R. M. Hynes, 1999, "Bankruptcy Exemptions and the Market for Mortgage Loans," Journal of Law and Economics, 42, 809–830.

Blundell, R., A. Gosling, H. Ichimura, and C. Meghir, 2007, "Changes in the Distribution of Male and Female Wages Accounting for Employment Composition Using Bounds," Econometrica, 75(2)(2), 323–363.

Boheim, R., and M. P. Taylor, 2000, "My home was my castle: Evictions and repossessions in Britain," Journal of Housing Economics, 9, 287–319.

Bowman, A. W., and A. Azzalini, 1997, Applied Smoothing Techniques for Data Analysis: The Kernel Approach with S-Plus Illustrations. Oxford University Press, Oxford, UK.

Boyes, W. J., D. L. Hoffman, and S. A. Low, 1989, "An econometric analysis of the bank credit scoring problem," Journal of Econometrics, 40(1), 3 – 14.

Bridges, S., and R. Disney, 2004, "Use of credit and arrears on debt among low income families in the United Kingdom," Fiscal Studies, 25(March), 1–25.

Campbell, J. Y., 2012, "Mortgage Market Design," Journal of Finance, 17, 1–33.

Campbell, J. Y., and J. F. Cocco, 2011, "A Model of Mortgage Default," NBER Working Papers 17516 17516, National Bureau of Economic Research.

Dell'Arricia, G., D. Igan, and L. Laeven, 2012, "Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market," Journal of Money, Credit and Banking, 44, 367–384.

Demyanyk, Y., and O. V. Hemert, 2011, "Understanding the Subprime Mortgage Crisis," Review of Financial Studies, 24(6), 1848–1880.

Domowitz, I., and R. Sartain, 1999, "Determinants of the Consumer Bankruptcy Decision," Journal of Finance, 54, 403–420.

Duygan, B., and C. Grant, 2009, "Household Arrears: What Role do Institutions Play?," Economic Policy, 57, 107–140.

Fay, S., E. Hurst, and M. J. White, 2002, "The Household Bankruptcy Decision," American Economic Review, 92(6), 706–718.

Foote, C. L., K. Gerardi, L. Goette, and P. S. Willen, 2010, "Reducing Foreclosures: No Easy Answers," NBER Macroeconomics Annual 2009, 24, 89–138.

Foote, C. L., K. Gerardi, and P. S. Willen, 2008, "Negative Equity and Foreclosure: Theory and Evidence," Journal of Urban Economics, 64(2), 234–245.

Grant, C., and M. Padula, 2013, "Using Bounds to Investigate Household Repayment Behaviour," Research in Economics, 64, 336–354.

Gross, D. B., and N. S. Souleles, 2002, "An Empirical Analysis of Personal Bankruptcy and Delinquency," Review of Financial Studies, 15(1), 319–347.

Guiso, L., P. Sapienza, and L. Zingales, 2013, "The Determinants of Attitudes toward Strategic Default on Mortgages," Journal of Finance, 68, 1473–1515.

Härdle, W., P. Hall, and J.S.Marron, 1988, "How Far Are Automatically Chosen Regression Smoothing Parameters From Their Optimum?," Journal of the American Statistical Association, 83(401), 86–95.

Jacobson, T., and K. Roszbach, 2003, "Bank lending policy, credit scoring and value-at-risk," Journal of Banking and Finance, 27(4), 615–633.

Karlan, D., and J. Zinman, 2009, "Observing Unobservables: Indentifying Information Asymmetries with a Consumer Credit Field Experiment," Econometrica, 77(6), 1993–2008.

Manski, C., 1989, "The anatomy of selection problem," Journal of Human Resources, 24, 343–360.

——— , 1990, "Nonparametric bounds on treatment effects," American Economic Review, 80, 319–323.

Manski, C., and J. V. Pepper, 2000, "Monotone Instrumental Variables, with an Application to the Returns to Schooling," Econometrica, 68(4), 997–1012.

Mayer, C., K. Pence, and S. M. Sherland, 2009, "The Rise in Mortgage Defaults," Journal of Economic Perspectives, 23(1), 27–50.

Mian, A., and A. Sufi, 2009, "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis," The Quarterly Journal of Economics, 124(4), 1449–1496.

Pagan, A., and A. Ullah, 1999, Nonparametric Econometrics. Cambridge University Press, Cambridge, UK.

Table 1. Summary Statistics

	All Households		Borrowers Who Repay		Borrowers In Arrears	
	mean	sd	mean	sd	mean	sd
income	30,828	25,590	35,296	28,205	20,384	15,437
age	44.9	8.5	44.7	8.4	43.4	8.1
couple	0.72	0.44	0.76	0.42	0.62	0.48
university	0.31	0.47	0.38	0.49	0.21	0.41
income fall	0.19	0.40	0.17	0.38	0.35	0.47
Applications (%)	74.4					
Acceptances (%)	71.8					
Arrears (%)	6.9					

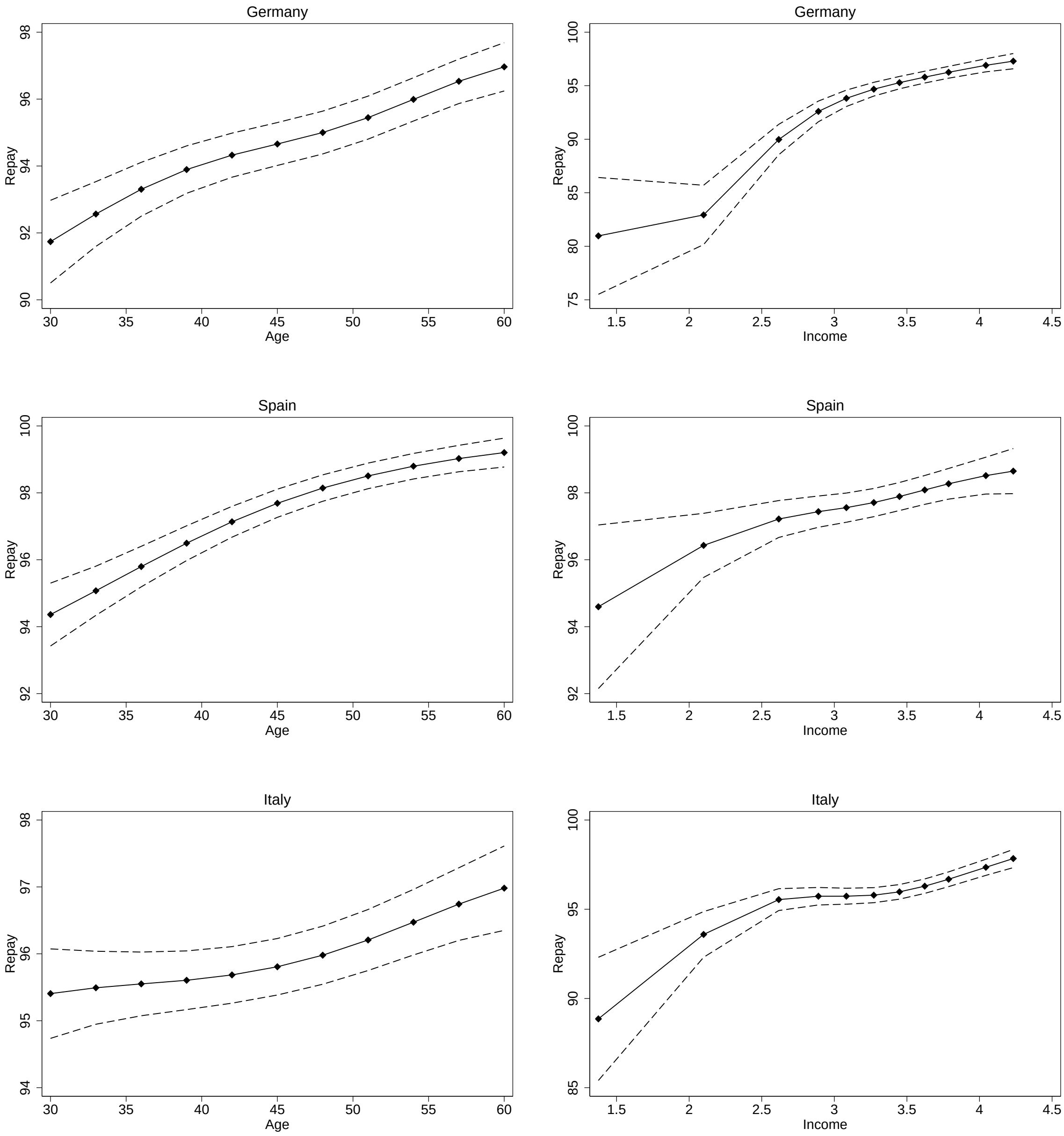
Note: Authors own calculations using 2008 wave of EU-SILC. Income is defined as the sum of labour income and transfers, less labour taxes (measured in annual euros). The table also reports the proportion of households headed by a couple, where the head attended university, and which reported a significant fall in income.

Table 2. Estimates of Repayment in Germany, Spain and Italy

	Naive	Borrow	Applicants			Propensity			
			Upper Bound	Tight Upper	Lower Bound	Upper Bound	Tight Upper	Tight Lower	Lower Bound
Country: Germany									
Couple									
0	94.75	93.25	93.47	93.25	90.23	94.72	94.55	90.80	72.64
	[95.63 93.87]	[94.38 92.12]	[94.56	[94.38	88.93]	[96.49	[96.36	88.31]	69.10]
1	94.65	93.24	93.34	93.24	91.77	94.62	94.54	92.02	73.71
	[95.30 94.00]	[94.06 92.42]	[94.14	[94.06	90.89]	[95.91	[95.85	90.37]	71.20]
Income Shock									
0	94.66	93.23	93.34	93.23	91.77	94.62	94.54	92.02	73.70
	[95.30 94.01]	[94.04 92.43]	[94.14	[94.04	90.89]	[95.91	[95.84	90.38]	71.19]
1	88.94	86.38	86.85	86.38	83.42	88.83	88.44	83.75	69.93
	[90.80 87.08]	[88.62 84.14]	[89.04	[88.62	81.01]	[92.68	[92.39	78.97]	64.64]
University									
0	94.66	93.24	93.34	93.24	91.77	94.63	94.54	92.02	73.72
	[95.30 94.01]	[94.04 92.43]	[94.14	[94.04	90.89]	[95.92	[95.85	90.38]	71.20]
1	96.51	95.56	95.57	95.56	94.58	96.46	96.42	94.74	75.42
	[97.13 95.89]	[96.35 94.78]	[96.36	[96.35	93.72]	[97.68	[97.66	93.09]	72.55]
Country: Italy									
Couple									
0	96.66	93.62	93.75	93.62	92.51	96.53	96.49	92.77	48.86
	[97.31 96.00]	[94.83 92.41]	[94.95	[94.83	91.22]	[97.82	[97.79	90.33]	44.89]
1	95.78	92.29	92.49	92.29	90.42	95.61	95.52	90.92	50.40
	[96.21 95.36]	[93.05 91.54]	[93.23	[93.05	89.59]	[96.58	[96.51	89.18]	47.96]
Income Shock									
0	95.79	92.33	92.44	92.33	90.40	95.58	95.49	90.90	50.29
	[96.21 95.37]	[93.09 91.57]	[93.18	[93.09	89.57]	[96.47	[96.40	89.28]	48.08]
1	91.52	85.50	86.02	85.50	83.31	92.02	91.80	84.89	49.99
	[92.34 90.71]	[86.85 84.15]	[87.32	[86.85	81.90]	[93.45	[93.27	82.51]	47.39]
University									
0	94.34	91.84	92.02	91.84	89.81	94.80	94.66	90.77	63.32
	[94.91 93.77]	[92.65 91.02]	[92.81	[92.65	88.93]	[95.43	[95.41	88.78]	62.41]
1	95.78	94.75	94.82	94.75	93.86	96.05	95.99	93.76	73.57
	[96.54 95.01]	[95.71 93.79]	[95.76	[95.71	92.84]	[96.79	[96.74	92.91]	71.68]
Country: Spain									
Couple									
0	97.52	97.13	97.16	97.13	97.01	97.53	97.53	97.11	85.08
	[98.65 96.38]	[98.41 95.84]	[98.45	[98.41	95.70]	[99.06	[99.06	95.35]	81.42]
1	97.71	97.33	97.35	97.33	97.13	97.70	97.69	97.19	84.20
	[98.14 97.29]	[97.82 96.84]	[97.84	[97.82	96.63]	[98.54	[98.54	96.19]	82.09]
Income Shock									
0	97.71	97.33	97.34	97.33	97.16	97.66	97.65	97.15	84.12
	[98.13 97.28]	[97.82 96.85]	[97.82	[97.82	96.66]	[98.49	[98.49	96.17]	82.06]
1	91.24	89.96	90.01	89.96	89.40	91.26	91.20	89.46	78.63
	[92.49 89.99]	[91.36 88.55]	[91.40	[91.36	87.96]	[93.83	[93.79	86.46]	75.20]
University									
0	97.71	97.32	97.30	97.32	97.17	97.69	97.69	97.18	84.15
	[98.14 97.29]	[97.81 96.84]	[97.79	[97.81	96.66]	[98.53	[98.52	96.19]	82.06]
1	98.97	98.88	98.87	98.88	98.87	98.95	98.95	98.84	91.18
	[99.35 98.59]	[99.28 98.48]	[99.27	[99.28	98.46]	[99.59	[99.59	98.14]	88.97]

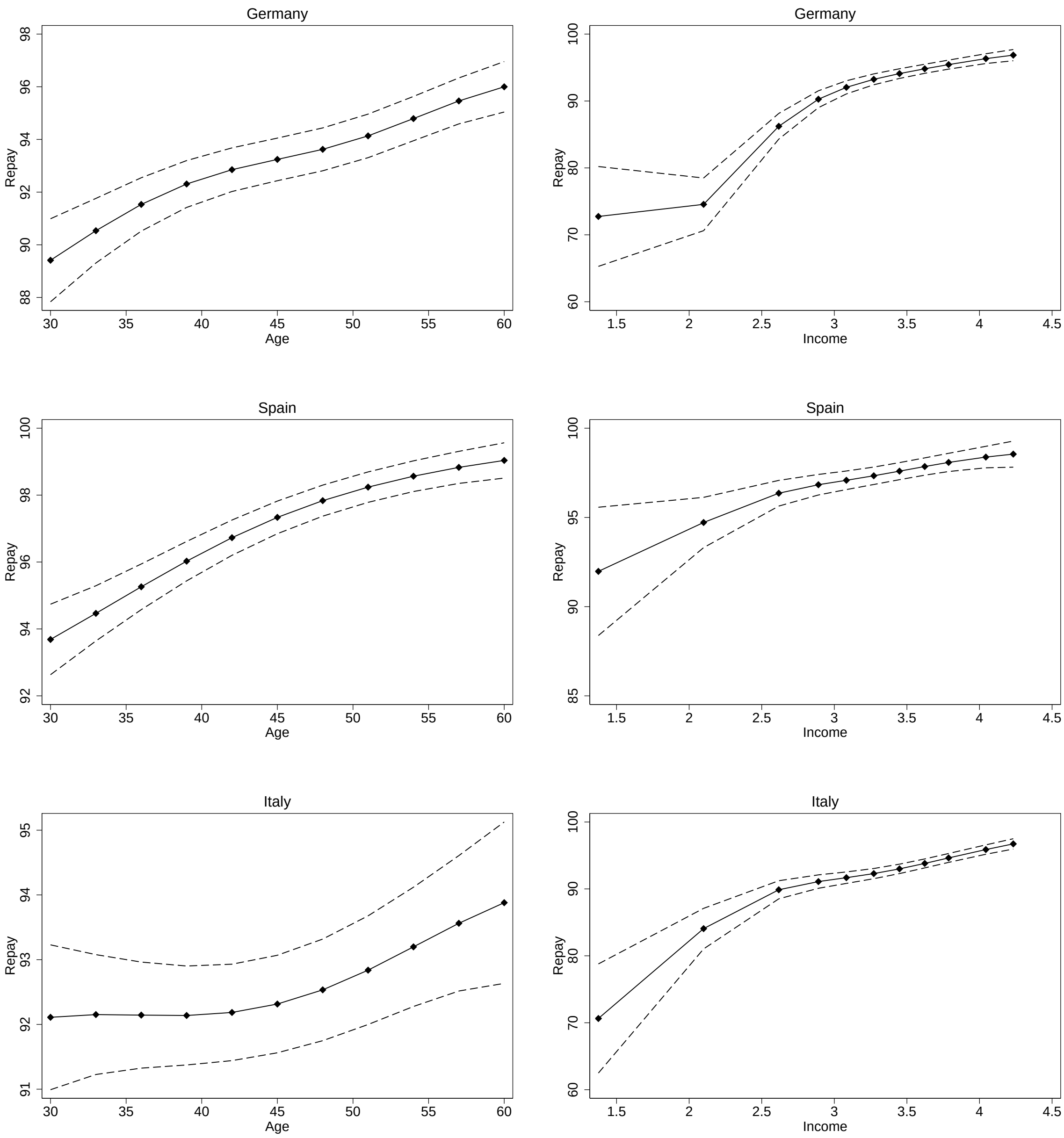
Note: The naive estimate assumes that all those households who do not have credit would have repaid their debts. The second column looks at arrears among households who actually receive credit. For the estimates of the propensity to repay among credit applicants, the upper bound assumes all applicants refused credit would repay; the lower bound assumes all applicants refused credit would not repay; the tightened upper bound assumes the applicants refused credit are weakly less likely to repay than applicants given credit. For the estimates of the propensity to repay among all households, the upper bound assumes all households without credit would repay; the lower bound assumes all applicants without credit would not repay. The 95 percent confidence interval or confidence region is shown in brackets below the estimates.

Figure 1. The Naive Estimate of the Effect of Age and Income on Repayment



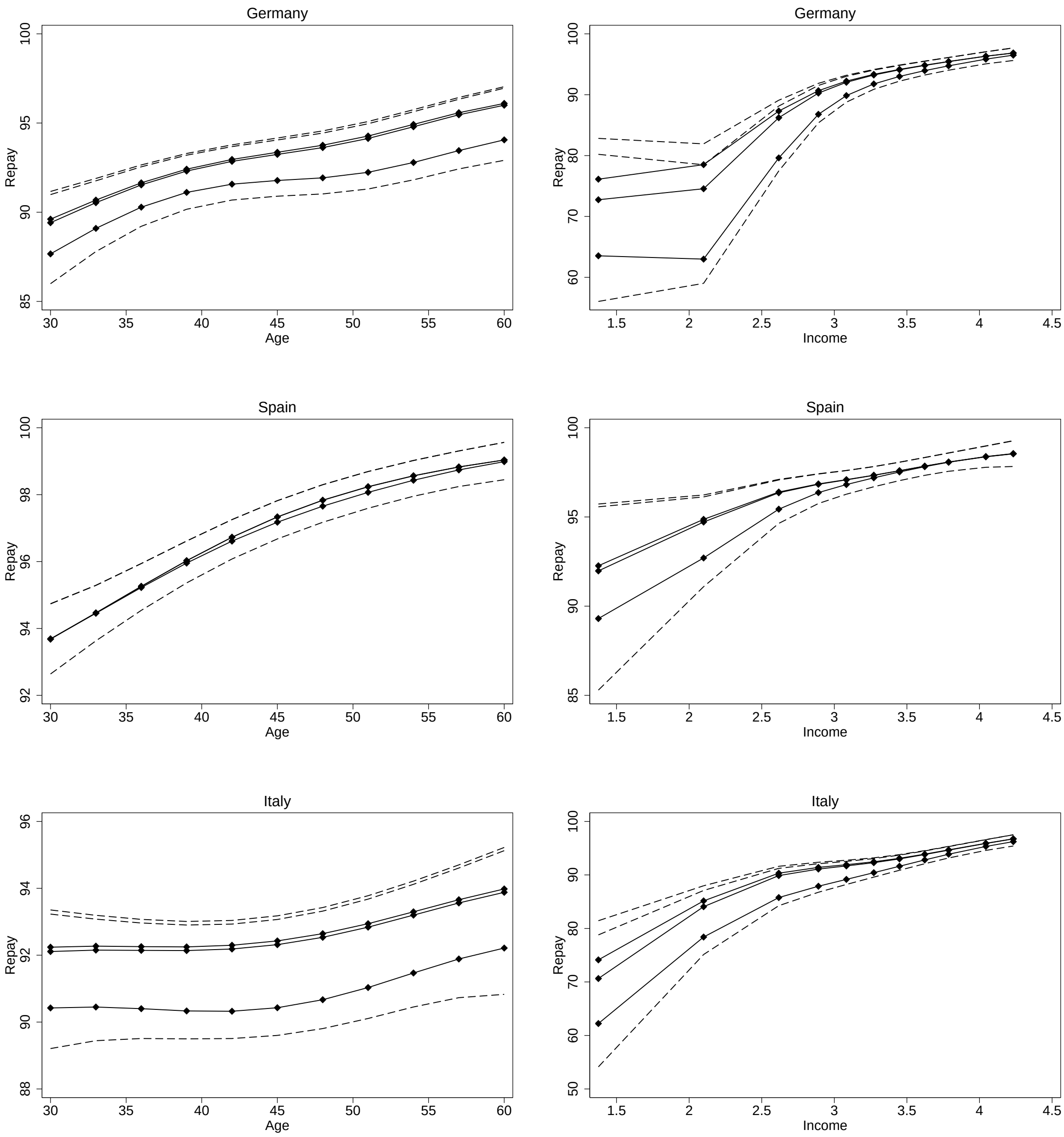
Note: Solid lines show the kernel estimates of the naive estimate of the percentage of households that repay (vertical axis) which assumes households who do not have a loan would have repaid. The left-hand side shows the effect of age on repayment, while the right-hand side shows the effect of income. Estimates for income are at eleven centiles of the Eurozone income distribution (where log-annual income/10000 is marked on the horizontal axis). Confidence intervals are drawn with dashed lines.

FIGURE 2. The Effect of Age and Income on Repayment If Given Credit



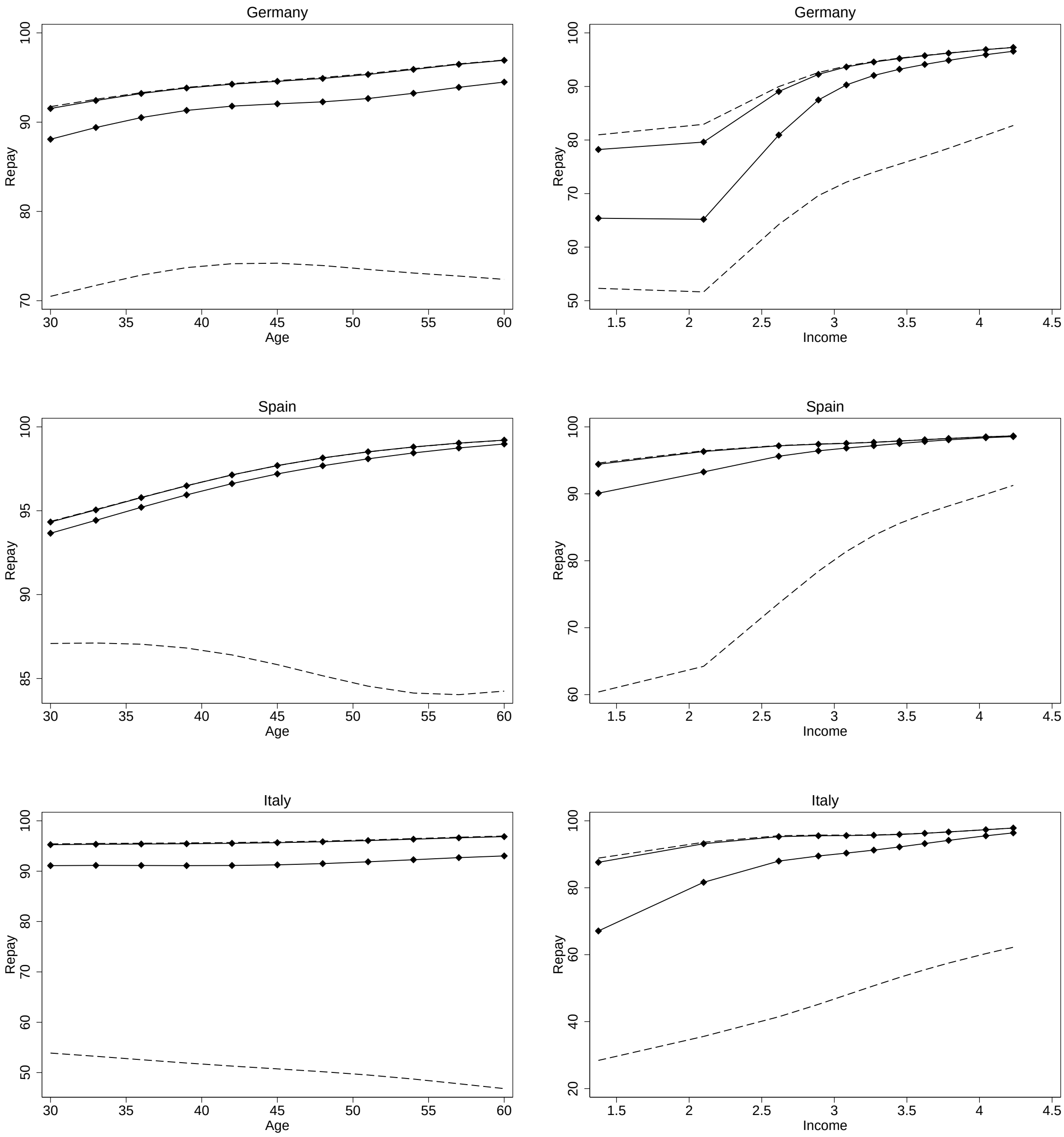
Note: Solid lines show the kernel estimates of the percentage of households that repay (vertical axis) among borrowers. The left-hand side shows the effect of age on repayment, while the right-hand side shows the effect of income. Estimates for income are at eleven centiles of the Eurozone income distribution (where log-annual income/10000 is marked on the horizontal axis). Confidence intervals are dashed.

Figure 3. The Effect of Age and Income on The Propensity to Repay if Applied for Credit



Note: These figures report kernel estimates of the propensity to repay (vertical axis) among credit applicants. The left-hand side shows the effect of age on repayment, while the right-hand side shows the effect of income. Estimates for income are at eleven centiles of the Eurozone income distribution (where log-annual income/10000 is marked on the horizontal axis). Solid lines show upper, tightened upper, and lower bounds for the estimates (confidence regions are dashed).

Figure 4. The Effect of Age and Income on the Propensity to Repay



Note: These figures report kernel estimates of the underlying propensity to repay (vertical axis) among all households. The left-hand side shows the effect of age on repayment, while the right-hand side shows the effect of income. Estimates for income are at eleven centiles of the Eurozone income distribution (where log-annual income/10000 is marked on the horizontal axis). Dashed lines show basic estimates of upper and lower bounds, solid lines show tightened upper and tightened lower bounds.