Does the Good Matter?

Evidence on Moral Hazard and Adverse Selection from Consumer Credit Market

Preliminary draft, Please do not cite

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January 15, 2007

Abstract

Default rates on instalment loans vary with type of the good purchased. This variation persists even after controlling for contract and consumer-specific characteristics. Using an Italian dataset of instalment loans between 1995-1999, we explore whether such variation is due to unobserved heterogeneity and selection (adverse selection) or due to the effect of the specific features of the good (moral hazard). We exploit the data on multiple contracts per individual to disentangle the two effects, and find that most of the variation is explained by selection. Individuals who buy motorcycles on credit are more likely to default on any loan, while those buying kitchen appliances and furniture units are more likely to repay, compared to average.

Keywords: consumer credit, default, adverse selection, moral hazard
JEL classification: D12, D14, D82

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1 Introduction

Why should loan to buy a fridge be repaid with a higher probability than loan to buy a motorcycle? It has been observed that similar instalment loans which finance purchases of different types of goods differ in the incidence of default. Table 1, which summarizes the repayment behavior on borrowers' first contracts with Findomestic Banca, a leading Italian bank, over the period 1995-1999, shows there is considerable variation among the default rates of loans financing different goods. Mobile phones, motorcycles and used cars are repaid least often, while furniture, kitchen appliances and new cars are at the other end of the repayment spectrum. The observed default rates range from 10 % to 2 %. We first show that the differences persist even after controlling for numerous contract-specific and consumer-specific factors, as well as for the potential selection bias due to the fact that default is observed only for those loan applications that have been accepted.

The remaining variation in default rates across goods, conditional on the observable borrower and contract characteristics and on the acceptance decision, may be explained by two different mechanisms, the selection effect and the good effect. The *selection effect* suggests that people who are more prone to defaulting are more likely to buy on credit certain goods such as motorcycles or mobile phones rather than other goods, while people who typically repay their loans are more likely to buy other types of goods on credit. The resulting variation in the default probability is then due to the unobserved individual heterogeneity and the selection of individuals with different repayment behavior to different types of goods. The variation in the default rates across different goods' categories then simply reflects the variation in the average level of repayment behavior among people buying specific type of goods on credit.[1]

On the other hand, the *good effect* may be present even when individuals are homogenous in their default inclinations, and suggests that it is the specific features of the good that affect the incentives to repay, such as high depreciation rate or low penalty for defaulting.

The aim of this paper is to bring evidence on which of the two mechanisms, whether the selection or the good effect, stand behind the observed variation in the default rates, and if both (which is not unlikely), which of the two dominates. Is it the specific features of the good, or rather the specific

[1] The present analysis considers only credit financed purchases of the goods. Consumer's choice whether to buy a good on credit or not, and which types of goods to buy on credit, is highly relevant but disregarded here due to data limitations. We discuss the potential implications of this omission on our results later.

Table 1: Default Rates per Good - Ranked in Descending Order

Good	Default Rate	No. of Contracts
Telecommunication	10.03%	14,090
Motorbikes	6.58%	9,841
(Used) Cars and Motor Homes	6.53%	2,357
Electr. Equipment (Brown Goods)	6.09%	26,376
Other	4.81%	8,131
Computers	3.98%	3,062
Furniture Units	3.75%	4,504
White Goods (Kitchen Appliances)	3.70%	5,454
New Cars and Motor Homes	2.10%	4,434

Source: Data described in Section 3, first observed contracts only.

features of the individuals who buy the good, what explains the observed differences in the default rates? E.g., is it the case that people who often don't repay their debts buy motorcycles on credit more often, or is it something about the motorcycles which makes their owners to not repay? Phrased in the standard microeconometric terminology: is it the good-specific causal effect that drives the variation in the default rates across different types of goods, or the selection effect related to the individual heterogeneity in the default behavior? Using terminology from the asymmetric information literature: is it the contract(good)-specific effect (*moral hazard*), or the fact that individuals with different default inclinations sort themselves to buy on credit different goods (*adverse selection*)? The present paper's objectives is to disentangle the two mechanisms, without giving them an explicit interpretation as to how they work. However, we do summarize our conjectures about the two mechanisms in this introduction and will invoke them again when interpreting our results.

Certain types of products, such as motorcycles, may be preferred by risk-loving individuals (e.g. young, single, renters in terms of the observed characteristics), who also tend to repay their loans less often on average. Other types of goods, such as household equipment, are likely to be purchased by more risk-averse individuals, those who have or are about to start a family, who are home owners etc. and who tend to repay their debts, compared to the average. The risk-association of particular types of goods and the positive correlation between risk aversion and repayment behavior may establish the observed patterns, as caused purely by the *selection effect*.

As for the *good effect*, two types of a good's characteristics may have impact on the repayment incentives. The first is related to the extent and duration of the utility the good brings to the consumer, as reflected by the rate with which the good depreciates. This may be given either by technical features of the good (its lifetime and how easily it breaks down), or to changes in preferences (especially in the case of goods that are highly subject to fashion). High depreciation rate and therefore high turnover of the good - if it easily breaks down or quickly becomes old-fashioned - is likely to reduce the incentives to repay. The second feature is related to the cost of default, namely the probability of punishment, i.e. the likelihood that the good, if not repaid, will be repossessed by the lender. The size and mobility of the good have effect on whether it can be repossessed easily, and the existence and efficiency of a second-hand market for that particular good affect the incentives of the lender to repossess it or not. New car is an example of the good that can be easily identified (due to compulsory car registration) and repossessed, and at the same time is worth repossessing, as it can be immediately sold on a used-car market.

There is both theoretical and empirical research on the optimal repayment decision. Papers like Wang and White (2000) study the decision to file for a bankruptcy, other papers consider the decision to default on a particular loan. However, to our knowledge, none of these works link the decision to default on an instalment loan to the kind of the good that has been financed by that loan. There are a few exceptions that mention the features of the good or its market as important. Iossa and Palumbo (2003, 2004) suggest that a default on the instalment loan when the product is defective establishes incentives for finance institutions to share product-failure responsibility. The authors show that such lender liability in consumer credit transactions helps to prevent market failure due to informational asymmetry between sellers and buyers about the product's quality.

We use an administrative dataset of instalment loan contracts of a leading Italian bank (Findomestic Banca) between 1995 and 1999 to estimate a model of the default probability. Multiple contracts per individual are observed, which allows us to disentangle the selection effect from the good effect. We use information about rejected applications to control for the potential bias due to the fact that default is observed only for those loan applications that have been accepted.

We find that most of the residual variation in default rates across the different goods, after controlling for the observable borrower and contract characteristics and for the acceptance decision, is due to individual heterogeneity and *selection*. Our results suggest that individuals who buy motorcycles are more likely than an average person to default on any type of loan. On the other hand, individuals who buy kitchen appliances and furniture units are less likely to default on their loans compared to the average. New cars and mobile phones are two types of goods where the good effect seems to matter as well, reducing the repayment probability in the earlier case and increasing it in the latter. Given that the contract terms vary only with the goods but not with individuals, the results show that there exists a cross-subsidy from the repaying individuals, when they buy a good that has a high average default rate, towards those who don't repay. We conclude that conditions of the loan should not depend only on the type of the good being purchased but also on the good-related type of the individual who applies for the loan. It also follows that previous loan applications may be used by credit-granting companies as an additional piece of information about the propensity to default even without or prior to observing the repayment behavior on the first loan.

The paper is organized as follows. The introduction is followed by a section that defines the specification of the problem and a section that describes the data. Econometric methodology is presented in the section that follows. Next comes the descriptive statistics and an overview of our main results. Finally, we discuss the sensitivity of our results and conclude. The Appendix contains definition of the key variables, full estimation results, and the results of the sensitivity analysis.

2 Specification of the Problem

An individual applies for an instalment loan to purchase a certain good and his application is accepted. His repayment behavior is assumed to follow Equation 1. D^*_{ijg} represents the unobserved propensity of an individual i to default on contract type j financing a purchase of the good g.

$$D^*_{ijg} = X_i\beta + Z_j\gamma + \delta_g + \mu_i + \varepsilon_{ij} \tag{1}$$

$D_{ijg} = (D^*_{ijg} > 0)$ is an indicator whether an individual i defaulted on a contract j financing good g

X_i is vector of individual-specific characteristics (such as disposable income, employment status, job tenure, home ownership, demographic characteristics etc.)

Z_j is vector of contract-specific characteristics[2] (such as length of the contract, size of the loan, interest rate, price of the good etc.)

[2] Similar to our data, contract characteristics are not person specific.The terms of the contract are posted next to the good to be purchased.

δ_g is an indicator of the good g being purchased (goods' fixed effects)[3]

μ_i is unobservable individual-specific heterogeneity (individual fixed or random effects)

ε_{ij} is iid error term assumed to be independent of all the RHS variables

There are I individuals, up to J contracts, and up to G types of goods. An observational unit is a "person-contract". Should all individuals have the same number of contracts J, the sample size would be $I * J$.

When only one contract is observed per person, the sample consists of I observations. Including a dummy variable for each type of good (δ_g) reveals some information about the size and significance of the "reduced form" effects of different types of the goods on the probability of default. It also shows whether the variation in the default probability across different types of the goods persists even when conditioning on the contract-specific and individual-specific characteristics.

If there is no unobservable individual heterogeneity (μ_i) in the default behavior, or if this heterogeneity is distributed randomly across the goods that the individuals buy and finance through credit (namely $E(\mu_i/g) = E(\mu_i)$ and μ_i is independent of the RHS variables), the estimated good-specific coefficients can be interpreted as the "structural" causal *good effects*, i.e. an effect a particular good has on the individuals' repayment behavior.

If this is not the case ($E(\mu_i/g) \neq E(\mu_i)$), it means that individuals with different unobservable default propensity buy different types of goods. This could fully explain the remaining variation in the default probability across different goods as captured by the estimated good-specific dummy variables. The dataset with one contract per person doesn't allow to control for μ_i directly. One possibility is to correct for the good-specific selection bias by estimating a multinomial model of the choice of the good to be bought on credit, together with the equation for the default probability (Equation 1). However, this approach rests on strong distributional assumptions and requires exclusion restrictions that are often hard to find.

Observing multiple contracts per individual allows to control for individual heterogeneity in an easier way, as multiple contract data helps the estimation in a similar way as panel data do compared to a cross-section (multiple ij observations allow to control for the individual specific heterogeneity μ_i). However, attrition is endogenous here, and the extent of the bias is substantial. In particular, even if people who default on their first

[3] There is no contract fixed effect, as all other contract related terms are observed.

contract were still to decide to apply for another contract (which is unlikely), the probability that the application will be accepted and the repayment behavior for that contract will be observed is close to zero. It is far from obvious how to model the selection process behind this kind of data, where the current behavior determines whether a subsequent contract is observed.[4]

This paper attempts to combine the two alternatives, while avoiding their shortcomings: as will be explained later, we estimate the default probability on only borrowers' accepted first contracts, while using the information about the goods financed by the subsequent accepted or rejected applications to capture the good-related individual heterogeneity.

3 Data

The data used in this paper comprises both accepted and rejected loan applications for instalment credit with Findomestic Banca, a major Italian bank which specializes in financing consumer durable goods. The dataset is a cross-sectional snapshot of contracts, containing contract features, borrower characteristics, as well as indicators of repayment behavior for the accepted contracts. The loans are not collateralized but if they are not repaid, contracts are sold to third parties (collecting agencies). Each borrower may have several contracts. All current and past contracts and applications up to 1999 (the year of extraction of the data) of a borrower are observed. The sampling has been performed randomly on a borrower level. The observed contracts and applications span over the period 1995-1999.

As the data includes multiple contracts and applications per individual, we could in principle use the panel data structure to control for the unobserved individual specific heterogeneity. However, as mentioned previously, endogenous attrition is likely to bias substantially the results. Although modeling the process of the subsequent applications conditional on the previous contracts' performance, is in principle possible, the insufficient information about the timing of the default in the data prevents us from being able to determine exactly what information is known to the bank about the preceding contracts (and their repayment outcomes) when the acceptance decision on the current contract is made. For these reasons, we propose and use an alternative solution to controlling for the *unobserved goods-type individual heterogeneity.*

[4] The set-up is similar to dynamic panel data models with endogenous attrition.

4 Econometric Methods

This section describes the three empirical models we estimate. So far, in Table 1 we have only presented the unconditional variation in the default probabilities across the different goods. The first question that we need to answer is whether the variation is still present after controlling for the observable individual and contract specific characteristics.

4.1 Model I

We therefore first estimate a simple model of the default probability as a function of the goods' indicators, also including the features of the contract and the individual characteristics of the borrowers, using a simple probit model. The significance of the goods' indicators (good-specific dummy variables) show whether the observed variation persists even when conditioning on these other factors. We call this simple binary model of the default probability *Model I*, and estimate it using the accepted first contracts only to avoid the endogenous attrition bias in the composition of the subsequent contracts.

4.2 Model II

Even in the absence of unobserved individual heterogeneity, estimation of Model I is subject to a selection bias due to censoring, as not all first applications are accepted and there may be a systematic difference between the repayment behavior on contracts that were accepted, compared to the repayment behavior on the rejected contracts had they been accepted, which may distort the estimation results.

In addition, acceptance rates also vary across different types of goods (see Table 2) which may further bias the estimated goods' indicators. We take this potential selection into account in *Model II*. The default probability is estimated on the subset of the accepted first applications, while the rejected first applications are used to correct for the selection bias due to the fact that the repayment behavior is only observed for people (contracts) who's first applications were successful, i.e. who were actually granted the credit. We use a bivariate probit model with the default probability equation and the acceptance decision equation to take into account the censoring of the contracts for which repayment behavior is observed. The model is estimated jointly by maximum likelihood. The identification of this model requires at least one exclusion restriction, a variable present in the selection equation

Table 2: Acceptance Rates per Good

Good	% Accepted	No. of Contracts
(Used) Cars and motor homes	64.6%	3,693
Motorbikes	75.1%	13,224
Telecommunication	78.1%	18,057
New Cars and motor homes	78.8%	5,709
Other	80.3%	10,162
Electr. equipment (Brown Goods)	83.2%	31,774
Computers	86.6%	3,545
Furniture Units	86.8%	5,215
White Goods (kitchen appliances)	88.5%	6,165

but excluded from the equation of the default probability.

We follow Alessie et al. (2005) when choosing the exclusion restriction. The advantage of the data at hand is that it spans over a period during which a reform was enacted in Italy, which put ceilings on the interest rates on certain consumer loans. It is likely that such a policy measure had an impact on the degree of credit rationing for the consumer loans that were affected by the reform. The exclusion restriction, which allows us to control for potentially endogenous credit rationing, is therefore a dummy variable that indicates whether the contract started before this so-called Usury Law reform came into effect (the beginning of 1997) or after. As the law affected the top interest rates, it is likely that it had also an impact on the acceptance rates (extent of credit rationing) of the loans with high interest rates. As will be shown in the section presenting our results, the coefficient from the selection equation suggests that this is indeed the case: the dummy variable that indicates that the contract (the application) originates from the period prior to the reform suggests that, controlling for any other factors (including the year dummy variables for the start of the contract), the acceptance rates fell after the reform. This outcome is consistent with the idea that a credit company in response to the reform, tries to maintain its expected return from credit (given the default probabilities) constant, i.e. making the rules stricter when some of the interest rates had to be lowered below the legal limit.

Similarly to Alessie et al. (2005), we assume that the Usury Law directly affected only the supply side of the market. The validity of the exclusion restriction hinges also on the assumption that any effect of the law on the individuals' default behavior is channeled solely through the interest rate, and through the change in the pool of the accepted applications, two factors that are both controlled for in the model.

We estimate Model II to find out whether the observed variation in the default rates across different types of the goods persists, even when the potential selection bias due to the fact that default is observed only for the accepted applications, is taken into account. The statistical significance of the goods' indicators reveals whether this is still the case.

If the variation in the default probabilities across the different goods is still present, we can ask the key question of this analysis: what drives this (remaining) variation? Is it the selection effect, due to different individual types buying different goods, or is it the causal effect of the good itself? Neither Model I or Model II can answer this question.

4.3 Model III - Preferred Model

In addition to the previous models, the preferred model makes use of the information from the subsequent applications to construct the individual goods-type indicators to control for the fact that individuals with different unobserved default risk possibly may sort themselves to different types of goods. However, to avoid endogenous attrition and the complex selection mechanisms, Equation 1 is still estimated on the first contracts only. The preferred specification uses rejected first applications as in Model II, to take into account the selection due to censoring.

To proxy the unobserved goods-type individual heterogeneity, we construct an individual-specific goods-type indicators M_i^g as follows: M_i^g equals one if among all the observed applications (including accepted and the rejected applications, first as well as subsequent) of individual i for instalment loans from the bank is at least one that applies for financing good g, and it equals zero otherwise.

As there are G types of goods observed, there are G indicators of this kind constructed and included in Equation 1 to capture the part of μ_i that is correlated with the type of the good. In other words, the above described method controls for any goods-related unobserved time-invariant individual heterogeneity μ_i^g through a certain kind of constructed fixed effects. It does however capture *only* the good-specific individual heterogeneity, and it still makes an assumption about the remaining unobserved individual heterogeneity to be randomly distributed across the contracts and goods.

The above mentioned indicators M_i^g, constructed from all instalment loan applications an individual filed at the bank during the given period, serve to control for the unobserved individual goods-type heterogeneity in the default risk. As there are nine types of goods, there are nine variables in the model each of which indicate whether an individual i ever (during the observed period) applied (at least once) for credit for that particular type of good.

With these indicators at hand, the following model is estimated:

$$\begin{aligned} D^*_{ijg} &= X_i\beta + Z_j\gamma + \delta_g + M_i^g + \varepsilon_{ij} \\ Y^*_{ij} &= Wb + u_{ij} \\ D_{ij} &= 1(D^*_{ij} > 0) \\ Y_{ij} &= 1(y^*_{ij} > 0) \\ D_{ij} \quad \text{is observed iff} \quad Y_{ij} &= 1 \end{aligned}$$

where the naming convention is as before, Y_{ij} indicates whether the application was accepted or not (selection equation), and W includes all Xs and Zs that are observed at the time of the acceptance decision about the loan application, and at least one more variable, an exclusion restriction which is the Usury Law dummy variable as described in Model II.

The error terms ε_{ij} and u_{ij} are assumed to be jointly normally distributed.

4.4 Overview of the Estimated Models

The three estimated models and their respective assumptions and features are therefore as follows.

Model I: Simple probit model of the default probability; estimated on the accepted first applications (contracts); controls for observed contract and individual specific characteristics; ignores selection due to censoring; ignores possible goods-related individual heterogeneity

Model II: Bivariate probit Model with one equation for the default probability and the other for the acceptance decision; estimated on all first applications; controls for selection due to censoring via credit rationing (using rejected applications); ignores possible goods-related individual heterogeneity

Model III: Preferred model - bivariate probit Model which includes the individual goods-type indicators constructed on the bases of all observed applications per individual; estimated on all first applications; controls for selection due to censoring (using rejected applications);

controls for possible goods-related individual heterogeneity using the additional information from multiple contracts

5 Descriptive Statistics

There are 75,458 accepted first loan applications and 16,020 rejected first applications in the data used for the estimation. The overall number of applications used to construct the individual goods-type indicators is 129,704.

Most of the individuals (62,156) in the sample have applied for only one type of the goods. There are 11,379 individuals who applied for two types of goods, 1,697 individuals who applied for three types, 207 who applied for four types, and 19 individuals who applied for five types of goods during the given period.

6 Results

The simple tabulation as shown in Table 1, without conditioning on any other factors, suggests that mobile phones, motorcycles, used cars and electrical appliances (brown goods) have the highest default rates, while furniture units, kitchen goods and especially new cars have the lowest default rates.

We next present the results from the estimation of the three models described above. We distinguish 9 categories of goods in our sample and choose the residual category titled "Other" as the base category.[5] The effect of the good on the probability of the default is therefore always relative to the category Other.

Only the goods' indicators (dummy variables whether the good X was financed with the loan) and, for the preferred model, also the coefficients of the goods-type individual specific heterogeneity $GI(X)$, where X is the number of the good category, are presented here. The impact of the different types of goods and the good-specific individual heterogeneity are expressed in terms of marginal effects. The list of the other right hand side variables that we condition on and the full estimation results can be found in Appendix.

Once we condition on the key individual-specific and contract-specific factors by a probit, the variation of the default rates across the different

[5] The reason is that it is a mixture of various unclassified goods and it is ranked in the middle according to the unconditional default rates across the good categories, and should more or less represent the average.

Table 3: Model I

Variable	Marg. Eff.	(Std. Err.)
New Cars and Motor Homes	-0.021**	(0.003)
(Used) Cars and Motor Homes	0.001	(0.005)
Motorbikes	0.008**	(0.003)
Electr. Equipment (Brown Goods)	0.013**	(0.003)
Computers	0.000	(0.004)
White Goods (Kitchen Appliances)	0.001	(0.003)
Furniture Units	-0.008**	(0.003)
Telecommunication	0.033**	(0.004)

Significance levels : † : 10% $*$: 5% $**$: 1%

Other is the Base Category.

goods is reflected by the significance of the marginal effects of the goods on the default probability, i.e. whether they are statistically significant from the base category a therefore also from each other. Table 3, which presents estimation results from Model I, shows that only five categories of goods are significantly different from the base category: Mobile phones, electrical equipment and motorcycles are repaid less often than average, while new cars and furniture units are repaid more often than average. When we compare the unconditional ranking of the default rates from Table 1 with the ranking of the marginal effects estimated in Model I in Table 3, we see that the ranking of the goods according to the default probability is more or less preserved, but kitchen appliances are ranked at a higher and used cars at a lower level than before, suggesting that selection on observable characteristics of the contracts and the borrowers drives part of the very low and very high unconditional default rates in these two cases. The results from Model I reveal that the variation in the default rates across the different good categories is present even when conditioning on the contract and individual characteristics. The estimates confirm the positive effect of mobile phones (0.033), electrical equipment (0.013), and motorcycles (0.008), and the negative effect of furniture units (-0.008) and new cars (-0.021) on the default probability.

In Model II, when we control for the selection due to censoring, i.e. the fact that repayment behavior is only observed for the accepted applications, the results do not qualitatively change. Table 4 shows that not only significance but even the magnitudes of the marginal effects estimated by Model

Table 4: Model II

Variable	Marg. Eff.	(Std. Err.)
Equation 1 : default		
New Cars and Motor Homes	-0.018**	(0.003)
(Used) Cars and Motor Homes	0.003	(0.005)
Motorbikes	0.007**	(0.003)
Electr. Equipment (Brown Goods)	0.012**	(0.003)
Computers	0.000	(0.004)
White Goods (Kitchen Appliances)	0.000	(0.003)
Furniture Units	-0.007**	(0.003)
Telecommunication	0.029**	(0.004)

Significance levels : † : 10% $*$: 5% $**$: 1%

Other is the Base Category.

I and Model II are fairly similar. Although selection matters for the estimation, and the correlation between the error terms of the default and the selection equations is found positive and significant (see full results of Model II in the Appendix), most of the goods' coefficients are affected only little compared to results from Model I: controlling for selection seems to reduce the magnitude (in absolute value) of some of the marginal effects, but the changes are minor. To summarize, the results from Model II reveal that the variation in default rates across different goods is still present, even after controlling for the censoring.

We next estimate Model III to find out whether it is the selection or the good effect which explains this remaining variation. Model III controls for the unobserved individual-specific heterogeneity due to sorting of people with different default risk to different types of goods via the constructed individual goods-type indicator. Table 5, which summarizes the results, reveals that the effect of the goods themselves on the default rate disappears for furniture units and is diminished for the electrical equipment, while it changes the sign for the motorcycles. The negative effect of new cars and the positive effect of mobile phones remains significant and substantial, but reduces by one third for the latter. The good effect of the mobile phones seems intuitive: they are probably easy to "hide" - not easy to repossess by the debt-collector, are often stolen, broken, or get quickly out of fashion etc., features that all lower their lifetime or increases their depreciation rate, and therefore possibly reduce the incentives of the borrowers to repay them.

The positive effect of the new cars may be harder to interpret. However, both relatively easy repossession and a well-developed and efficient second-hand market for the used cars may increase the threat of the punishment (repossession) and increase the probability of repaying in this case.

The results further reveal, that the previously documented negative effect of the furniture units and, to some extent, electrical equipment, are due to selection: it is not the effect of the two types of goods but rather the people who buy them that reduces the default probability. The marginal effects of the goods-type individual heterogeneity shows that selection among different types of goods is substantial and relevant for the observed variation in the default rates: Individuals who buy kitchen appliances, furniture units, but also computers and electrical equipment (and the “Other” category goods) are less likely to default, while those who buy motorcycles have a higher probability of default (although only at a 10 % significance level).

In case of the motorcycles, it seems that both a selection (increasing the default probability) and a good effect (reducing the default probability) are at work: while not-repaying people seem to buy motorcycles more often, the good has a positive effect on repayment. A similar argument (the two counteracting effects although with opposite signs) holds also for the electrical equipment: while repaying people buy electrical equipment, electrical equipment makes individuals repay less often.

The results of the selection effect seem to be consistent with the common sense. It is predominantly young, single, risk-loving individuals, who possibly don’t have much property or reputation at risk, and don’t bare too many responsibilities, who buy motorcycles and who may also be more prone to default. Individuals who buy kitchen appliances or furniture units on the other hand probably have (or are about to start) a family, are home-owners, and lead a more steady life. As default may be too costly for them, they tend to repay their debts more when compared to the average.

To summarize, much of the across-good variation in the default probability can be explained by selection rather than the effect of the good. Individuals who buy kitchen appliances, furniture units, and computers are less likely to default their loans than the average person. The pure “causal” goods’ effect remains only for the mobile phones and new cars, the first positive while the other negative. For motorcycles and the electrical equipment, both effects seem to be at play, although good effect is more important for the former and selection for the latter.

Table 5: Model III - Preferred Model

Variable	Marg. Eff.	(Std. Err.)
Equation 1 : default		
New Cars and Motor Homes (1)	-0.022**	(0.004)
(Used) Cars and Motor Homes (2)	-0.006	(0.006)
Motorbikes (3)	-0.009*	(0.004)
Electr. Equipment (Brown Goods) (4)	0.009†	(0.005)
Computers (5)	0.002	(0.008)
White Goods (Kitchen Appliances) (6)	0.008	(0.007)
Furniture Units (7)	-0.004	(0.006)
Telecommunication (8)	0.018**	(0.006)
GI(1)	0.002	(0.005)
GI(2)	0.001	(0.005)
GI(3)	0.008†	(0.004)
GI(4)	-0.007**	(0.002)
GI(5)	-0.009*	(0.004)
GI(6)	-0.013**	(0.003)
GI(7)	-0.011**	(0.004)
GI(8)	-0.001	(0.003)
GI(9)	-0.008**	(0.003)

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Other (9) is the Base Category.

7 Sensitivity Analysis

As the coefficients of the individual goods-type indicators are identified off the individuals who are observed to apply for credit for more than one type of good, to check the robustness of our results, we estimate Model III only using the accepted first contracts of individuals who have applications for loans for more than one type of goods in the data. However, we use all first rejected applications to control for the selection. The sample size thus reduces to 13,302 accepted first applications and (again) 16,020 rejected first applications.

The estimates, presented in Table 6, underline even more the conclusion that all the observed variation in the default rates across the goods is due to selection, i.e. sorting of individuals to different types of goods. The only good effect left is that of new cars, but the coefficient is significantly different from the base category only at the 10 % level. The positive good effect of the mobile phones, the positive effect of electrical equipment and the negative effect of motorcycles on the default probability disappear when only multiple good-types applications are used for the estimation.

In addition, when we focus only on multiple good-types applications, the observed variation in the default rates across goods due to selection is more or less reduced to only three good categories, and these are kitchen appliances, furniture units, and motorcycles. Though only the first has a highly significant marginal effect, while the latter two are significant only at the 10 % significance level. As mentioned above, in both cases it is the sorting of individuals to buying the different goods on credit, which drives the above-average default probability on the loans for motorcycles, and the bellow-average probability on the loans for kitchen appliances and furniture units.

Compared to the results from the preferred model, the sensitivity analysis with multiple good-types applications changes the significance of some of the effects but preserves their signs - with the only exception: the good effect of the motorcycles, which was negative significant, becomes positive but insignificant, while the magnitude of the effect of individual heterogeneity of individuals buying motorcycles increases. As pointed out above, it suggests that the selection effect for the motorcycles dominates the good effect, if there is any.

The present analysis suffers from an important limitation which however cannot be dealt with, with the present data. First, the approach followed in this paper considers only consumer behavior, while taking the creditors' behavior as given. The full equilibrium approach would be preferable but the

Table 6: Sensitivity Results - Multiple GI Information Only

Variable	**Marg. Eff.**	**(Std. Err.)**
Equation 1 : default		
New Cars and Motor Homes (1)	-0.033†	(0.017)
(Used) Cars and Motor Homes (2)	-0.014	(0.016)
Motorbikes (3)	0.003	(0.012)
Electr. Equipment (Brown Goods) (4)	0.012	(0.011)
Computers (5)	-0.012	(0.014)
White Goods (Kitchen Appliances) (6)	0.000	(0.012)
Furniture Units (7)	-0.002	(0.013)
Telecommunication (8)	0.021	(0.014)
GI(1)	0.004	(0.009)
GI(2)	0.002	(0.009)
GI(3)	0.014†	(0.008)
GI(4)	-0.007	(0.007)
GI(5)	-0.012	(0.009)
GI(6)	-0.021**	(0.008)
GI(7)	-0.015†	(0.008)
GI(8)	-0.004	(0.006)
GI(9)	-0.011	(0.007)

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Other (9) is the Base Category.

lack of data restricts us only to a partial-equilibrium focus here. Second, the estimation focuses only on individuals who buy the various goods on credit.[6] Neither the decision to buy on credit, nor the choice of which of the goods should be financed through credit and which paid on the spot, is modeled or estimated here. Both choices may be in principle endogenous to the repayment behavior, which may bias our results. Given the data at hand, we are compelled to assume that these choices are both orthogonal to the default propensity.

There is however a third potential problem, which is the endogenous attrition. Individuals that tend to repay their debts are more likely to apply

[6]The fact that the data come from only one company should not bias the data too much, as at the time when the data were extracted, Findomestic Banca was the dominant player at the instalment credit market in Italy.

Table 7: Sensitivity Results - 2 and 3 GI Information Only

Variable	**Marg. Eff.**	**(Std. Err.)**
	Equation 1 : default	
New Cars and Motor Homes (1)	-0.031†	(0.018)
(Used) Cars and Motor Homes (2)	-0.014	(0.017)
Motorbikes (3)	0.005	(0.012)
Electr. Equipment (Brown Goods) (4)	0.013	(0.011)
Computers (5)	-0.012	(0.014)
White Goods (Kitchen Appliances) (6)	0.000	(0.012)
Furniture Units (7)	-0.003	(0.014)
Telecommunication (8)	0.021	(0.015)
GI(1)	0.001	(0.009)
GI(2)	0.000	(0.009)
GI(3)	0.014	(0.009)
GI(4)	-0.007	(0.007)
GI(5)	-0.011	(0.009)
GI(6)	-0.021*	(0.009)
GI(7)	-0.015†	(0.009)
GI(8)	-0.004	(0.007)
GI(9)	-0.011	(0.008)

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Other (9) is the Base Category.

again for credit than those who do not.[7] Therefore, individuals who repaid their first loan may be more likely to apply again, and thus have more information about their goods-type individual heterogeneity revealed in the data.[8] The correlation between the information on individual heterogeneity and the repayment behavior on the first loan is not however obvious, as it is also the variation in the goods applied for to be financed through credit that matters. Individuals who (for any reason) tend to buy different types of goods on credit will also tend to have more of the GI indicators equal to one. We explore this potential bias with a second sensitivity analysis, where we use individuals who are observed to have applied only for two or three

[7] We use all applications for instalment loans (both rejected and accepted) to construct the goods-type individual heterogeneity indicator, so it is really the probability of multiple applications rather than multiple accepted contracts that matter here.

[8] There is a higher chance that they have more GI indicators equal to one.

different types of goods.[9] The sample size thus reduces to 13,076 accepted first applications and (again) 16,020 rejected first applications. Conditioning on three or four pieces of information leaves us with too few individuals to render the model estimable under the same specification. The results from the sensitivity analysis that conditions on two or three good-types applications are summarized in Table 7. The results are almost identical to the results from the previous sensitivity analysis, the only difference is that the selection effect of the motorcycles is not even weakly significant now.

Overall, the sensitivity analysis confirms the importance of the selection versus the good effect. It shows that the positive (reducing probability of default) selection effect of kitchen appliances and furniture units and the negative good effect of the new cars are robust across the specifications.

8 Conclusion

The default rates on instalment loans vary with the type of the good purchased on credit. Loans to buy mobile phones and motorcycles have a much higher risk of not being repaid than loans to buy furniture or kitchen appliances. The aim of this paper has been to explore whether the observed variation is due to individuals with different repayment behavior selecting themselves to buy different types of goods (the *selection effect*) or due to specific features of the goods' themselves that affect the incentive to repay in different ways (the *good effect*).

The analysis uses data on instalment loans from a major Italian bank, Findomestic Banca, during the period of 1995-1999 to estimate a model of the probability of default. Multiple contract observations per individual allow us to disentangle the selection effect from the good effect, and identify which of the two dominates.

We first show that the unconditional variation in default rates across different goods persists even after conditioning on numerous contract-specific and individual-specific characteristics in the model of the probability of default. This remains true even when we take into account the potential bias from the fact that the repayment behavior is observed only for the accepted applications. Using bivariate probit model with censoring, we estimate the default probability and the acceptance decision jointly, with the

[9] We use individuals with both two and three pieces of information on the individual heterogeneity together, because conditioning on only one of them - e.g. imposing the sum of the GI coefficients equal two - introduces perfect multicolinearity to the model. It follows that one of the GI indicators has to be dropped and the corresponding good-type individual specific heterogeneity effects cannot be estimated.

good-specific dummy variables present. Usury Law enacted in the middle of the observed period provides us with the exclusion restriction for the selection equation, describing the acceptance decision by the creditor. The estimated goods' indicators measure the residual cross-good variation in the probability of default. They are significant and sizable, suggesting that the differences in the repayment behavior across goods exist even when controlling for the observable characteristics and for the acceptance decision.

To avoid endogenous attrition and the complex selection process of the subsequent applications, and due to the lack of the exact timing information on subsequent contracts in the data, we estimate the default probability using only the accepted first contracts, and the rejected first applications to control for the censoring. However, we use the subsequent applications per individual to proxy the unobserved individual goods-type heterogeneity in order to disentangle the selection and the good effect.

The preferred model, which includes both the good-specific dummy variables and the individual goods-types indicators constructed from the multiple contracts observations, reveals that most of the cross-good variation can be explained by selection. We therefore conclude that it is different types of people (with different propensity to default) that sort themselves to different types of goods, which drives the observed variation in the repayment behavior across different types of goods. In particular, the results suggest that individuals who buy kitchen appliances and furniture units are on average less likely to default on their loans. We also find some evidence that individuals who buy motorcycles are more likely than an average individual to default on any type of loan.

The purely "causal" good effect on the default probability remains only for new cars and mobile phones. The first is negative, suggesting that higher threat of repossession may increase the incentives to repay a new car. On the other hand, the effect of mobile phones is positive - they are less likely to be repossessed, and are strongly influenced by fashion, which increases their turnover and reduces the borrowers' incentives to repay. However, sensitivity analysis shows that only the effect of the new cars is robust. The conclusion that the selection effect drives the variation in the default probability, is therefore even more emphasized.

We conclude that conditions of the loan and the acceptance decision should not depend only on the type of the good being purchased but also on the good-related type of the individual who applies for the loan. It also follows that previous applications may be used by credit-granting companies as an additional information about the propensity to default even without or prior to observing the repayment behavior on the first loan.

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A Definition of the Key Variables

interann interest rate (IRR) computed by the author[10]

good1-good9 type of good indicators

GI1-GI9 goods-type of individual (construction described in the text)

_Iprov_2-_Iprov_33 indicator of the province of residence

insured indicator whether the contract has been insured

intwho1 indicator that the interest rate is paid by the borrower

intwho3 indicator that the interest rate is paid by the dealer

exp work experience

expsq work experience squared

hown indicator for homeownership

mort indicator for mortgage

_Ies_2 public employees

_Ies_3 self-employed

_Ies_4 retired

_Ies_5 others

yd disposable income

ydsq disposable income squared

Nkids number of children

mstat indicator for married

Nmonths length of the contract in months

priceD price of the good purchased

priceDsq price of the good squared

[10] I am grateful to Stefan Hochguertel for providing me the code to calculate IRRs from Alessie et al. (2005)

paybank payments made by bank (vs. postal order)

_Iorig_2 - _Iorig_4 origin of the contract (dealer who sells the good)

amountD size of the loan

amountDsq size of the loan square

year97-year99 year of the evaluation (dummy variables)

dy2-dy5 indicator of the year of the inception (dummy variables)

Ybank90 tenure with the bank (was a customer before 1990)

_Iagency_X bank's agency indicator (dummy variables)

pre_ref indicator whether contract started before the Usury Law was enacted or after

B Appendix - Full Estimation Results

This section contains the full estimation results for the three models and the sensitivity analysis. In the models that use the bivariate probit model to control for the selection bias due to the fact that only accepted loan applications are observed, only the default equation and the estimate of the cross-equation correlation of the error terms are presented. The estimates of the selection equation (the acceptance decision) are subject to the privacy restrictions of the data provider. They are available from the author under strict confidentiality conditions.

Table 8: Legend for the Types of Goods

New Cars and Motor Homes	Good 1
(Used) Cars and Motor Homes	Good 2
Motorbikes	Good 3
Electr. Equipment (Brown Goods)	Good 4
Computers	Good 5
White Goods (Kitchen Appliances)	Good 6
Furniture Units	Good 7
Telecommunication	Good 8
Other	Good 9

Table 9: Model I

Variable	Coefficient	(Std. Err.)
interann	0.735**	(0.119)
good1	-0.462**	(0.089)
good2	0.021	(0.068)
good3	0.108**	(0.038)
good4	0.185**	(0.034)
good5	0.004	(0.057)
good6	0.012	(0.047)
good7	-0.140**	(0.050)
good8	0.386**	(0.036)
_Iprov_2	-0.024	(0.117)
_Iprov_3	0.147†	(0.081)
_Iprov_4	-0.179*	(0.078)
_Iprov_5	0.124	(0.077)
_Iprov_6	0.161†	(0.085)
_Iprov_7	-0.174*	(0.083)
_Iprov_8	-0.048	(0.080)
_Iprov_9	-0.025	(0.075)
_Iprov_10	0.018	(0.084)
_Iprov_11	0.020	(0.083)
_Iprov_12	0.153	(0.096)
_Iprov_13	-0.023	(0.087)
_Iprov_14	-0.115	(0.079)
_Iprov_15	-0.039	(0.083)
_Iprov_16	0.160*	(0.076)
_Iprov_17	0.026	(0.073)
_Iprov_18	0.016	(0.078)
_Iprov_19	-0.008	(0.079)
_Iprov_20	0.125	(0.094)
_Iprov_21	-0.101	(0.085)
_Iprov_22	-0.107	(0.088)
_Iprov_23	-0.020	(0.099)
_Iprov_24	0.069	(0.089)
_Iprov_25	0.128	(0.095)
_Iprov_26	-0.016	(0.073)
_Iprov_27	-0.048	(0.079)
_Iprov_28	-0.224*	(0.107)
_Iprov_29	0.094	(0.077)

_Iprov_30	-0.160	(0.105)
_Iprov_31	0.049	(0.092)
_Iprov_32	0.039	(0.101)
_Iprov_33	$0.159^{\dagger}$	(0.084)
insured	0.023^{**}	(0.007)
intwho1	0.102	(0.065)
intwho3	$0.114^{\dagger}$	(0.062)
exp	-0.022^{**}	(0.003)
expsq	0.000^{**}	(0.000)
hown	-0.213^{**}	(0.019)
mort	-0.321^{**}	(0.057)
_Ies_2	-0.051^{*}	(0.024)
_Ies_3	0.364^{**}	(0.025)
_Ies_4	0.006	(0.030)
_Ies_5	0.008	(0.054)
yd	-0.006^{**}	(0.001)
ydsq	0.000	(0.000)
Nkids	-0.030^{**}	(0.009)
mstat	0.053^{**}	(0.014)
Nmonths	0.001	(0.002)
priceD	0.000^{**}	(0.000)
priceDsq	0.000^{**}	(0.000)
paybank	-1.092^{**}	(0.032)
_Iorig_2	-0.074	(0.077)
_Iorig_3	$-0.064^{\dagger}$	(0.034)
_Iorig_4	$-0.052^{\dagger}$	(0.029)
amountD	0.000^{**}	(0.000)
amountDsq	0.000^{**}	(0.000)
year97	0.502^{**}	(0.041)
year98	0.972^{**}	(0.049)
year99	1.519^{**}	(0.054)
dy2	-0.258^{**}	(0.039)
dy3	-0.691^{**}	(0.048)
dy4	-1.169^{**}	(0.054)
dy5	-1.641^{**}	(0.061)
Ybank90	-0.084^{**}	(0.028)
Intercept	-1.988^{**}	(0.110)

Significance levels : $\dagger$: 10% $\quad *$: 5% $\quad **$: 1%

Other (9) is the Base Category.

Table 10: Model II

Variable	Coefficient	(Std. Err.)
Equation 1 : default		
interann	0.635**	(0.121)
good1	-0.362**	(0.094)
good2	0.046	(0.068)
good3	0.098**	(0.038)
good4	0.167**	(0.034)
good5	0.003	(0.056)
good6	0.000	(0.047)
good7	-0.116*	(0.050)
good8	0.353**	(0.037)
_Iprov_2	-0.060	(0.117)
_Iprov_3	0.155†	(0.080)
_Iprov_4	-0.156*	(0.078)
_Iprov_5	0.124	(0.076)
_Iprov_6	0.151†	(0.084)
_Iprov_7	-0.146†	(0.083)
_Iprov_8	-0.054	(0.079)
_Iprov_9	-0.025	(0.074)
_Iprov_10	0.001	(0.083)
_Iprov_11	0.007	(0.082)
_Iprov_12	0.157†	(0.095)
_Iprov_13	-0.010	(0.086)
_Iprov_14	-0.104	(0.078)
_Iprov_15	-0.018	(0.083)
_Iprov_16	0.138†	(0.076)
_Iprov_17	0.007	(0.073)
_Iprov_18	0.032	(0.077)
_Iprov_19	-0.015	(0.078)
_Iprov_20	0.115	(0.093)
_Iprov_21	-0.086	(0.084)
_Iprov_22	-0.096	(0.087)
_Iprov_23	-0.006	(0.098)
_Iprov_24	0.059	(0.088)
_Iprov_25	0.124	(0.094)
_Iprov_26	-0.018	(0.072)

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... table 10 continued

Variable	Coefficient	(Std. Err.)
_Iprov_27	-0.033	(0.079)
_Iprov_28	-0.203†	(0.107)
_Iprov_29	0.086	(0.076)
_Iprov_30	-0.153	(0.104)
_Iprov_31	0.058	(0.091)
_Iprov_32	0.021	(0.100)
_Iprov_33	0.151†	(0.083)
insured	0.025**	(0.007)
intwho1	0.087	(0.064)
intwho3	0.091	(0.062)
exp	-0.017**	(0.003)
expsq	0.000**	(0.000)
hown	-0.177**	(0.022)
mort	-0.290**	(0.058)
_Ies_2	-0.036	(0.024)
_Ies_3	0.343**	(0.026)
_Ies_4	0.002	(0.029)
_Ies_5	-0.049	(0.056)
yd	-0.006**	(0.001)
ydsq	0.000	(0.000)
Nkids	-0.035**	(0.009)
mstat	0.040**	(0.014)
Nmonths	-0.003	(0.002)
priceD	0.000**	(0.000)
priceDsq	0.000**	(0.000)
paybank	-0.986**	(0.042)
_Iorig_2	-0.075	(0.077)
_Iorig_3	-0.071*	(0.033)
_Iorig_4	-0.084**	(0.030)
amountD	0.000**	(0.000)
amountDsq	0.000**	(0.000)
year97	0.507**	(0.041)
year98	0.974**	(0.048)
year99	1.515**	(0.054)
dy2	-0.298**	(0.040)
dy3	-0.742**	(0.049)
dy4	-1.221**	(0.054)

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... table 10 continued

Variable	Coefficient	(Std. Err.)
dy5	-1.697**	(0.061)
Ybank90	-0.082**	(0.028)
Intercept	-1.929**	(0.111)
	Equation 2 : accept	
	Equation 3 : athrho	
Intercept	0.279**	(0.093)

Significance levels : † : 10% * : 5% ** : 1%

Table 11: Model III - Preferred Model

Variable	Coefficient	(Std. Err.)
	Equation 1 : default	
interann	0.630**	(0.121)
good1	-0.515**	(0.129)
good2	-0.104	(0.115)
good3	-0.145†	(0.080)
good4	0.134*	(0.068)
good5	0.023	(0.115)
good6	0.113	(0.091)
good7	-0.059	(0.103)
good8	0.240**	(0.072)
GI1	0.026	(0.074)
GI2	0.019	(0.080)
GI3	0.109*	(0.052)
GI4	-0.105**	(0.034)
GI5	-0.158†	(0.089)
GI6	-0.242**	(0.062)
GI7	-0.190*	(0.078)
GI8	-0.020	(0.039)
GI9	-0.135**	(0.050)
_Iprov_2	-0.062	(0.117)
_Iprov_3	0.160*	(0.080)
_Iprov_4	-0.155*	(0.078)

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... table 11 continued

Variable	**Coefficient**	**(Std. Err.)**
_Iprov_5	0.127†	(0.076)
_Iprov_6	0.156†	(0.084)
_Iprov_7	-0.136†	(0.083)
_Iprov_8	-0.052	(0.079)
_Iprov_9	-0.020	(0.074)
_Iprov_10	0.001	(0.083)
_Iprov_11	0.010	(0.082)
_Iprov_12	0.156	(0.095)
_Iprov_13	-0.007	(0.086)
_Iprov_14	-0.101	(0.078)
_Iprov_15	-0.009	(0.083)
_Iprov_16	0.138†	(0.076)
_Iprov_17	0.010	(0.073)
_Iprov_18	0.034	(0.077)
_Iprov_19	0.003	(0.078)
_Iprov_20	0.115	(0.093)
_Iprov_21	-0.085	(0.084)
_Iprov_22	-0.091	(0.087)
_Iprov_23	0.001	(0.099)
_Iprov_24	0.065	(0.088)
_Iprov_25	0.128	(0.094)
_Iprov_26	-0.014	(0.072)
_Iprov_27	-0.037	(0.079)
_Iprov_28	-0.198†	(0.107)
_Iprov_29	0.090	(0.076)
_Iprov_30	-0.151	(0.104)
_Iprov_31	0.052	(0.091)
_Iprov_32	0.019	(0.100)
_Iprov_33	0.155†	(0.083)
insured	0.025**	(0.007)
intwho1	0.085	(0.064)
intwho3	0.088	(0.062)
exp	-0.017**	(0.003)
expsq	0.000**	(0.000)
hown	-0.180**	(0.022)
mort	-0.292**	(0.058)
_Ies_2	-0.033	(0.024)

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... table 11 continued

Variable	Coefficient	(Std. Err.)
_Ies_3	0.341**	(0.026)
_Ies_4	0.002	(0.029)
_Ies_5	-0.047	(0.056)
yd	-0.006**	(0.001)
ydsq	0.000	(0.000)
Nkids	-0.034**	(0.009)
mstat	0.042**	(0.014)
Nmonths	-0.003	(0.002)
priceD	0.000**	(0.000)
priceDsq	0.000**	(0.000)
paybank	-0.985**	(0.042)
_Iorig_2	-0.075	(0.077)
_Iorig_3	-0.072*	(0.033)
_Iorig_4	-0.090**	(0.030)
amountD	0.000**	(0.000)
amountDsq	0.000**	(0.000)
year97	0.507**	(0.041)
year98	0.976**	(0.048)
year99	1.513**	(0.054)
dy2	-0.302**	(0.040)
dy3	-0.751**	(0.049)
dy4	-1.236**	(0.055)
dy5	-1.716**	(0.061)
Ybank90	-0.084**	(0.028)
Intercept	-1.768**	(0.122)
Equation 2 : accept		
Equation 3 : athrho		
Intercept	0.282**	(0.094)

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 12: Sensitivity Results I - Multiple GI Information

Variable	Coefficient	(Std. Err.)
Equation 1 : default		

Continued on next page...

... table 12 continued

Variable	**Coefficient**	**(Std. Err.)**
interann	0.808**	(0.303)
good1	-0.553†	(0.290)
good2	-0.166	(0.209)
good3	0.037	(0.116)
good4	0.125	(0.095)
good5	-0.140	(0.183)
good6	0.003	(0.129)
good7	-0.021	(0.149)
good8	0.201†	(0.104)
GI1	0.040	(0.088)
GI2	0.018	(0.092)
GI3	0.140*	(0.069)
GI4	-0.075	(0.063)
GI5	-0.145	(0.100)
GI6	-0.262**	(0.076)
GI7	-0.187*	(0.090)
GI8	-0.043	(0.063)
GI9	-0.125†	(0.067)
_Iprov_2	-0.508	(0.396)
_Iprov_3	0.001	(0.182)
_Iprov_4	-0.403*	(0.180)
_Iprov_5	-0.029	(0.177)
_Iprov_6	0.061	(0.194)
_Iprov_7	-0.483*	(0.192)
_Iprov_8	-0.413*	(0.179)
_Iprov_9	-0.222	(0.161)
_Iprov_10	-0.186	(0.184)
_Iprov_11	-0.077	(0.185)
_Iprov_12	-0.162	(0.265)
_Iprov_13	-0.388†	(0.202)
_Iprov_14	-0.180	(0.173)
_Iprov_15	-0.194	(0.181)
_Iprov_16	-0.089	(0.188)
_Iprov_17	-0.154	(0.160)
_Iprov_18	-0.092	(0.179)
_Iprov_19	-0.350*	(0.170)
_Iprov_20	0.080	(0.245)

Continued on next page...

... table 12 continued

Variable	Coefficient	(Std. Err.)
_Iprov_21	-0.311	(0.207)
_Iprov_22	-0.199	(0.200)
_Iprov_23	-0.118	(0.217)
_Iprov_24	-0.050	(0.188)
_Iprov_25	-0.009	(0.232)
_Iprov_26	-0.208	(0.161)
_Iprov_27	-0.236	(0.181)
_Iprov_28	-0.651*	(0.262)
_Iprov_29	-0.060	(0.175)
_Iprov_30	-0.364	(0.231)
_Iprov_31	-0.265	(0.242)
_Iprov_32	-0.140	(0.263)
_Iprov_33	0.017	(0.193)
insured	0.004	(0.016)
intwho1	0.072	(0.145)
intwho3	0.010	(0.140)
exp	-0.020**	(0.008)
expsq	0.000†	(0.000)
hown	-0.198**	(0.053)
mort	-0.352*	(0.154)
_Ies_2	-0.045	(0.059)
_Ies_3	0.314**	(0.064)
_Ies_4	0.070	(0.078)
_Ies_5	-0.159	(0.148)
yd	-0.014**	(0.005)
ydsq	0.000	(0.000)
Nkids	-0.032	(0.020)
mstat	0.043	(0.035)
Nmonths	-0.003	(0.006)
priceD	0.000*	(0.000)
priceDsq	0.000	(0.000)
paybank	-0.959**	(0.195)
_Iorig_2	-0.235	(0.187)
_Iorig_3	-0.106	(0.090)
_Iorig_4	-0.316**	(0.091)
amountD	0.000**	(0.000)
amountDsq	0.000	(0.000)

Continued on next page...

... table 12 continued

Variable	Coefficient	(Std. Err.)
year97	0.546**	(0.089)
year98	1.020**	(0.108)
year99	1.531**	(0.126)
dy2	-0.354**	(0.102)
dy3	-0.796**	(0.134)
dy4	-1.168**	(0.169)
dy5	-1.469**	(0.227)
Ybank90	-0.154*	(0.074)
Intercept	-1.376**	(0.270)
Equation 2 : accept		
Equation 3 : athrho		
Intercept	-0.010	(0.172)

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 13: Sensitivity Results II - 2 and 3 GI Information Only

Variable	Coefficient	(Std. Err.)
Equation 1 : default		
interann	0.811**	(0.304)
good1	-0.487†	(0.293)
good2	-0.165	(0.213)
good3	0.049	(0.118)
good4	0.134	(0.097)
good5	-0.138	(0.184)
good6	0.004	(0.131)
good7	-0.030	(0.151)
good8	0.206†	(0.106)
GI1	0.008	(0.098)
GI2	-0.002	(0.101)
GI3	0.134†	(0.077)
GI4	-0.079	(0.071)
GI5	-0.133	(0.107)
GI6	-0.259**	(0.084)

Continued on next page...

... table 13 continued

Variable	Coefficient	(Std. Err.)
GI7	-0.179†	(0.097)
GI8	-0.043	(0.072)
GI9	-0.129†	(0.076)
_Iprov_2	-0.516	(0.397)
_Iprov_3	-0.001	(0.182)
_Iprov_4	-0.408*	(0.180)
_Iprov_5	-0.029	(0.178)
_Iprov_6	0.066	(0.194)
_Iprov_7	-0.487*	(0.192)
_Iprov_8	-0.416*	(0.179)
_Iprov_9	-0.219	(0.162)
_Iprov_10	-0.214	(0.186)
_Iprov_11	-0.079	(0.186)
_Iprov_12	-0.161	(0.266)
_Iprov_13	-0.393†	(0.202)
_Iprov_14	-0.184	(0.173)
_Iprov_15	-0.215	(0.182)
_Iprov_16	-0.093	(0.188)
_Iprov_17	-0.168	(0.160)
_Iprov_18	-0.116	(0.180)
_Iprov_19	-0.349*	(0.170)
_Iprov_20	0.073	(0.245)
_Iprov_21	-0.370†	(0.211)
_Iprov_22	-0.223	(0.202)
_Iprov_23	-0.145	(0.220)
_Iprov_24	-0.044	(0.188)
_Iprov_25	-0.039	(0.237)
_Iprov_26	-0.211	(0.161)
_Iprov_27	-0.235	(0.181)
_Iprov_28	-0.650*	(0.263)
_Iprov_29	-0.063	(0.176)
_Iprov_30	-0.356	(0.231)
_Iprov_31	-0.264	(0.243)
_Iprov_32	-0.132	(0.264)
_Iprov_33	0.018	(0.194)
insured	0.003	(0.017)
intwho1	0.060	(0.146)

Continued on next page...

... table 13 continued

Variable	Coefficient	(Std. Err.)
intwho3	-0.002	(0.141)
exp	-0.021**	(0.008)
expsq	0.000†	(0.000)
hown	-0.191**	(0.054)
mort	-0.344*	(0.154)
_Ies_2	-0.048	(0.060)
_Ies_3	0.313**	(0.064)
_Ies_4	0.061	(0.078)
_Ies_5	-0.159	(0.149)
yd	-0.015**	(0.005)
ydsq	0.000	(0.000)
Nkids	-0.032	(0.020)
mstat	0.044	(0.035)
Nmonths	-0.003	(0.006)
priceD	0.000*	(0.000)
priceDsq	0.000	(0.000)
paybank	-0.954**	(0.197)
_Iorig_2	-0.268	(0.193)
_Iorig_3	-0.100	(0.090)
_Iorig_4	-0.313**	(0.092)
amountD	0.000**	(0.000)
amountDsq	0.000	(0.000)
year97	0.539**	(0.090)
year98	1.004**	(0.109)
year99	1.515**	(0.127)
dy2	-0.359**	(0.103)
dy3	-0.802**	(0.134)
dy4	-1.173**	(0.170)
dy5	-1.473**	(0.227)
Ybank90	-0.164*	(0.075)
Intercept	-1.339**	(0.280)
Equation 2 : accept		
Equation 3 : athrho		
Intercept	-0.009	(0.174)

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%