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Consumer Credit:

Evidence from Italian Micro Data

by

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PRELIMINARY
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Abstract. In this paper we analyse unique data on credit applications received by the leading provider of consumer credit in Italy (Findomestic). This data set covers a five year period (1995-1999) and contains information on both accepted and rejected applications. During this period the consumer credit market has much expanded in Italy and a new law has come into force that sets a limit to interest rates charged to consumers (the usury law). We investigate ways in which the law may have affected the consumer credit market and show how the applicants pool has changed over time in comparison to a representative sample of the Italian population.
We compute behavioural changes by controlling for changes in the observable characteristics of the Findomestic clientele and argue that, under suitable identifying assumptions, these changes can be given a structural interpretation. If the usury shock is assumed to have directly affected credit supply but not credit demand, we can estimate a demand equation. Our key finding is that demand is interest rate elastic, something that may explain why the consumer credit industry has been traditionally reluctant to give its interest rates adequate publicity.

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1. Introduction

The consumer credit market is rapidly developing in several European countries (Diez-Guardia, 2000). Italy is no exception (total consumer credit rose 20% in 1997, 21.5% in 1998, 18.8% in 1999 – see Table 1), despite the relatively high saving rate: the saving rate of the household sector (corrected for expected inflation) was 14.4% in 1995, 14.2% in 1998, even though it fell slightly in 1999 (see Table 1).

Traditionally, Italian consumers could borrow limited amounts and only in order to purchase either their home (Guiso and Jappelli, 1999) or some major durable item, such as a car (Brugiavini and Weber, 1994). Over the 1990s, though, consumer credit has become much more widely available. The instalment credit market has grown considerably and covers now a number of relatively minor items, such as motor scooters, mobile phones, white and brown durables. Credit cards (a form of revolving credit) have also become much more widespread and are competing with the more established payment (debit) cards.

Table 1: Some macroeconomic indicators for Italy

	1995	1996	1997	1998	1999
Long term (10-year) interest rate on government debt	12,21%	9.40%	6.86%	4.88%	4.73%
CPI inflation	5,2%	4,0%	2,0%	2,0%	1.7%
GDP growth	7.9%	5.7%	4.1%	4.2%	2.9%
Personal sector saving rate	19.4	19.1	17.2	15.4	14.2
Personal sector saving rate (inflation adjusted)	14.4	14.8	14.2	14.2	13.2
Growth in consumer credit	5.1%	11.9%	20.0%	21.5%	18.8%
Disposable Income growth	4.7%	5.5%	2.8%	2.2%	2.4%

Source: Bank of Italy – **Relazione del Governatore 1998 and 1999**
Note: All interest and growth rates are nominal

Table 2 contains information on flows in the Italian consumer credit industry. The data are provided by ASSOFIN, an association of Italian banks and financial intermediaries covering 95% of the consumer credit market. The bulk of consumer credit (83%; excluding mortgages) consists of finalised loans to purchase particular goods. Especially loans for vehicles are important. Personal loans, not necessarily finalised to the acquisition of durable goods, make up about 9% of the market, credit cards and revolving credit about 7%. The latter group shows among the highest growth, however. In terms of number of contracts, revolving or credit cards are most widespread (56%), followed by instalment and other finalised loans (40%). Personal loans are of least importance (3%). The latter have relatively high average amounts, however (about € 4,000 as opposed to an average of € 1,400 per contract). We will later focus on data of a particular lender, Findomestic Banca, a member of ASSOFIN. Findomestic's share in the overall consumer credit market in 1998 amounted to 13.2%; excluding the market for vehicle loans (dominated by captives of automobile producers), their share was 27.3%. They are the largest provider of personal loans and the largest provider of other loans (finalised and revolving) excluding vehicles.

Table 2: The Italian Consumer Credit Industry					
	amounts financed		# contracts financed		
Flows	1998	growth	1998	growth	Average amount (1000 €)
(direct) personal loans	9.4%	25.6%	3.4%	33.2%	3.98
Finalised loans					
-- cars and motorcycles	60.5%	18.1%	12.8%	13.2%	6.83
-- industrial vehicles	2.4%	54.5%	0.1%	59.5%	38.29
-- other finalised loans	19.7%	15.8%	27.5%	13.0%	1.03
credit cards / revolving	6.7%	39.7%	56.1%	56.1%	0.17
Other	1.3%	72.7%	0.2%	50.1%	9.47
Consumer Credit (billion €/million contracts)	14.30	21.5%	9.93	28.9%	1.44

Source: ASSOFIN
Note: growth: annual change with respect to 1997

Possibly as a result of the increased importance of consumer credit, Italian parliament passed in 1996 a bill regulating interest rates that apply to all loans made to the personal sector. This law aimed at preventing consumers from falling in the hands of loan sharks - "usurai"- and is therefore known as "Legge sull'usura" (Usury Law). A controversial aspect concerns the definition of usury interest rates as those rates that exceed by more than 50% average market rates on similar loans (these are known as benchmark rates and are now published quarterly by Bank of Italy, as detailed below).

In evaluating the effects of this law (if any) on consumer credit, we must keep in mind that the late 1990's were characterised by other important changes in the macroeconomic environment. The late 1990's were a period of low growth for the Italian economy (in particular, the average annual growth of real disposable income for Italian households was a modest 0.54%) and of rapidly falling inflation and interest rates (see Table 1). The key change was brought about by the success of the Italian Lira application to join the new Euro currency (1997-98)[1].

In this paper, we investigate ways in which the law may have affected the consumer credit market and show how the applicants pool has changed over time in comparison to a representative sample of the Italian population.

[1] The Euro was introduced on January, 1st 1999. The decision on which countries would and could join was taken in May 1998 – Italy's participation had been in doubt because of high public debt. By December 1997 the prospects for Italy looked sufficiently good that Parliament delegated Government to fulfil the legal obligations required for the third stage of Monetary Union. See Mancini, Rigacci Hay and Donzitti, (2000) for a thorough review of the changes in Italian law brought about by the start of the Euro.

This paper is organised as follows. Section 2 describes the data used in this study. Section 3 provides a short characterisation of the Findomestic clientele and discusses trends therein and differences with respect to the overall Italian population. Section 4 discusses key data patterns both in interest rates and in contractual amounts and provides *prima facie* evidence on the likely impact of the Usury Law. Section 5 proposes a decomposition of observed changes in the distribution of credit contract amounts that allows for composition effects. It does so by comparing the Findomestic early and late samples to two corresponding waves of the Bank of Italy SHIW, so that the consequences of time-varying selectivity can be assessed. Section 6 puts forward some tentative conclusions.

2. Data description

Findomestic is the leading financial intermediary supplying consumer credit throughout Italy. Their key fields of operation are instalment credit (finalised to the purchase of a particular good) and revolving credit (they issue a credit card, CARTA AURA, where regular monthly payments are encouraged). In recent years, they also increased activities in the market for (non-finalised) personal loans.

Findomestic made a large data set available to the Finance and Consumption Chair at the European University Institute. The data cover the 1995-1999 period and contain detailed information on some 200,000 loan applications of some 120,000 individuals. The data set is a random sample (of all new applications made since June 1st 1995) from the bank's administrative data base and contains all applications and contracts of sampled individuals . Both rejected and approved applications have been retained. Even though identifying information has been stripped from the data, a range of valuable demographic characteristics next to applicant's (and spouse's) income and area of residence are available. The data is documented in Hochguertel (2000).

We chose to concentrate on the first contact between would-be-customers (applicants) and Findomestic. The question of the success of first time applications is particularly interesting to investigate in view of the sudden increase in number of first time applicants for this form of credit in the late 1990s (the dynamic aspects of the credit relationship are an interesting subject of further research). To this end, we merged the contract and reject files and kept the first contract for each customer. The resulting data set contains some 121,000 observations spread over the period 1995Q3-1999Q2. Quarterly numbers of observations range from 4400-5400 early on (1995Q3-1996Q1), to 6600-6900 in 1996-1997 (1996Q2-Q4, 1997Q1), to 8500-9800 in the later part of the sample (1997Q2-1999Q2).

By concentrating on first contracts we can take observations in any one period as representative of the underlying population (of newly made applications for a first contract). This would not be the case with the full set of contracts, because the data is a random sample of all new applications made since June 1st 1995 onwards and therefore does not provide an accurate picture of all outstanding contracts at any point in time (and particularly in 1995 or early 1996).

The Findomestic data set is by construction a choice-based sample: data are only recorded for those consumers who decide to apply to Findomestic for credit. Two issues arise: the sample is not representative of the population of Italian consumers and its composition is likely to change systematically over time, in response to changes in interest rates and other business cycle factors.

For this reason we compare the Findomestic sample to two waves of a representative sample, the Survey of Household Income and Wealth run by Bank of Italy. The SHIW is a survey of the Italian population that has been run on a continuous basis for a long period of time (see Brandolini and Cannari, 1994, for a description of the early waves; D'Alessio and Faiella, 2000, present the recently released 1998 wave). The sample size was 8135 households in 1995, 7147 in 1998; this reflects changes in sample design and response rates (57% in 1995, 43.9% in 1998). Population weights are provided. For comparability purposes (in Findomestic the sampling unit is the financially independent individual, not the household) we have used information on SHIW household members aged 18 or over who report positive personal income and tried to make variable definitions as consistent as possible. However, we were unable to provide a reasonably accurate match for professional codes.
A further feature of the Findomestic data is worth mentioning: over the period June 1995-January 1996 income is missing for around 10% of the sample. As shown in the Appendix, after that period the proportion of missing income observations falls to an average of 3%. The high number of missing income records considerably hinders the effort to compare of 1995 Findomestic data with 1995 SHIW data conditioning on income. For this reason we consider instead Findomestic data covering the 5-month period from March to July 1996. Even though this generates a time discrepancy, it is worth pointing out that the field work for SHIW takes place between March and July, mostly because this is the time of the year when tax returns are filed and households are most likely to recall their income well. A similar time shift for 1998 was not necessary (and was hard to implement because 1999 Findomestic data are incomplete).

3. Characterising the Findomestic clientele: some trends

In Table 3 we show descriptive statistics for the two samples. For the SHIW samples population weights are used throughout, even though these are constructed for households, not individuals (overall there are 14003 individuals in 1995 and 12115 in 1998). The Findomestic sample in 1996 (1998) includes all individuals who applied for their first contract between March and July in 1996 (and the whole of 1998). There are 10941individuals in 1996, 35570 in 1998.

We first show regional frequencies. We notice that the Findomestic sample has higher relative frequencies than the corresponding SHIW sample in Southern and Central regions, and lower ones in the North. However, the importance of the North increased markedly in 1998, mostly at the expense of Central Italy.
We also see that the age structure is relatively stable over the period in both samples, but the Findomestic sample is much younger. A split by residential status reveals that tenants are over-represented in the Findomestic sample, and the group of young people living with their parents is stable and in line with SHIW 1995. If we look at marital status, we

find that Findomestic has many more single adults and fewer widows/widowers than SHIW, which is hardly surprising.

Household income (defined as the sum of the earnings of the applicant and his/her spouse, at 1996 prices) is a variable of particular interest in our analysis, despite the presence of some missing income observations in the Findomestic sample (2.17% in 1996 and 1.00% in 1998).

We can easily check that in the Findomestic sample the tails of the income distribution are underrepresented, even though to a lesser extent in 1998. In fact, SHIW 1998 has more individuals whose household income falls short of the 1.34m mark (24.15% as opposed to 21.14%) and many more of the group with over 2.34m monthly income (43.6% as opposed to 31.56 %).[2]

Table 3: Comparing sample averages

	SHIW all>=18 with income		Findomestic	
Region	1995	1998	1996	1998
North	50.52	50.30	29.67	35.32
Central	19.04	19.50	25.18	21.68
South	30.34	30.21	45.15	43.00
Residential status	1995	1998	1996	1998
Owner	55.82	57.98	48.54	48.50
Tenant	17.83	17.33	25.07	25.11
Living with parents	26.34	24.69	26.39	26.39
Marital status	1995	1998	1996	1998
Single	19.69	20.37	30.04	31.03
Married	64.67	63.76	61.57	60.70
Divorced	2.48	2.97	4.32	4.39
Widow	13.16	12.90	4.07	3.88
Age	1995	1998	1996	1998
<=25	7.59	5.59	16.86	14.82
26-35	18.22	17.64	31.21	30.79
36-45	17.70	19.03	24.19	24.58
46-55	16.56	16.75	16.33	16.33
56-65	15.39	14.72	8.47	9.56
>65	24.54	25.28	2.94	3.92
Number of children	1995	1998	1996	1998
0	66.14	66.95	53.01	54.53
1	16.23	16.63	18.47	18.68
2	14.18	13.28	20.70	19.87
3 or more	3.45	3.14	7.82	6.91

[2] As noted above, the profession code is unlikely to be consistently defined across the two data sources: in Findomestic a number of codes exist for shop assistants and employees (including Findomestic employees and associates) that do not match the SHIW classification. However, a comparison across years is possible and reveals an increase in street vendors and other low skill self-employed workers, as well as an increase in (manual) workers in the private sector. We observe declines for craftsmen and for public sector manual workers.

Household income	1995	1998	1996	1998
Inch<=1000	17.42	14.67	9.84	10.69
1000<inch<=1340	9.85	9.48	9.83	10.45
1340<inch<=1500	7.10	5.70	11.42	8.25
1500<inch<=1670	7.89	6.55	8.04	9.42
1670<inch<=1816	3.44	4.32	9.78	8.27
1816<inch<=2000	6.85	5.96	11.34	10.83
2000<inch<=2340	9.46	9.69	8.25	9.53
2340<inch<=2927	11.02	12.22	9.77	11.98
2927<inch<=3700	9.71	10.51	9.77	9.53
Inch>3700	17.27	20.89	9.78	10.05
Not known	0.00	0.00	2.17	1.00

To summarise the changes in the Findomestic sample over the years, we estimated the conditional probability of being in the 1998 sample as opposed to the 1996 sample. The conditioning variables are income (in 1996 prices), profession, age, marital status, region and number of dependent children. The probit estimates are shown in Table 4: the first column of estimates refers to all types of credit contracts, while the second refers to instalment credit and the third to all other credit (revolving and personal loans). At the bottom of the table we report number of observations (of the 46389 applications in either 1996 or 1998, 38276 were applications for instalment credit and 8113 for other credit), as well as some measures of goodness of fit.

- Household income. The pattern of coefficients is mixed for the probability of being in the sample, with negative coefficients for incomes in the relatively low 1.34-1.5 and high 1.67-1.816 ranges (control is the top income group) and positive elsewhere. The picture is also blurred for instalment credit (with mostly negative coefficients), more clear cut for other credit (with the largest increases at the two ends of the income distribution)
- Profession (control group: manager, executive, professional) explains relatively little in the first column (all loans): the only significant coefficients are on public sector workers (negative) and on other profession - student, housewife, retired etc. -- (positive). Significant effects are also hard to find in the other two columns, except that all coefficients are negative for other credit (the top income group has increased over time).
- Residential status dummies (home owner is the control) are insignificant if we consider all credit applications. They are both positive for instalment credit and both negative (and significant) for other credit.
- Age effects (measured by dummy variables) are highly significant (the control group here is age<25). Notably, there are major increases in applications by middle-aged consumers, but also by the elderly (age>65). This last group has become particularly active in the instalment credit market.
- Regional effects are strong (the North is the control group) -- with a clear decrease of Central and, to a lesser extent, Southern regions over time
- The effects of family composition are only strong for families with 3 or more children, whose weight decreases over time (reference group: no children).

Table 4: Probability of being in Findomestic in 1998 versus Findomestic 1996

	All loans		Instalment credit		Other credit	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Income (reference: income>3700)						
Income missing	-0.5581	0.0603	-0.2868	0.1074	-0.4548	0.0835
inch<=1000	0.0181	0.0321	-0.0673	0.0362	0.3674	0.0760
1000<inch<=1340	-0.0121	0.0320	-0.0827	0.0358	0.2815	0.0769
1340<inch<=1500	-0.2558	0.0317	-0.3372	0.0356	0.1232	0.0748
1500<inch<=1670	0.0294	0.0320	-0.0431	0.0358	0.3521	0.0764
1670<inch<=1816	-0.1428	0.0312	-0.2359	0.0349	0.2903	0.0743
1816<inch<=2000	-0.0547	0.0294	-0.1329	0.0331	0.2893	0.0670
2000<inch<=2340	0.0660	0.0309	-0.0049	0.0343	0.3906	0.0764
2340<inch<=2927	0.0965	0.0291	0.0401	0.0327	0.3149	0.0669
2927<inch<=3700	-0.0298	0.0295	-0.0788	0.0331	0.1540	0.0684
Profession (reference: manager (private)						
Street vendor, seasonal worker	0.0008	0.0690	0.1011	0.0765	-0.3988	0.1648
Salesman, shop assistant	-0.1151	0.0764	-0.0521	0.0853	-0.3116	0.1758
Craftsman, various professions	-0.1368	0.0680	-0.0651	0.0756	-0.3562	0.1611
Established professional	-0.1007	0.0836	-0.0650	0.0940	-0.2059	0.1886
Civil servant , teacher	-0.1686	0.0731	-0.1078	0.0810	-0.3878	0.1737
Private sector (manual) worker	0.0112	0.0652	0.0888	0.0725	-0.2464	0.1533
Clerk, shop assistant	-0.0459	0.0659	0.0107	0.0732	-0.2068	0.1547
Public sector (manual) worker	-0.1680	0.0658	-0.1028	0.0731	-0.3656	0.1559
Retired	-0.2070	0.0696	-0.1159	0.0773	-0.5044	0.1645
Farmer, housewife, student, soldier, other	0.1403	0.0792	0.2891	0.0970	-0.2235	0.1637
Residential status (reference: owner)						
Tenant	-0.0118	0.0166	0.0100	0.0183	-0.1426	0.0407
living with parents	0.0392	0.0222	0.0517	0.0248	-0.0672	0.0515
Age (reference: age<=25)						
26-35	0.1495	0.0224	0.1657	0.0249	0.0911	0.0520
36-45	0.2412	0.0269	0.2471	0.0299	0.2326	0.0633
46-55	0.2674	0.0294	0.2689	0.0326	0.2351	0.0701
56-65	0.4160	0.0372	0.4391	0.0411	0.3271	0.0892
>65	0.5620	0.0506	0.6552	0.0561	0.1351	0.1209
Marital status (reference: single)						
Married	-0.1325	0.0236	-0.1674	0.0267	0.0275	0.0524
Divorced	-0.1210	0.0365	-0.1103	0.0410	-0.2014	0.0816
Widow	-0.1916	0.0417	-0.2202	0.0462	-0.1408	0.1006
Region (reference: north)						
Central	-0.1787	0.0178	-0.1195	0.0199	-0.4119	0.0419
South	-0.1173	0.0159	-0.0597	0.0174	-0.4115	0.0412
Number of children (reference: 0)						
1	0.0075	0.0203	0.0433	0.0223	-0.1457	0.0496
2	-0.0370	0.0206	0.0005	0.0227	-0.2040	0.0511
>3	-0.1015	0.0283	-0.0813	0.0305	-0.1733	0.0797
Constant term	0.8100	0.0690	0.7323	0.0767	1.1187	0.1624

	All loans	Instalment credit	Other credit
Observations	46389	38275	8113
pseudo R2	0.01	0.01	0.05
Log likelihood	-25005.33	-20812.51	-4069.78
chi2-test	693.09	528.39	395.20
df	35.00	35.00	35.00

4. The Usury Law of 1996

The late surge in the number of applications coincides with the coming into effect of the "Legge sull'usura". This controversial law that sets a ceiling to interest rates charged to borrowers also requires the Bank of Italy to collect and publish a whole range of interest rates, some of which (five in all) apply to different types of consumer. As Table 5 reveals, the interest rates charged by (non-bank) financial intermediaries to personal customers vary widely according to the type and size of contract. These interest rates have also fallen over time, but their differentials have not been reduced (they have increased in proportional terms). Also, there is a major asymmetry in the definition of loan types: for personal loans/revolving credit there is only one cut off point (at 10m), while for instalment credit there are two (at 2.5m and 10m).

Table 5- Benchmark Interest Rates

	Amount	96Q4	97Q1	97Q2	97Q3	97Q4	98Q1	98Q2	98Q3	98Q4	99Q1	99Q2	99Q3
Personal Loans / Revolving Credit	0-10	28.81	29.08	**28.82**	**27.07**	**27.25**	26.96	24.64	24.22	22.91	**23.56**	22.13	21.56
	Over 10	25.23	24.28	21.42	**22.00**	**20.20**	19.76	18.70	17.77	**16.19**	16.72	15.67	15.95
Instalment Credit (HP etc.)	0- 2.5	32.49	31.55	30.32	**31.27**	29.59	30.10	**29.52**	27.47	26.89	**27.01**	25.36	24.97
	2.5-10	23.90	23.70	22.67	**22.90**	21.84	**21.34**	**20.64**	18.11	17.61	16.59	15.51	15.46
	Over 10	18.18	17.17	15.74	15.52	14.48	14.23	13.69	12.25	11.47	11.06	10.70	10.64

Source: Bank of Italy.

These are average quarterly market rates for non-bank financial intermediaries, adjusted for changes in the official discount rate. All amounts are in million lira (Lira 1m=Euro 516)

The usury law was passed in March 1996. Its key element for our purposes is the following: no credit contract can set an interest rate higher than 1.5 times the published benchmark rate. The benchmark rate is the average interest rate on the type of loan prevailing two quarters earlier, after an adjustment has been made for the change in the official discount rate. The Bank of Italy was made responsible for collecting market interest rates by type of loan, computing their averages and publishing the corresponding benchmark rates. This required establishing procedures for data collection, and almost a year passed before the first benchmark rates were published. In fact, 1997 Q2 is the first quarter when banks and financial intermediaries were banned from setting their rates higher than 150% of the benchmark rates. The relevant rates for that quarter are shown in the column marked 96Q4 in Table 5.

To clarify the likely impact of the law, we plot in Figure 1 the effective rates of return on small (less than 2.5 million) instalment credit contracts signed in the first two quarters of 1996 (before the law came into force). Our data do not contain contractual rates, so we computed effective rates from information on size and duration of the loan and the (constant) monthly instalment, for all new instalment contracts. We were not able to compute interest rates for revolving credit contracts, though.

In all four quadrants of Figure 1 (relating to the whole country, and to the three macro-regions) we also plot two vertical lines: the one corresponding to 150% of average rates for small instalment credit and the one corresponding to 150% of average rates for revolving credit below the 10m mark (the closest substitute). In both cases we take the average rates for 1996Q4, because we have little data on average rates in 1996Q1 and 1996Q2. We know from ASSOFIN that instalment credit rates were reasonably stable over 1996, though. [3]

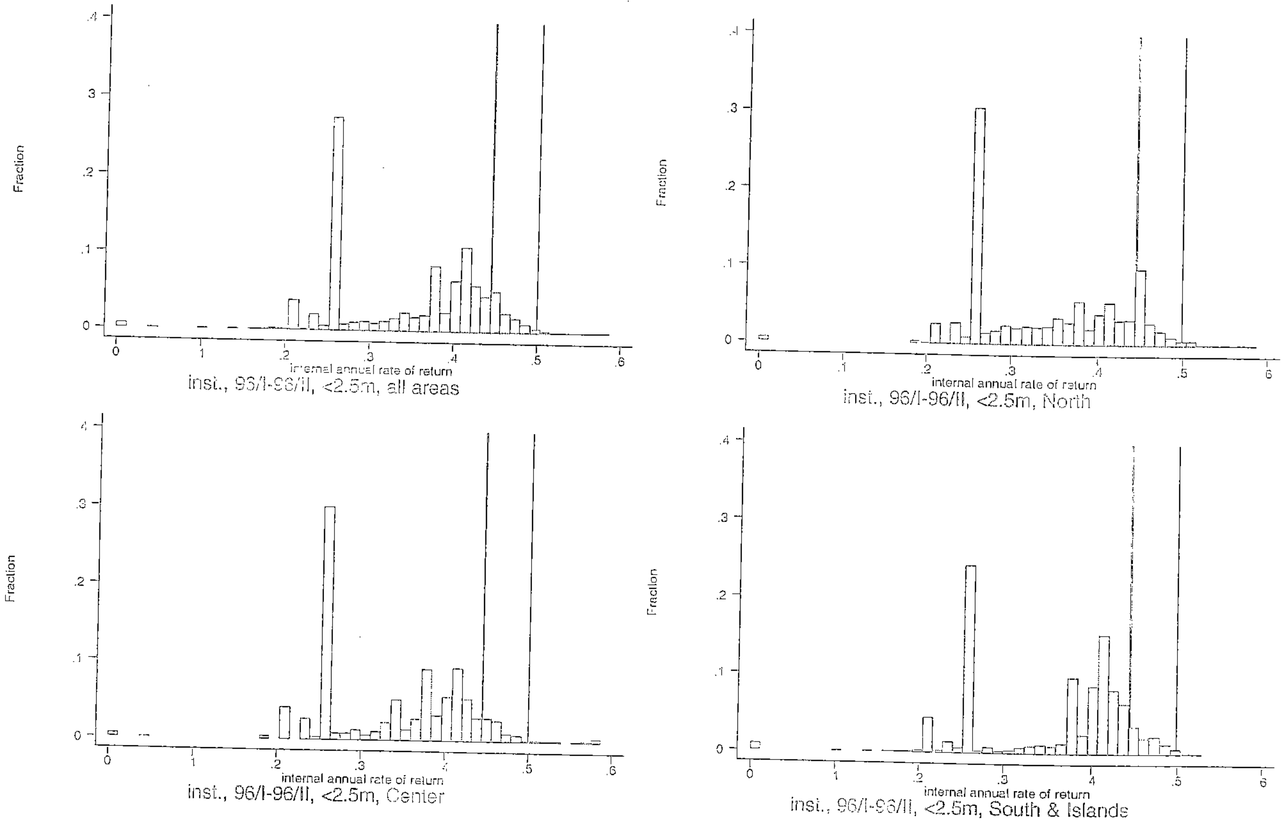

Figure 1: Effective rates for small instalment credit (<2.5m)

In Figure 1, the line for instalment credit is to the right of the line for revolving credit, suggesting that the law could cause substitution out of revolving credit towards instalment credit, but not vice versa.

We see that in very few cases the effective interest rate for instalment credit exceeds the relevant limit (that is, the vertical line on the far right): given that instalment credit rates stayed relatively constant in 1996, we can conclude that the law was unlikely to affect the operation of this segment of the consumer credit market. We cannot rule out, though, an effect on revolving credit contracts.

[3] As shown in Figure 5 later on, in the Findomestic sample this is true for contracts above 2.5m, while there was a decrease for small instalment contract rates. By taking the end-of-year benchmark we therefore consider the lowest possible limit.

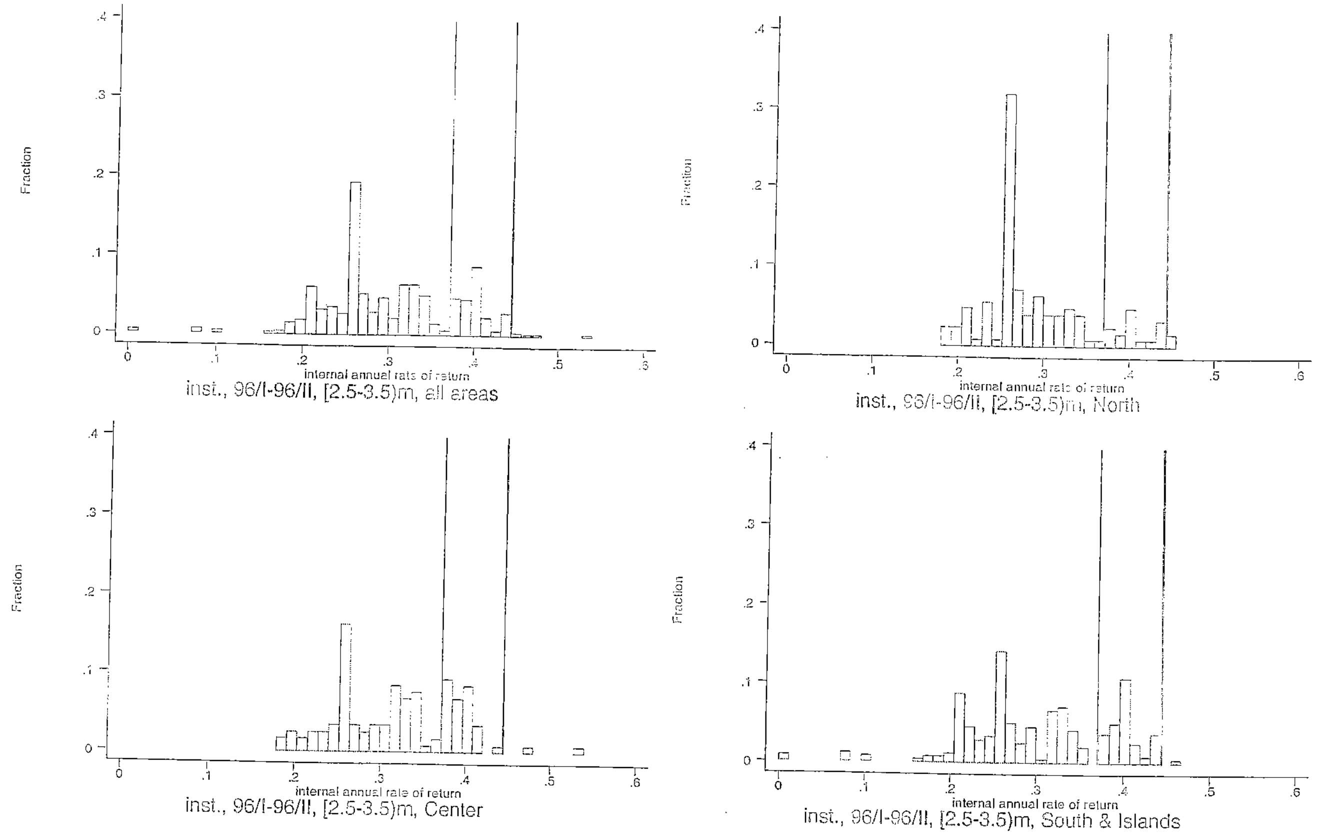

Figure 2: Effective rates for medium instalment credit (2.5m<y≤3.5m)

A very different picture emerges when we plot effective rates for instalment credit in the 2.5-3.5m range, as in Figure 2. Here (and in the next two figures) the vertical lines relative position is inverted: on the far right is the line corresponding to revolving credit, whereas the line corresponding to instalment credit is closer to the centre of the figure. If we look at the histograms in Figure 2 we notice that a significant proportion (29%) of all contracts had effective rates in excess of what the limit would have been had the law come into force earlier. This proportion was larger for Central and Southern Italy than for Northern Italy. Interestingly, almost all these contracts had rates below the limit for revolving credit. This suggests that the law may have generated sizeable substitution out of instalment credit towards revolving credit.

Figures 3 and 4 (relating to medium-large, 3.5-10m, and large instalment credit contracts) tell a similar story. Figure 3 covers contracts in the 3.5-10m range: the right tail of the distribution is less fat than in Figure 2, but still a reasonable number of contracts lies in the region between the vertical lines. Only in the North are such contracts very few in number. In Figure 4, corresponding to contracts of over 10m, the vertical lines are moved to the left compared to Figures 2 and 3 (as Table 5 reveals average rates are lower for contracts above the 10m mark), but far fewer contracts are in the right region.

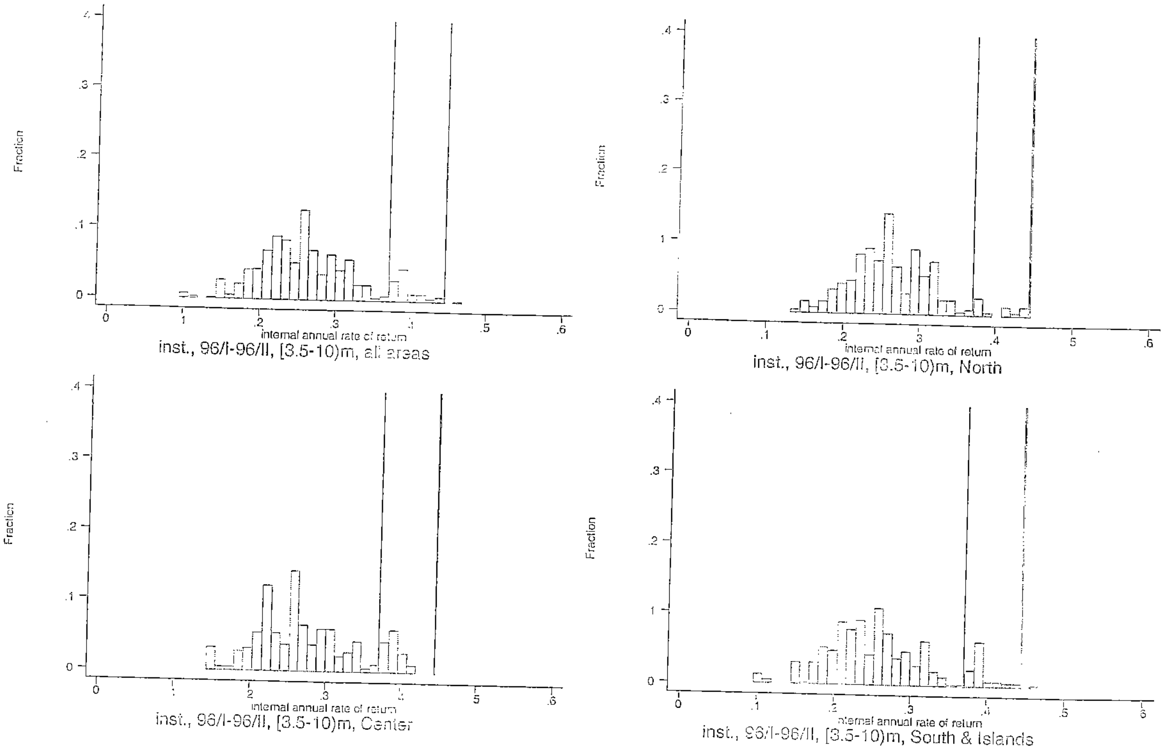

Figure 3: Effective rates for medium-large instalment credit (3.5m<y≤10m)

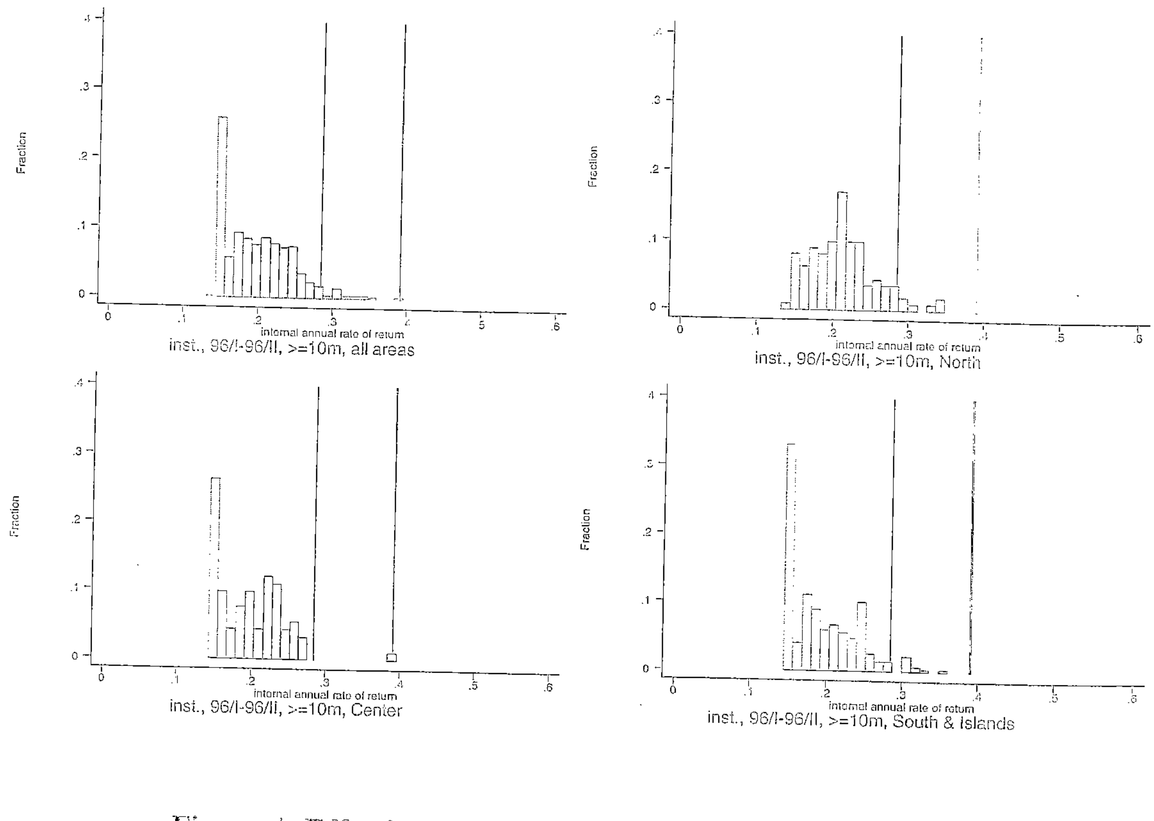

Figure 4: Effective rates for large instalment credit (>10m)

When we plot similar figures for 1998 effective rates of return, we find similar patterns for small credit contracts and for contracts over 10m, but one striking difference for medium contracts: while the 1996 distributions for medium contracts are bimodal (as shown in Figures 2 and 3), the 1998 distributions are clearly unimodal. The mode at the right tail of the distribution has disappeared.

The key conclusion to be drawn from these figures is that at least one particular segment of the market (the 2.5-3.5m interval) might have been affected by the law, in the sense that instalment credit contracts could have been substituted by revolving credit contracts.

The usury law came into force at a time of falling nominal rates (as documented in Table 1, long term government yields fell from 12.12% in 1995 to 4.88% in 1998). This has the important implication that the usury law was unlikely to have further effects on consumer credit after its first impact. Recall that the benchmark rate is in fact set on the basis of prevailing rates six months earlier: when market rates are falling the benchmark rate is higher than it would be if the benchmark was the current average rate[4].

It is possible, if unlikely, that the law had an impact on median interest rates. As a way to evaluate departures in 1997Q2 from the underlying trends, we plot median effective (internal) rates of return on instalment credit contracts in the Findomestic sample (see Figure 5). As explained above, similar rates for revolving credit contracts cannot be computed, but the general pattern of decreasing interest rates is clear. However, most of the fall had taken place prior to the coming into force of the usury law (marked by a vertical line in Figure 5).

[4] The law makes a correction for changes in the official discount rate, but these were smaller over the period: from 8.5% in 1995 to 5% in 1998

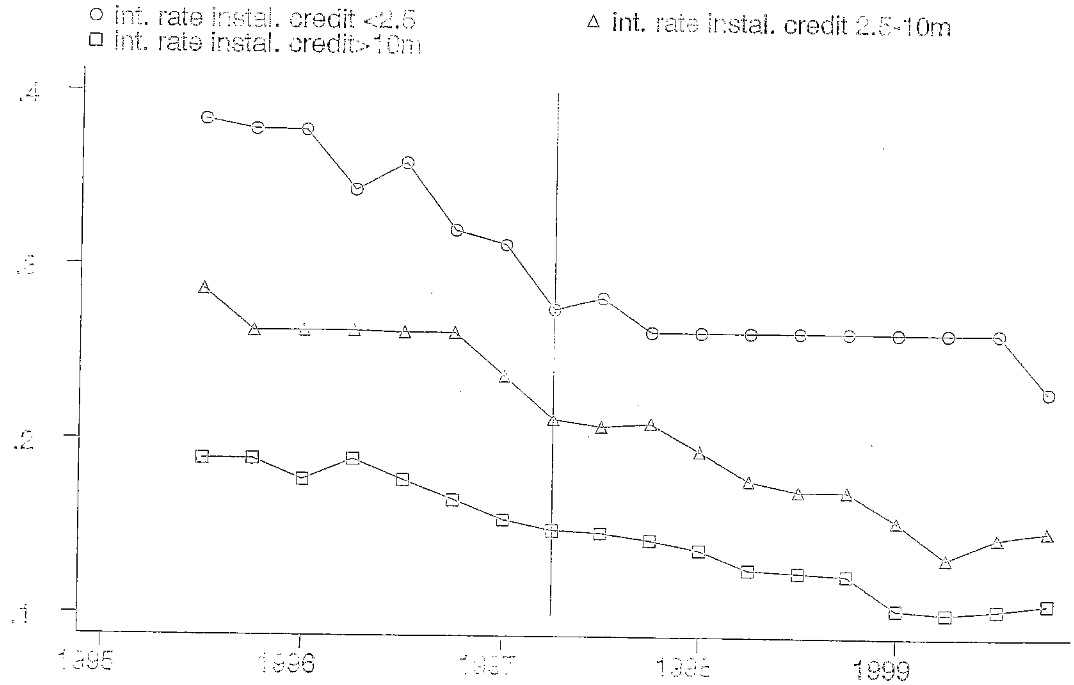

Figure 5: Effective Rates of Return

A further feature worth noting in Figure 5 is that median rates on small contracts did not fall over the period 1997Q4-1999Q3: as a consequence the rate differential between small and medium size instalment loans widened considerably over the period. The sluggishness of these rates is consistent with the hypothesis that high interest revolving credit contracts with limits below 2.5 million may have been replaced by small instalment credit contracts.

We also show in Figure 6 average effective rates for instalment credit applications in the 2.5-3.5m range. It is apparent that immediately after usury law came into force the gap between the rates on these medium-sized credit applications and small applications narrowed considerably. After 1997, however, this gap widened again. Thus credit around 3m became relatively more onerous after 1997Q1 and this may be responsible for an increase in demand for smaller credit amounts.

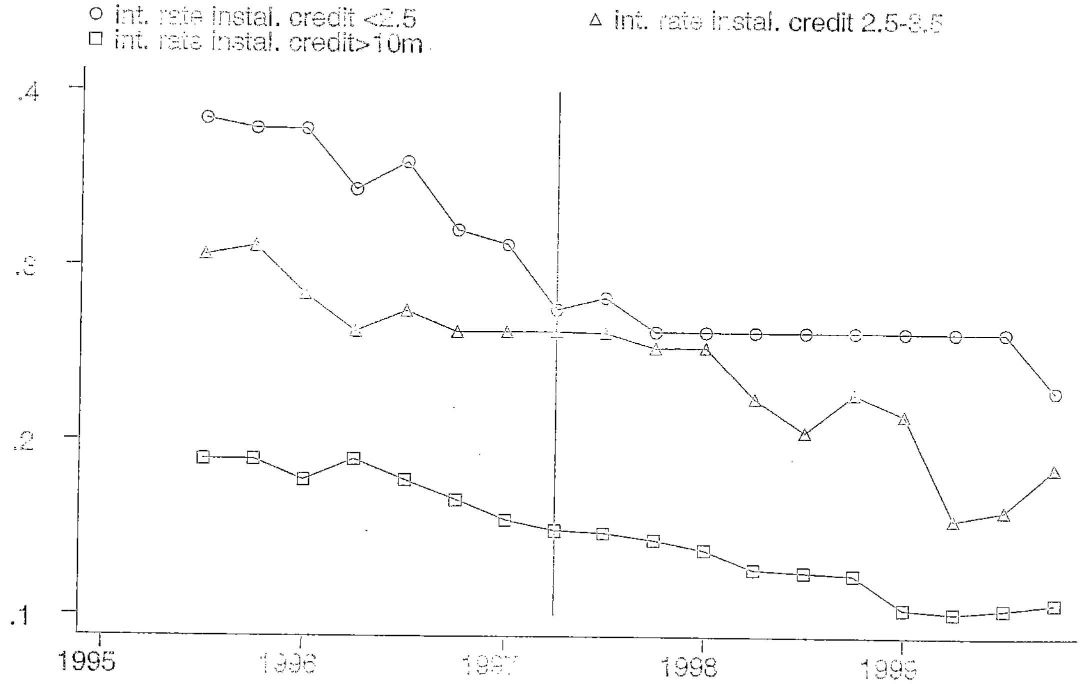

Figure 6: Effective Rates for Amounts Around 3m

Another question to ask is whether the change in legislation brought about major changes in the rejection probability, as some theoretical models of credit rationing would imply. *Prima facie* evidence suggests otherwise: the sample rejection rate varies between 17.4% and 22.8%, with no obvious time pattern (for instance, we observe peaks in 1995Q3 and 1999Q2, troughs in 1996Q1 and 1999Q1). Once allowance is made for changes in a number of relevant variables, some time effects are found, though. In a probit equation that controls for region of residence and other social and demographic characteristics, type of good to be bought, household income and type/amount of credit applied for, both nominal interest rates and inflation have a small, but significant, negative impact on the rejection probability. Given that both inflation and nominal rates were falling over time, this implies that rejection rates would have gone up had the other variables stayed constant.

The evidence we discussed so far leads us to believe that the usury law had little or no impact on median interest rates (even though it might have affected differentials) and on credit rationing, but that it could have caused reshuffling across loan types. For loans below 2.5m it might have favoured substitution out of revolving credit into instalment credit; for loans above this threshold (and particularly just above) it most likely had the opposite effect.

A simple way to check for the presence of reshuffling is to look at the proportion of contracts within the Findomestic sample in 1996Q2 and 1997Q2. In particular, other things being equal, we might expect an increase in the proportion of instalment contracts below 2.5m at the expense of revolving credit contracts. We also expect a decrease in medium instalment contracts (2.5-3.5m) towards revolving credit. Prima facie evidence on this is mixed. As expected we do find an increase in small instalment contracts (from 48.06% to 50.23%), a decrease in medium instalment contracts (from 16.01% to 11.11%) and an increase on medium revolving credit contracts (from 4.44% to 5.17%). However, we also find a sharp increase in small revolving credit contracts (from 4.83% to 8.02%) that is at variance with our expectations.

Another way to check for the reshuffling effects brought about by the change in legislation is to estimate the density function of amounts applied for before and after 1997Q2. For comparability with the evidence presented later on, we compare 1996 and 1998 (however, we take the whole of 1996 to ensure adequate sample size for estimation).

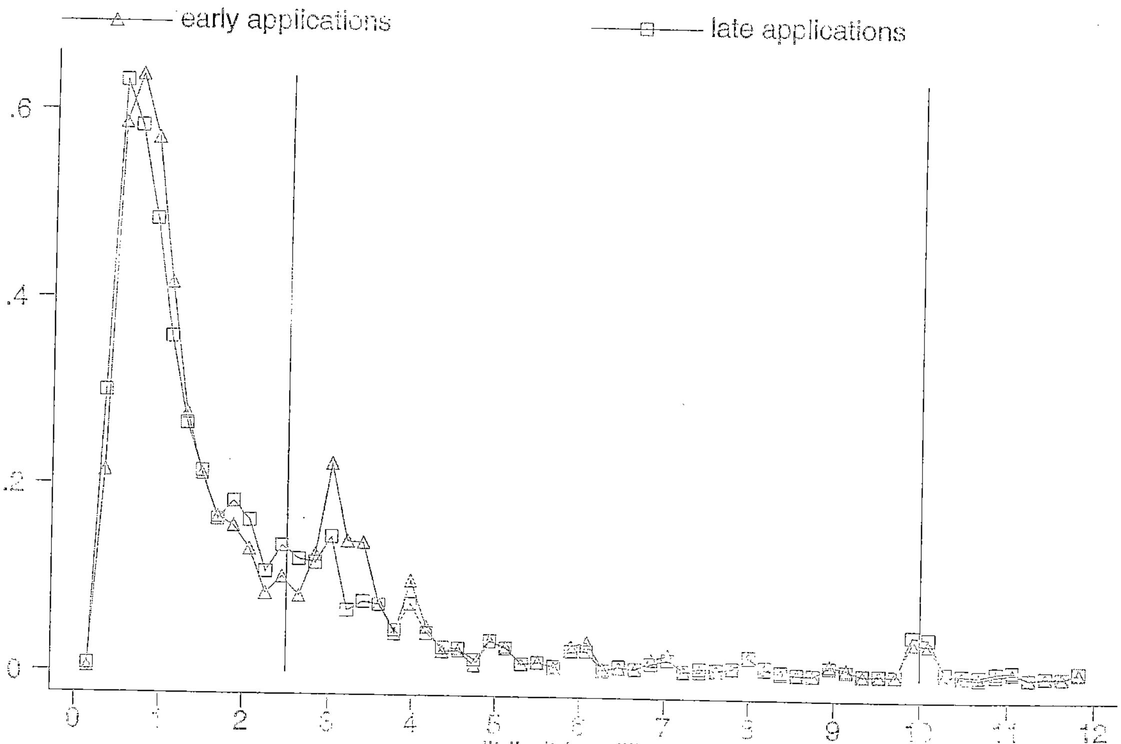

Figure 7: Instalment Credit - density f's all appl's

In Figure 7 we plot the estimated density functions for instalment credit applications in 1996 (early applications: 20780 cases) and 1998 (late applications: 29191 cases). For convenience, all 1996 applications for amounts exceeding 12m have been set to 12.1m, and this explains the (minor) peak on the far right (1998 applications have been top-coded at 18m instead). Of interest to us is the marked decrease in the frequency of applications in the 3m region, that agrees well with the reshuffling hypothesis discussed above. The slight increase in the frequency of small applications (less than 1m) is also consistent with the hypothesis, but is in fact explained by the rapid development in mobile phone market.[5]

[5] Fortunately, for instalment credit applications we always know the type of good the consumer wishes to buy. When we compare types of goods in our early and late sub-sample we do indeed note a surge in applications to buy phones (from 15.9 to 19.7% of instalment credit applications) – in line with the remarkable growth in the mobile phones market experienced in Italy over the period. This also contributed

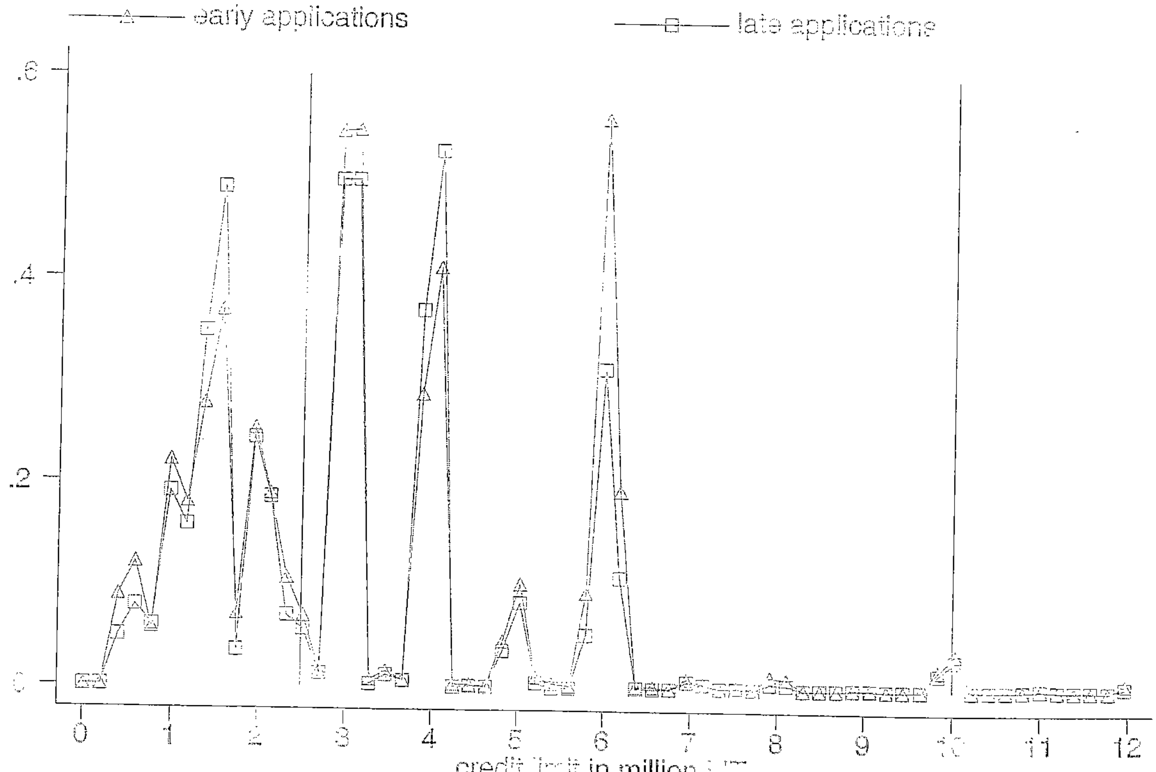

Figure 8: Revolving Credit - density f's all appl's

Figure 8 plots density functions for revolving and personal credit applications. Given the smaller sample size in both periods (4779 in 1996, 7184 in 1998) the estimated densities are noisier. Both the late surge in small loan applications and the late fall in medium applications are at variance with the reshuffling hypothesis. Another striking feature is the halving of the 6m peak, but this is concentrated in one particular region and probably reflects changes of administrative nature within Findomestic.

With revolving credit contracts the issue arises of what amount we should consider: the outstanding balance or the credit limit. In the data, we find that for a non-negligible number of valid contracts (2,485) the balance exceeds the limit. This probably reflects delays in recording payments into accounts. For this reason we use the credit limit throughout and this accounts for major spikes around integer multiples of 1 million, and particularly the 3 million mark (this is also the standard ATM monthly limit).

to the persistence of applications for small amounts in the late sub-sample. We checked for the importance of this composition effect by focusing on applications for other goods. We can still see a reduction in applications around the 3-3.5m mark, while there is no longer evidence of an increase in small amount rejections after.

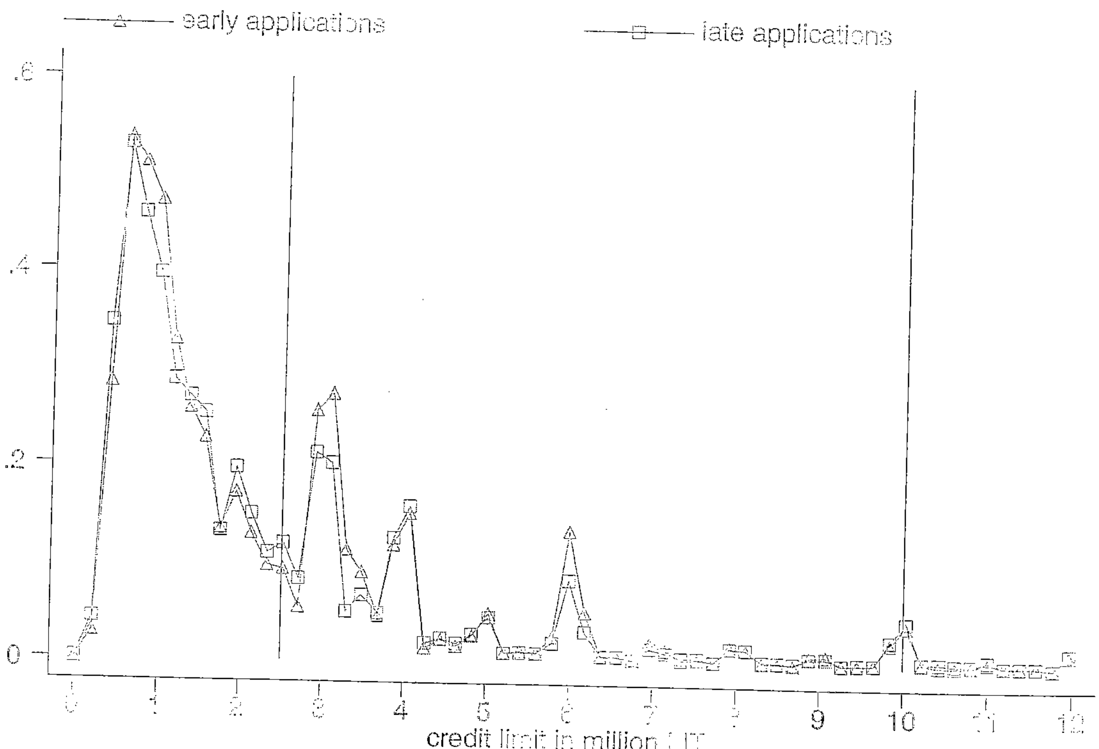

Figure 9: All Loans - density f's all appl's

In Figure 9 we present densities for all applications, irrespective of contract type. If changes over time revealed by Figures 7 and 8 were entirely due to reshuffling the densities in Figure 9 should overlap. In fact we observe decreases in applications around the 3m and 6m marks. Increases of applications in excess of 12m (normally for the purchase of cars) are not shown in Figure 9, but should be kept in mind when interpreting all these graphs.

So far we have lumped together all applications, irrespective of their success. It is in fact possible that the patterns highlighted above are entirely explained by rejections and therefore do not affect actual credit market transactions. In Figure 10 we plot density functions for accepted applications only (80.32% of all 1996 applications, 81.18% in 1998). In Figure 11 we show instead density functions for rejected applications. We detect little differences across the two figures, with the possible exception that the drop in applications around 3m was more pronounced for rejections than for acceptances.
A natural question worth investigating is what happened to those applicants who wanted goods worth 3m. A possibility is that they were prepared to pay a larger down-payment, to keep interest charges low. We cab check if this happened by investigating how the down-payment to price ratio changed between early and late sub-samples. For all types of instalment credit contracts we find that the proportion of zero down-payment applications rose. This is also true for smaller amount contracts, where the two most common down-payments are zero and 10%. Thus we conclude that the usury law did not cause applicants to increase the down payment as a way to cut the required amount below the 2.5m threshold.

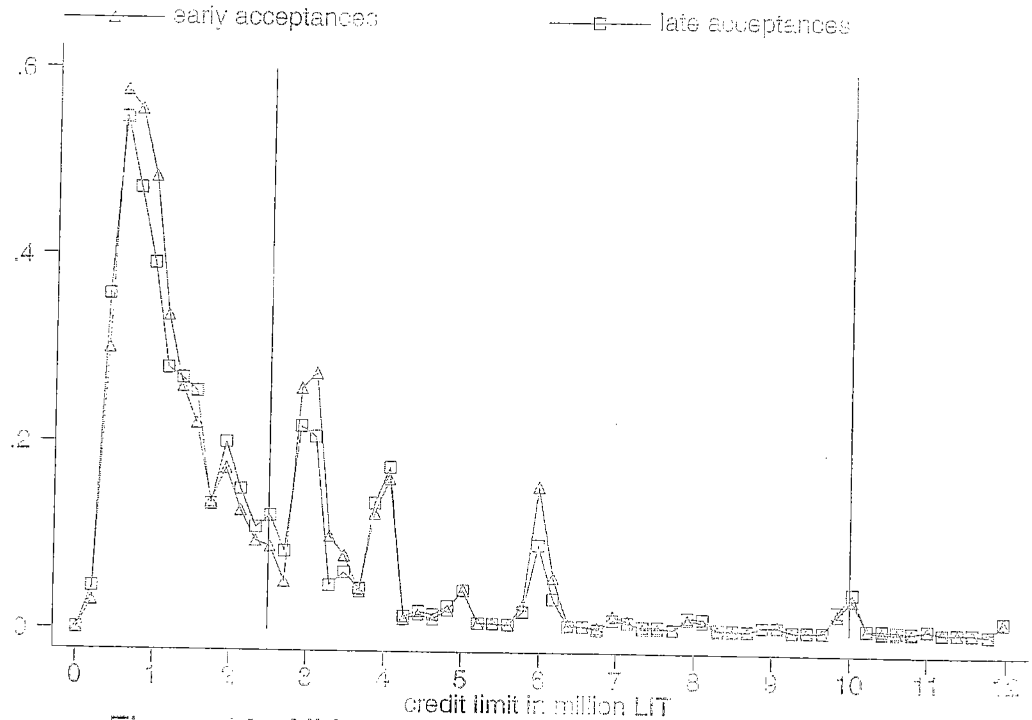

Figure 10: All Loans - density f's acceptances

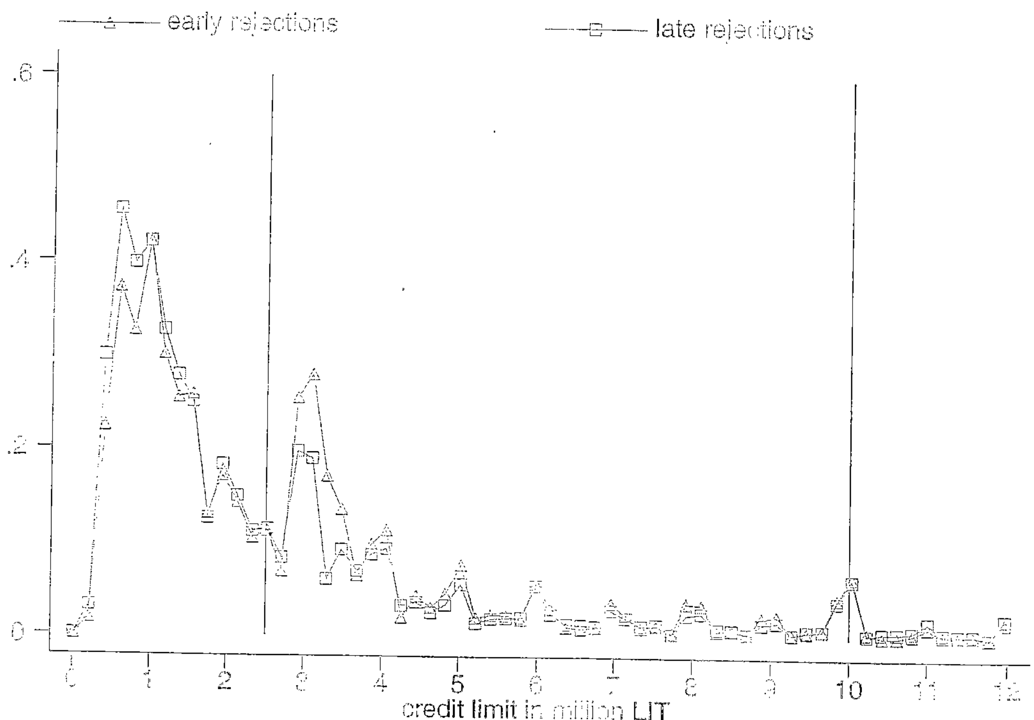

Figure 11: All Loans - density f's rejections

5. Composition Effects and Counterfactual Densities

We can summarise our findings presented in the previous section as follows: when usury law came into force, instalment credit contracts just above the 2.5m mark became less common. Fewer individuals applied for instalment credit in the 2.5-3.5m range: those who got credit for such amounts also paid higher interest (relative to instalment credit contract in the 3.5-10m range) . On the other hand, revolving credit applications for small amounts became more common, and the fall in revolving credit contracts for medium-sized loans was limited. Usury law may have caused this reshuffling of applications towards revolving credit, because it set a 2.5m threshold on only one type of contract.

This however is only one possible explanation. Another explanation relies on the strong market growth of the late 1990's. It is quite conceivable that in the late sub-sample the pool of applicants changed. Possibly as a result of lower interest rates or of easier access new consumers started applying for credit. Of these new entrants those who applied for smaller (or very large) amounts were more easily refused credit, because of some characteristics that we have not controlled for. As a way to check for changes in the applicants' pool we compare the Findomestic sample to the representative SHIW data.

Table 6 provides some statistics on credit limit for all loan types. The average amount shows a small overall nominal increase (4.31%). The median amount instead fell sharply (-21.4%), largely as a result of the relative increase in the importance of small contracts. As the last six columns show, the proportion of loan applications for less than 2.5m increased from 57% to 64%, with a corresponding drop in medium-sized applications (2.3-3.5m).

Next we present similar statistics by broad region. There is substantial variability in the means both in starting levels (from 2.84m to 3.09m) and in growth rates (from −0.81% to 9.44%). The next three columns show similar computations for median amounts: these stayed constant in the North, but fell in nominal terms in the other two macro-regions. The final six columns reveal the proportion of small-size loans increased mostly in the Centre and South, while in the North there was a slight increase in large loans (over 3.5m).

Splits by residential status and marital status are shown next. It is interesting to notice tenants and singles were the only two groups whose average amount fell (median amount decreased for all groups) and that the highest amounts are requested by the divorced. A split by age is quite revealing. We already stressed that the age structure is relatively stable over the period in both samples, that the Findomestic sample is much younger and that average credit limits peak in mid age in both years. Their growth in average amount is surprisingly highest for the over 56 age groups. Growth rates in median values are instead highest (least negative) for the broad over 65 age group.
We present further splits by number of dependent children (in the Findomestic sample families with children are over-represented) and by income class. Of interest is the relative growth in average amount for incomes in 1.67-2.34 range.

The first and last terms are likely to have opposite sign by construction. Indeed, if the Findomestic sample did not change compared to the population (SHIW) they should cancel out.
Note that the third term uses the same density function for the relevant characteristic, but different conditional density functions, one estimated on the 1998 Findomestic sample and the other one in the 1995 Findomestic sample. For this reason we can think of it as capturing changes in behaviour (and in selectivity).[6]

Our analysis so far is fully non-parametric but only controls for one observed characteristic at a time. Given that several factors appear to play a role, it makes sense to go for a semiparametric multivariate extension, as suggested in DiNardo, Fortin and Lemieux (1996).

Let x denote a vector of attributes we have in all samples that affect the variable under investigation, *amount*. Then the counterfactual density $f^*(amount_t|S_\tau)$ can be related to the observed density $f(amount_t|F_t)$ as follows:

$$f^*(amount_t \mid S_\tau) = \int f(amount_t \mid F_t)\Psi_{S\tau Ft}(x)\,dF(x \mid F_t)$$

where the weighting function Ψ is defined as:

$$\Psi_{S\tau Ft}(x) = \frac{\Pr(S_\tau \mid x)}{\Pr(F_t \mid x)} \frac{\Pr(F_t)}{\Pr(S_\tau)}$$

that is it weighs the probability attached to each observation in F_t by the conditional probability of observing a similar observation in S_τ.[7]
If we specify a parametric functional form for the conditional densities in Ψ (a probit or logit specification) an estimate can be found and used to compute the same counterfactuals as before.

In Table 7 we report results from decomposing average amounts and proportions of contracts by loan size as shown above. To construct the Ψ weights we ran probits for the following combinations: F98 *versus* S98, F95 *versus* S95 and S95 *versus* F96. The choice of attributes is confined to variables common to and comparable across all data sets: this rules out profession (hard to code consistently across SHIW and Findomestic). We therefore used household income as well as residential status, marital status, age group, region and dependent children dummy indicators (30 variables in all), but still obtained highly significant coefficients and reasonably high pseudo R^2 (in the .19-.23 range).

In the upper half of the Table (denoted 7a) we report actual and counterfactual statistics in levels. We see from the first two columns that for all loans the actual average rose from 2.96m in 1996 to 3.10m in 1998 (these numbers differ slightly from those in Table

[6] Our decomposition differs in several respects from the one suggested by DiNardo, Fortin and Lemieux (1996), who concentrate on attributing the change in wages across years to changes in observable factors, keeping behaviour constant.
[7] This quantity relates to the propensity score of Rosenbaum and Rubin (1983).

6, because we dropped missing income observations to estimate the probit models), and the proportion of loans under 2.5m rose from 57.34% to 64.69%. The next three columns show the counterfactuals described above. The bottom half of the Table (denoted 7b) reports the corresponding changes. Thus the average increase in loan size was .13m, but it would have been .37m had sampling and population changes not taken place. Of particular importance is the way the Findomestic sample differed in the population in 1998 (second column), that helped reduce the average amount by .405m. The proportions of small loans rose by 7.35%, medium loans fell by 7.2%, leading to a very small decrease in large loans. In two of the three cases (small and medium loans) the behavioural change would have been smaller than observed, had it not been for composition effects. In the case of large loans, instead, changes in behaviour alone would have implied a substantial increase (2.3%).

The pattern highlighted above is also found for instalment credit: average amounts increased even more, proportions of small loans increased and medium loans fell lower and the proportion stayed the same. Almost all the increase in small loans is attributable to behavioural changes, while half the decrease in medium loans is due to composition effects. Once more, large loans would have increased (3.35%) had the sample composition stayed constant.

In the case of other credit, behavioural effects dominate average amounts and all proportions. In particular, average amount fell considerably (.525m), and the proportion of small loans rose by 8.85%. There was a smaller fall in medium loans (2.96%) and a remarkable reduction in large loans (5.89%).

Table 7a: Multivariate Decompositions – Levels

	τ(y95;F95)	τ(y98;F98)	τ(y98;S98)	τ(y98;S95)	τ(y95;S95)
ALL LOANS					
τ= E(y)	2.9646	3.0984	3.5036	3.4107	3.0380
τ= E(ln(y))	0.6516	0.5814	0.7008	0.6724	0.6503
τ= p(y≤2.5.)	0.5734	0.6469	0.6098	0.6184	0.5822
τ= p(2.5<y≤3.5.)	0.1949	0.1228	0.1309	0.1289	0.1882
τ= p(3.5<y)	0.2317	0.2303	0.2594	0.2527	0.2296
INSTALMENT					
τ= E(y)	2.7878	3.0232	3.7192	3.5675	2.9122
τ= E(ln(y))	0.5708	0.4961	0.6756	0.6383	0.5795
τ= p(y≤2.5.)	0.6141	0.6931	0.6287	0.6424	0.6339
τ= p(2.5<y≤3.5.)	0.1894	0.1071	0.1191	0.1162	0.1583
τ= p(3.5<y)	0.1965	0.1998	0.2522	0.2414	0.2079
OTHER CREDIT					
τ= E(y)	3.9803	3.4547	3.4226	3.4324	3.9474
τ= E(ln(y))	1.1159	0.9853	0.9735	0.9797	1.0407
τ= p(y≤2.5.)	0.3398	0.4283	0.4483	0.4443	0.3604
τ= p(2.5<y≤3.5.)	0.2266	0.1970	0.1905	0.1903	0.2264
τ= p(3.5<y)	0.4336	0.3747	0.3612	0.3654	0.4132

Table 6 – All loan applications - amounts

	Average			Median			P(am≤2.5)		P(2.5<am≤3.5)		P(am>3.5)	
	1996	1998	%-Δ	1996	1998	%-Δ	1996	1998	1996	1998	1996	1998
Total	*2.99*	*3.12*	*4.31*	***2.00***	*1.57*	*-21.40*	*0.57*	*0.64*	***0.20***	***0.13***	*0.23*	*0.23*
Region	1996	1998	%-Δ	**1996**	1998	%-Δ	**1996**	1998	**1996**	1998	**1996**	**1998**
North	2.84	3.11	9.44	1.72	1.73	0.44	0.60	0.63	0.18	0.13	0.22	0.24
Central	2.97	2.95	-0.81	2.00	1.70	-15.00	0.56	0.54	0.21	0.14	0.23	0.21
South	3.09	3.21	3.89	2.00	1.50	-25.00	0.55	0.66	0.21	0.11	0.24	0.23
Residential status	**1996**	**1998**	%-Δ	**1996**	1998	**%-Δ**	**1996**	1998	**1996**	**1998**	**1996**	**1998**
Owner	3.14	3.38	7.60	2.30	1.90	-17.46	0.53	0.61	0.22	0.15	0.25	0.25
Tenant	2.72	2.67	-1.78	1.60	1.49	-6.88	0.63	0.69	0.17	0.11	0.20	0.20
Living with parents	2.96	3.06	3.24	1.85	1.43	-22.87	0.58	0.67	0.19	0.10	0.23	0.23
Marital status	1996	1998	%-Δ	1996	1998	%-Δ	1996	1998	**1996**	**1998**	1996	1998
Single	2.97	2.94	-1.06	1.88	1.47	-21.60	0.58	0.67	0.19	0.11	0.23	0.22
Married	3.02	3.21	6.35	2.00	1.74	-13.10	0.55	0.63	0.21	0.13	0.24	0.24
Divorced	3.11	3.33	7.22	2.00	1.77	-11.61	0.59	0.62	0.16	0.12	0.26	0.26
Widow	2.52	2.82	12.05	1.57	1.50	-4.40	0.60	0.67	0.21	0.13	0.19	0.21
Age	**1996**	1998	%-Δ	**1996**	1998	%-Δ	1996	**1998**	**1996**	1998	**1996**	**1998**
<=25	2.78	2.78	-0.21	1.60	1.24	-22.45	0.61	0.70	0.18	0.09	0.21	0.21
26-35	2.89	2.98	3.19	1.80	1.50	-16.67	0.60	0.66	0.17	0.11	0.23	0.22
36-45	3.07	3.21	4.43	2.25	1.85	-17.69	0.53	0.62	0.22	0.14	0.25	0.24
46-55	3.29	3.44	4.52	2.70	2.00	-25.93	0.49	0.59	0.24	0.15	0.27	0.26
56-65	3.14	3.48	10.88	2.00	1.80	-10.00	0.57	0.51	0.21	0.13	0.22	0.26
>65	2.43	2.68	10.39	1.42	1.40	-1.41	0.63	0.69	0.20	0.11	0.17	0.20
Number of children	**1996**	**1998**	%-Δ	1996	**1998**	%-Δ	1996	1998	**1996**	**1998**	1996	**1998**
0	3.12	3.27	4.57	2.00	1.50	-25.00	0.56	0.64	0.19	0.12	0.25	0.25
1	2.87	3.05	6.42	1.90	1.63	-14.41	0.58	0.65	0.19	0.13	0.23	0.22
2	2.78	2.85	2.60	1.94	1.68	-13.66	0.57	0.65	0.21	0.14	0.22	0.21
3 or more	2.90	2.87	-1.00	2.00	1.59	-20.45	0.55	0.67	0.25	0.13	0.20	0.20
Household income	1996	1998	%-Δ	**1996**	1998	%-Δ	1996	**1998**	1996	**1998**	**1996**	**1998**
Income<=1000	3.06	3.47	13.50	2.00	1.50	-24.85	0.54	0.63	0.24	0.13	0.22	0.24
1000<inc<=1340	2.74	2.74	-0.01	1.74	1.30	-25.14	0.59	0.69	0.19	0.10	0.22	0.20
1340<inc<=1500	2.97	2.79	-5.95	1.86	1.43	-23.05	0.59	0.68	0.19	0.11	0.23	0.21
1500<inc<=1670	2.81	2.83	0.47	2.00	1.45	-27.50	0.58	0.66	0.20	0.12	0.22	0.22
1670<inc<=1816	2.77	3.12	12.54	1.50	1.50	0.28	0.62	0.65	0.17	0.12	0.21	0.24
1816<inc<=2000	2.81	2.97	5.75	1.80	1.53	-15.00	0.60	0.65	0.18	0.13	0.22	0.21
2000<inc<=2340	2.79	3.08	10.40	1.88	1.64	-12.59	0.57	0.65	0.20	0.11	0.23	0.23
2340<inc<=2927	3.06	3.18	3.82	1.90	1.65	-13.11	0.58	0.64	0.18	0.13	0.24	0.23
2927<inc<=3700	3.06	3.09	0.74	2.00	1.80	-10.00	0.57	0.63	0.20	0.14	0.24	0.24
Income>3700	3.54	3.64	2.68	2.59	1.99	-23.19	0.50	0.60	0.22	0.14	0.29	0.26
Not known	4.08	5.03	23.34	3.00	3.00	0.00	0.24	0.30	0.42	0.37	0.34	0.32

The substantive question we want to ask is the following: how much of the observed change in amount is due to changes in individual behaviour, how much is due to changes in the underlying population, and how much is due to changes in the applicants pool (i.e. the Findomestic sample)?

In order to address this question we construct counterfactual amounts by exploiting information on both data sources, along the lines of DiNardo, Fortin and Lemieux (1996). To explain our method, let us consider the dichotomous variable sex and let us denote by *f(amount)* the density function under investigation. We can write:

$$f_t(amount \mid F_t) = f_t(amount \mid F_t, male_t)P_t(male_t \mid F_t) + f_t(amount \mid F_t, female_t)P_t(female_t \mid F_t)$$

where F denotes Findomestic. Now define the counterfactual density corresponding to the SHIW sample in t (S):

$$f_t^*(amount \mid S_t) = f_t(amount \mid F_t, male_t)P_t(male_t \mid S_t) + f_t(amount \mid F_t, female_t)P_t(female_t \mid S_t)$$

The difference between these two densities can be imputed to sampling differences in period t across the two surveys, for given behaviour (the conditional density function of amount given sex is taken from the Findomestic sample).

This method can be used to construct a number of different counterfactuals and can of course be applied to all sort of discrete and (at least in principle) continuous variables. If we are prepared to make enough parametric assumptions we can also extend this method to the multivariate case.

Let us consider arithmetic averages (a similar principle applies to any other statistic of interest). These can be used to produce the following decomposition for any one of the characteristics considered in Table 6:

$$\begin{aligned}
&E(amount_{1998} \mid F_{1998}) - E(amount_{1995} \mid F_{1996}) = \\
&[E(amount_{1998} \mid F_{1998}) - E^*(amount_{1998} \mid S_{1998})] + [E^*(amount_{1998} \mid S_{1998}) - E^*(amount_{1998} \mid S_{1995})] + \\
&[E^*(amount_{1998} \mid S_{1995}) - E^*(amount_{1995} \mid S_{1995})] + [E^*(amount_{1995} \mid S_{1995}) - E(amount_{1995} \mid F_{1996})]
\end{aligned}$$

The increase in average amount in the Findomestic survey can be decomposed into the following components:

- the difference in 1998 amounts due to sampling differences in 1998;
- the changes brought about by changes in the population across the two years;
- the changes in behaviour over the years, for given (1995) population characteristics;
- the difference in 1995 amounts due to sampling differences in 1995-6.

Table 7b: Multivariate Decompositions -Differences					
	τ(y98;F98)-τ(y95;F95)	τ(y98;F98)-τ(y98;S98)	τ(y98;S98)-τ(y98;S95)	τ(y98;S95)-τ(y95;S95)	τ(y95;S95)-τ(y95;F95)
ALL LOANS					
τ= E(y)	0.1338	-0.4052	0.0929	0.3727	0.0734
τ= E(ln(y))	-0.0702	-0.1194	0.0283	0.0221	-0.0013
τ= p(y≤2.5.)	0.0735	0.0371	-0.0086	0.0362	0.0088
τ= p(2.5<y≤3.5.)	-0.0721	-0.0081	0.0019	-0.0592	-0.0067
τ= p(3.5<y)	-0.0014	-0.0291	0.0067	0.0230	-0.0021
INSTALMENT					
τ= E(y)	0.2354	-0.6960	0.1517	0.6553	0.1244
τ= E(ln(y))	-0.0747	-0.1795	0.0373	0.0589	0.0087
τ= p(y≤2.5.)	0.0790	0.0643	-0.0136	0.0085	0.0198
τ= p(2.5<y≤3.5.)	-0.0823	-0.0120	0.0029	-0.0420	-0.0311
τ= p(3.5<y)	0.0033	-0.0524	0.0108	0.0335	0.0113
OTHER CREDIT					
τ= E(y)	-0.5256	0.0321	-0.0098	-0.5149	-0.0330
τ= E(ln(y))	-0.1306	0.0119	-0.0062	-0.0610	-0.0752
τ= p(y≤2.5.)	0.0885	-0.0200	0.0041	0.0839	0.0205
τ= p(2.5<y≤3.5.)	-0.0296	0.0065	0.0002	-0.0361	-0.0001
τ= p(3.5<y)	-0.0589	0.0135	-0.0043	-0.0477	-0.0204
Notes: y denotes amount in million LIT; τ denotes the sample statistic that is computed					

We also computed the same statistics by taking *f(amount|F95)* as the benchmark instead, but results were not much affected.[8]

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[8] That is, we specified the following, alternative decomposition:

$$E(amount_{1998} \mid F_{1998}) - E(amount_{1995} \mid F_{1995}) =$$

$$[E(amount_{1998} \mid F_{1998}) - E^*(amount_{1998} \mid S_{1998})] + [E^*(amount_{1998} \mid S_{1998}) - E^*(amount_{1995} \mid S_{1998})] +$$

$$[E^*(amount_{1995} \mid S_{1998}) - E^*(amount_{1995} \mid S_{1995})] + [E^*(amount_{1995} \mid S_{1995}) - E(amount_{1995} \mid F_{1995})]$$

6. Econometric estimation

In Table 7 we have also shown what part of changes in E(amount) is not attributable to changes in Findomestic sample, and should therefore be explained in terms of behaviour. These behavioural changes are a simple difference estimator. If we look at difference in E(amount) across contract types, ΔE(instalment)-ΔE(other credit), we have a difference in difference estimator. We can compute similar statistics for interest rates (based upon internal rates of return and published statistics) and estimate the effect of the interest rate on consumer credit.

We shall argue that, under reasonable conditions the quantity:

$$\frac{\Delta E(instalment) - \Delta E(other\ credit)}{\Delta r(instalment) - \Delta r(other\ credit)}$$

can be interpreted as a supply effect of the interest rate on credit.

Let us assume that by taking differences across loan types we are removing common macroeconomic effects, but that the usury law represents a pure supply shock, with differential effects on the two types of loans. Let us specify individual demand as follows:

$$\log(amount_{it}^{D}) = c_i + \alpha(r_{it} - R_t) + \delta m_t + \varepsilon_{it}^{D} \qquad (1)$$

where r_{it} is the interest rate on credit type i at time t, R_t is a competing interest rate (such as the deposit rate), m_t denotes macro shocks, and ε_{it} has zero mean over all subgroups. [9]

Let us further assume each financial intermediary's supply is

$$\log(amount_{it}^{S}) = c_i^{S} + \gamma(r_{it} - R_t) + m_t + \beta_i u_t + \varepsilon_{it}^{S} \qquad (2)$$

where again ε_{it} has zero mean over all subgroups, but u_t (the usury shock) does not. We set u_t=0 before 1997, u_t=1 after it. (the "i" subscript denotes loan type, either instalment credit or other credit).

In order to estimate the parameter α, the identifying assumptions are:

1. the interest rate coefficients α and γ do not vary across loan types
2. the macro shock m_t affects loan types in the same way.

Then u_t is a valid instrument for demand (it correlates with the explanatory variable, but not with the error term), and is what is used for the double difference estimator above. This estimator can be computed directly in a standard instrumental variable setting by regressing the observed logarithm of amount on the actual interest rate, a time dummy

[9] This specification assumes that customers treat credit types as perfect substitutes, except for an intercept term. It also rules out zero demand, but only for econometric convenience: in our data amount is always positive.

and a credit-type dummy. The interest rate is treated as endogenous and instrumented by the interaction between the time dummy and the credit type dummy. We can focus on behavioural changes (i.e.: correct for composition effects) by p-score weighting all observations.

In Table 8, column 1, we report a set of p-score weighted IV estimates for equation (1): the interest rate parameter is negative and well determined, and implies a median elasticity of –2.57, a perhaps surprisingly large value in absolute terms.[10] The first stage regression for the interest rate shows that the interaction term is a powerful instrument: the F-test for instrument significance (reported at the bottom of the table) strongly rejects the null of a zero coefficient of the usury law dummy in the first stage regression for r_{it}.

In column 2 of Table 8 we show IV estimates that take into no account changes in sample composition: we see that the interest rate effect estimate is much smaller in absolute value when changes in the sample composition are not taken into account.

Columns 3 and 4 report OLS estimates of equation (1). The point estimates presented in column 3 differ from those in column 1: the Hausman test reported in column 1 of Table 8 strongly rejects the null of exogeneity, whereas column 4 estimates are fairly close to column 2 estimates (and the Hausman test fails to reject the null).

Table 8: The demand for consumer credit (no background characteristics)

	(1)	(2)	(3)	(4)
Dependent variable: Log(amount)	IV p-score weighted	IV unweighted	OLS p-score weighted	OLS unweighted
Interest rate	-10.094	-5.937	-6.942	-6.788
	(1.121)**	(1.032)**	(0.061)**	(0.057)**
Year=1998	-0.445	-0.332	-0.272	-0.378
	(0.063)**	(0.057)**	(0.013)**	(0.012)**
Instalment credit	-0.069	-0.270	-0.177	-0.237
	(0.040)	(0.042)**	(0.012)**	(0.011)**
Constant	10.501	9.554	9.642	9.786
	(0.306)**	(0.283)**	(0.022)**	(0.021)**
Observations	30623	30623	30623	30623
R-squared	0.26	0.34	0.32	0.35
F-test of instrument significance	102.82 (1,30621)	93.70 (1,30621)	..	..
No. Observations	30623.00	30623.00	30623.00	30623.00
Median interest elasticity	-2.574	-1.514	-1.770	-1.731
Mean interest elasticity	-2.631	-1.547	-1.809	-1.769
Hausman test for exogeneity (p-value)	0.003	0.408		
Standard errors in parentheses				
* significant at 5%; ** significant at 1%				

[10] For instalment credit and personal loans we were able to compute the effective rates of return; for revolving credit we used average rates applicable in the first three quarters of 1996 and all four quarters of 1998 as provided by ASSOFIN. Note that we had to discard instalment credit observations where the interest was partly or wholly paid by the dealer.

In both equations (1) and (2) we can introduce further conditioning variables. Demand is likely to be affected by customer characteristics such as age, income, region and family composition. These variables might also affect supply through the financial intermediary's assessment of customer credit risk, and their effect is likely to have changed after usury law came into force (the evaluation of low income customers may have changed as the result of the existence of an interest rate cap). Supply will also be affected by factors relating to the financial intermediary's relative position in the market degree of market competition and so on.

In Table 9 we show estimates for specifications that allow for the role of income and all the observable characteristics listed in Table 6.

In the first column we report p-score weighted Instrumental Variable results for the case where the only additional instrument is the usury law dummy. Even in this context the instrument is highly significant in the first stage regression for the endogenous variable r_{it}. In this just-identified case, conditioning on a full set of demographic indicators (income decile, age, marital status, residential status, region, number of dependent children), we get a smaller but comparable median estimate of the elasticity (-1.65). This is quite close to the corresponding OLS estimate (median elasticity: -1.70) reported in column 4 (as already noticed while discussing Table 8, p-score weighting has little effect on OLS estimates).

If we believe the usury dummy enters the supply equation not only as an intercept shift, but also interacted with customer characteristics, we can add instruments to the list and gain over-identifying restrictions. In particular, we add to the list the interaction between the usury dummy the income decile dummies on the assumption that applicant's income became a more important piece of information to Findomestic after usury law came into force (this is borne out by the fall in missing income records discussed in the Appendix).

Estimation results for this over-identified case are shown in columns 2 (p-score weighted) and 3 (unweighted). As we see from the F-statistics reported at the bottom of the Table, the set of instruments is jointly highly significant for the endogenous variable, r_{it}. The Sargan test for instrument validity (i.e. for the validity of the overidentifying restrictions) fails to reject the null at the 99% significance level.

The interest rate coefficient in column 2 is smaller than found in all other specifications and implies a median elasticity of −1.1 . The corresponding Hausman test strongly rejects the null of exogeneity of the interest rate variable. The unweighted IV estimate of the coefficient is instead much more in line with previous evidence, and implies an elasticity of -1.702 (the Hausman test fails to reject the null in this case). Rather oddly, in this case and in the corresponding unweighted OLS case of column 5, only one of the income decile dummies has a significant coefficient, whereas in all other cases they are highly significant.

Similar results (elastic credit demand) obtain when equation (1) is estimated by ordered probit (interval regression), ranking credit amounts in three classes (0-2.5m; 2.5m-3.5m; over 3.5m).

Our evidence is in line with that recently reported in Gross and Souleles for the US (they find a –1.3 elasticity) and is similarly at variance with the 'underestimation hypothesis' in Ausubel (1991). A demand elasticity in the –1.1/-1.7 range may be compatible with the notion that customers mostly care about monthly repayments (and therefore cut their application 1% when the interest rate rises by 1%). However, its micro and macro economics implications are wide-ranging and potentially important.

Table 9: The demand for consumer credit (with background characteristics, 9 extra instruments: income interacted with usury)

Dependent variable: Log(amount)	IV p-score w. just identified	IV p-score weighted	IV unweighted	OLS p-score weighted	OLS unweighted
Interest rate	-5.453	-4.012	-7.016	-6.674	-6.596
	(1.091)**	(0.755)**	(0.894)**	(0.060)**	(0.057)**
Year=1998	-0.253	-0.121	-0.397	-0.265	-0.375
	(0.060)**	(0.043)**	(0.049)**	(0.012)**	(0.012)**
Instalment credit	-0.231	-0.315	-0.193	-0.224	-0.209
	(0.039)**	(0.028)**	(0.035)**	(0.011)**	(0.012)**
1000<inch<=1340	0.059	0.054	-0.032	0.060	-0.036
	(0.021)**	(0.022)*	(0.023)	(0.021)**	(0.021)
1340<inch<=1500	0.110	0.105	0.002	0.110	-0.001
	(0.023)**	(0.024)**	(0.021)	(0.023)**	(0.020)
1500<inch<=1670	0.116	0.117	-0.011	0.116	-0.014
	(0.032)**	(0.033)**	(0.023)	(0.032)**	(0.022)
1670<inch<=1816	0.073	0.085	-0.012	0.072	-0.013
	(0.022)**	(0.023)**	(0.021)	(0.022)**	(0.021)
1816<inch<=2000	0.130	0.122	0.010	0.131	0.007
	(0.023)**	(0.024)**	(0.021)	(0.023)**	(0.020)
2000<inch<=2340	0.162	0.158	0.022	0.162	0.021
	(0.022)**	(0.023)**	(0.023)	(0.022)**	(0.022)
2340<inch<=2927	0.138	0.121	0.007	0.140	0.006
	(0.021)**	(0.021)**	(0.022)	(0.019)**	(0.022)
2927<inch<=3700	0.135	0.142	0.029	0.134	0.029
	(0.021)**	(0.021)**	(0.022)	(0.020)**	(0.022)
Inch>3700	0.218	0.243	0.078	0.215	0.080
	(0.022)**	(0.020)**	(0.022)**	(0.013)**	(0.022)**
Constant	9.579	8.858	9.801	9.641	9.676
	(0.323)**	(0.225)**	(0.266)**	(0.036)**	(0.035)**
Observations	30623	30623	30623	30623	30623
R-squared	0.37	0.33	0.37	0.37	0.37
F-test of instruments' significance	92.93 (1,30580)	20.69 (10,30571)	12.70 (10,30571)	--	-
No. obs.	30623.00	30623.00	30623.00	30623.00	30623.00
Median interest elasticity	-1.648	-1.102	-1.789	-1.702	-1.682
Mean interest elasticity	-1.684	-1.046	-1.829	-1.739	-1.719
Sargan test of over-identifying restrictions		$X^2(9)$=21.25 (0.012)	$X^2(9)$=20.93 (0.013)		
Hausman test on exogeneity (p-value)	0.846	0.000	0.638		

Standard errors in parentheses; * significant at 5%; ** significant at 1%

In this specification we controlled for income, residential status, marital status, region, no. of kids and age

7. Other than first applications

This paper has focused on first-time applicants at Findomestic. An analysis of repeat business (follow-up applications and contracts) is beyond the scope of the paper, but we wish to highlight some patterns found in the data.

The overall composition of loan types (instalment, revolving, personal) differs substantially when all contracts per customer are taken into account. Both revolving credit and personal loans are (relatively) more numerous and weigh more heavily in terms of limits and amounts. We have broken down first and other applications by quarter. The results are not presented here in detail for brevity. It emerges that the subsequent applications (or repeat business), become more important over time, from less than a third to almost half of all applications. Whereas first applications are dominated by instalment loan applications, the importance of personal loans and revolving credits is increasing for subsequent applications. Revolving credit is dominated by so-called '*bicontratti*': these are pre-approved credit cards with a predetermined limit issued to customers that have shown reliable repayment behaviour (typically in instalment contracts) in the past. Rejection rates differ as well. At first applications, revolving and instalment credit have about equal rejection rates, whereas rejection rates of personal loans are about three times higher. For repeat business, overall rejection rates drop sharply, in particular they half for personal loans. The rejection rates for revolving loans are much lower, due to the large fraction of pre-approved *bicontratti* (no rejections), and somewhat higher for standard revolving credits.

There are also substantial differences in terms of type of follow-up application when conditioning on the first application. Applicants that started with an instalment credit application, are much more likely to apply for a subsequent, revolving credit than first-time applicants for other credit products. There is a strong time trend in the raw data, however. The probability of applying for subsequent instalment credits and personal loans increases, whereas the probability of applying for subsequent revolving credits declines with time. This trend can also be observed when we condition on individuals that have applied for a revolving credit in the first place. Yet, they are more likely to subsequently apply for an instalment credit than any of the other loan types. There is also an interesting finding in terms of amounts. Since amounts applied for are highest for personal loans, people that have applied for a personal loan in the first instance, apply for higher amounts for the other two types (revolving and instalment). If we exclude motor cycles (typically motor scooters) or telephony (typically cell phones) from the analysis, we do see similar trends over time. However, it is not true anymore that first-time instalment applicants apply subsequently for more revolving credit. They are more likely to reapply for instalment loans.

Returning to the central question of the paper, we can also investigate if people whose instalment credit contract had an effective interest rate above the (would-be) usury limit were more likely than others to be offered a pre-approved *bicontratto*. Table 12 shows, by instalment loan size, the number of contracts that were below and above the usury limit in 1996Q1 and 1996Q2 (these correspond to the tails of the densities shown in

Figures 1-4). We distinguish between applicants that were or were not offered a *bicontratto* ever after.

Table 10: Effect of Usury Law on Pre-Approved Revolving Credit

	Below usury limit			Above usury limit		
Loan size	N. obs.	*Bicontratto*: no	*Bicontratto*: yes	N. obs.	*Bicontratto*: no	*Bicontratto*: yes
<2.5m	3984	37.80	62.20	71	35.21	64.79
2.5-3.5m	360	45.00	55.00	121	62.81	37.19
3.5-10m	726	59.23	40.77	85	84.71	15.29
>10m	447	69.57	30.43	23	78.26	21.74
Total	5517	43.67	56.33	300	63.67	36.33

There were only about 300 observations above the usury rate limit (out of 5817 instalment contract applications in the two quarters), mostly concentrated in the 2.5-3.5m interval (121 out of 300). For small loans below the 2.5 million mark, almost two-thirds of instalment contracts that were below the usury limit triggered a follow-up *bicontratto*. For contracts above the limit, roughly the same percentage were sent a pre-approved credit card.

Of greater interest to us is what happens to the next two groups of loans, where revolving credit did afford a less tight rate constraint. Surprisingly, offers were made much more frequently to customers whose rate was below the limit than above. For instance, in the 2.5-3.5m range 55% of customers below the limit were offered a *bicontratto*, only 37.19% of customers above the limit. This patterns is confirmed for larger loan size classes.

On the basis of this evidence, we can rule out that the bank tried to reshuffle loan types by simply sending more revolving cards to 'people at risk'. This finding is robust to changes in definition: we looked at those cases that were offered a *bicontratto* within the year before the usury law came into force (1996QII-1997QI), and we looked at not only *bicontratti* but all revolving credit. We also conditioned on applicants with at least 2 applications to the bank. None of these changed our conclusions.

8. Conclusions

In this paper we have analysed unique data on credit applications received by the leading provider of consumer credit in Italy. This data set covers a five year period (1995-1999) and contains information on both accepted and rejected applications. During this period the consumer credit market has much expanded in Italy and a new law has come into force that sets a limit to interest rates charged to consumers (the usury law).

In the paper we have investigated ways in which the law may have affected the consumer credit market and have shown how the applicants pool has changed over time in comparison to a representative sample of the Italian population.

We have then argued that behavioural changes can be computed by controlling for changes in the observable characteristics of the Findomestic clientele. We have further argued that under suitable identifying assumptions these changes can be given a structural interpretation. If the usury shock is assumed to have directly affected credit supply but not credit demand, we can estimate a demand equation. Our key finding is that demand is interest rate elastic, something that may explain why the consumer credit industry has been traditionally reluctant to give its interest rates adequate publicity.

Much remains to be investigated on the dynamic nature of consumer credit: in this paper we have concentrated on first contracts only, but the analysis of repeat contracts is of great research interest given the likely strategic interactions between credit supplier and its established customers.

References

Ausubel, Lawrence (1991) 'The Failure of Competition in the Credit Card Market', *American Economic Review*, 81, 50-81

Brugiavini Agar and Guglielmo Weber (1994) 'Durables and Nondurables Consumption: Evidence from Italian Household Data', in A. Ando, L. Guiso and I. Visco (eds.) Saving and Wealth Accumulation, Cambridge University Press, pp. 305-329.

Brandolini, Andrea and Luigi Cannari (1994) 'Methodological Appendix: The Bank of Italy's Survey of Household Income and Wealth', in A. Ando, L. Guiso and I. Visco (eds.) Saving and Wealth Accumulation, Cambridge University Press, pp. 369-386.

D'Alessio, Govanni and Ivan Faiella (2000) 'I Bilanci delle Famiglie Italiane nell'Anno 1998', in Banca d'Italia: Supplementi al Bollettino Statistico, 22, pp. 5-80.

Diez-Guardia, Nuria (2000) 'Consumer Credit in the European Union' ECRI Research Report, No. 1. European Credit Research Institute, Brussels.

DiNardo, John, Nicole M. Fortin and Thomas Lemieux (1996) 'Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach', *Econometrica*, 64(5), 1001-1044

Gross, David B. and Nicholas S. Souleles (2001) 'Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data', NBER WP 8314

Guiso, Luigi and Tullio Jappelli (1999) 'Private Transfers, Borrowing Constraints and the Timing of Home-Ownership', CSEF WP 17.

Hochguertel, Stefan (2000) "Findomestic Data: Description and Codebook", mimeo, EUI-FCC

Mancini, Marina, Elena Rigacci Hay and Natalino Ronzitti (2000) 'Italian Report', in Euro Spectator: Implementing the Euro, Law Department, EUI WP 2000/7.

Manski, Chuck F. and S. Lerman (1977) 'The Estimation of Probabilities from Choice-Based Samples', *Econometrica*, 45, 1977-88

Rosenbaum, Paul R. and Donald R. Rubin (1983) 'The Central Role of the Propensity Score in Observational Studies for Causal Effects', *Biometrika*, 70(1), 41-55.

APPENDIX A – Analysis of Missing Income Applications

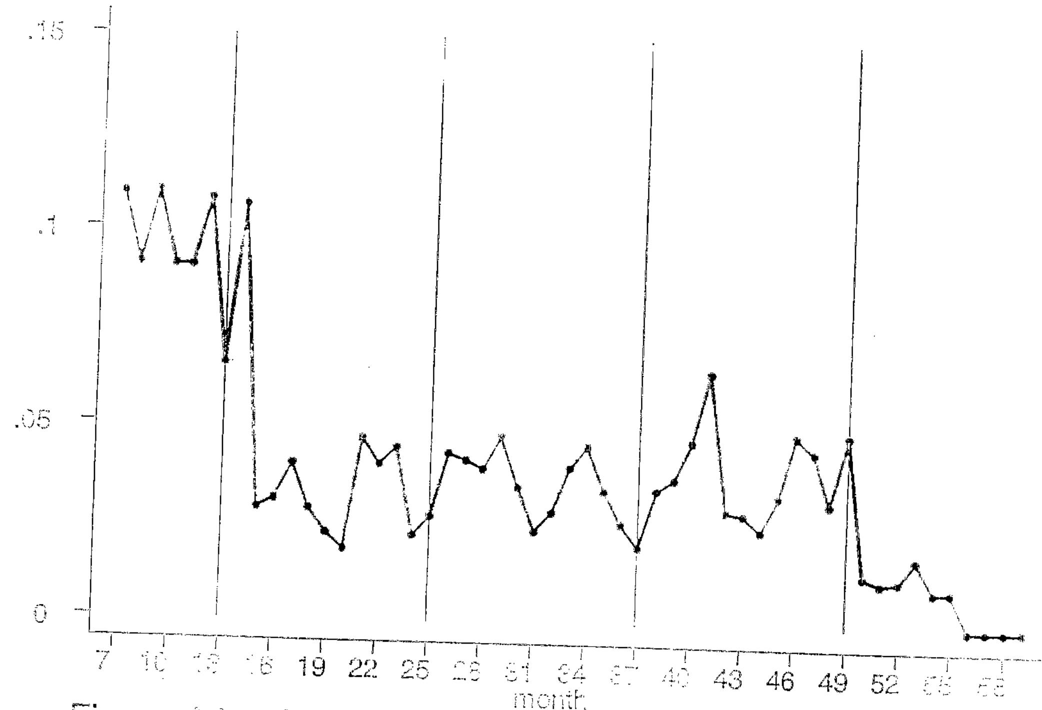

Figure A1: missing income cases, first apps

To investigate what drives the choice not to report income (at first applications), we define an indicator variable taking the value 1 if household income is missing. For the entire sample, this concerns about 3% of all observations. Figure A1 shows the sample proportion of missing income applications over time. It is evident that missing income for our sample is particularly important in the first year, but drops thereafter. Running a probit of the missing income indicator on other explanatory variables, we not only find strong year effects, but also significant contributions of other factors. Applicants for instalment and personal loans are more likely not to report income than those applying for revolving credit, strong regional effects are found for residents in Tuscany, and (to a lesser extent) Sicily, who are more likely to fail to report income than those in Lazio (Rome). Also, the item bought matters. Applicants intending to buy motor vehicles are more likely to not report income than buyers of furniture; the largest effect however is found for those where the contract has not been finalised and the item bought is not recorded. Dealer characteristics also play a strong role. Applications filed via a *telematica* (remote terminal) are more likely not to have income included than those submitted by fax or phone. Applications where the customer pays the interest charge in full are also more likely to have income missing than those where the dealer pays the interest. Demographics of applicants are likewise important. Applicants working in the public sector without career opportunities are among the least likely not to report their income. In general, professions associated with higher income stability are more likely to have income missing. The estimated age function is non-linear; about hump-shaped until age 50, and increasing thereafter. Tenants are more likely, people living with relatives less likely not to report income than outright homeowners. Married and widowed individuals are more likely to report their incomes than singles. In addition to year effects, we also find seasonal patterns; incomes are more likely not to be reported during the first half of the year. Table A1 reports Wald tests of joint significance. The full specification is available from the authors on request. A specification with year dummies alone has a Pseudo-R^2 of 4.6%; including the full set of other variables results in a Pseudo- R^2 of 44.9%.

Table A1: Determinants of Missing Income (Probit)			
all loan types, first applications			
variable group	DF	Wald test	p-value
contract type	2	183.96	0.0000
region	12	567.15	0.0000
item bought	14	935.92	0.0000
origin of contract	4	766.18	0.0000
who pays interest	2	104.20	0.0000
profession	10	2041.13	0.0000
age	3	21.76	0.0001
residential status	4	76.32	0.0000
number of children	3	17.55	0.0005
marital status	5	151.83	0.0000
calendar month	11	232.99	0.0000
calendar year	4	2258.53	0.0000
Pseudo R^2	0.4487		
N observations	120153		
Percentage y=1	2.94		

8. Conclusions

In this paper we have analysed unique data on credit applications received by the leading provider of consumer credit in Italy. This data set covers a five year period (1995-1999) and contains information on both accepted and rejected applications. During this period the consumer credit market has much expanded in Italy and a new law has come into force that sets a limit to interest rates charged to consumers (the usury law).

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Much remains to be investigated on the dynamic nature of consumer credit: in this paper we have concentrated on first contracts only, but the analysis of repeat contracts is of great research interest given the likely strategic interactions between credit supplier and its established customers.

References

Ausubel, Lawrence (1991) 'The Failure of Competition in the Credit Card Market', *American Economic Review*, 81, 50-81

Brugiavini Agar and Guglielmo Weber (1994) 'Durables and Nondurables Consumption: Evidence from Italian Household Data', in A. Ando, L. Guiso and I. Visco (eds.) Saving and Wealth Accumulation, Cambridge University Press, pp. 305-329.

Brandolini, Andrea and Luigi Cannari (1994) 'Methodological Appendix: The Bank of Italy's Survey of Household Income and Wealth', in A. Ando, L. Guiso and I. Visco (eds.) Saving and Wealth Accumulation, Cambridge University Press, pp. 369-386.

D'Alessio, Giovanni and Ivan Faiella (2000) 'I Bilanci delle Famiglie Italiane nell'Anno 1998', in Banca d'Italia: Supplementi al Bollettino Statistico, 22, pp. 5-80.

Diez-Guardia, Nuria (2000) 'Consumer Credit in the European Union' ECRI Research Report, No. 1. European Credit Research Institute, Brussels.

DiNardo, John, Nicole M. Fortin and Thomas Lemieux (1996) 'Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach', *Econometrica*, 64(5), 1001-1044

Gross, David B. and Nicholas S. Souleles (2001) 'Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data', NBER WP 8314

Guiso, Luigi and Tullio Jappelli (1999) 'Private Transfers, Borrowing Constraints and the Timing of Home-Ownership', CSEF WP 17.

Hochguertel, Stefan (2000) "Findomestic Data: Description and Codebook", mimeo, EUI-FCC

Mancini, Marina, Elena Rigacci Hay and Natalino Ronzitti (2000) 'Italian Report', in Euro Spectator: Implementing the Euro, Law Department, EUI WP 2000/7.

Manski, Chuck F. and S. Lerman (1977) 'The Estimation of Probabilities from Choice-Based Samples', *Econometrica*, 45, 1977-88

Rosenbaum, Paul R. and Donald R. Rubin (1983) 'The Central Role of the Propensity Score in Observational Studies for Causal Effects', *Biometrika*, 70(1), 41-55.

APPENDIX A – Analysis of Missing Income Applications

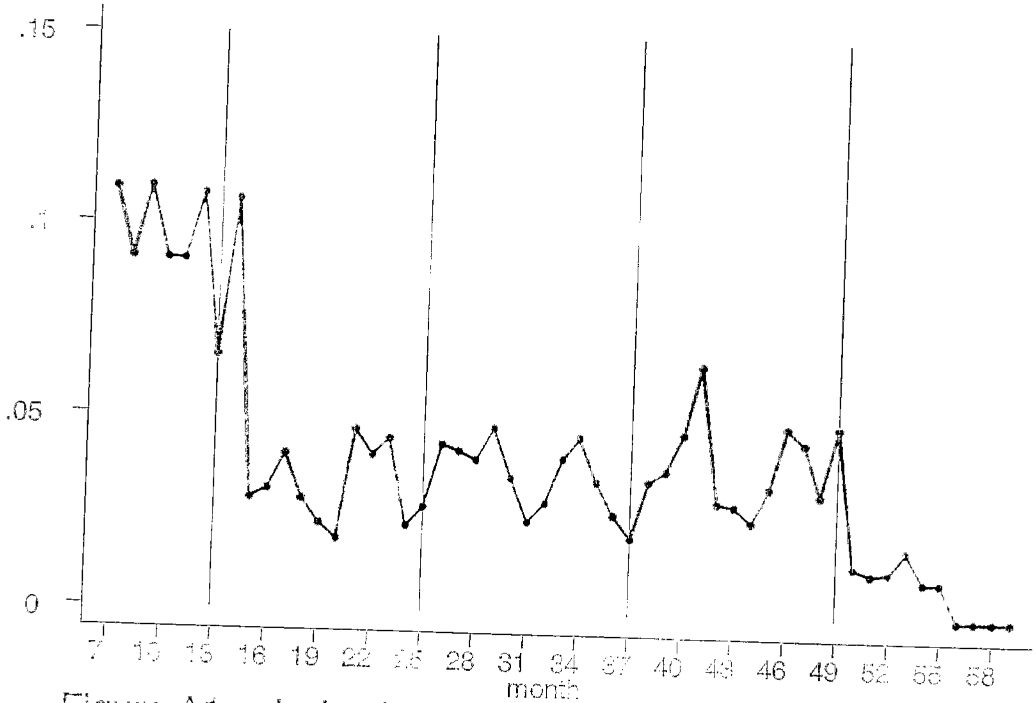

Figure A1: missing income cases, first apps

To investigate what drives the choice not to report income (at first applications), we define an indicator variable taking the value 1 if household income is missing. For the entire sample, this concerns about 3% of all observations. Figure A1 shows the sample proportion of missing income applications over time. It is evident that missing income for our sample is particularly important in the first year, but drops thereafter. Running a probit of the missing income indicator on other explanatory variables, we not only find strong year effects, but also significant contributions of other factors. Applicants for instalment and personal loans are more likely not to report income than those applying for revolving credit, strong regional effects are found for residents in Tuscany, and (to a lesser extent) Sicily, who are more likely to fail to report income than those in Lazio (Rome). Also, the item bought matters. Applicants intending to buy motor vehicles are more likely to not report income than buyers of furniture; the largest effect however is found for those where the contract has not been finalised and the item bought is not recorded. Dealer characteristics also play a strong role. Applications filed via a *telematica* (remote terminal) are more likely not to have income included than those submitted by fax or phone. Applications where the customer pays the interest charge in full are also more likely to have income missing than those where the dealer pays the interest. Demographics of applicants are likewise important. Applicants working in the public sector without career opportunities are among the least likely not to report their income. In general, professions associated with higher income stability are more likely to have income missing. The estimated age function is non-linear; about hump-shaped until age 50, and increasing thereafter. Tenants are more likely, people living with relatives less likely not to report income than outright homeowners. Married and widowed individuals are more likely to report their incomes than singles. In addition to year effects, we also find seasonal patterns; incomes are more likely not to be reported during the first half of the year. Table A1 reports Wald tests of joint significance. The full specification is available from the authors on request. A specification with year dummies alone has a Pseudo-R^2 of 4.6%; including the full set of other variables results in a Pseudo- R^2 of 44.9%.

Table A1: Determinants of Missing Income (Probit)			
all loan types, first applications			
variable group	DF	**Wald test**	p-value
contract type	2	183.96	0.0000
region	12	567.15	0.0000
item bought	14	935.92	0.0000
origin of contract	4	766.18	0.0000
who pays interest	2	104.20	0.0000
profession	10	2041.13	0.0000
age	3	21.76	0.0001
residential status	4	76.32	0.0000
number of children	3	17.65	0.0005
marital status	5	151.83	0.0000
calendar month	11	232.99	0.0000
calendar year	4	2258.53	0.0000
Pseudo R^2	0.4487		
N observations	120153		
Percentage y=1	2.94		