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Does the Good Matter?

Evidence on Moral Hazard and Adverse Selection from Consumer Credit Market

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Abstract

Default rates on instalment loans vary with type of the good purchased. Using an Italian dataset of instalment loans between 1995-1999, we first show that the variation persists even after controlling for contract and individual-specific characteristics, and for the potential selection bias due to credit rationing. We explore whether the residual variation in the default rates across the different types of goods is due to unobserved individual heterogeneity (*selection effect*) or due to the effect of the specific characteristics of the good (*good effect*). We claim that the two effects may be interpreted as adverse selection and 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 the selection effect. Individuals who buy motorcycles on credit are more likely to default on any loan, while those buying kitchen appliances, furniture and computers are more likely to repay, compared to average. We conclude that there is asymmetric information in the consumer credit market, mostly in the form of adverse selection.

Keywords: consumer credit, default, adverse selection, moral hazard

JEL classification: D12, D14, D82

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1 Introduction

Why should a loan to buy a fridge be repaid more often than a 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 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, can be driven by two alternative 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 features of the individuals who buy the good, that explain the observed

[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 likely to be relevant but disregarded here due to data limitations.

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

Type of the Good	**Default**
New Cars and Motor Homes	2.22%
White Goods (Kitchen Appliances)	3.69%
Furniture	3.75%
Computers	3.79%
Other	4.79%
Electr. Equipment (Brown Goods)	6.08%
(Used) Cars and Motor Homes	6.64%
Motorbikes	6.90%
Telecommunication	10.06%

Source: Findomestic data, individuals' first instalment loans, 1995-1999.

differences in the default rates? For example, is it the case that people who tend to not repay their debts buy motorcycles on credit more often, or is it something about the motorcycles which makes their owners to not repay? We claim that, in the context of the contract theory, the two effects may be interpreted as adverse selection and moral hazard. In this sense, the paper brings further evidence on whether there is asymmetric information in the consumer credit market, and shows whether it is in the form of adverse selection or in the form of moral hazard.

We use an administrative dataset of instalment loan contracts of a leading Italian bank (Findomestic Banca) between 1995-1999 to estimate a model of the probability of default. 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 unobserved individual heterogeneity and the selection effect. 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, furniture and computers 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.

We conclude that there is asymmetric information in the consumer credit market in Italy, and most of it is in the form of adverse selection. Given that the contract terms vary only with the goods but not with individuals, the results suggest that the repaying individuals, when they buy a good that has a high average default rate, cross-subsidize those who don't repay. We propose that conditions of the loan should not depend only on the type of the good being purchased but also on the goods-related type of the individual who applies for the loan. The information about types of goods financed through previous loan applications may be used by credit-granting companies to help assess the risk of default.

The paper is organized as follows. The next section discusses the two effects and shows their econometric counterparts. We then present the estimation methodology, followed by the description of the data. The section with the main results comes next. Finally, we explore the sensitivity of our results and conclude. The Appendix contains definitions of variables, full estimation results, and results of the sensitivity analysis.

2 Selection Effect versus Good Effect

The focus of this paper is the variation in default rates across different types of goods. Table 2 shows that Findomestic Banca, the lender who provided us with the data, is aware of this variation and translates it into both the interest rates charged on loans for different types of goods, as well as into the acceptance decision rules applied to loan applications for different types of goods. Although the relationship between the observed unconditional default rates, the acceptance rates and the average levels of interest rates is not perfectly monotonic, as other factors come into play as well, it is clear that applications for loans to finance the goods that have higher default rates have typically higher interest rates and are rejected more often. The features of the contracts in our data do not vary with individuals. The conditions of the loan are posted next to the good that is offered to be bought on credit. Acceptance decisions, on the other hand, are based on the individual characteristics of the applicant, but also vary with contract types and with the type of the good purchased on credit.

In this paper, we do not model lender's behavior. We consider the conditions of the contracts and the acceptance strategy as a particular equilibrium outcome. It is the "residual" cross-good variation in the default rates that we are interested in. The aim of this paper is to explain the variation in the default rates across loans for different types of goods, which remains

Table 2: Default, Acceptance Rates, Interest Rates

Type of the Good	**Default**	**Accepted**	**IRR**
New Cars and motor homes	2.22%	78.8%	13.5%
White Goods (kitchen appliances)	3.69%	88.5%	28.9%
Furniture	3.75%	86.8%	20.2%
Computers	3.79%	86.6%	22.0%
Other	4.79%	80.4%	23.3%
Electr. equipment (Brown Goods)	6.08%	83.2%	27.7%
(Used) Cars and motor homes	6.64%	64.6%	17.5%
Motorbikes	6.90%	75.1%	20.3%
Telecommunication	10.06%	78.1%	28.9%

Source: Findomestic data, individuals' first instalment loans, 1995-1999.

after we control for the individual and contract-specific characteristics and the acceptance decision. In particular, we explore whether this variation is caused by the *selection effect* or the *good effect*. In the first case, the variation is driven by the unobserved individual heterogeneity in the propensity to default, which is correlated with the type of the good purchased on credit. In the second, the variation directly reflects the "causal" good effect, i.e. the effect of the features of the good purchased on credit on the incentives to repay.

The main question may be phrased as follows: Is it the specific unobserved features of the individuals who buy the good, or rather the specific features of the good itself, that explain the observed differences in the default rates? Our objective is to disentangle the two effects, without giving an explicit interpretation as to how they work. However, we do summarize our conjectures about the two types of mechanisms next and will invoke them again when interpreting our results.

Certain types of products, such as motorcycles, may be preferred by risk-loving individuals, 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 variation in the default rate, as caused purely by the *selection effect*.

As for the *good effect*, two types of the 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 of the good is likely to reduce the incentives of its owner to repay it. The second feature is related to the cost of default, namely the probability of punishment - the likelihood that the good, if not repaid, will be repossessed by the lender. The size and mobility of the good determine how easily it can be repossessed, while the existence and efficiency of a second-hand market for the good affect the incentives of the lender to repossess it or not. A 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 transformed into money on the 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 them links 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.

There is a growing empirical research that tests whether there is asymmetric information in various consumer markets. See Chiappori and Salanié (2003) for an overview. We claim that the two alternative explanations of the residual variation in the default rates across different types of goods, the selection effect and the good effect, may be interpreted as adverse selection and moral hazard. In this respect, the present paper extends this literature by providing evidence on the existence and the particular form of the asymmetric information in the consumer credit market.

2.1 Econometric Specification of the Problem

An individual applies for an instalment loan to purchase a certain type of the good and his application is accepted. His repayment behavior is assumed to follow Equation 1. D^*_{ij} is the propensity of an individual i to default on contract j, where only an indicator $D_{ij} = 1(D^*_{ij} > 0)$, whether the contract has been defaulted or not, is observed. Each contract finances a purchase of a particular type of the good k, and there are K types of the goods.

$$D^*_{ij} = X_i\beta + Z_j\gamma + \sum_{k=1}^{k=K} G^k_{ij} + \mu_i + \varepsilon_{ij} \tag{1}$$

X_i is vector of individual-specific characteristics

Z_j is vector of contract-specific characteristics[2]

G^k_{ij} is an indicator for the type of the good purchased, $G^{(k)}_{ij} = 1$ if good type k was financed through contract j of individual i and $G^{(k)}_{ij} = 0$ otherwise

μ_i is unobservable individual-specific heterogeneity

ε_{ij} is an error term, uncorrelated with the explanatory variables, as well as uncorrelated with μ_i

The G^k_{ij} indicators are the good fixed effects, and capture any non-random unobserved heterogeneity which is good-specific. There are no contract fixed effects, as all other contract related terms are observed. Equation 1 allows us to define the two potential sources of the unexplained variation in the default rates across different types of goods (the selection effect and the good effect) in econometric terms.

If there is no unobserved individual heterogeneity in the propensity to default, or if it is uncorrelated with the type of the good being purchased, $E(\mu_i/G^k_{ij}) = E(\mu_i)$ for all k, the unexplained residual variation in the default rates across different types of the goods is driven by the good effect, i.e. the effect of the good-specific characteristics on repayment behavior. Namely, $G^k_{ij} \neq 0$ for at least some k.

On the other hand, if $G^k_{ij} = 0$ for all k, there are no true good effects and the residual variation in the default rates across different types of goods is driven by the selection effect. Namely, it implies that the unobserved individual heterogeneity μ_i is not distributed randomly across different types

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

of goods, so that $E(\mu_i/G_{ij}^k) \neq E(\mu_i)$ for at least some k. In words, individuals with different levels of the unobserved component of the propensity to default sort themselves to buy different types of goods.

There are many applications in empirical economic research, in labor economics in particular, that try to distinguish a true causal effect of a particular variable from the selection effect due to unobserved individual heterogeneity that is correlated with this variable. To do this typically requires panel data. If multiple contracts per individual are observed, we can control for the unobserved individual heterogeneity μ_i in Equation 1 with individual fixed effects, and therefore directly estimate the true good effects G_{ij}^k, and test whether they are significantly different from zero.

However, attrition is endogenous here, and the extent of the bias is substantial. In particular, even if people who defaulted on their first contract still 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 very small. It is far from obvious how to model the selection process, where the current behavior determines whether a subsequent contract is observed.[3] This procedure imposes many distributional assumptions and requires rich enough data to give reliable estimates.

Although we have information on multiple contract applications and multiple contracts per individual in our data, the timing of the sequence of the contracts, of their repayment evaluation, and of the subsequent contract's acceptance decision is imprecise.[4] At the same time, to answer our question about whether the selection effect or the good effect dominates the unexplained cross-good variation in default rates, does not necessarily require to control for the general individual specific heterogeneity component μ_i (provided it is uncorrelated with explanatory variables in the model other than the good-specific dummy variables). As will be explained shortly, to avoid endogenous attrition as well as the assumptions it imposes on the data, we choose to estimate Equation 1 only on individuals' first contracts, while using the information about the goods financed by the current as well as subsequent accepted and rejected applications to capture the goods-related part of the individual heterogeneity.

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

[4] Namely, it is not clear when the repayment behavior on current contract is observed in relation to the acceptance decision on the future contract.

3 Estimation Methods - Three Models

This section describes the three empirical models we estimate. So far, we have only presented (in Table 1) the unconditional variation in the default probability across different goods. The first question to ask is whether this variation is still present even after controlling for the observable individual and contract-specific characteristics, and when taking into account the potential selection bias due to the fact that repayment behavior is only observed for the accepted loan applications. We therefore estimate Model I, in which the probability of default is a function of the individual-specific and contract-specific variables, using the accepted first loan applications of the individuals in our sample. We then add to Model I a selection equation for the acceptance decision, and estimate Model II, using both the accepted and the rejected first loan applications.

In both models, we include the binary indicators for the type of the good purchased. These good-specific dummy variables capture any potential cross-good variation of the default probability that is not explained by the observed characteristics, and/or by the selection bias due to credit rationing.

3.1 Model I

In Model I, we estimate a simple binary model of the default probability, as described by Equation 2, using only the accepted first loan applications of the individuals in our sample, to avoid the endogenous attrition in the composition of the subsequent accepted loan applications.

The propensity to default is estimated by a simple probit model as follows

$$D^*_{ij} = X_i\beta + Z_j\gamma + \sum_{k=1}^{k=K} G^k_{ij} + \omega_{ij} \tag{2}$$

where

X_i includes functions of individual characteristics such as gender, age, marital status, number of children, disposable income, employment status, job tenure, home ownership, renting, tenure with the bank, and geographic indicators for the province of residence

Z_j includes functions of contract characteristics such as length of the contract, size of the loan, interest rate (internal rate of return), price of the good purchased, loan insurance, means of payments, the dealer of the good, whether dealer pays the interest rate, etc.

ω_{ij} is a composite error term, assumed to follow normal distribution and to be uncorrelated with the explanatory variables

The estimated good-specific dummy variables $\hat{G}^k_{ij}$ capture the residual differences in the propensity to default across different types of goods, i.e. differences that are unexplained by the model.

The main objectives of the estimation of Model I is to show whether the observed unconditional variation in the default rates across different types of goods persist even after controlling for all the observable individual and contract-specific characteristics X_i and Z_j.

3.2 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, as shown in Table 2, acceptance rates also vary across different types of goods which may further bias the estimated good-specific dummy variables. We take this potential selection into account in Model II. The default probability is estimated on the subset of the accepted first loan applications, while the rejected first applications are used to correct for the selection bias due to credit rationing. In Model II, we use an equation for D^*_{ij}, the propensity of an individual i to default on a loan j, that is identical to Model I, and add a second equation for Y^*_{ij}, a latent index that determines bank's decision whether to accept an application of an individual i for loan j or not. Model II is described as follows

$$
\begin{aligned}
D^*_{ij} &= X_i\beta + Z_j\gamma + \sum_{k=1}^{k=K} G^k_{ij} + \omega_{ij} \quad \text{and} \quad D_{ij} = 1(D^*_{ij} > 0) \\
Y^*_{ij} &= W\delta + u_{ij} \quad \text{and} \quad Y_{ij} = 1(y^*_{ij} > 0) \\
& \quad D_{ij} \quad \text{is observed iff} \quad Y_{ij} = 1
\end{aligned}
$$

$W \supset X_i, Z_j$ and the G^k_{ij} indicators[5]

ω_{ij} **and** u_{ij} are assumed to be jointly normally distributed

[5] As date of birth is missing for the rejected loan applications, age is not included in the acceptance decision equation. In addition, indicators for an agency (bank's branch)

Given the distributional assumptions, the system of the two equations corresponds to the bivariate probit model with censoring,[6] and is estimated jointly by maximum likelihood. The identification requires at least one exclusion restriction, a variable present in the selection equation but excluded from the equation for the default probability.

We follow Alessie et al. (2005) in our choice of the exclusion restrictions. The advantage of the data at hand is that it spans over a period during which so called Usury Law was enacted in Italy, a reform that put ceilings on the interest rates on certain consumer loans. It is likely that this policy measure had an impact on both the interest rates, as well as the degree of credit rationing in case of the loans that were affected by the reform.

More specifically, the exclusion restriction that we use to estimate Model II is 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. However, the interest rates typically vary with the size of the loan, so that loans of different sizes have been affected unequally.[7] We therefore interact the Usury Law dummy variable with the size of the loan and the size of the loan squared, to be able to capture this variation.

Using this reform as an exclusion restriction, we assume that while the reform had an impact on the interest rates and the acceptance decisions, it had no direct impact on the default behavior. In other words, we claim that once we control for the acceptance decision and condition on the interest rate and other variables in the model, the reform has not altered the propensity to default. The validity of the exclusion restriction therefore hinges 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.

Model II is estimated on all first loan applications. It controls for the potential selection bias due to credit rationing (using rejected applications) but ignores any unobserved individual heterogeneity that would be correlated with the type of the good being financed. We estimate Model II to find out whether the observed variation in the default rates across different

that administers the loans are used instead of the indicators for the province of residence in the acceptance decision equation. The two are highly correlated, and only one set can be in each of the equations. While place of residence is likely to matter more for default behavior, the agency fixed effect is crucial for the acceptance decision they make.

[6] As described for example in Greene (2003).

[7] In addition, the interest rate ceilings imposed by the reform also vary for three categories of instalment loans, as given by its size.

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 good-specific dummy variables $\hat{G}_{ij}^k$ reveals whether this is still the case.

3.3 Model III - Preferred Model

As has been pointed out, the good-specific dummy variables $\hat{G}_{ij}^k$ in the equation of the probability of default, estimated by Model I and Model II using the cross-sectional data of the accepted first loan applications, capture the residual cross-good variation in default rates. If we find that the estimated $\hat{G}_{ij}^k$ are statistically significant, we conclude that the variation in the default probability across different types of goods is still present, even after controlling for the observed characteristics and for the potential selection bias due to credit rationing. However, we cannot say anything about what drives this residual variation. $\hat{G}_{ij}^k$ represent a reduced-form estimates of this variation, which brings no evidence on its source. Namely, the estimates of the good-specific dummy variables $\hat{G}_{ij}^k$, if statistically significant, may be interpreted either as the selection effect or the good effect. In the first case, it captures the mean value of the unobserved individual propensity to default of individuals buying different types of the good,[8] in the second, it simple estimates the true good effects G_{ij}^k.[9]

If we find that the residual variation is still present, we next explore what is its cause. Is it the selection effect, due to the unobserved individual heterogeneity in the propensity to default that is correlated with the type of the goods individuals buy on credit, or is it the causal effect of the good itself? Neither Model I or Model II can answer this question. To show whether it is the selection effect or the good effect what drives the residual variation, we estimate Model III, in which we use subsequent loan applications to help us disentangle μ_i^k from G_{ij}^k.

[8] For illustration, lets imagine that the unobserved individual heterogeneity component in the propensity to default varies only with the type of the good purchased but is uncorrelated with the rest of the explanatory variables, e.g. $\mu_i = \mu^k + \nu_i$, where ν_i is an iid error term. The good-specific dummy variables, $\hat{G}_{ij}^k$, would simply estimate μ^k, the average levels of μ_i in different goods' categories.

[9] 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 $E(\mu_i/k) = E(\mu_i)$ and μ_i is independent of the explanatory variables), the estimated good-specific dummy variables can be interpreted structurally as the "causal" good effects, i.e. an effect the particular good has on the individuals' repayment behavior.

Model III is identical to Model II except for the goods-type related individual heterogeneity indicators T_i^k, constructed from the multiple loan applications and included in the equation of the propensity to default.

$$
\begin{aligned}
D_{ij}^* &= X_i\beta + Z_j\gamma + \sum_{k=1}^{k=K} G_{ij}^k + + \sum_{k=1}^{k=K} T_i^k + \varepsilon_{ij} \quad \text{and} \quad D_{ij} = 1(D_{ij}^* > 0) \\
Y_{ij}^* &= W\delta + u_{ij} \quad \text{and} \quad Y_{ij} = 1(y_{ij}^* > 0) \\
& \quad D_{ij} \quad \text{is observed iff} \quad Y_{ij} = 1
\end{aligned}
$$

ε_{ij} **and** u_{ij} are assumed to be jointly normally distributed

$W \supset X_i, Z_j$ and the G_{ij}^k indicators and the exclusion restriction: Usury Law indicator and its interaction with the loan size and the squared loan size

The goods-type related indicators T_i^k are based on all the loan applications, first and subsequent, regardless whether accepted or rejected, observed for each individual in the sample. They are constructed as follows: $T_i^k = 1$ if at least one of the credit applications, accepted or rejected, was to finance a good of the type k, and $T_i^k = 0$ otherwise.

The number of different goods applied for, as well as their mixture vary across individuals. As there are K types of goods observed, there are K indicators constructed and included in the default equation to capture the part of μ_i that is correlated with the type of the good.

The above described method controls for any goods-related unobserved time-invariant individual heterogeneity μ_i^k through a certain kind of constructed fixed effects. It does however capture *only* the goods-related individual heterogeneity, and it still makes an assumption about the remaining unobserved individual heterogeneity to be randomly distributed across individuals and goods, and to be uncorrelated with the other explanatory variables.

Similar to Model II, we estimate Model III as a bivariate probit model with censoring by maximum likelihood. It is estimated on the first loan applications, using rejected applications to control for the potential selection bias due to credit rationing. We exploit the multiple loan applications by the same individual to construct the goods-type related indicators T_i^k in order to control for the unobserved individual heterogeneity in the propensity to default, which is correlated with the type of the good purchased on credit. As Model III controls for the individual heterogeneity related to type of goods purchased, the estimated good-specific dummy variables $\hat{G}_{ij}^k$ reflect the true good effect, while the estimated goods-type related indicators $\hat{T}_i^k$ capture the goods-related individual heterogeneity, i.e. the selection effect.

4 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, i.e. collecting agencies. Each borrower may have several contracts. All current and past contracts and applications of the sample of borrowers are observed up to 1999, the year of extraction of the data. The sampling has been performed randomly on a borrower level. The observed contracts and applications span over the period 1995-1999.

In total, there are 75,447 accepted first loan applications and 16,024 rejected first applications in the data used for the estimation. Table 3 presents the means of the key variables for the sample of the accepted first loan applications that is used for the estiamtion of the propensity to default. See Alessie et al.(2005) for a detailed description of the data and the discussion to what extent it is representative of Italian population.

The key factor of the repayment behavior that this paper is interested in is the type of the good being purchased on credit. We construct nine categories of the goods, based on the information about the good financed through a particular contract. Table 4 shows the distribution of the contracts in our sample (the accepted first loan applications) across the nine different types of goods. Both proportions and the absolute sample size for the nine good categories are presented.

5 Results

We next discuss the results from the estimation of the three models described above. As the nine good-specific dummy variables add to one, one of the good types is excluded as a base category. We choose the category titled "Other", which ranks in the middle according to the unconditional default rates compared across the good categories and more or less corresponds to the average default rate in the sample, to be excluded. The effect of the good

Table 3: Summary Statistics - Accepted First Loan Applications

Variable	Mean	Variable	Mean
Default	0.06		
Female	0.27	Interest rate (IRR)	17%
Age	39.5	Size of the loan	1,397*
Married	0.64	Maturity of the loan	12.4
Num. of kids	0.87	Price of the good	1,955*
Profession tenure	8.6	Contract insured	0.19
Hownownership	0.48	Buyer pays interest	0.62
Mortgage	0.04	Dealer pays interest	0.36
Household Income	15,200*	Payment by bank	0.31
With bank before 1990	0.20		
Private employees	0.51		
Public employees	0.22		
Self-employed	0.13		
Retired	0.12		

∗ in EUR, deflated to year 2000 values

Definitions of the variables are presented in the Appendix.

Table 4: Distribution of Accepted First Loans Across the Type of Goods

Type of the Good	% of individuals	N of Individuals
New Cars and Motor Homes	2.2%	3,745
(Used) Cars and Motor Homes	6.9%	2,088
Motorbikes	6.6%	9,178
Electr. Equipment (Brown Goods)	6.1%	26,069
Computers	3.8%	2,978
White Goods (Kitchen appliances)	3.7%	5,398
Furniture	3.7%	4,296
Telecommunication	10.1%	13,951
Other	4.8%	7,744
Total	100%	75,447

on the probability of the default is therefore always measured relative to the category Other. The estimated good-specific dummy variables capture the residual cross-good variation as follows: if the coefficient of the dummy variable for a particular good category is statistically significant and positive, it means that the propensity to default on that particular good is higher than the average default rate.

As discussed in the introduction, the unconditional tabulation of the default rates across different types of goods, as shown in Table 1, suggests that mobile phones, motorcycles, used cars and electrical appliances are typically repaid least often, while furniture, kitchen goods and especially new cars have the lowest default rates. When we list the estimated good-specific dummy variables, we present the estimates for the different types of goods in the order given by the ranking of their unconditional default rates, starting from the lowest to the highest. In this way, it is easy to see both whether the order of the goods' contributions to the propensity to default corresponds to the unconditional cross-good variation in the default, as well as whether a particular good has above or below-average effect on the default. As the main focus of the paper is the residual cross-good variation in the default rates, only the estimates of the goods-related variables (good-specific dummy variables $\hat{G}_{ij}^{k}$ and the goods-type individual heterogeneity indicators $\hat{T}_{i}^{k}$) are presented here. The impact of the different types of goods and the impact of the goods-type individual heterogeneity on the probability of default are expressed in terms of marginal effects. The list of the other explanatory variables that we condition on, as well as the full estimation results can be found in Appendix.

Most of the estimated effects of the individual and the contract-specific characteristics are stable across the three models and in line with prior expectations. As for the individual level characteristics, marital status, job tenure, disposable income, home ownership, having a mortgage, being a public employee, and being a client of the bank prior to 1990 decrease the probability of default, while self-employment status as well as the number of children increase it. In terms of the contract features, interest rate, size of the loan, as well as its length increase the probability of default, while price of the good, contract insurance, and payments by bank rather than postal orders reduce it. The exclusion restrictions in the acceptance decision equation - the Usury Law enactment, a dummy variable that indicates that the contract application originates from the period prior to the reform, also interacted with the size of the loan and the size of the loan squared - are all significant. The coefficients suggest that, controlling for any other factors, including the year dummy variables for the start of the contract, the acceptance rates fell after the reform, but less so for the bigger loans. This suggest that, in response to the reform and given the default probabilities, the bank tries to maintain the same expected return from credit, by making the rules stricter in cases where the interest rates had to be lowered below the legal limit. The estimates also confirm the differing effect of the law by the size of the loan. Table 5 presents the marginal effects of the good-specific dummy variables $\hat{G}_i^k$, estimated by Model I and Model II. The standard errors are given in parenthesis.

Table 5: Results Model I and Model II

	Model I		Model II	
New Cars	-0.022**	(0.002)	-0.022**	(0.003)
Kitchen Appl.	0.001	(0.003)	0.001	(0.003)
Furniture	-0.008**	(0.003)	-0.008**	(0.003)
Computers	-0.001	(0.004)	0.000	(0.004)
Electrical Eq.	0.013**	(0.003)	0.013**	(0.003)
Used Cars	0.000	(0.005)	0.001	(0.005)
Motorbikes	0.006*	(0.003)	0.006*	(0.003)
Mobile Phones	0.030**	(0.004)	0.030**	(0.004)

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

Other is the Base Category. Ordered by unconditional default rates.

It is apparent that the results from Model I and Model II are almost identical and reach the same conclusions in all relevant aspects. This means that despite the fact that the estimated correlation between the residuals in the acceptance decision and the default equation is positive and statistically significant, the selection bias for the good indicators is negligible.

The results in Table 5 show that even when we condition on the key individual-specific and contract-specific factors, as in Model I, and also control for the potential selection bias due to credit rationing, the variation of the default rates across different types of goods is still present. This variation is captured by the significance of the marginal effects of the goods on the default probability - whether they are statistically significant from the base category, and therefore also from average and from each other. The results suggest 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 are repaid more often than average.

When we compare the ranking of the goods by the unconditional default rates, as given by the order in which their are presented, with the ranking given by the signs and the magnitudes of the estimated marginal effects, we see that the ordering of the goods according to their effect on the probability of default is more or less preserved. There are, however, three exceptions. Kitchen appliances are ranked at a higher and used cars at a lower level than before, i.e. closer to the average from which they are both statistically undistinguishable, suggesting that selection on observable characteristics of the contracts and the borrowers drives part of the rather low and rather high unconditional default rates in these two cases. On the other hand, electrical equipment, which ranks in the middle of the unconditional default rates, has a sizable and highly significant effect on the probability to default that moves it down in the ranking to the second least repaid good, just after the mobile phones. Overall, the estimates from the first two models reveal the positive effect of mobile phones (0.030), electrical equipment (0.013), and motorcycles (0.006), and the negative effect of furniture (-0.008) and new cars (-0.022) on the default probability. Model I and II have confirmed that the cross-good variation in the default rate, as captured by the reduced form estimates of the good-specific dummy variables $\hat{G}_{ij}^{k}$, persists even after controlling for the observed individual-specific and good-specific characteristics and for the potential selection bias due to credit rationing. We next explore the estimation results of Model III in order to find out whether it is the selection or the good effect which explains this residual 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 indicators $\hat{T}_{i}^{k}$. Table 8 presents the results from Model III. When controlling for the goods-type related individual heterogeneity, the effect of the goods on the default rate, as measured by the estimated good-specific dummy variables $\hat{G}_{ij}^{k}$, which now capture the true good effect, increases in magnitude only for the new cars (from -0.022 to -0.025). The positive good effects of the electrical equipment and the mobile phones are reduced from 0.013 to 0.011 and from 0.030 to 0.020 respectively. The good effect of furniture disappears, while it decreases in significance and even changes the sign for the motorcycles.

Summarizing the left half of Table 8 which shows the results for the true good effect, we conclude that while new cars (and also somewhat motorcycles) reduce the incentive to default, electrical equipment and, in particular, mobile phones increase it. However, the significance and the magnitude of many of the estimated good-specific dummy variables decline, suggesting that it is the selection effect rather than the good effect that is captured by the reduced-form indicators $\hat{G}^k_{ij}$, estimated in Model I and Model II.

Table 6: Model III - Preferred Model

	Good effect		Selection effect	
New Cars	-0.025**	(0.003)	0.002	(0.005)
Kitchen Appl.	0.009	(0.008)	-0.013**	(0.003)
Furniture	-0.005	(0.006)	-0.011**	(0.004)
Computers	0.001	(0.008)	-0.010*	(0.005)
Other	Base	Base	-0.008**	(0.003)
Electrical Eq.	0.011*	(0.005)	-0.007**	(0.002)
Used Cars	-0.008	(0.006)	0.001	(0.006)
Motorbikes	-0.009†	(0.005)	0.008†	(0.004)
Mobile Phones	0.020**	(0.007)	-0.002	(0.003)

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

Ordered by unconditional default rates.

Marginal effects, standard errors in parenthesis.

The results for the selection effect, presented in the right half of the table, confirm this as well. The previously documented negative effect of the furniture is driven by selection: it is not the effect of furniture but rather the kind of people who buy them that reduces their default rate. The marginal effects of the goods-type individual heterogeneity show 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, as well as computers, electrical equipment and Other goods are less likely to default, while those who buy motorcycles have an above-average propensity to default (although the effect is significant only at a 10 % level). Based on the results from Model III, we conclude that the selection effect explains most of the residual cross-good variation in the default rates.

We interpret the results as follows. The mobile phones may have a positive good effect on the probability of default for two potential reasons. First, they are easy to "hide", and therefore not as easy to repossess by the debt-collector, so that the penalty for default is low. Second, they are frequently stolen, often brake, and get quickly out of fashion, which are all features that shorten their lifetime and increases their depreciation rate, and therefore possibly reduce the incentives of the borrowers to repay them. The negative effect of the new cars, on the other hand, may be explained by the high penalty of default given by the high risk of repossession. Cars are registered and relatively easy to find and repossess and a well-developed and efficient second-hand market for the used cars increases the incentive to repossess.

In case of the motorcycles, it seems that both the selection effect, which increases the default probability, and the good effect, which reduces the default probability, are at work. While not-repaying people seem to buy motorcycles more often, the good has a positive effect on repayment, possibly for similar reasons as cars. The two counteracting effects are also present for electrical equipment, although with opposite signs. While repaying people buy electrical equipment, electrical equipment makes individuals repay less often, possibly for similar reasons as mobile phones.[10]

The results for 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 and furniture, on the other hand, probably have, or are about to start, a family, are home-owners, and lead a more steady life. It is likely that they are more risk-averse and default is more costly for them, so that they tend to repay their loans with an above-average probability.

To summarize, much of the cross-good variation in the default probability is explained by the selection effect rather than the effect of the good. Individuals who buy kitchen appliances, furniture, and computers are less likely to default their loans than an average person. The true "causal" good effect explains the above-average default rates of the mobile phones and the bellow-average default rates of the new cars. For motorcycles and the electrical equipment, both effects seem to be at play and have opposite effects on the propensity to default.

6 Sensitivity Analysis

The construction of the individual goods-type indicators T_i^k as well as the identification of the selection versus the good effect hinge on the fact that we observe multiple loan applications per individual, and more precisely, individuals applying for multiple types of goods. Table 7 summarizes the distribution of the goods information we have on individuals in our sample.

[10] Electrical equipment is uneasy to repossess, and evolves at a rather high seed, making the new good soon obsolete or out of fashion.

While there are 62,145 individuals who we observe applying for only one type of the good, there are 13,302 who have multiple goods information. 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.

Table 7: Distribution of the Multiple Goods Information across Individuals

	Freq	%
1	62,145	82.37
2	11,379	15.08
3	1,697	2.25
4	207	0.27
5	19	0.03
Total	75,447	100.00

The coefficients of the individual goods-type indicators T_i^k in Model III are identified *off* the individuals who are observed to apply for credit for more than one type of the good. If we observed only one loan application, or more precisely - if we observed only single good information - per individual,[11] the good-specific dummy variables G_{ij}^k and the individual goods-type indicators T_i^k could not be identified from each other. To test the validity of our identification strategy as well as the robustness of our results, we re-estimate Model III using only the accepted first contracts of individuals who have applied for more than one type of good in the data. We also condition on the multiple goods applications for the rejected first applications that are used to control for the selection bias due to credit rationing.

The estimates, presented in Table 8, further strengthen the conclusion that all the observed variation in the default rates across the goods is due to selection. The only good effect left is that of new cars and mobile phones. While the negative marginal effect of the new cars on the probability of default stays more or less unchanged (at the value of -0.024), the good effect of the mobile phones is reduced in both the magnitude (0.015) and significance - it is significantly different from the base category only at the 10 % level. The positive effect of electrical equipment and the negative effect of

[11] Note, that the number of the different types of the goods applied for (i.e. number of $T_i^k = 1$ per individual) is equal or smaller than the number of the applications, as individuals may apply multiple times for the same type of the good.

Table 8: Sensitivity Results - Individuals with Multiple Good Information

	Good effect		Selection effect	
New Cars	-0.024**	(0.008)	0.003	(0.007)
Kitchen Appl.	-0.001	(0.009)	-0.016**	(0.004)
Furniture	0.001	(0.011)	-0.010†	(0.005)
Computers	-0.010	(0.010)	-0.010†	(0.006)
Other	Base	Base	-0.007†	(0.004)
Electrical Eq.	0.009	(0.007)	-0.005	(0.005)
Used Cars	-0.010	(0.011)	0.001	(0.007)
Motorbikes	0.003	(0.009)	0.010†	(0.006)
Mobile Phones	0.015†	(0.009)	-0.004	(0.005)

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

Ordered by unconditional default rates.

Marginal effects, standard errors in parenthesis.

motorcycles on the default probability disappear when only multiple good-type applications are used for the estimation.

In addition, when we focus only on individuals with multiple goods applications, the observed variation in the default rates across goods due to selection remains for five good categories, but disappears for the electrical equipment. However, only the selection effect for kitchen appliances is highly significant, while the other four categories are significant only at the 10 % significance level. This is not surprising, as conditioning on the multiple goods observations, we are already selecting a particular group of loan applicants who - given the acceptance process - are likely to be a more homogenous group and have a lower propensity to default. The results of the sensitivity analysis suggest that except for the negative true good effect of the new cars and the positive true good effect of the mobile phones, it is the sorting of individuals to buying the different goods on credit, which drives the variation in the default rates across the different types of goods. We conclude that the individuals who buy kitchen appliances, furniture, computers and Other goods on credit tend to have bellow-average propensity to default, while individuals who buy on credit motorcycles are on average more likely to default.

7 Policy Implications

As mentioned before, the features of the contracts do not vary with individuals but only with the goods to be purchased on credit. They are posted next to the product that is offered for purchase. Acceptance decision vary with individual characteristics but also by the type of the good. This would be the correct strategy for the Findomestic Banca if it is the good effect that drives the cross-good variation in the default rates. In particular, by setting the interest rates higher and the acceptance rules stricter for the types of the goods with the high default rates, the bank may target similar expected returns from the loans on different types of goods. However, we have shown that it is the selection effect rather than the good effect that drives the cross-good variation in the default rates. This implies that the type of the good being purchased on credit is only an imprecise indicator of the repayment probability and that there is asymmetric information between the lender and the borrower, which leads to inefficiencies under the current arrangements. In particular, whenever individuals with high repayment discipline buy on credit a good that has a high default rate, they cross-subsidize, i.e. pay higher interest rate and face stricter acceptance rules, the high default risk individuals who are the ones who typically buy this good on credit. Individual-specific contract features would yield higher efficiency in this context.

Our results also suggest that information from multiple loan applications helps capture the individual heterogeneity that is correlated with the type of the good purchased on credit. Previous applications may be therefore employed by credit-granting companies as an additional information about the individual's propensity to default. These can be used even without, or prior to, observing the repayment behavior on past loans.

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 rather due to specific features of the goods 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 predominates.

We first show that the variation in default rates across different types of 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 good-specific dummy variables present. The Usury Law enacted in the middle of the observed period provides us with exclusion restrictions for the selection equation that describes the acceptance decision by the creditor. The estimated good-specific dummy variables 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 types of 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 probability of default using only accepted first contracts, employing 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 identify the selection effect and the good effect.

The preferred model, which includes both the good specific dummy variables, as well as the individual goods-types indicators constructed from the multiple contract observations, reveals that most of the cross-good variation can be explained by selection. We conclude that it is different types of people, with different unobserved propensity to default, that sort themselves to different types of goods, which drives the residual variation in the repayment behavior across different types of goods. In particular, the results suggest that individuals who buy kitchen appliances, furniture and computers are on average less likely to default on their loans, while those who buy motorcycles are on average more likely 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. 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 therefore possibly reduces the borrowers' incentives to repay.

Using contract theory to interpret our results, we provide evidence that asymmetric information is present in the consumer credit market under analysis, and that it is mostly in the form of adverse selection. Our findings suggest 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 goods-related type of the individual who applies for the loan.

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A Definition of the Key Variables

Left-hand-side Variables

default is a binary indicator whether a loan has been defaulted (equals 1 if defaulted and 0 otherwise). As some of the contracts are evaluated still before the end of the contract, we use an indicator for a severe and a very severe delay (more than five months) in the monthly payment, as viewed from the perspective of the evaluation date.[12]

accept is a binary indicator whether a loan application has been accepted (equals 1 if accepted and 0 otherwise)

Individual Characteristics of the Loan Applicants / Borrowers

female is a binary indicator for gender (equals 1 if the individual who applied for the loan is a woman)

age is individual's age (not available for rejected applications)

agesq is age squared and divided by 100 (not available for rejected applications)

married is a binary indicator of individual's marital status (equals 1 if married and 0 otherwise)

Nkids is the number of dependent children the individual has

exp is the individual's work experience in a given profession

expsq is the work experience squared and divided by 100

hown is a binary indicator for home-ownership (equals 1 if an individual owns his or her apartment or house and 0 otherwise)

mort is an indicator for mortgage (equals 1 if an individual has a mortgage and 0 otherwise)

_Ies_2 is a binary indicator for employment status that equals 1 if an individual is a public employees (private employee is a base category)

_Ies_3 is a binary indicator for employment status that equals 1 if an individual is a self-employed (private employee is a base category)

_Ies_4 is a binary indicator for employment status that equals 1 if an individual is retired (private employee is a base category)

_Ies_5 is a binary indicator for employment status that equals 1 if an individual has other employment status (private employee is a base category)

[12] An informal discussion with another instalment loan lender revealed that contracts on which a payment is delayed by more than three moths typically remain not repaid; it is the third month of the delay that is critical for saving the loan, i.e. when it is still worthwhile to act to get repaid.

lnyd is the logarithm of the net annual household labor income expressed in year 2000 Euros

Ybank90 is a binary indicator for the tenure with the bank (equals 1 if an individual was a Findomestic Banca customer before 1990)

Contract Characteristics - Terms of the Instalment Loan

interann is the annual interest rate (IRR) on the given loan, computed by the author[13]

amountD is the size of the loan, (in hundreds) expressed in year 2000 Euros

amountDsq is the size of the loan squared, divided by 100

Nmonths is the length of the contract (in months)

priceD is the price of the good purchased, (in hundreds) expressed in year 2000 Euros

priceDsq is price of the good squared, divided by 100

insured is a binary indicator for insurance against seriously adverse events leading to inability to repay (equals 1 the contract has been insured and 0 otherwise)

intwho1 is a binary indicator that equals 1 if the interest rate is paid by the borrower (base category is when both the borrower and the dealer pays part of the interest rate)

intwho3 is a binary indicator that equals 1 if the interest rate is paid by the dealer (base category is when both the borrower and the dealer pays part of the interest rate)

paybank is a binary indicator for the means of payments (equals 1 if payments made by bank and 0 if payments made by postal order)

_Iorig_2 - _Iorig_4 are indicators for the origin of the contract, i.e. the dealer who sells the good (there are four broad types of the dealers - Telematica, Corriere, Fax Contratto, and Telefono - Telematica is the base category)

Geographical and Time Fixed Effects

prov are binary indicators of the province of individual's residence (province fixed effects)

year97-year99 are binary indicators for the year of the evaluation of the contract (evaluation year fixed effects)

[13]The author is grateful to Stefan Hochguertel for providing her with the code to calculate IRRs from Alessie et al. (2005)

dy2-dy5 are binary indicators for the year of the inception of the contract (inception year fixed effects)

Exclusion Restrictions

pre_ref is a binary indicator that equals 1 if the contract started before the Usury Law was enacted and 0 otherwise

pre_ref*amountD is the Usury Law dummy indicator interacted with the size of the loan

pre_ref*amountDsq is the Usury Law dummy indicator interacted with the squared size of the loan

agency are binary indicators that describe the bank's agency in which the contract was administered (agency fixed effect)

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 9: Full results - Model I

Variable	**Coefficient**	**(Std. Err.)**
good==New Cars and motor homes	-0.492**	(0.089)
good==White Goods (kitchen appliances)	0.017	(0.047)
good==Furniture	-0.131**	(0.050)
good==Computers	-0.011	(0.057)
good==Electr. equipment (Brown Goods)	0.182**	(0.034)
good==(Used) Cars and motor homes	0.002	(0.068)
good==Motorbikes	0.086*	(0.038)
good==Telecommunication	0.363**	(0.036)
female	-0.020	(0.019)
age	-0.006	(0.005)

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... table 9 continued

Variable	Coefficient	(Std. Err.)
agesq	0.009	(0.006)
married	-0.218**	(0.022)
Nkids	0.020*	(0.009)
exp	-0.019**	(0.003)
expsq	0.033**	(0.009)
hown	-0.151**	(0.020)
mort	-0.258**	(0.058)
_Ies_2	-0.060*	(0.024)
_Ies_3	0.364**	(0.025)
_Ies_4	-0.004	(0.041)
_Ies_5	-0.016	(0.055)
lnyd	-0.045**	(0.017)
Ybank90	-0.077**	(0.028)
interann	0.697**	(0.128)
amountD	0.030**	(0.003)
amountDsq	-0.009**	(0.001)
Nmonths	0.003	(0.002)
priceD	-0.014**	(0.002)
priceDsq	0.003**	(0.000)
insured	0.061*	(0.024)
intwho1	0.098	(0.065)
intwho3	0.107†	(0.063)
paybank	-1.102**	(0.032)
_Iorig_2	-0.066	(0.078)
_Iorig_3	-0.046	(0.034)
_Iorig_4	-0.031	(0.029)
prov==ALESSANDRIA	-0.020	(0.117)
prov==ANCONA	0.133†	(0.081)
prov==BARI	-0.182*	(0.078)
prov==BOLOGNA	0.111	(0.077)
prov==BRESCIA	0.161†	(0.085)
prov==CAGLIARI	-0.200*	(0.083)
prov==CASERTA	-0.047	(0.080)
prov==CATANIA	-0.017	(0.075)
prov==COSENZA	0.004	(0.084)
prov==FIRENZE	-0.001	(0.083)
prov==GENOVA	0.151	(0.096)

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... table 9 continued

Variable	Coefficient	(Std. Err.)
prov==LATINA	-0.026	(0.087)
prov==LECCE	-0.128	(0.079)
prov==MESSINA	-0.046	(0.084)
prov==MILANO	0.144†	(0.076)
prov==NAPOLI	0.040	(0.073)
prov==PADOVA	0.006	(0.078)
prov==PALERMO	-0.006	(0.079)
prov==PERUGIA	0.112	(0.094)
prov==PESCARA	-0.113	(0.085)
prov==PISA	-0.118	(0.088)
prov==PISTOIA	-0.036	(0.100)
prov==REGGIO C.	0.060	(0.089)
prov==RIMINI	0.105	(0.095)
prov==ROMA	-0.026	(0.073)
prov==SALERNO	-0.052	(0.080)
prov==SASSARI	-0.242*	(0.108)
prov==TORINO	0.088	(0.077)
prov==TRAPANI	-0.161	(0.105)
prov==UDINE	0.036	(0.093)
prov==VARESE	0.026	(0.101)
prov==VERONA	0.144†	(0.084)
year97	0.491**	(0.041)
year98	0.961**	(0.048)
year99	1.508**	(0.054)
dy2	-0.275**	(0.039)
dy3	-0.720**	(0.047)
dy4	-1.199**	(0.054)
dy5	-1.676**	(0.061)
Intercept	-1.354**	(0.201)

N	75447
Log-likelihood	-14595.881
$\chi^2_{(75)}$	5833.996

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

Table 10: Model II

Variable	Coefficient	(Std. Err.)
Equation 1 : default		
good==New Cars and motor homes	-0.453**	(0.091)
good==White Goods (kitchen appliances)	0.011	(0.047)
good==Furniture	-0.122*	(0.050)
good==Computers	-0.007	(0.057)
good==Electr. equipment (Brown Goods)	0.177**	(0.034)
good==(Used) Cars and motor homes	0.013	(0.068)
good==Motorbikes	0.086*	(0.038)
good==Telecommunication	0.354**	(0.036)
female	0.032	(0.029)
age	-0.006	(0.005)
agesq	0.009	(0.006)
married	-0.210**	(0.023)
Nkids	0.017†	(0.010)
exp	-0.017**	(0.003)
expsq	0.028**	(0.009)
hown	-0.140**	(0.021)
mort	-0.249**	(0.058)
_Ies_2	-0.056*	(0.024)
_Ies_3	0.358**	(0.025)
_Ies_4	-0.014	(0.041)
_Ies_5	-0.038	(0.055)
lnyd	-0.039*	(0.017)
Ybank90	-0.077**	(0.028)
interann	0.673**	(0.128)
amountD	0.028**	(0.003)
amountDsq	-0.009**	(0.002)
Nmonths	0.001	(0.002)
priceD	-0.013**	(0.002)
priceDsq	0.003**	(0.000)
insured	0.056*	(0.024)
intwho1	0.091	(0.065)
intwho3	0.099	(0.062)
paybank	-1.051**	(0.039)
_Iorig_2	-0.065	(0.078)

Continued on next page...

... table 10 continued

Variable	**Coefficient**	**(Std. Err.)**
_Iorig_3	-0.048	(0.034)
_Iorig_4	-0.043	(0.029)
prov==ALESSANDRIA	-0.036	(0.117)
prov==ANCONA	0.133†	(0.081)
prov==BARI	-0.172*	(0.078)
prov==BOLOGNA	0.108	(0.077)
prov==BRESCIA	0.153†	(0.085)
prov==CAGLIARI	-0.190*	(0.083)
prov==CASERTA	-0.051	(0.080)
prov==CATANIA	-0.018	(0.075)
prov==COSENZA	-0.003	(0.084)
prov==FIRENZE	-0.011	(0.083)
prov==GENOVA	0.150	(0.096)
prov==LATINA	-0.023	(0.087)
prov==LECCE	-0.124	(0.079)
prov==MESSINA	-0.039	(0.084)
prov==MILANO	0.132†	(0.076)
prov==NAPOLI	0.031	(0.073)
prov==PADOVA	0.011	(0.078)
prov==PALERMO	-0.011	(0.079)
prov==PERUGIA	0.105	(0.094)
prov==PESCARA	-0.108	(0.085)
prov==PISA	-0.116	(0.088)
prov==PISTOIA	-0.033	(0.100)
prov==REGGIO C.	0.054	(0.089)
prov==RIMINI	0.101	(0.095)
prov==ROMA	-0.031	(0.073)
prov==SALERNO	-0.047	(0.079)
prov==SASSARI	-0.235*	(0.107)
prov==TORINO	0.081	(0.077)
prov==TRAPANI	-0.158	(0.105)
prov==UDINE	0.034	(0.092)
prov==VARESE	0.017	(0.101)
prov==VERONA	0.137	(0.084)
year97	0.493**	(0.041)
year98	0.959**	(0.048)
year99	1.505**	(0.054)

Continued on next page...

... table 10 continued

Variable	Coefficient	(Std. Err.)
dy2	-0.293**	(0.039)
dy3	-0.742**	(0.048)
dy4	-1.223**	(0.054)
dy5	-1.702**	(0.061)
Intercept	-1.408**	(0.202)
Equation 2 : accept		
Available from the author upon request		
Equation 3 : athrho		
Intercept	0.131*	(0.060)
N	91471	
Log-likelihood	-42124.477	
$\chi^2_{(75)}$	3072.618	

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

Table 11: Model III - Preferred Model

Variable	Coefficient	(Std. Err.)
Equation 1 : default		
good==New Cars and motor homes	-0.598**	(0.127)
good==White Goods (kitchen appliances)	0.115	(0.092)
good==Furniture	-0.072	(0.104)
good==Computers	0.021	(0.116)
good==Electr. equipment (Brown Goods)	0.149*	(0.068)
good==(Used) Cars and motor homes	-0.129	(0.116)
good==Motorbikes	-0.142†	(0.081)
good==Telecommunication	0.254**	(0.072)
T^k for New Cars and motor homes	0.025	(0.075)
T^k for White Goods (kitchen appliances)	-0.226**	(0.062)
T^k for Furniture	-0.176*	(0.078)
T^k for Computers	-0.157†	(0.090)
T^k for Other	-0.128*	(0.051)
T^k for Electr. equipment (Brown Goods)	-0.104**	(0.035)

Continued on next page...

... table 11 continued

Variable	**Coefficient**	**(Std. Err.)**
T^k for (Used) Cars and motor homes	0.018	(0.081)
T^k for Motorbikes	$0.101^{\dagger}$	(0.053)
T^k for Telecommunication	-0.024	(0.040)
female	0.031	(0.029)
age	-0.005	(0.005)
agesq	0.008	(0.006)
married	-0.207^{**}	(0.023)
Nkids	$0.017^{\dagger}$	(0.010)
exp	-0.017^{**}	(0.003)
expsq	0.028^{**}	(0.009)
hown	-0.144^{**}	(0.021)
mort	-0.252^{**}	(0.058)
_Ies_2	-0.053^{*}	(0.024)
_Ies_3	0.356^{**}	(0.025)
_Ies_4	-0.010	(0.041)
_Ies_5	-0.036	(0.055)
lnyd	-0.040^{*}	(0.017)
Ybank90	-0.079^{**}	(0.028)
interann	0.670^{**}	(0.128)
amountD	0.028^{**}	(0.003)
amountDsq	-0.008^{**}	(0.002)
Nmonths	0.001	(0.002)
priceD	-0.014^{**}	(0.002)
priceDsq	0.003^{**}	(0.000)
insured	0.055^{*}	(0.024)
intwho1	0.089	(0.065)
intwho3	0.096	(0.063)
paybank	-1.051^{**}	(0.039)
_Iorig_2	-0.066	(0.078)
_Iorig_3	-0.050	(0.034)
_Iorig_4	$-0.049^{\dagger}$	(0.029)
prov==ALESSANDRIA	-0.037	(0.117)
prov==ANCONA	$0.138^{\dagger}$	(0.081)
prov==BARI	-0.171^{*}	(0.078)
prov==BOLOGNA	0.111	(0.077)
prov==BRESCIA	$0.159^{\dagger}$	(0.085)
prov==CAGLIARI	-0.180^{*}	(0.083)

Continued on next page...

... table 11 continued

Variable	Coefficient	(Std. Err.)
prov==CASERTA	-0.048	(0.080)
prov==CATANIA	-0.013	(0.075)
prov==COSENZA	-0.003	(0.084)
prov==FIRENZE	-0.007	(0.083)
prov==GENOVA	0.149	(0.096)
prov==LATINA	-0.020	(0.087)
prov==LECCE	-0.120	(0.079)
prov==MESSINA	-0.030	(0.084)
prov==MILANO	0.133†	(0.076)
prov==NAPOLI	0.035	(0.073)
prov==PADOVA	0.013	(0.078)
prov==PALERMO	0.006	(0.079)
prov==PERUGIA	0.106	(0.094)
prov==PESCARA	-0.107	(0.085)
prov==PISA	-0.111	(0.088)
prov==PISTOIA	-0.026	(0.100)
prov==REGGIO C.	0.061	(0.089)
prov==RIMINI	0.106	(0.095)
prov==ROMA	-0.026	(0.073)
prov==SALERNO	-0.050	(0.079)
prov==SASSARI	-0.230*	(0.107)
prov==TORINO	0.085	(0.077)
prov==TRAPANI	-0.156	(0.105)
prov==UDINE	0.028	(0.092)
prov==VARESE	0.016	(0.101)
prov==VERONA	0.141†	(0.084)
year97	0.493**	(0.041)
year98	0.961**	(0.048)
year99	1.504**	(0.054)
dy2	-0.297**	(0.040)
dy3	-0.751**	(0.048)
dy4	-1.236**	(0.054)
dy5	-1.720**	(0.061)
Intercept	-1.258**	(0.208)
Equation 2 : accept		
Available from the author upon request		

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... table 11 continued

Variable	Coefficient	(Std. Err.)
N	91471	
Log-likelihood	-42102.247	
$\chi^2_{(84)}$	3106.05	

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

Table 12: Sensitivity Results - Individuals with Multiple Good Information only

Variable	Coefficient	(Std. Err.)
Equation 1 : default		
good==New Cars and motor homes	-0.495†	(0.273)
good==White Goods (kitchen appliances)	-0.010	(0.129)
good==Furniture Units	0.008	(0.146)
good==Computers	-0.155	(0.183)
good==Electr. equipment (Brown Goods)	0.119	(0.093)
good==(Used) Cars and motor homes	-0.148	(0.204)
good==Motorbikes	0.043	(0.113)
good==Telecommunication	0.186†	(0.100)
T^k for New Cars and motor homes	0.040	(0.088)
T^k for White Goods (kitchen appliances)	-0.242**	(0.076)
T^k for Furniture Units	-0.157†	(0.090)
T^k for Computers	-0.150	(0.100)
T^k for Other	-0.107	(0.067)
T^k for Electr. equipment (Brown Goods)	-0.070	(0.063)
T^k for (Used) Cars and motor homes	0.013	(0.092)
T^k for Motorbikes	0.126†	(0.069)
T^k for Telecommunication	-0.051	(0.063)
female	-0.117*	(0.050)
age	-0.019†	(0.012)
agesq	0.027*	(0.014)
married	-0.224**	(0.054)
Nkids	0.023	(0.022)
exp	-0.015*	(0.007)

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... table 12 continued

Variable	Coefficient	(Std. Err.)
expsq	0.022	(0.024)
hown	-0.126**	(0.048)
mort	-0.289†	(0.153)
_Ies_2	-0.039	(0.056)
_Ies_3	0.300**	(0.062)
_Ies_4	-0.013	(0.098)
_Ies_5	-0.183	(0.136)
lnyd	-0.113**	(0.044)
Ybank90	-0.146*	(0.074)
interann	0.923**	(0.302)
amountD	0.031**	(0.012)
amountDsq	-0.005	(0.007)
Nmonths	-0.004	(0.005)
priceD	-0.016†	(0.008)
priceDsq	0.002	(0.004)
insured	-0.046	(0.055)
intwho1	0.019	(0.144)
intwho3	-0.013	(0.136)
paybank	-0.920**	(0.079)
_Iorig_2	-0.258	(0.188)
_Iorig_3	-0.084	(0.088)
_Iorig_4	-0.315**	(0.073)
prov==ALESSANDRIA	-0.475	(0.380)
prov==ANCONA	-0.016	(0.181)
prov==BARI	-0.408*	(0.179)
prov==BOLOGNA	-0.037	(0.176)
prov==BRESCIA	0.049	(0.193)
prov==CAGLIARI	-0.493**	(0.188)
prov==CASERTA	-0.410*	(0.178)
prov==CATANIA	-0.207	(0.160)
prov==COSENZA	-0.200	(0.183)
prov==FIRENZE	-0.098	(0.184)
prov==GENOVA	-0.166	(0.262)
prov==LATINA	-0.381†	(0.201)
prov==LECCE	-0.187	(0.172)
prov==MESSINA	-0.201	(0.173)
prov==MILANO	-0.105	(0.181)

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... table 12 continued

Variable	Coefficient	(Std. Err.)
prov==NAPOLI	-0.152	(0.159)
prov==PADOVA	-0.109	(0.178)
prov==PALERMO	-0.343*	(0.168)
prov==PERUGIA	0.083	(0.241)
prov==PESCARA	-0.309	(0.206)
prov==PISA	-0.184	(0.199)
prov==PISTOIA	-0.119	(0.215)
prov==REGGIO C.	-0.052	(0.187)
prov==RIMINI	-0.042	(0.231)
prov==ROMA	-0.217	(0.160)
prov==SALERNO	-0.232	(0.180)
prov==SASSARI	-0.645*	(0.261)
prov==TORINO	-0.075	(0.173)
prov==TRAPANI	-0.368	(0.231)
prov==UDINE	-0.259	(0.242)
prov==VARESE	-0.154	(0.258)
prov==VERONA	-0.017	(0.193)
year97	0.561**	(0.089)
year98	1.030**	(0.108)
year99	1.541**	(0.125)
dy2	-0.381**	(0.084)
dy3	-0.838**	(0.106)
dy4	-1.225**	(0.124)
dy5	-1.552**	(0.154)
Intercept	0.017	(0.504)
Equation 2 : accept		
Available from the author upon request		
Equation 3 : athrho		
Intercept	0.371†	(0.223)
N	13865	
Log-likelihood	-4173.64	
$\chi^2_{(84)}$	596.54	

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