Consumer Credit:

Evidence from Italian Micro Data

by

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August 27th, 2002

Abstract. In this paper we analyse unique data on credit applications received by the leading provider of consumer credit in Italy (Findomestic). The data set covers a five year period (1995-1999) during which the consumer credit market rapidly 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 affected credit supply but not credit demand, that is if the usury law had a differential impact on the supply of various types of credit but a uniform impact on demand, we can identify and estimate a demand equation. Our key finding is that demand is interest rate elastic, particularly in the North, where the consumer credit market is more competitive.

Acknowledgements: This paper was written while the authors were associated with the Finance and Consumption Chair at the European University Institute, whose financial support is gratefully acknowledged. We are grateful for suggestions by Orazio Attanasio, Giuseppe Bertola, Luigi Guiso, , Michaelis Haliassos, Franco Peracchi, Nick Souleles, and an anonymous referee as well as for comments by audiences at the EUI-FCC Conference on the Economics of Consumer Credit (March 2001), the 2001 NBER Summer Institute, the TMR Saving and Pensions Evian meeting, the FCC-ExCEM Workshop on Evolving Credit Markets and Business Cycle Dynamics, and seminar participants at the Universities of Padova and Toulouse, and the Tinbergen Institute. We also thank Fabio Faini and Riccardo Grazzini for help with the Findomestic data set used in this paper. We are solely responsible for the analysis and the views expressed in this paper.

Introduction

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. Information is also available on the type of credit applied for (instalment, revolving, personal loan) and on the terms of repayment.

During this period the consumer credit market rapidly expanded in Italy and a new law came in force in April 1997 that sets a limit to interest rates charged to consumers (the usury law). These limits change over time and differ by amount and by type of credit. For instance, in April 1997 a bank could charge as much as 48.73% on small instalment credit (amounting to less than € 1,300), but the limit was set at 43.21% for revolving credit within the same class (credit limit less than € 1,300). The limits for medium-sized credit (between € 1,300 and € 5,200) were quite different: the limit for revolving credit was still 43.21%, but a much smaller 35.85% limit applied to instalment credit.

If these limits set by the law had been binding for all types of credit, we might expect after April 1997 a decrease in interest rates charged to successful applicants as well as an increase in rejection rates, other things being equal. If instead they only affected some market segments (such as medium-sized instalment contracts) we should observe substitution across credit types taking place.

In our data, we find little evidence of widespread credit rationing. Median interest rates fell over the sample period, but so did many other market rates, and much of the fall took place before the law came in force. Also, rejection rates stayed roughly constant over the period. However, we do find prima facie evidence that substitution took place across credit types – a large fraction of medium sized credit applicants moved away from instalment credit towards revolving credit.

We then argue that these changes can be given a structural interpretation if we are prepared to assume that the usury shock directly affected credit supply but not credit demand. To be more precise, what we assume is that the coming into force of the usury law had a differential impact on the supply of various types of credit, while it had a uniform impact on demand (if any). Our key finding is that credit 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. We also estimate a higher (median) demand elasticity in the North (where there is more competition in the credit card market) than in Central or Southern Italy.

The paper is organised as follows. Section 1 provides background information on the consumer credit market in Italy. Section 2 describes the data on first contracts (first applications) we use and Section 3 shows in what ways the Findomestic clientele changed over the sample years. Section 4 describes the workings of the usury law and investigates its likely impact on Findomestic. Section 5 presents estimation results for the demand equation and discusses their interpretation. Section 6 concludes the paper.

1. The Consumer Credit Market in Italy

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 on collateralised loans on homes (Guiso and Jappelli, 2002) or cars (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 goods. 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 amounted to 13.2% in 1998; 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%	23.6%	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**					

Largely as a result of a press campaign against loan sharks, 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].

[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.

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, on which 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).

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. Therefore, we chose to concentrate on the first contact between would-be-customers (applicants) and Findomestic. 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 applications 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 applications, 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 we 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 Appendix A, 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 the 1995 Findomestic data with 1995 SHIW data when 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 10941 individuals 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.[2]
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

[2] We follow standard definitions and label as "Centre" the regions Tuscany, Umbria, Marche, and Lazio; "North" is everything north of "Centre", the remainder is "South".

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 %).[3]

To summarise the changes in the Findomestic sample over the years, we also estimated the conditional probability of being in the 1998 sample as opposed to the 1996 sample. This way we did not have to restrict attention to variables common to both the Findomestic data base and the SHIW. The conditioning variables are household income and partner's income (in 1996 prices), profession, age of both applicant and spouse, marital status, region and number of dependent children. The logit estimates are shown in Table B1 in Appendix B. These estimates are further used in Section 5 in the econometric analysis of credit demand to correct for changes in composition of the Findomestic clientele over time.

[3] 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.

Table 3: Comparing sample averages

	SHIW		Findomestic	
	all≥18 with income			
Region	1995	1998	1996	1998
North	50.62	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	6.59	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
Household income Y. Amounts are in thousands LIT (LIT 1000= € 0.516)	1995	1998	1996	1998
Y<=1000	17.42	14.67	9.84	10.69
1000<Y <=1340	9.85	9.48	9.83	10.45
1340<Y <=1500	7.10	5.70	11.42	8.25
1500<Y <=1670	7.89	6.55	8.04	9.42
1670<Y <=1816	3.44	4.32	9.78	8.27
1816<Y <=2000	6.85	5.96	11.34	10.83
2000<Y <=2340	9.46	9.69	8.25	9.53
2340<Y <=2927	11.02	12.22	9.77	11.98
2927<Y <=3700	9.71	10.51	9.77	9.53
Y>3700	17.27	20.89	9.78	10.05
Not known	0.00	0.00	2.17	1.00

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 that lenders could charge to borrowers 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 credit. As Table 4 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, roughly € 5,200), while for instalment credit there are two (at 2.5m - € 1,300 - and 10m).

Table 4- 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 (LIT 1m= € 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 4.

To clarify the likely impact of the law, we plot in Figure 1 the effective rates of return on small (less than LIT 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. These should match the legally relevant rates. We do not have contract-specific interest rates for revolving credit, though, but we know that Findomestic charged the same rate to all its customers and we know what the market rate was in each quarter.[4]

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 thin one corresponding to 150% of average rates for small instalment credit and the thick one corresponding to 150% of average rates for revolving credit below the LIT 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.[5]

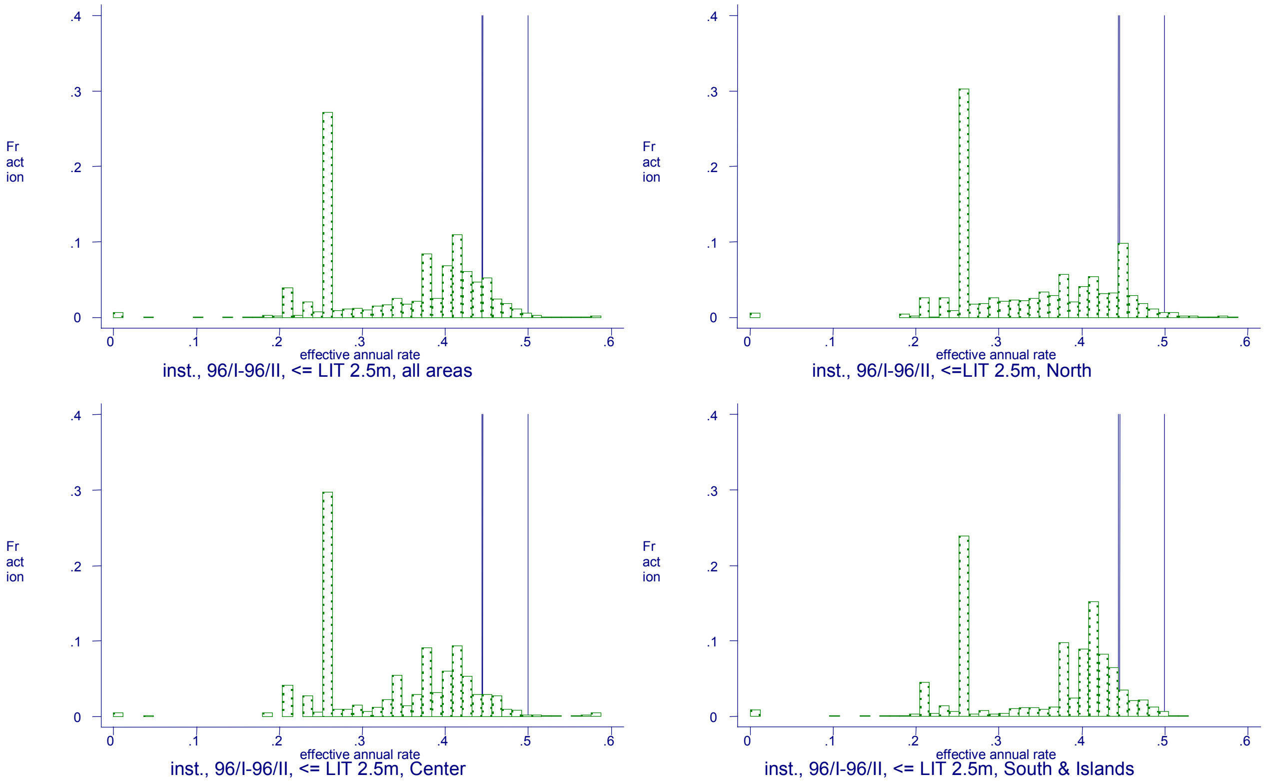

Figure 1: Effective rates for small instalment credit (≤ LIT 2.5m)

As Figure 1 reveals, high interest rates (exceeding 45%) on instalment contracts were not completely uncommon in 1996, partly because of the high fixed costs of credit finance

[4] To clarify: fore instalment contracts, we compute the internal rate of return on all first applications where the customer pays the whole interest and the dealer pays none. The cash flows involved are the cash price of the good, the original down-payment and all contractual repayments that the customer is committed to make over the duration of the contract.
[5] As shown in Figure 6 later on, in the Findomestic sample this is true for contracts above LIT 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.

that affect small contracts disproportionately more. For example, in the data we find instalment contracts to purchase mobile phones or other small appliances worth € 200 with a 6-month repayment period. When instalments are €37.1 a month the APR for the contract works out at 45%, even though the total repayment is € 222.6, i.e. 11% higher than the total amount borrowed.

In Figure 1, the (thin) line for instalment credit is to the right of the (thick) line for revolving credit, suggesting that the law could cause substitution out of revolving credit towards instalment credit, but not vice versa. To clarify how the law could induce substitution across credit types let us consider a customer who intended to buy a commodity worth less than LIT 2.5m, and was prepared to pay a high interest rate for its finance (in excess of 45%, but less than 50%). Had the law been in force in 1996, Findomestic could only accept her application upon the condition that she signed an instalment credit contract rather than a revolving credit contract.

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.

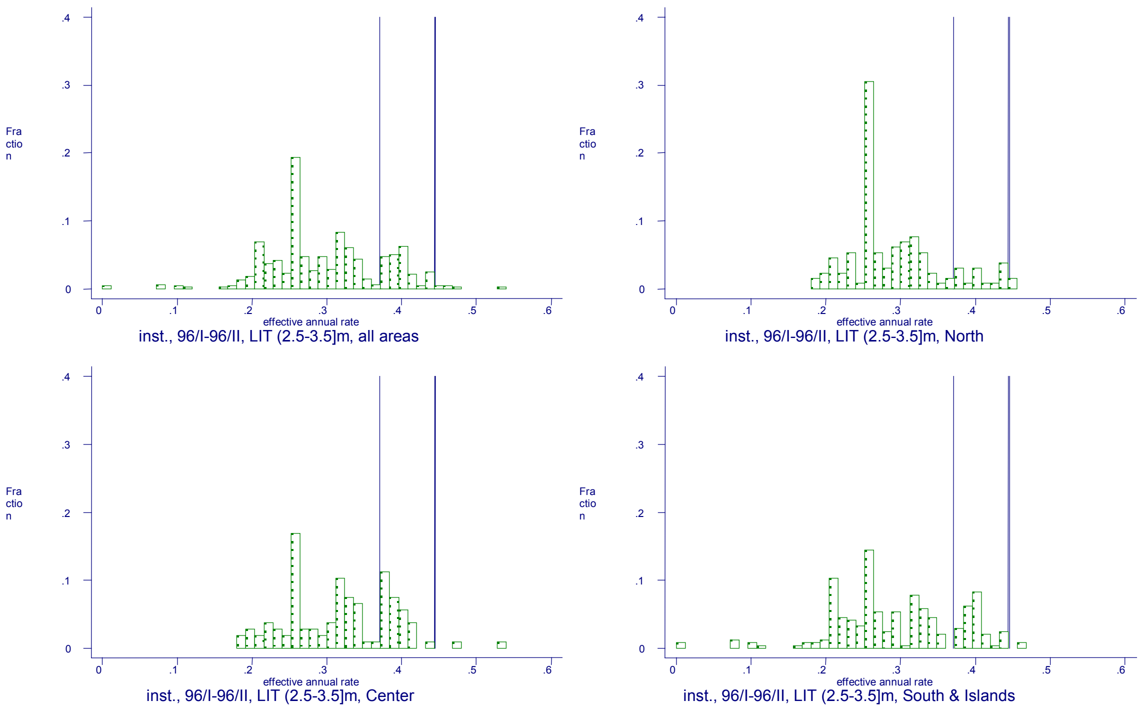

Figure 2: Effective rates for medium instalment credit (LIT 2.5m<y≤LIT 3.5m)

A very different picture emerges when we plot effective rates for instalment credit in the LIT 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 (thick) line corresponding to revolving credit, whereas the (thin) 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, LIT 3.5-10m, and large instalment credit contracts) tell a similar story. Figure 3 covers contracts in the LIT 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 LIT 10m, the vertical lines are moved to the left compared to Figures 2 and 3 (as Table 4 reveals average rates are lower for contracts above the 10m mark), but far fewer contracts are in the right region.

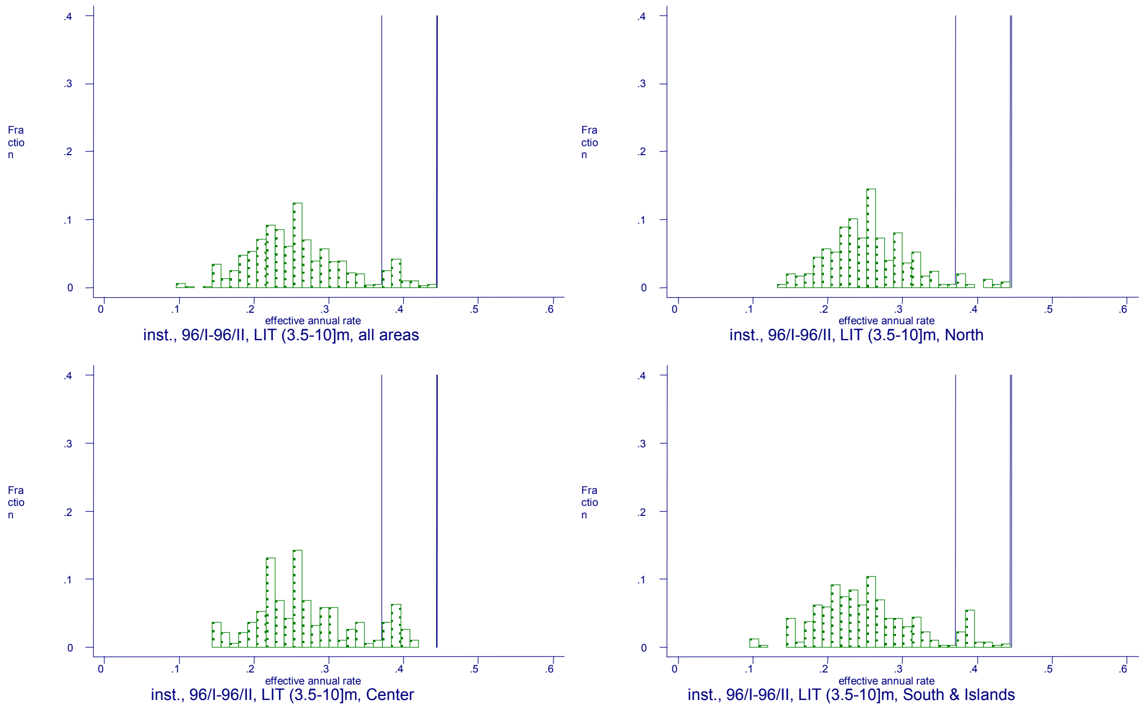

Figure 3: Effective rates for medium-large instalment credit (LIT 3.5m<y≤LIT 10m)

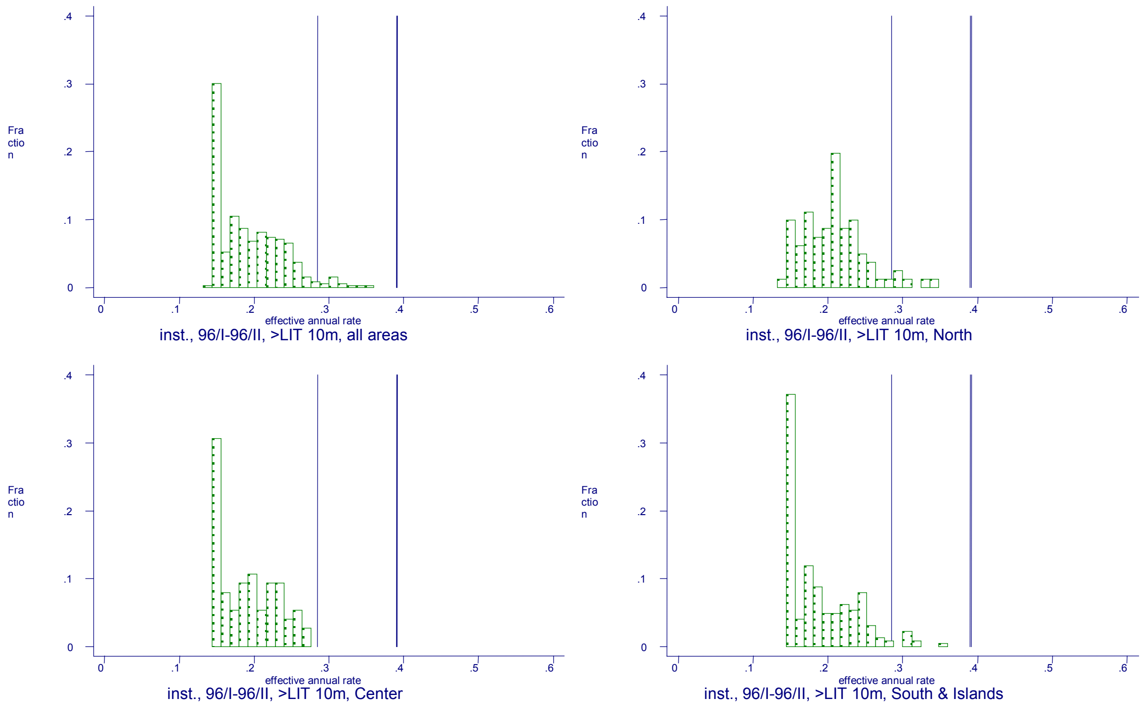

Figure 4: Effective rates for large instalment credit (>LIT 10m)

In Figure 5 we plot similar figures for 1998 effective rates of return for the whole of the country. As before the thick line corresponds to the legal limit for revolving credit contracts and the thinner line to the limit for instalment credit. We have taken the limit that applied in 1998Q3 but contracts over the whole year: this may explain why we observe (particularly in the NE quadrant) rates beyond the limit (the actual limit was roughly 2% higher for contracts signed in 1998Q1, for instance). Of course measurement error may be responsible for some more extreme outliers in all four quadrants.

Comparing 1996 and 1998, we find similar patterns for small credit contracts and for contracts over LIT 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.[6]

[6] Another surprising feature in Figure 5 is the presence of many zero-rated contracts for small instalment credit. This could be the result of aggressive marketing strategies in the small durable goods sector.

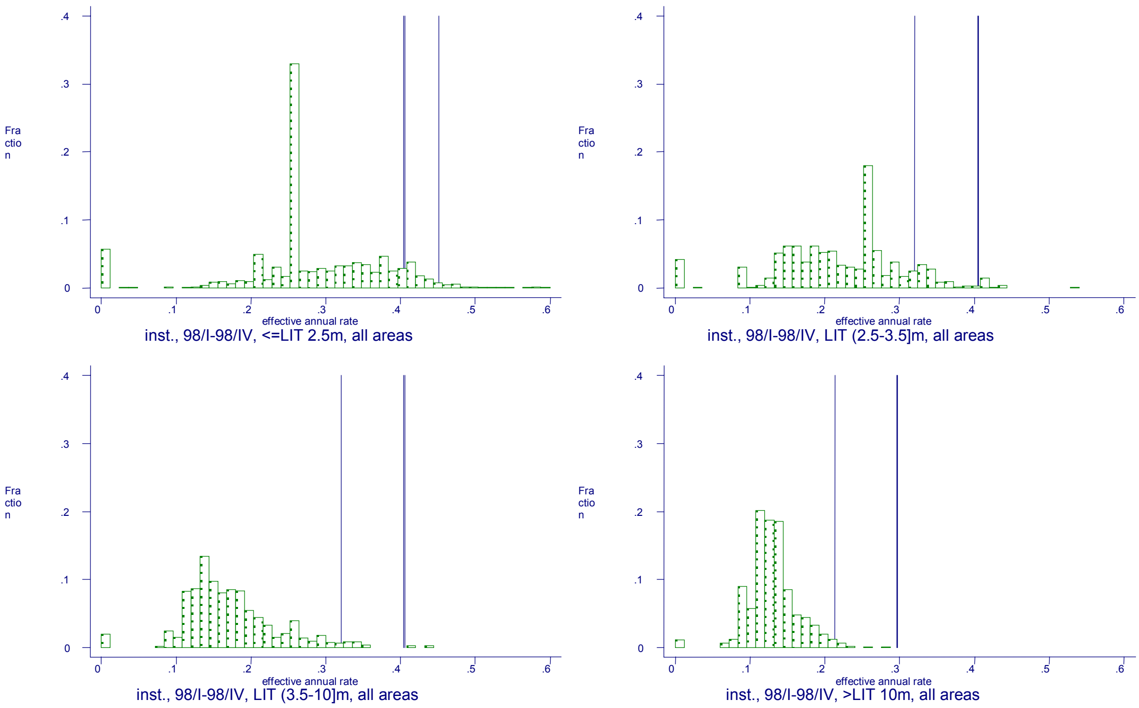

Figure 5: Effective rates for instalment 1998 credit contracts

The key conclusion to be drawn from these figures is that at least one particular segment of the market (the LIT 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 (another possibility would be to split an instalment credit contract into two: this however would go against sound commercial practice, given that the same good would be used as collateral for two loans, and might have been challenged in court. To our knowledge, instalment contracts were not split to circumvent the law).

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.[7]

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 rates of return on instalment credit contracts in the Findomestic sample (see Figure 6). 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 6).

[7] 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

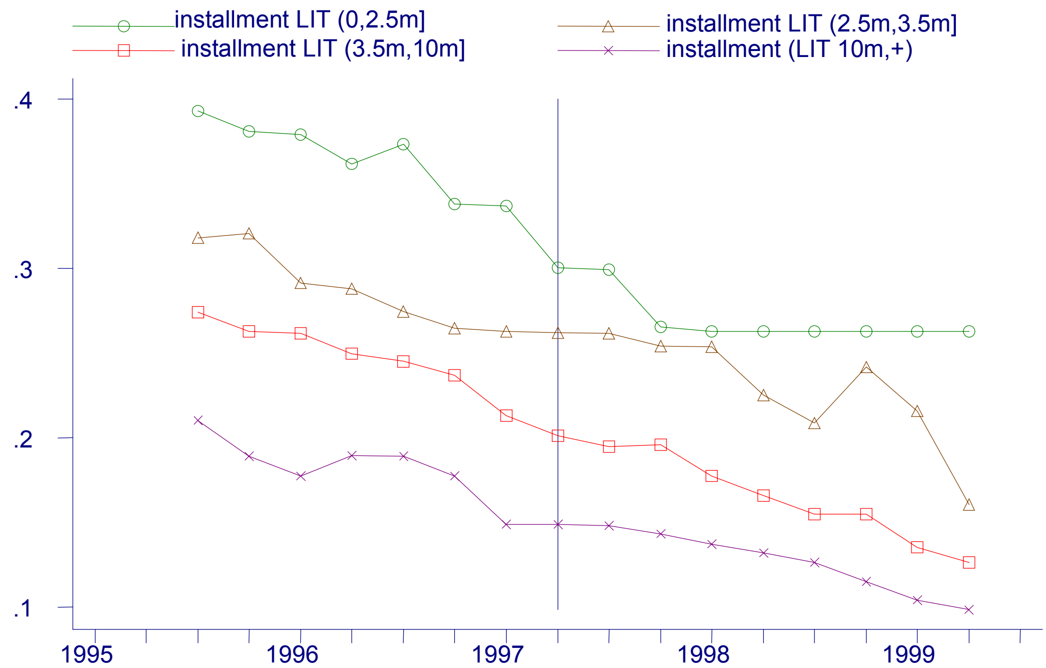

Figure 6: Effective Rates of Return

A further feature worth noting in Figure 6 is that median rates on small contracts did not fall over the period 1997Q4-1999Q3: as a consequence the rate differential between small (≤ LIT 2.5m) and medium-large (> LIT 3.5m) 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 LIT 2.5 million may have been replaced by small instalment credit contracts. We also show median effective rates for instalment credit applications in the LIT 2.5-3.5m range, a potentially interesting group of contracts as we have seen above. It is apparent that immediately after the usury law came into force the gap between the rates on these medium-sized credit applications and small applications narrowed considerably. After 1998Q1, however, this gap widened again. Thus credit around LIT 3m became relatively more onerous in 1997 and this may be responsible for an increase in demand for smaller credit amounts or for revolving credit contracts.

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 LIT 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 LIT 2.5m at the expense of revolving credit contracts. We also expect a decrease in medium instalment contracts (LIT 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).

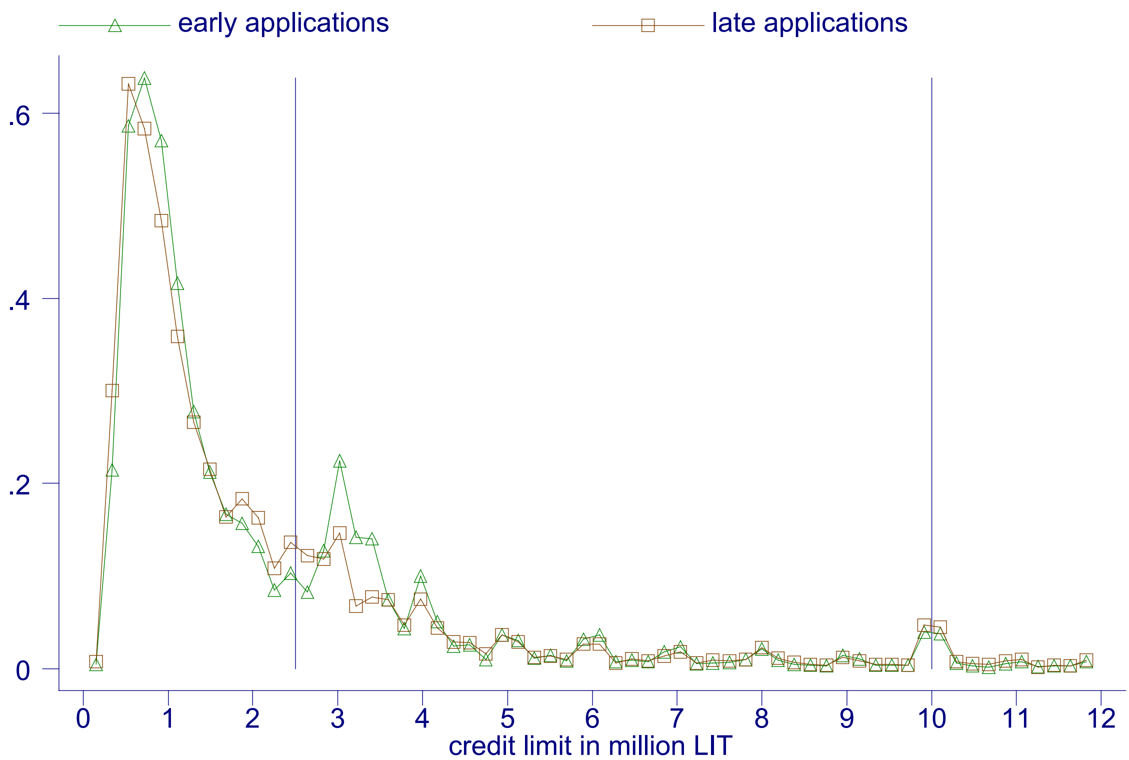

Figure 7: Instalment Credit - density f's all appl's

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 LIT 12m have been set to LIT 12.1m, 1998 applications have been top-coded at LIT 18m instead. Of interest to us is the marked decrease in the frequency of applications in the LIT 3m region, which agrees well with the reshuffling hypothesis discussed above. The slight increase in the frequency of small applications (less than LIT 1m) is also consistent with the hypothesis, but is in fact explained by the rapid development in the mobile phone market.[8]

[8] 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 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 LIT 3-3.5m mark, while there is no longer evidence of an increase in small amount rejections after.

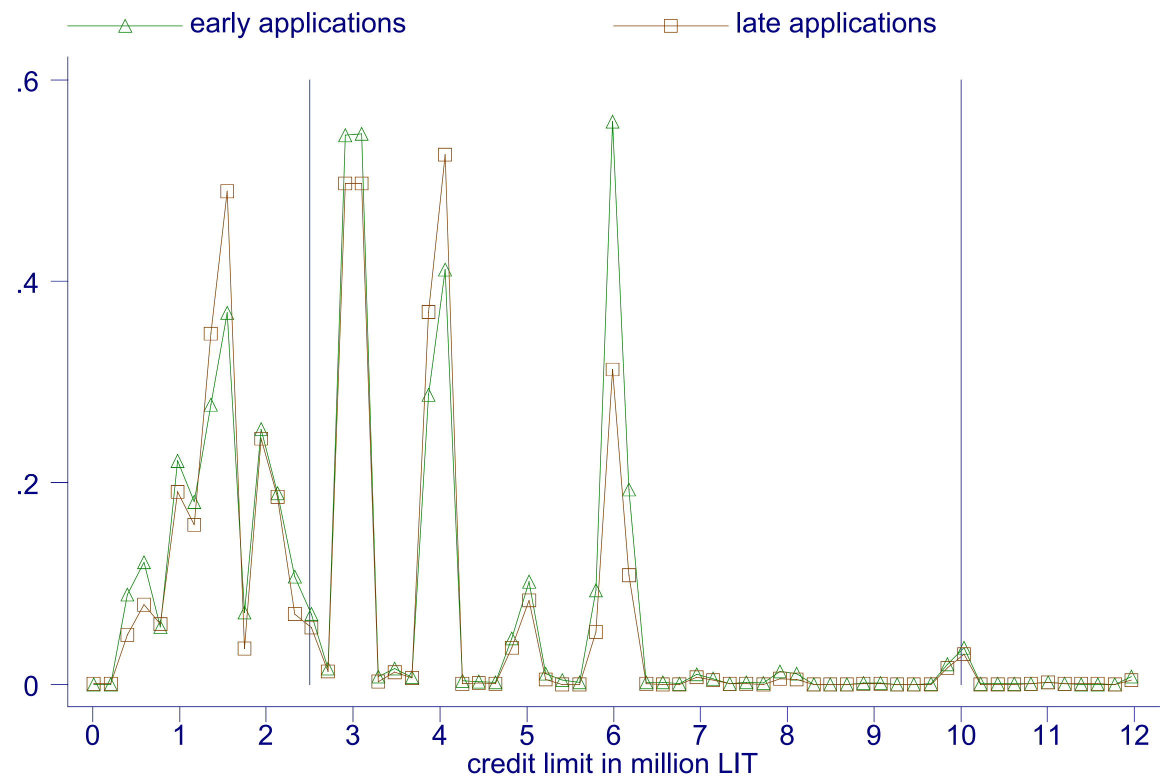

Figure 8: Revolving Credit - density f's all appl's

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 LIT 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. For rejected applications we only observe the credit limit. For accepted applications, both credit limit and outstanding balance are known, but we do 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 these reasons we use the credit limit throughout and this accounts for major spikes around integer multiples of LIT 1 million, and particularly the LIT 3 m mark (this is also the standard ATM monthly limit).[9]

[9] Our estimation results are qualitatively similar when we use the outstanding balance rather than the credit limit for accepted applications.

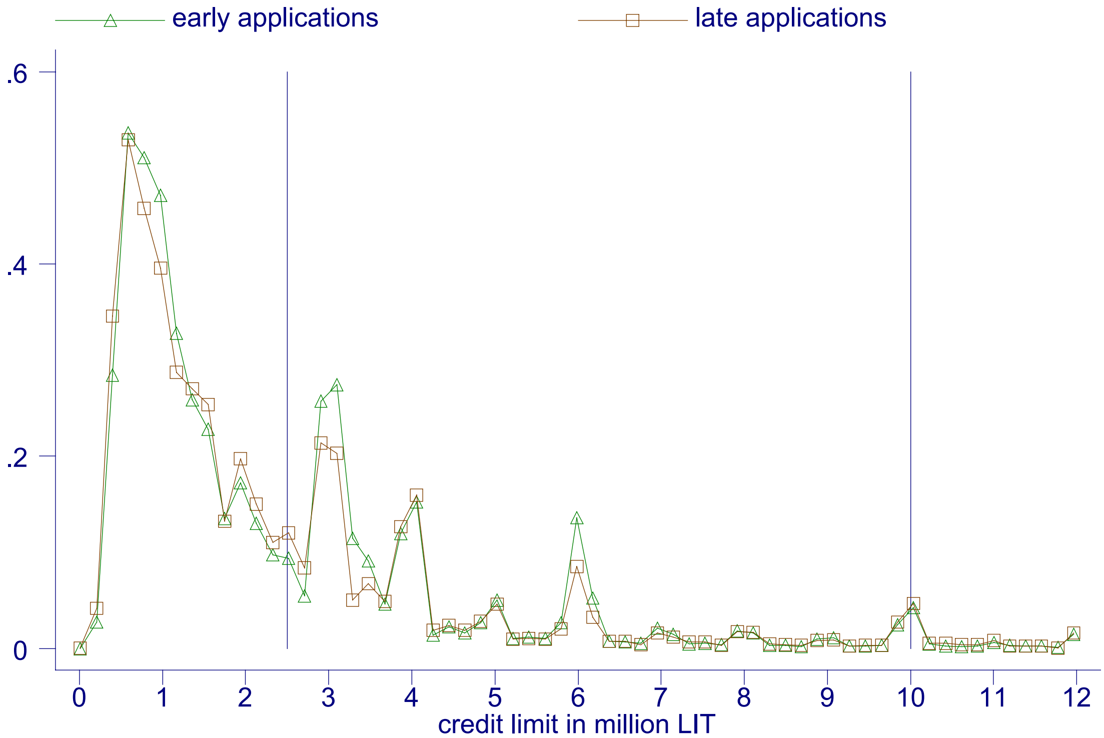

Figure 9: All Loans - density f's all appl's

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 (one-to-one substitution across loan types) the densities in Figure 9 should overlap. In fact we observe decreases in applications around the LIT 3m and LIT 6m marks. Increases of applications in excess of LIT 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 LIT 3m was more pronounced for rejections than for acceptances. A natural question worth investigating is what happened to those applicants who wanted goods worth LIT 3m. A possibility is that they were prepared to pay a larger down-payment, to keep interest charges low. We can 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 LIT 2.5m threshold.

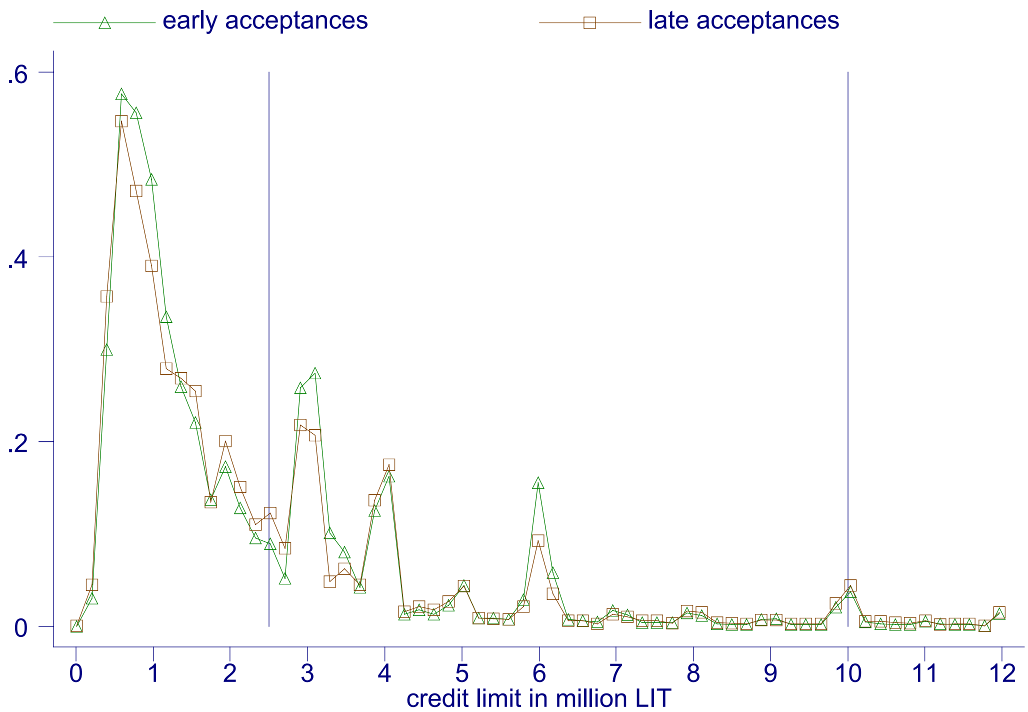

Figure 10: All Loans - density f's acceptances

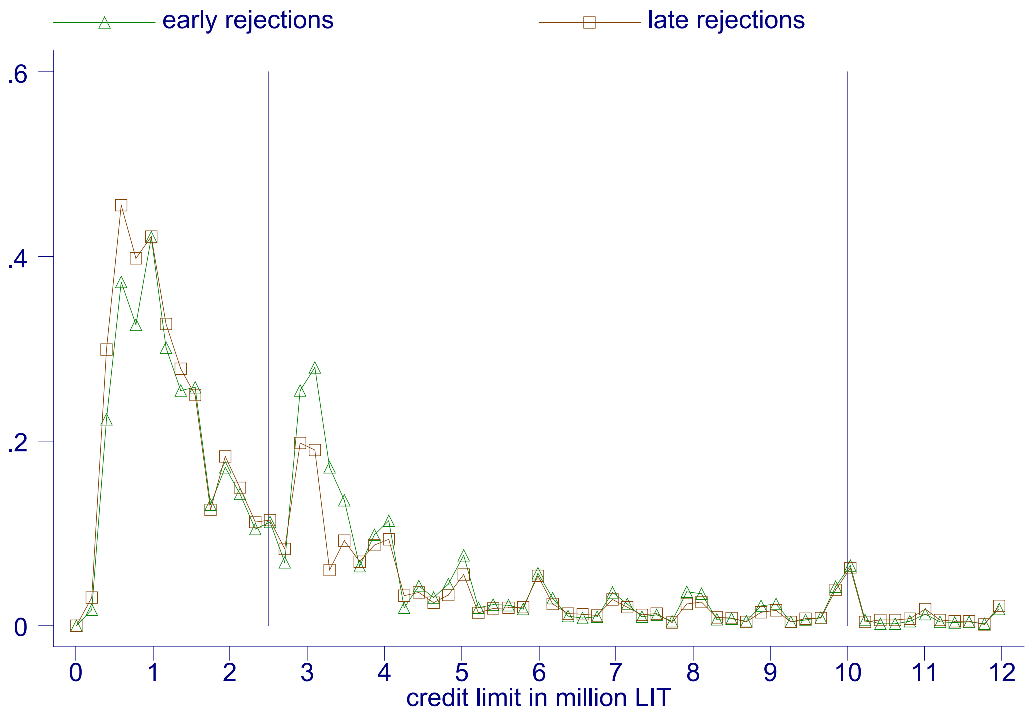

Figure 11: All Loans - density f's rejections

5. Econometric estimation

The changes discussed in the previous section are rather complex and certainly reflect the operation of a number of different factors (including changes in the Findomestic clientele, as discussed in Section 3 and Appendix C). One of these factors is the exogenous usury law shock. It is interesting to see whether the substitution across credit types induced by the law can be used to identify the price elasticity of credit demand.

In this Section we provide estimates of this important elasticity by exploiting the usury law shock as an instrument. In its simplest form, we can think of our estimation procedure as a difference in difference estimator: we take the time difference in E(*log(amount)*) across contract types, ΔE(*log(instalment)*)-ΔE(*log(other credit)*), and also compute similar statistics for interest rates (based upon internal rates of return and published statistics) to estimate the effect of the interest rate on consumer credit. Under suitable identification assumptions, the quantity:

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

can be interpreted as the effect of the interest rate on the demand for consumer credit.

Let us assume that by taking differences across loan types we are removing common macroeconomic effects, but that the usury law represents a supply shock with differential effects on the two types of loans. Let us specify an individual customer's demand for credit (either type) as follows (a customer-subscript is dropped for notational convenience):

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

where r_{it} is the interest rate paid by the customer on credit type i at time t, R_t is a competing interest rate (such as the deposit rate), m_t is a macro shock and ε_{it} has zero mean over all subgroups (i.e. over contract type i and period t). Crucially, the intercept term is allowed to depend on the credit type, i (either instalment credit or other credit), but the coefficient on m_t is not.[10]

This specification assumes that customers treat credit types as perfect substitutes, except for an intercept term that captures fixed differences in their characteristics. The key difference between revolving loans and instalment contracts is their duration: with the former, loan maturity is potentially infinite; with the latter, it is normally finite and relatively short. One of the questions we need to address is whether contracts offered by the bank changed in maturity in response to the introduction of the usury law. Since we allow for both a fixed loan-type effect and a common time effect in our regressions, we

[10] This specification rules out zero demand, but only for econometric convenience: in our data amount is always positive. A natural extension of this specification to cover zero and negative amounts is provided by the inverse hyperbolic sine function.

need to check if average maturity changed over time across loan types. Revolving credit contracts did not change over time, and therefore potential duration remained indefinite. As for instalment loans, we can test formally whether or not average or median maturity significantly changed between 1996 and 1998. For this, we regress the number of months (contract duration) of all first applications on a year dummy and indicators for the item bought. The latter is necessitated by the fact that different types of items bought go along with different lengths of financing period, and we know that the composition of goods financed has changed over time (for instance, a surge in mobile telephone purchases, see Section 4, esp. footnote 8). We find no time effect, neither for the (conditional) average maturity, nor for the (conditional) median maturity. The picture also does not change when we allow for various background characteristics and for propensity score weighting.[11]

This rather stable pattern prompts us to conclude that there is no differential time effect in loan maturity. Hence, we would not expect our estimates to suffer from a neglected maturity effect.

Let us further assume that for a financial intermediary supply is

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

where again ε_{it} has zero mean over all subgroups and an f index (denoting firms) is suppressed for convenience. In equation (2) we stress the presence of u_t, "the usury shock" that does not have zero mean and has a differential effect on supply according to the credit type. We set $u_t = 0$ before 1997, $u_t = 1$ after it. As above, m_t is a macro shock (whose coefficient we normalise to unity): by definition it captures the general effects of all aggregate shocks, including the usury law shock, in both supply and demand equations.

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

1. the interest rate coefficient α does not vary across loan types
2. the macro shock m_t affects loan types in the same way.
3. there is a differential impact of usury on supply, i.e. β depends on loan type i.

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 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 (this we shall refer to as the usury law dummy).

[11] We use the same sample as for our main estimates, below.

To better assess our estimation procedure it is useful to look at some simple diagrams of market demand and supply (see Figure 12).

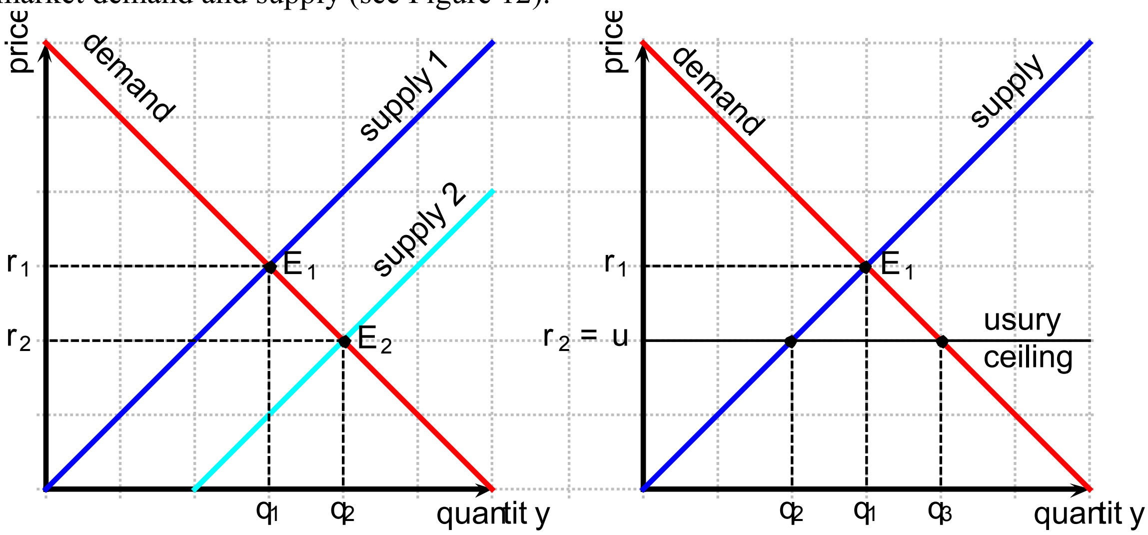

Figure 12: The operation of usury law with no market segmentation

There we show two standard pictures that can represent the effects of usury shock on the credit market. The left panel takes the view that the usury shock had no effect on demand, but shifted outwards the supply curve. The equilibrium interest rate would thus fall from r_1 to r_2, while credit would increase from q_1 to q_2. Our estimator would then capture the slope of the demand curve. The right panel represents instead the coming into force of the law as a cap to all interest rates: the equilibrium interest rate would then fall to r_2, with desired quantity rising to q_3 and actual quantity falling to q_2. The difference between q_3 and q_2 would be the demand gap generated by credit rationing. Given that we use as a dependent variable notional credit demand (amount of credit applied for) rather than actual credit granted, our estimation procedure would still retrieve the slope of the demand curve.

In fact neither simple picture in Figure 12 fully captures the substitution across credit types discussed in Section 4. A better picture in this respect is presented in Figure 13, where the supply curves of instalment and revolving credit are shown separately (left panel) and then aggregated (right panel). In the left panel, the line to the left represents revolving credit and the line to the right instalment credit. When the usury ceiling is set, we assume it only affects instalment credit (this is a fair description of the most relevant market segment, that for medium-sized contracts). For the sake of simplicity, we set the limit at 20%. The aggregate supply curve becomes a broken line at q_1, as shown in the right panel: the equilibrium quantity falls from q_2 to q_3, the interest rate rises, instalment credit becomes less important relative to revolving credit.

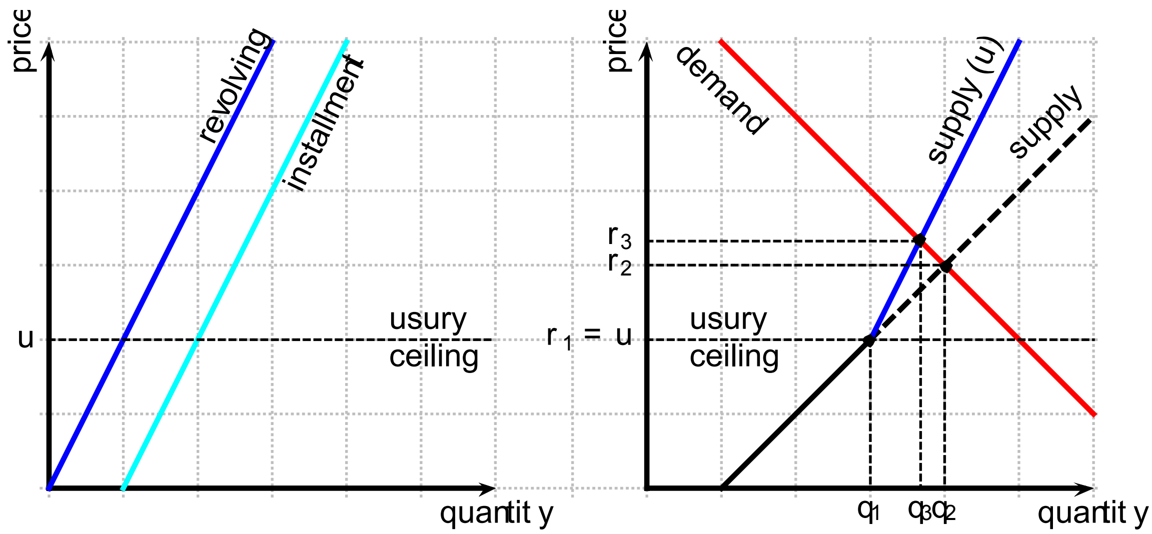

Figure 13: The operation of usury law with market segmentation

The picture in Figure 13 does not correspond directly to equation (2) above, but it is fully compatible with the difference in difference estimation method used in this Section.

The important issue remains of correcting for the non-random nature of our sample. Our (choice-based) sample is non-random in a number of ways:

a) it excludes all individuals who do not wish to borrow;
b) it excludes all would-be borrowers who do not apply to Findomestic for credit;
c) it is affected by composition changes over time.

If a) was the only problem, we could follow Heckman (1979) and specify a sample selectivity equation (to be estimated on a representative sample like SHIW). For identification, a variable must be found that affects selectivity but does not affect demand for credit and this variable should be observed in both the representative sample and the choice-based sample. None of the variables present in both SHIW and Findomestic is likely to meet this criterion. In practice, b) is likely to be as much of a problem as a), and this makes this type of selectivity corrections extremely hard.[12]

The best we can do is therefore to correct for composition effects that relate to observable characteristics, along the lines discussed in Appendix C.[13] In particular, we can focus on behavioural changes (i.e.: correct for composition effects) by p-score weighting all observations. This requires making the strong "missing at random" assumption described in Rubin (1976): conditioning upon observable characteristics, the probability of observing a certain value of the variable of interest is independent of the data source. This assumption becomes less strong the more variables one can condition upon. In this section we do not attempt to relate composition changes to changes in the population as we do in Appendix C, because this involves comparing two different data sources and

[12] Given its dominant position, Findomestic may be able to attract applications from relatively safe customers. Also, public sector employees have access to relatively cheap credit that is paid back as an additional payroll deduction (so-called "cessione del quinto dello stipendio").

[13] See also Manski and Lerman (1977).

restricts the choice of conditioning variables. We instead rely on a p-score function that estimates the probability of being in the Findomestic sample in 1998 rather than in the 1996 as a (logit) function of as many characteristics as possible. Estimation results are presented in Appendix B.

In Table 5, 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 –2.14, a perhaps surprisingly large value in absolute terms.[14] The first stage regression for the interest rate shows that the interaction term is a powerful instrument: the F-test for instrument significance strongly rejects the null of a zero coefficient of the usury law dummy in the first stage regression for r_{it}.

Table 5: 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	-8.402	-5.922	-6.675	-6.788
	(1.326)**	(1.033)**	(0.093)**	(0.057)**
Year=1998	-0.504	-0.332	-0.420	-0.378
	(0.074)**	(0.057)**	(0.018)**	(0.012)**
Instalment credit	-0.207	-0.271	-0.288	-0.237
	(0.055)**	(0.042)**	(0.017)**	(0.011)**
Constant	10.288	9.549	9.831	9.786
	(0.365)**	(0.283)**	(0.035)**	(0.021)**
Observations				
R-squared	0.35	0.34	0.37	0.35
F-test of instrument significance	187.95 F(1,30618)	93.62 F(1,30618)		
No. Observations	30622			
Median interest elasticity	-2.142	-1.510	-1.702	-1.731
Q1 – interest elasticity	-2.520	-1.777	-2.003	-2.037
Q3 – interest elasticity	-1.867	-1.316	-1.484	-1.509
Mean interest elasticity	-2.189	-1.543	-1.739	-1.769
	(0.346)	(0.269)	(0.024)	(0.015)
Hausman exogeneity test (p-value)	0.018	0.399		

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

In column 2 of Table 5 we show IV estimates that do not take into account changes in sample composition: this results in a smaller estimate of the interest rate effect (in absolute value).[15] However this is going to be consistent only under the extremely strong

[14] 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.

[15] The weighted estimates we present are in fact two-step GMM estimates for the two equation system that includes the logit and the demand function equations. This way standard errors and test statistics take into

assumption that data are missing completely at random, something that we do not wish to assume.
Columns 3 and 4 report OLS estimates of equation (1). The point estimates presented in column 3 are significantly different from those in column 1: the Hausman test reported in column 1 of Table 5 rejects the null of exogeneity. Column 4 estimates are instead fairly close to column 2 estimates (and the Hausman test fails to reject the null).

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 the usury law came into force (for instance: the evaluation of low income customers may have changed as the result of the existence of an interest rate cap). Also, as argued in Section 4, the effect of the usury shock is likely to have been stronger in the medium-credit segment of the market. Supply will also be affected by factors relating to the financial intermediary's relative position in the market, the degree of market competition and so on. If we had data for different firms, we could exploit this information to further identify demand.

We can therefore specify a more general model for demand and supply as follows:

$$\log(amount_{it}^{D}) = c_i + \alpha\,(r_{it} - R_t) + \delta m_t + \vartheta_i' z_t^D + \varepsilon_{it}^D \quad (3)$$

$$\log(amount_{it}^{S}) = c_i^s + \gamma\,(r_{it} - R_t) + m_t + \varphi' z_t^S + \beta_i (z_t^M) u_t + \varepsilon_{it}^S \quad (4)$$

where Z^D denotes a set of (customer-specific) income and demographic variables affecting demand, Z^S denotes variables affecting supply (that may include Z^D if the financial intermediary enjoys market power) and Z^M denotes variables that predict the choice of the market segment. We allow the coefficients on variables affecting demand to vary according to loan type – in principle they could also vary with time, even though we do not find these effects to be significant.
Crucially, in the supply equation we do allow for differential effects of time and type of credit for those variables that affect the choice of market segment. This implies that the cubic polynomial in *log(household income)* that appears in Z^D is allowed to have different coefficients in 1996 and 1998 in equation (4) (where it is part of Z^M). Further, its coefficients are also allowed to vary differently according to the credit type ("instalment" versus "other").

In Table 6 we show estimates for specifications that allow for the role of income and all the observable characteristics listed in Appendix B in Z^D. Compared to Table B, we restrict household income and age effects to cubic polynomial functions (i.e. we drop the age and income dummies that were not significant in the demand equations). This helps give an economic interpretation to parameter estimates. However, here we also allow for differential effects of income according to the type of credit.

account the estimation error of the p-score weights. For further details see Crépon, Kramarz and Trognon (1998) and Abowd, Crépon and Kramarz (2001).

In the first column we report p-score weighted IV 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 (polynomials in log(household income) and age, marital status, residential status, region, number of dependent children, partner's income and age), we get a smaller median estimate of the elasticity (-1.116). This is also smaller than the corresponding OLS estimate (median elasticity: -1.589) reported in column 4 (as already noticed while discussing Table 5, p-score weighting has little effect on OLS estimates), even though the Hausman test fails to reject the null at the 5% level (it rejects at the 10% level, though). Of some interest is the pattern of coefficients of the *log(income)* polynomial that is quite different for instalment and other credit contracts.

If we believe the usury dummy enters the supply equation not only as an intercept shift, but also interacted with customer characteristics (i.e. that β_i is a non-trivial function of Z^M), we can add instruments to the list and gain over-identifying restrictions. In particular, we add to the list the interaction between the type of credit dummy, the usury dummy and the log(income) polynomial 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 Appendix A), particularly in the medium-credit segment of the market.

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, the set of instruments is jointly highly significant for the endogenous variable, $r_{it.}$ The Sargan-Hansen test for instrument validity (i.e. for the validity of the overidentifying restrictions) fails to reject the null at the 1% significance level in column 2, but decisively rejects in column 3.

Given that the column (2) specification exploits more information than column (1) and is not rejected on statistical grounds, we can take its implied median elasticity of –1.2 as our favourite estimate. However, we should keep in mind that there is variability in elasticity estimates across sample observations (the first quartile is –1.413, the third is –1.047) and that the estimation error also affects the precision of the elasticity at the sample mean (that coincides here with the mean elasticity).[16]

[16] One of the drawbacks of instrumental variables estimation is the loss of precision, as revealed in Table 6. The standard error in column (2) is 0.240, in column (4) is 0.023. Thus the OLS elasticity estimate is ten times more precise than the IV estimate.

Table 6: The demand for consumer credit (with background characteristics)

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log(amount)	IV p-score w. Just identified	IV p-score weighted	IV unweighted	OLS p-score weighted	OLS unweighted
Interest rate	-4.575	-5.161	-6.716	-6.232	-6.389
	(1.122)**	(0.920)**	(0.952)**	(0.088)**	(0.057)**
Year=1998	-0.287	-0.318	-0.383	-0.373	-0.366
	(0.061)**	(0.049)**	(0.051)**	(0.014)**	(0.012)**
Instalment credit	0.633	0.433	0.334	0.492	0.357
	(0.216)**	(0.195)*	(0.192)	(0.129)*	(0.180)*
log(y)	-0.616	-0.749	-0.737	-0.636	-0.735
	(0.172)**	(0.142)**	(0.129)**	(0.169)**	(0.128)**
$\log(y)^2$	0.134	0.159	0.157	0.136	0.157
	(0.035)**	(0.028)**	(0.026)**	(0.034)**	(0.026)**
$\log(y)^3$	-0.007	-0.009	-0.008	-0.007	-0.008
	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Instalment credit *log(y)	0.415	0.628	0.621	0.480	0.618
	(0.240)	(0.203)**	(0.154)**	(0.220)*	(0.154)**
Instalment credit $*\log(y)^2$	-0.161	-0.203	-0.192	-0.164	-0.194
	(0.054)**	(0.046)**	(0.034)**	(0.050)**	(0.034)**
Instalment credit $*\log(y)^3$	0.012	0.014	0.013	0.011	0.013
	(0.003)**	(0.003)**	(0.002)**	(0.003)**	(0.002)**
Constant	9.367	9.696	10.298	9.864	10.201
	(0.390)**	(0.338)**	(0.338)**	(0.202)**	(0.186)**
Observations			**30622**		
R-squared	0.39	0.41	0.39	0.41	0.39
F-test of instruments' significance	139.78 F(1,30565)	21.22 F(7,30559)	15.92 F(7,30559)	-	-
Median interest elasticity	-1.166	-1.201	-1.713	-1.589	-1.629
Q1	-1.372	-1.413	-2.015	-1.870	-1.917
Q3	-1.017	-1.047	-1.493	-1.385	-1.420
Mean interest elasticity	-1.192	-1.227	-1.750	-1.624	-1.665
	(0.292)	(0.240)	(0.248)	(0.023)	(0.015)
Over-identifying restrictions test		$\chi^2(6)=13.44$ (0.037)	$\chi^2(6)=18.62$ (0.005)		
Hausman test on exogeneity (p-value)	0.052	0.065	0.730		

Standard errors in parentheses; * significant at 5%; ** significant at 1%. In this specification we further control for residential status, marital status, region, number of children, applicant's age, and partner's income and age.

Our evidence is in line with that recently reported in Gross and Souleles (2002) for the US (they find a –1.3 elasticity) and is similarly at variance with the 'underestimation hypothesis' in Ausubel (1991). Gross and Souleles also show that credit demand is less elastic (around -.8) at the industry-wide level (net elasticity) than at the firm level (gross elasticity), presumably because the consumer treats different credit cards as close substitutes.

In our case, we do not have industry-wide demand data, but can exploit the knowledge that Findomestic faces more competition in the North compared to the Centre and South. In particular, in Central and Southern regions Findomestic has exclusive deals with retailers for many goods. Consequently, we may be able to interpret our estimates for these regions as relating to the market demand function.

In Table 7 we show estimates of demand elasticities when we allow α to be region-specific. Parameter estimates and test statistics are not reported to save space, but are available upon request.

The upper portion of Table 7 relates directly to Table 5: the interest rate variable and the instalment dummy are interacted with Central and Southern region dummies, and the usury law dummy is also interacted with these regional indicators to generate the necessary instruments. These interaction terms turn out to be quite significant. The overall median elasticity estimates are broadly in line with those reported in Table 5 except for column 1: the overall median elasticity in column (1) is –1.591 as opposed to –2.142. Of great interest to us is its regional variability: the elasticity is higher in the North (–1.985) than in the South (–1.591) and Centre (–1.288). A formal Hausman test strongly rejects the null of parameter equality across columns (1) and (3).

The lower portion of Table 7 presents estimates for a model comparable to the specification in Table 6. The set of conditioning variables now covers the following interactions: the interest rate variable and the credit type indicator are interacted with Central and Southern region dummies, as before, and the interaction between the usury law dummy and the broad regional indicators as extra instruments. The over-identifying restrictions test in column (2) fails to reject the null at the 1% significance level, while Hausman tests strongly reject for both columns (1) and (2) (the corresponding OLS estimates are in Column (4)). Column (3) over-identifying restrictions are instead strongly rejected.

Both just-identified and over-identified models imply an overall median elasticity just below unity (this contrasts sharply with OLS estimates that produce elasticities around –1.6). In all cases, we find that demand is much more elastic in the North than in Central and Southern Italy. Column (2) elasticity estimates for the last two regions hover around –.8, in agreement with Gross and Souleles estimated market elasticity.[17]

[17] To the extent that binding liquidity constraints are more wide spread in the South and Centre than in the North, our finding is also consistent with Attanasio, Goldberg and Kyriazidou (2000). They present evidence that liquidity constraints decrease the interest rate elasticity of credit demand (car loans in their case).

A demand elasticity in the lower part of the estimated (–.8/–1.5) range may be compatible with the notion that customers mostly care about keeping monthly repayments in a fixed relation to their income, given loan duration. However, its micro and macro economic implications are wide-ranging and potentially important.

Table 7: Region-specific price elasticities

A. Models without background characteristics

	IV p-score weighted		IV unweighted		OLS p-score weighted		OLS unweighted	
	Median	Mean	Median	Mean	Median	Mean	Median	Mean
Total	-1.591	-1.668	-1.511	-1.564	-1.714	-1.734	-1.719	-1.766
North	-1.985	-2.034	-1.930	-1.977	-1.667	-1.708	-1.652	-1.692
Central	-1.288	-1.297	-1.077	-1.085	-1.663	-1.676	-1.708	-1.721
South	-1.591	-1.599	-1.511	-1.519	-1.777	-1.785	-1.836	-1.845

B. Models with background characteristics

	IV p-score w. just identified		IV p-score weighted		IV unweighted		OLS p-score weighted		OLS unweighted	
	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
Total	-0.999	-1.125	-0.943	-1.094	-1.641	-1.740	-1.609	-1.620	-1.625	-1.662
North	-1.588	-1.627	-1.520	-1.557	-2.163	-2.216	-1.554	-1.592	-1.561	-1.600
Central	-0.663	-0.668	-0.728	-0.734	-1.251	-1.261	-1.562	-1.574	-1.612	-1.624
South	-0.999	-1.004	-0.943	-0.948	-1.641	-1.649	-1.657	-1.665	-1.719	-1.727

6. 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 rapidly 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 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 shown how 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, that is, if the usury law had a differential impact on the supply of various types of credit, whereas it had a uniform impact on demand (if any), we can identify and 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. We also find that demand elasticity is higher in the North where there is more competition in the consumer credit market.

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.

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APPENDIX A – Analysis of Missing Income Applications

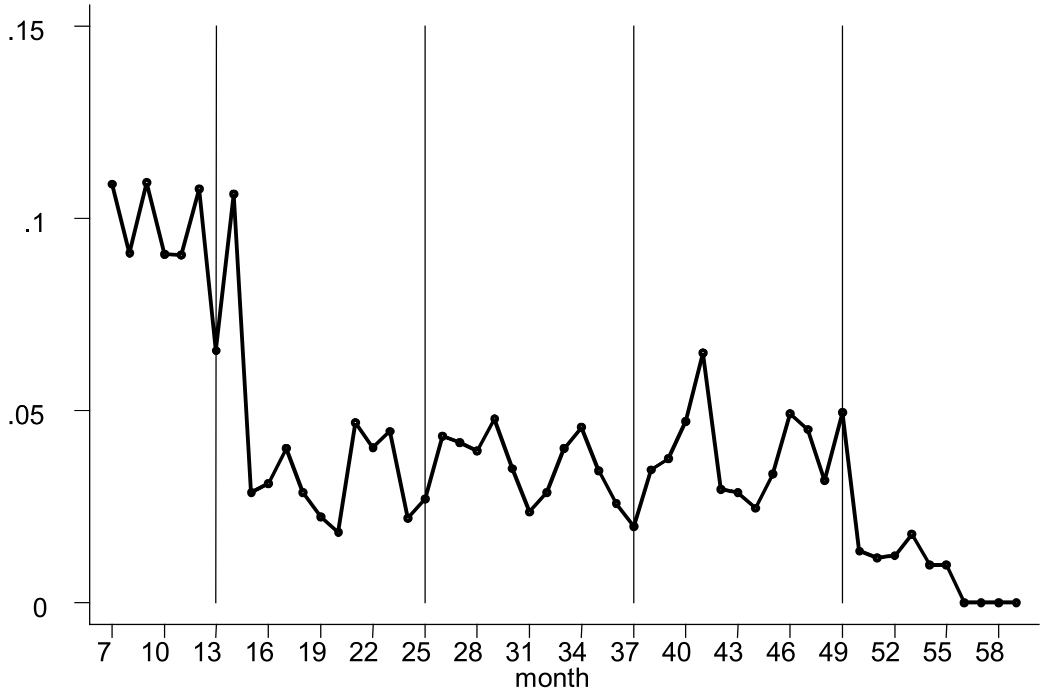

Figure A1: missing income cases, first apps

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		

APPENDIX B - Probability of being in Findomestic sample in 1998 versus 1996

Here we present the estimates used to construct the p-score weight used in Section 5. The dependent variable is a binary indicator taking value 1 if the observation belongs to the 1998 Findomestic sample, 0 if it belongs to the 1996 Findomestic sample.

Table B1: Estimates of the Logit model

	Coef.	Std. Err.	t-value
Household income (reference: income<=1000)			
1000<Y<=1300	0.2619	0.0792	3.31
1300<Y<=1500	0.3067	0.0869	3.53
1500<Y<=1621	0.8113	0.1017	7.98
1621<Y<=1800	0.5167	0.1031	5.01
1800<Y<=2000	0.7800	0.1103	7.07
2000<Y<=2281	1.3307	0.1245	10.68
2281<Y<=2800	1.1194	0.1327	8.43
2800<Y<=3620	1.4603	0.1537	9.5
Y>3620	1.9368	0.1909	10.14
Log(Y) = log(household income)	-0.3755	0.2810	-1.34
$Log^2(Y)$	0.1491	0.0663	2.25
$Log^3(Y)$	-0.0176	0.0041	-4.36
Income partner			
No partner	3.3639	0.6542	5.14
Incs = income of partner	0.0797	0.0143	5.59
$Incs^2$	-0.0007	0.0004	-1.58
$Incs^3$	0.0000	0.0000	0.52
Income partner missing	0.4442	0.0908	4.89
Residential status (reference: owner)			
Tenant	-0.1063	0.0805	-1.32
Living with parents	-0.1202	0.0375	-3.21
Other	0.0162	0.0497	0.33
Age (reference: age<=25)			
Age 26-30	-0.2052	0.0823	-2.49
Age 31-35	-0.4395	0.1229	-3.58
Age 36-40	-0.4923	0.1670	-2.95
Age 41-45	-0.6259	0.2178	-2.87
Age 46-50	-0.7125	0.2761	-2.58
Age 51-55	-0.5268	0.3330	-1.58
Age 56-60	-0.3938	0.3933	-1
Age 61-65	-0.2094	0.4458	-0.47
Age >65	0.0625	0.5039	0.12
Age	0.1842	0.1347	1.37
Age^2	-0.1567	0.0324	-4.83
Age^3	0.0347	0.0113	3.07
Ap = age of partner	0.1241	0.0369	3.36
Ap^2	-0.0905	0.0198	-4.56
Ap^3	0.0230	0.0077	3
Marital status (reference: single)			

Married	-0.1980	0.0629	-3.15
Divorced	-0.2352	0.0802	-2.93
Widow	-0.2822	0.0968	-2.92
Region (reference: Piemonte, Valle d'Aosta, Liguria)			
Lombardia	0.2884	0.0647	4.45
Trentino, Veneto, Friuli	0.3384	0.0793	4.27
Emilia Romagna	0.2178	0.0839	2.6
Toscana	-0.0369	0.0726	-0.51
Umbria, Marche	0.0403	0.0973	0.41
Lazio	-0.0822	0.0622	-1.32
Abruzzo, Molise	-0.0930	0.0995	-0.93
Campania	-0.1406	0.0633	-2.22
Puglia, Basilicata	0.1050	0.0713	1.47
Calabria	0.1253	0.0880	1.42
Sicilia	-0.0131	0.0648	-0.2
Sardegna	-0.1509	0.0813	-1.85
Number of children (reference: 0)			
= 1	0.0158	0.0454	0.35
= 2	-0.1377	0.0467	-2.95
>=3	-0.1675	0.0638	-2.62
Profession (reference: other			
Small farmer	-0.4326	0.3435	-1.26
Tradesman	-0.1875	0.2492	-0.75
Shop assistant	-0.5015	0.2576	-1.95
Craftsman, various professions	-0.4981	0.2480	-2.01
Permanent professional	-0.1955	0.2770	-0.71
Manager (private)	0.1652	0.4129	0.4
Executive	-0.2525	0.3349	-0.75
Public sector manager	-0.1691	0.3687	-0.46
Civil servant , teacher	-0.7260	0.2575	-2.82
Private sector blue collar worker	-0.2498	0.2440	-1.02
White collar worker	-0.3448	0.2460	-1.4
Public sector employee, army	-0.5759	0.2464	-2.34
Worker in a state agency	-0.7415	0.2563	-2.89
Retired	-0.7801	0.2502	-3.12
Housewife, student, soldier	-0.4559	0.2838	-1.61
Constant term	0.8100	0.0690	0.7323
Observations	30622		
Pseudo R^2	0.0344		
Log likelihood	-15391.7		
χ^2-test	1095.15		
Degrees of freedom	68		

APPENDIX C: Composition Effects and Counterfactual Densities

We can summarise our findings presented in Section 4 as follows: when usury law came into force, instalment credit contracts just above the LIT 2.5m mark became less common. Fewer individuals applied for instalment credit in the LIT 2.5-3.5m range: those who got credit for such amounts also paid higher interest (relative to instalment credit contract in the LIT 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 LIT 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 C1 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 LIT 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 LIT 2.84m to LIT 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 LIT 3.5m).

Splits by residential status and marital status are shown next. It is interesting to notice that 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.

Table C1 – All loan applications – amounts (expressed in million lira)

	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	0.64	0.21	0.14	0.23	0.21
South	3.09	3.21	3.69	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	0.56	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	0.61	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**
Y<=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<Y<=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<Y<=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<Y<=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<Y<=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<Y<=2000	2.81	2.97	5.76	1.80	1.53	-15.00	0.60	0.65	0.18	0.13	0.22	0.21
2000<Y<=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<Y<=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<Y<=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
Y>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 C1:

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

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 1996 amounts due to sampling differences in 1995-6.

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 1996 Findomestic sample. For this reason we can think of it as capturing changes in behaviour (and in selectivity). 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).[18]

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:

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

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.[19]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 C2 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, F98 *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 C2a) we report actual and counterfactual statistics in levels. We see from the first two columns that for all loans the actual average rose from LIT 2.96m in 1996 to LIT 3.10m in 1998, and the proportion of loans under LIT 2.5m rose from 57.34% to 64.69%.[20] The next three columns show the counterfactuals described above. The bottom half of the Table (denoted C2b) reports the corresponding changes. Thus the average increase in loan size was LIT .13m, but it would have been LIT .37m had sampling and population changes not taken place. If we look at the average

[18] 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.
[19] This quantity relates to the propensity score of Rosenbaum and Rubin (1983).
[20] These numbers may differ slightly from those in Table C1, because we dropped missing income observations to estimate the probit models.

of *log(amount)* we observe a 7% decline in the data – that corresponds to a 2% behavioural increase.

Of particular interest to us is the proportion of small, medium and large loans. We learn from the first portion of Table C2b that small applications increased by 7%, and medium applications fell by the same amount, leaving large applications unchanged. This is the result of composition changes as well as behavioural responses. Had the Findomestic sample evolved the same way as the population, the rise in small amount applications would have been 3.6%, the fall in medium applications would have been 5.9% and there would have been a 2.3% increase in large applications. The lower segment of Table C2b computes similar statistics for instalment credit contracts. In this case there is an even sharper drop in medium-sized applications (-8.2%), half of which was behavioural (-4.2%).

Table C2a: Multivariate Decompositions – Levels

	τ(y96;F96)	τ(y98;F98)	τ(y98;S98)	τ(y98;S95)	τ(y96;S95)
ALL LOANS					
τ= E(y)	2.9646	3.0984	3.5036	3.4107	3.0380
τ= E(log(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(log(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(log(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 C2b: Multivariate Decompositions –Differences					
	τ(y98;F98)-τ(y96;F96)	**τ(y98;F98)-τ(y98;S98)**	**τ(y98;S98)-τ(y98;S95)**	**τ(y98;S95)-τ(y96;S95)**	**τ(y96;S95)-τ(y96;F96)**
ALL LOANS					
τ= E(y)	0.1338	-0.4052	0.0929	0.3727	0.0734
τ= E(log(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(log(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(log(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|F96)* as the benchmark instead, but results were not much affected.[21]

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

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