

Household investment behaviour: empirical investigations of durable consumption, returns to human capital, and borrowing restrictions.

Mario Padula

University College London

PhD in Economics

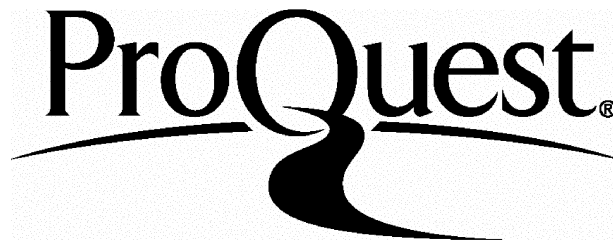
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Abstract

The thesis focuses on durable consumption, educational choices and borrowing restrictions and is made of four chapters.

The first chapter estimates the Euler equation when the utility of durable and non-durable consumption is non-separable. It uses microdata on non-durable and durable consumption from a US rotating panel, the Consumer Expenditure Survey (CEX). We concentrate on cars (new and used) and find an estimate of the intertemporal rate of substitution higher than in the case where durable goods are not conditioned on.

The second chapter constructs a household level measure of the stock of cars using an American data-set, the Consumer Expenditure Survey (CEX), documents some stylized facts and estimate a model of infrequent adjustment.

A definition of return to human capital that accounts for uncertainty is the object of the third chapter. Jobs differ also for the uncertainty of their associated earnings. If markets are incomplete, risk-averse individuals value less risky jobs. Using data from the Italian the Survey of Household Income and Wealth (SHIW), and the American Panel Study of Income Dynamics (PSID), we find an extra-return due to uncertainty, which is higher in Italy than in the US.

The fourth chapter focuses on the interaction between the quality of judicial enforcement and borrowing restrictions at the households level. Using Italian data drawn from the Survey of Household Income and Wealth (SHIW), we test if the probability of being liquidity constrained and the amount of household debt are affected by the quality of judicial enforcement. The lower it is, the higher the probability of being liquidity constrained, the lower the amount of debt.

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Introduction

This work studies household level investment problems and is made of four chapters. The first two chapters deal with consumer durables, the third with the interplay between educational choices and uncertainty, the fourth studies how the quality of judicial enforcement affects borrowing restrictions. The four chapters are tied together by a truly micro-economic approach. To empirically investigate households level problems, we used throughout micro-data.

The first chapter estimates an Euler equation and accounts for durable consumption. If durables are not separable in utility from non-durables, estimating the Euler equation without conditioning on them leads to incorrect inference. We use microdata on non-durable and durable consumption from a US rotating panel, the Consumer Expenditure Survey (CEX), and concentrate on cars (new and used). Apart from housing, they represent the largest share of durable expenditure in the sample. We find an estimate of the intertemporal rate of substitution higher than in the case where durable goods are not conditioned on, while the evidence of excess sensitivity is more mixed. This chapter contributes to the existing literature by highlighting the effect of intratemporal non-separabilities on households choices and on the empirical performance of a now standard model. We estimate a conditional model in that we take as given the choice of how much durable households want to consume. Future work plan to estimate an unconditional model.

The second chapter constructs a household level measure of the stock of cars using an American data-set, the Consumer Expenditure Survey (CEX). It devises a flexible and feasible methodology that could be implemented with reasonably rich source of information and extended to other durable goods. The availability of such measure is of crucial importance when the choice of durable goods is studied. This is because the standard assumption in the literature is that the flow of services that households enjoy from a

durable good is proportional to its stock. This is true whatever is the model for durable consumption, i.e. whether the adjustment cost is convex or non-convex. Moreover, the chapter documents some stylized facts and estimates a (s,S) rule. To the best of my knowledge, these facts are not documented elsewhere and require further investigation. Finally, this new data are used for estimating a model of intermittent adjustment. This is not novel and gives results roughly comparable to those available in the literature.

The third chapter measures the return to education by accounting for differences in wage and unemployment risk confronted by individuals with different levels of education. The risk component of educational choices is often underrated. Namely, the return to education is estimated neglecting uncertainty that is likely to play a role in most individuals life. Uncertainty comes into the picture because different jobs expose to different probability of unemployment and to different degree of wage risk; and because markets are incomplete and individuals risk-averse. We, thus, argue that a measure of return to education based only on the expected post-schooling wages can be misleading. We estimate the implicit return to schooling under four different scenarios: no uncertainty, unemployment risk, wage risk, and both wage and unemployment risk. This is so because individuals possibly face two sources of risk: unemployment and wage risk. The empirical analysis uses US and Italian microeconomic data. The US data come from the Panel Study of Income Dynamics (PSID), the Italian data from the Survey of Households Income and Wealth (SHIW). We, thus, focus on two countries that greatly differ for labor market institution, in view of the role that institutions have in shaping the uncertainty faced by individuals. The main finding is that the return of schooling is downward biased if no account is made for risk. We find that the return to education that compensates for unemployment risk is higher to that for wage risk and that the extra-return is higher in Italy than in the US.

The fourth chapter investigates the effect of judicial costs on households debt, merging data drawn from a representative Italian sample, the Survey of Household Income and Wealth (SHIW), with data on the performance of judicial districts. We concentrate on collateralized or secured debt. This chapter falls in the literature that looks at how institutional factors affects outcomes in the financial markets. We use an Italian data set for two reasons. First, Italy represents an almost natural experiment: the performance of legal districts greatly differs across region, while the law is the same. Second, we can distinguish liquidity from not liquidity constrained households

in the sample using a simple indicator variable.¹ This allows us to circumvent the problem of identifying the two group of individuals using in-sample information and identification restrictions hard to defend. We estimate a probit model to test the hypothesis that the working of courts affects the probability that households are credit constrained. Moreover, we estimate a tobit model for the amount of debt to investigate if borrowing by those who are not rationed in the credit market is also sensitive to judicial costs. We find that the working of the judicial system impacts on probability of being credit constrained: the lower the quality of judicial enforcement, the higher the probability of being liquidity constrained. We also show that the amount of debt held by non-constrained households decreases when the quality of the judicial enforcement worsen. We provide a light theoretical framework for interpreting these two findings, the bottom line being that the lower the performance of judicial districts, the lower the shadow value of the collateral for the lender, i.e. the bank.

¹This is possible because individuals are asked if they have been turned down from credit.

Chapter 1

Euler equations and durable goods

1.1 Introduction

A number of explanations have been suggested for the empirical failure of the life-cycle/permanent income hypothesis (LC/PI) through the testing of the Euler equation for non-durable consumption (for a recent survey see Browning and Lusardi [17]).

This work suggests that omitting durable goods from the set of ‘regressors’ in the Euler equation leads to biased estimates of the parameters of interest. Thus, this work belongs to the set of contributions that consider the misspecification of preferences as a possible source of bias in the estimate of the Euler equation.

Since the work of Mankiw [47], the literature has tried to assess the ability of the LC/PI model to generate the observed patterns of durable goods expenditure. Despite the wide interest that durability has encountered among researchers, very little attention has been paid to investigate the role of durability for the dynamic properties of the non-durable consumption in *itself*. One noticeable exception is the article by Bernanke [12], who models the *joint* behavior of non-durable and durable expenditures using U.S. aggregate data and finds the non-separability between durable and non-durable goods to be unimportant.

There are several grounds on which the omission of the durable goods might endanger the empirical evaluation of the LC/PI model. First of all, if

the durable goods are non-separable in utility from the non-durable goods, not conditioning on them would lead to biased inference. They bring an element of intertemporal non-separability into the individual problem. The presence of intertemporal non-separabilities makes the inference on the model much harder. This is so because individuals try to smooth a *weighted average* of past and present consumption. An increase of consumption today depresses the marginal utility of consumption tomorrow, which makes the change in consumption to display a negative serial correlation. If the changes in income are negatively correlate (for instance, if they follow an MA(1) with negative coefficient) credit constraints are observational equivalent to durability.

Moreover, while non-durable consumption is equivalent to the flow of services individuals enjoy, this is not the case for durable goods. This distinction is not vacuous since the theory delivers predictions in terms of what individuals enjoy. This means that individuals can still smooth over the flow of services from a durable good when they are liquidity constrained (see Browning and Crossley [16]). For instance, if they receive a negative shocks they may delay the date at which the old durable good is replaced.

Last, since stock of durable goods, such as cars, exhibit an hump-shaped life-cycle profile, they can account for the concavity of the non-durable life-cycle profile observed in the micro data. They can play a role complementary or substitute to that of the demographics.

The main goal of this work is to see if the available results on the estimation of Euler equation for *non-durable consumption* are robust to the omission of the durable goods. The key parameters are those governing the intertemporal substitution of non-durable consumption, the non-separability of non-durable versus durable goods and the excess sensitivity parameter. We perform a conditional exercise that is robust to the determinants of the intratemporal choice over non-durable and durable goods. In other words, the validity of the results does not depend on the particular nature of the cost of adjusting the stock of durable goods. The omitted variable argument introduced above is effectively independent of whether or not the feasibility set the individuals face is convex.

Mainly due to a problem of data availability, the main difficulty being how to measure the stock of durable goods, there are not many studies using durable goods in an Euler equation framework.¹ A subset of them tackles the

¹See, for example, Alessie et al. [1], Bernanke [11], [12] and Hayashi [35], Lam [44].

issue of the estimation using microdata. The aggregation issues relevant to non-durable consumption, that the presence of non-convex adjustment cost can exacerbate even further, recommends to use a sample of microdata. The data are from a representative American survey, the Consume Expenditure Survey.

This work focuses on cars. They represent the most important component of the durable expenditure in the US data, apart from housing.

The chapter is organized as follows. In Section 2 an estimable model is derived and identification is discussed. Section 3 describes the data and the procedure used to compute the value of the stock of cars, while Section 4 discusses the estimation and the results. The last section concludes.

1.2 What can be and what cannot be identified from the Euler equation

The question we want to address here is whether the omission of durable goods from the Euler equation for non-durable consumption matters. To do this, we estimate an Euler equation that includes the change of the stock of durable goods. This section derives the first-order condition to be exploited in the estimation and discusses what parameters can be recovered from the estimation of such equation.

The model used here has a conditional nature. In fact, it neglects the mechanism governing the intratemporal allocation between durable and non-durable goods. This is justified by making an argument similar to that used by Browning and Meghir [18] to address the non-separability of consumption from labor choices.

In principle both the neoclassical and a non-convex adjustment cost model could be integrated in this approach using a flexible enough stochastic specification. In exposing the model, we assume that the household's feasibility set is convex. Simple algebra shows that the Euler equation holds in the same form when non-convexities are present.

In deriving the Euler equation we follow the non-conventional approach taken by Attanasio and Browning [7]. Instead of specifying an utility function, they model the log of the indirect marginal utility of the consumer's expenditure. The main advantage of following this approach in the present context is to avoid the need of imposing any restriction on the parameters

to guarantee that the marginal utility has the usual properties.

First, we specify the within period indirect utility which take the following form:

$$V(p, x, z) = v\left(\frac{x}{\alpha(p, z)}, z\right) + \psi(p, z) \quad (1.1)$$

where p is the price vector, x is the total outlay, $\alpha(p, z)$ is a price index that depends of a set of conditioning variable z . This work comes to the role of durable goods including the stock of vehicles in the set of the conditioning variables. Finally, ψ is homogeneous of degree zero in p .

Next, we turn to the identification of the intertemporal rate of substitution. As shown by Browning [15] in a multi-goods model, the intertemporal elasticity of substitution is defined as

$$\eta(p, z, x) = \frac{V_x}{xV_{xx}} = \frac{v_c}{cv_{cc}} \quad (1.2)$$

where $c = \frac{x}{\alpha(p, z)}$. The Euler equation for household h is:

$$E_t[\rho\lambda_{ht+1}(1 + R_{t+1})] = \lambda_{ht} \quad (1.3)$$

where λ_{ht} is the marginal utility of wealth, ρ is the discount rate and R_{t+1} is the nominal interest rate. It holds in the usual form, independently of the intratemporal allocation condition. This is so because the Euler equation is a condition that relates to the ability of the consumer to smooth utility and, ultimately, wealth over time and states of nature. A more general problem is which aspects of preferences and, in the present notation, which aspects of the function $V(\cdot)$ can be recovered and which cannot from the estimation of the Euler equation. In particular, Euler equations allow to identify a subset of the preference parameters set. To identify the full set of parameters, one needs also the within-period marginal rate of substitution. Thus, in this exercise the stock of durable goods is treated as a conditioning good. This makes the estimates presented here to possess a partial information nature.

To estimate equation (1.3) one needs to observe λ_{ht} . To make λ_{ht} observable we differentiate the Lagrangean associated with the consumer's problem with respect to c , thus obtaining the envelope condition that allows us to rewrite (1.3) as:

$$v_{c_{ht+1}}(1 + R_{t+1})\frac{\alpha(p_t, z_t)}{\alpha(p_{ht+1}, z_{ht+1})}\rho = v_{c_{ht}}\varepsilon_{ht+1} \quad (1.4)$$

where $E_t[\varepsilon_{ht+1}] = 1$. Now, we assume that:

$$\ln v_{c_t}(c_{ht}, z_{ht}) = \frac{1}{\sigma} (-\ln c_{ht} + \beta q_{ht} + \gamma k_{ht}) \quad (1.5)$$

where the vector of shifters z is partitioned in two parts: a vector of pure taste shifters and k , which is the stock of vehicles. The choice of this specification deserves some comments. First, this specification makes the model linear in the parameters of interest after log-linearizing. Second, this preference specification consistently aggregates over consumers. Attanasio and Weber [2] show that the bias arising from inconsistent aggregation can be dramatic. Third, the methodology used to construct the stock of vehicles requires it to enter linearly the estimating equation. This is so because the stock of vehicles is computed at cohort level as an average. Fourth, with this specification the marginal utility of not owning cars is finite.²

According to (1.5), taste shifters act as state variable in the households' problem. These variables shift the utility the households enjoy from a given consumption bundle. Consequently, they are treated as conditioning variable in the estimation. Notice that the possible endogeneity of fertility and labor supply decisions is not theoretically addressed. However, appropriate instrumenting 'solve' the question from an empirical point of view. Using the above specification, the envelope condition and after log-linearizing, (1.3) can be written as:

$$E_t(\Delta \ln c_{ht+1} - const - \beta' \Delta q_{ht+1} - \sigma R_{t+1} - \gamma' \Delta k_{ht+1}) = 0 \quad (1.6)$$

where the constant term depends on the moments of order higher than one of the distribution of the growth rate of non-durable consumption conditional on the interest rate and absorbs the discount rate, while the expected value is taken with respect to the information available at time t . Thus, we omit from the estimating equation the variance of the growth rate of the consumption. We are very well aware of the fact that the omission of this term can generate an omitted variable bias akin to that considered here and believe that the precautionary motive for saving could be a potential important explanation of the observed pattern of non-durable consumption (see Carroll [22]). However, we would argue that whether or not this omission is 'relevant' is an empirical question which that be handled testing the specification of the model. The

²The log of the marginal utility of non-durable consumption is a linear function of the stock of durable goods.

only condition needed to estimate consistently the Euler equation is that the chosen instruments are orthogonal to expectation error. Equation (1.6) provides the orthogonality condition used in the estimation.

From the model above, it is apparent that the household is assumed to enjoy the consumption of a homogeneous non-durable good. This is far from being correct if some goods entering the definition of the aggregate are luxuries and some other necessities because luxuries and necessities display different elasticities to permanent income. However, we have chosen not to address the issues directly related to the bias coming from aggregation over non-durable goods. This choice can be justified, at least in part, on the ground of the results in Attanasio and Weber [3]. They estimate two sets of equations: one which uses the parameter estimated in a previous stage from a full demand system, the other where a Stone Price index is used. They do not find evidence that the coefficient of the interest rate coefficient is biased if a Stone Price index is used instead of estimating a full demand system.

It is worth noting that the model turns out to be a two goods model: non-durable vs. durable goods (cars). The two step budgeting idea proposed by Browning [19] operates: in a first step consumers decide how much resources to devote to the consumption ‘today’ and ‘tomorrow’, in a second step they decide how they allocate their consumption within each period.

The exercise performed here can be regarded as concentrating on the first step only. The question of what is lost when doing this is empirical.³ Given that only the intertemporal allocation condition for non-durable consumption is used in estimation, the present approach can be viewed as a partial information approach. Efficiency could be enhanced using both the intratemporal and intertemporal conditions,⁴ consistency is not in general an issue.⁵

³In general, from a demand system with non-durable goods the full system of preferences can be identified up to a monotonic transformation, which is identified by the intertemporal condition.

⁴Conditioning on the relative prices to control for the intratemporal piece of information does not seem viable as long as households with no cars are observed.

Alternatively, we could split the sample by car ownership and then allow for a correction mechanism.

⁵The argument does not go through smoothly when households are liquidity constrained and durable goods can be used as a collateral. In this case the Euler equation has a different form and the possibility of using the durable goods as a collateral make the intertemporal allocation condition not independent of the intratemporal allocation condition. However, this dependence goes through the stock of vehicles at time t that is given when conditioning

1.3 The data

The sample of data is drawn from the Consumer Expenditure Survey (CEX) ran by the U.S. Bureau of Labor Statistics (BLS). The CEX provides a unique opportunity for the exercise proposed here. It gives very detailed information about the model, the brand, the vintage and a rich set of characteristics to evaluate the stock of cars present in each household at each instant in time.

The CEX is a rotating panel: households are interviewed for four consecutive quarters and then replaced. For a full description of the CEX, a useful reference is Attanasio and Weber [3].

The CEX data used in the present work come from the expenditure files (containing information on non-durable and durable expenditure), from the family files (containing demographics) and from owned vehicle Part B (detailed questions) and Part C (disposal) files. These last two files provide information on the stock and on the disposal of vehicles respectively and have been run since 1984.

Data on expenditure and demographics are available since 1980 (since that date the (BLS) has been running the Survey on a continuous basis), but considerations about the quality of them suggest discarding the first two years of the Survey. The latest interviews included were carried out in the 1st quarter 1996.

The CEX is run by the BLS to construct the Consumer Price Index (CPI). This ensures the representativeness of the sample and the consistency of the expenditure categories with the corresponding price data.

We select out non-urban households, households residing in a student housing, households with incomplete income response, those aged more than 73 and less than 21. Overall, we are left with 217056 interviews .

Given the rotating nature of the sample, we allocate households to 13 cohorts, by year of birth. Each cohort, but cohort 1, 12 and 13, covers an interval of 5 years of birth. The first cohort group those individuals born in 1909, the second those born between 1910 and 1914, the eleventh those born between 1955 and 1959. Table 1 reports the cohort definition.

on information available at that time.

1.3.1 Expenditure, demographics and macro-data

The main results refer to a basic measure of non-durable consumption. The inclusion of the so-called semi-durable and of small durable goods does not seem to affect consistently the pattern of the results. Non-durable consumption includes expenditure on food (defined as the sum of food at home, food away from home, alcohol and tobacco) and expenditure on other non-durable goods and services, such as heating fuel, public and private transport and personal care. Semi-durable consumption includes expenditure on clothing (defined as the sum of men, women, boy and girl clothing) and footwear, while small durable goods include computers, toys, pets, and household appliances. Due to their peculiar nature, we leave out housing, health and personal education expenditure.

The expenditure data consists of monthly figures and refer to the three months before the interview. To construct quarterly data, at least two possibilities can be explored. Averaging monthly data or picking just one month. We take this second alternative to avoid time aggregation bias (if the expenditure variables are measured with a white error time averaging makes them to contain a MA(2) error). To simplify further the error structure only the first month preceding the interview is retained.

In order to control for heterogeneity, a few demographics and labor supply variables are included in our preferred specification. Namely, we control for family size, the potential non-separability between consumption and leisure and for female labor market participation.

Three measures of income are considered: the wage and salary income received by family members in the 12 months preceding the interview, total family income before taxes, total family income after taxes.

The interest rate is the return on Municipal Bonds, that is tax-exempt, thus avoiding the need to compute the marginal tax rate. The *Economic Report of President 1996* reports an average of A graded bonds as computed by Standard and Poor. The CPI's published monthly by BLS are the price data used to compute the real counterpart of the expenditure variable considered here. Such indices are region-specific, which adds some cross-sectional variability. As stressed before, these price indices match exactly the expenditure categories considered. For data consistency, we use the CPI's version before the recent revision. With the CPI's on hand, household-specific price indices data are computed as weighted geometric average, using as a weight the budget share of each expenditure category (i.e. a Stone Price Index is

computed). Thus, we do not estimate a demand system.

In figures 1.1 and 1.2 the log of non-durable consumption and the log of the family income after taxes are plotted against the age of the head of the household. Non-durable consumption is computed as the sum of all the expenditure categories. The profile of both consumption and income is hump-shaped. This called for a rejection of the LC-PI model in its simplest version (see Carroll and Summers [23]).

Figure 1.3 plots family size against age of the household's head. The profile of the family size is hump-shaped, too. This could take account for the shape of the non-durable consumption, as pointed out by Attanasio and Weber [3]. We guess that the concavity of the non-durable consumption profile could also be related to the fact that household seem to accumulate durable goods at the earlier stage of their life and later to decumulate, as shown in figure 1.4.

1.3.2 Vehicle expenditure and the stock of vehicles

In what follows the term vehicles and cars will be used as synonymous, even if the CEX definition of vehicles is broader.⁶ The CEX allows to distinguish between expenditure for new and used vehicles. This distinction is not minor given that new and used vehicles are expected to have different depreciation patterns. Accordingly, two trade-in allowance variables are defined: for new and used vehicles. Moreover, information on the amount received by the household for sold vehicles and the amount reimbursed to the household for vehicle damage or theft are recorded.

In sum, three definitions of vehicle net expenditure apply. The first is total vehicle expenditure, given by the expenditure for new vehicle plus expenditure for used vehicles minus the trade-in allowance for new vehicles minus the trade-in allowance for used vehicles minus the amount of vehicles that have been sold or reimbursed. The other two definitions distinguish between new and used total vehicle expenditure.

Quarterly stock of vehicles is computed iterating the cohort average version of the following:

$$k_{ct+1} = (1 - \delta)k_{ct} + i_{ct+1} \quad (1.7)$$

where c stands for cohort. As initial condition we use the cohort average of the stock of cars data at household level drawn from the Attanasio's study

⁶In the definition used here, motorbikes, boats and airplanes are not included.

on (S,s) rules [5]. These values are reported in table 1.2 below.

The methodology used is similar to that in Alessie, Devereux and Weber [1] with UK data: the difference is that they compute the value of stock of vehicles from a data source (The National Travel Survey for the type and age of car owned and The Glass's Guide for the price of car) and, then, impute it to the households in Family Expenditure Survey using a reduced form equation that relates households characteristics to the car value.⁷ Before going into the details of how the value of the stock of vehicles is computed, it is worth mentioning some of the aspects of the procedure adopted by Attanasio [5]. In that paper the author uses data from the owned vehicles Part B and Part C files of the CEX.⁸ These files record very detailed information on the vehicles owned by each household (type of vehicle, vehicle year, vehicle make model and other information aiming to correctly price the vehicle). When the price of the vehicle is not available, the data from the *Kelly Blue Books* are used. These books provide a wide range of prices on used vehicles and allow to evaluate the stock of vehicles at a given date in a reasonably precise way.

In the present framework, we could follow two routes to compute the quarterly stock of vehicles. The above formula could be iterated at a monthly basis and then the quarterly stock is computed; or the quarterly expenditure is computed first and then the formula is iterated quarterly. To minimize the number of iterations,⁹ the second route is chosen.¹⁰ The stock of vehicles is computed in real terms along the lines described in the previous section. Given that the starting year is 1984, equation (1.7) is iterated back and forward.

The missing piece of information needed to implement the above procedure is the depreciation rate. The depreciation has both a physical and an economic nature. In principle, it could be estimated from the price data.¹¹ Given that the main purpose of the exercise is not to model the depreciation

⁷The main similarity is the use of the perpetual inventory method.

⁸The first year of available data is 1984.

⁹Potentially, an error is associated with each iteration. In fact, if households systematically underreport their disposal of vehicles, the procedure tends to underestimate the stock when integrating back and overestimate when integrating forward.

¹⁰Estimation results with the stock of vehicles computed as in the first approach, however, do not differ in a substantial way.

¹¹However, the estimation of the depreciation rate from the price data is not trivial. Endogeneity caveats apply since the choice of a given car and its depreciation rate are potentially simultaneous.

patterns of the cars, we assume that the stock of cars depreciates geometrically. Some of the available evidence suggests that this is not a bad approximation (see, for instance, Hall [33]). Thus, we construct our measure of stock of cars under various assumptions on the depreciation rate. Two set of experiments are performed. In the first set (rows numbered from 1 to 4 in table 3) the depreciation rate is assumed to be the same for new and used cars. In the second (rows numbered from 5 to 10) we set three different depreciation rates: one for new cars, one for used cars and one for the starting value of the stock of cars. The full description of the experiments is provided in table 3. The depreciation rate in the row 3 is roughly equal to that estimated for motor vehicles by the Bureau of Economic Analysis (BEA).

It is not easy to assess the quality of this procedure.¹² One way to do it is to compare the stock of cars so obtained with that obtained from Attanasio [5]. That amounts to compare the value of end-of-period stock of cars. From this, it seems that the values obtained here are reasonably close to the value obtained from the Attanasio's [5] data.

In figure 1.5 the stock of cars is plotted against time for each cohort. The first four graphs from the left correspond to the experiments numbered from 1 to 4. The rest of the figure refers to experiment from 5 to 10. In these last, which allow for different depreciation pattern for new and used cars, the stock of cars increases for young cohorts and then becomes flat when cohorts age.

1.4 Estimation

Synthetic panel techniques are used because the data come in form of time-series of cross-section. We assume that the condition¹³ under which the synthetic panel approach is valid are satisfied. More precisely, the grouping criteria is assumed to be exogenous and the individual information set to smoothly aggregate up to its cohort analogous (about this last problem, see Pischke [52]). Given that the main goal of the work is to obtain a model

¹²We have compared the change of the stock of cars obtained from these calculations with a measure of the aggregate obtained from the data on autos published by the BEA. Averaging over all the experiments, we obtain figures roughly comparable to that of the BEA.

¹³The debate on the virtue and limitations of using grouped data is huge: the issue 59 of the *Journal of Econometrics* surveys it.

that is comparable to those already existing in the literature using the same data, this does not seem to be a dramatic simplification .

In the estimation, we exclude the first, the second, the third, the last two cohorts. This should prevents my estimates from being contaminated by extreme outliers and gives us a balanced synthetic panel, which simplifies the construction of the estimator. We end up with $T = 56$ (quarterly data are used) and $C = 8$. The cell-size is not constant over time and over cohorts. No cell-size correction is allowed for. This does not bias the estimates if the number of households for each cell is large, which is, on average, around 250 households. The stochastic structure comes mainly from the rational expectation hypothesis (REH). The theory delivers restrictions on the dynamic properties of the Euler equation residuals, which turn to be the expectation errors. These have to be orthogonal to the past information. Formally,

$$E(\eta_{ht+1}|\mathfrak{S}_{ht}) = 0 \tag{1.8}$$

where η_{ht+1} is the residual of the Euler equation at time $t + 1$ and \mathfrak{S}_{ht} is the set of past information. In panel or pseudo-panel data, the sample analog of (1.8) could be either the cross-sectional or the time series mean. Notice, however, that there are no theoretical reasons to exclude that expectation errors are correlated across households. This is indeed the case when market are incomplete. So, consistency relies on the availability of a long panel.¹⁴

Regarding the grouped variables as variables measured with error adds an other component to the model. This last makes the Euler equation residual follow an MA(1) process.¹⁵

All variables are treated as endogenous in the estimation.¹⁶ The stochastic structure described above leads to choice of lagged 2 and more instruments, which are assumed to be orthogonal to the omitted terms in the Euler equation. This assumption is used in the literature and its violation invalidates. Along with the literature, we assume the instruments are orthogonal to higher moments of the joint distribution of the growth rate of consumption and interest rate.

¹⁴It is worth stressing that under market incompleteness the Euler equation cannot be estimated in the cross-section. This is the so-called Chamberlain critique. Even in the case we can estimate the Euler equation with a cross-section, there is no guarantee that the interest rate displays enough variability to identify the main parameter of interest.

¹⁵The variables in levels contains a white error.

¹⁶It has been pointed out that at quarterly level family size variable are not endogenous. Treating them as exogenous do not change the results.

The matrix of instruments for each cohort is stacked. Alternatively, we could have chosen a set of instrument different for each cohort. Given that households can be interviewed more than once, if fixed effects matter, some care has to be paid to the construction of the instrument matrix to ensure consistency (see Attanasio and Weber [3]). Therefore, we form instruments lagged by two periods using only individuals at their fifth interview, those lagged by three using both individuals at their fifth and at their fourth interview while those lagged by four exclude only individuals at their second interview.

The model is, then, estimated using a GMM technique. The construction of the weighting matrix reflects the presence of MA(1) residuals and the fact that we allow for these residuals to be contemporaneously correlated among cohorts. The Hayashi and Sims [36] estimator is used. It first (forward-)filters out from the model the serial dependence and, then, allows for heteroskedasticity of an unknown form. Under the REH, backward filtering would lead to inconsistent estimates.

In order to control for the effect of demographics, which tend to concavify the life-cycle consumption profile, we include the growth rate of family size. Moreover, the non-separability with the female labor supply decision is addressed conditioning on a variable measuring the number of earners in each households. Experimenting with a dummy for the working wife does not deliver different results. Potentially the number of earners is a better measure for dealing with non-separability between labor supply and consumption decision when the consumption unit does not simply include the head of the households and his spouse.

We report here the results using as income variable wage and earnings perceived by the family members in the 12 months before the interview. While the point estimates of the interest rate and the stock of cars coefficients do not sensibly change with the income measure used, in few cases the evidence on the overidentifying restrictions reject the null.

For the sake of comparability, a standard Euler equation is estimated without including the stock of cars variables: this is called the baseline model and is reported in table 4. The estimated coefficients are reasonably comparable with those found in the previous exercise using these data. The Sargan test does not reject the overidentifying restrictions.

In the second column of table 4, the previous specification is augmented by the growth rate of income, as defined above. This is a standard excess sensitivity test: under the null individuals should not react to forecastable

income innovations. In a regression context, this asks for the coefficient on the growth rate of income to be zero. Two things should be noticed: the coefficient on the growth rate of income is virtually zero and the Sargan test does not reject the null at the standard level. In the other two columns of table 4 we report the same specifications as before, but estimated using OLS. Comparing these estimates with those obtained using GMM gives an informal check of the quality of the instruments. According to the picture displayed in this table, there is *no* evidence of excess sensitivity.

Next, we turn to the estimation of the baseline specification augmented by the change of the stock of cars. Moreover, we check if the inclusion of the stock of cars variable makes the excess sensitivity test to deliver a different answer. We report two set of results relating to two experiments on the depreciation rate. The same pattern is found in the full set of results, which, thus, are not reported. In table 1.5 the assumed depreciation rate is 0.0375. As in table 1.4, the first two columns report coefficients estimated using GMM, while the last two columns those estimated using OLS.

The specification chosen seems to work well. The Sargan test does not reject the overidentifying restrictions and the OLS estimate are not close to their GMM homologue. The interest rate coefficient is higher than in the baseline case. This generates a much steeper non-durable consumption profile. This effect may be due to the non-separability with durable goods. Suppose that the interest rate increases. Individuals might want to postpone both non-durable and durable consumption. On the other hand, the increase of the interest rate causes the user cost to increase, thus reducing the stock of durable goods today and at all future dates. If this last effect is prevailing, the increase in the interest rate reduce the stock of durable goods. This affects the marginal utility of non-durable consumption if preferences are not separable. If the non-durable and the durable goods are substitute, the marginal utility of non-durable consumption increases when the stock of durable goods decreases. In this case the effect of the interest rate the growth rate of non-durable is reinforced. The opposite is true when non-durable and durable goods are complement in utility.

The coefficient of the changes of the stock of cars is significant at a standard level and negative. This suggests that non-separabilities are important and that non-durable and durable goods are substitute. This results contrasts with the available evidence using macrodata (Bernanke [12]).

Finally, the excess the excess sensitivity test is passed: when we condition on the growth rate of the stock of cars, the coefficient on the growth rate of

income dramatically drops. This makes the non-separability between durable and non-durable goods to be potentially relevant for the estimation of the Euler equation and the empirical testing of the model.

A similar pattern arises from table 1.6, which assumes three different depreciation rates, for new, for used and for the initial stock of vehicles. The coefficients of the interest rate and of the change of the stock of vehicles are smaller (in absolute value), while the evidence on excess sensitivity does not change. Again, the specification seems to be successful in view of the fact that the GMM coefficients are statistically different from their OLS homologue and that the overidentifying restriction test is passed.

From this first round of estimates, we can conclude that the non-separabilities between non-durable and durable goods may be an issue in that omitting durable goods from the estimation of the Euler equation amounts to omit a relevant variable. In other words, this omission makes the parameters of interest to be biased. On the other hand, it is not clear if the inclusion of the stock of durable goods can 'solve' the excess sensitivity puzzle. This is so because also in the baseline specification the coefficient on the growth rate of income does not appear to be statistically different than zero. In particular, this lack of statistical significance could be due to the inability to instrument the growth rate of income: the rank test is 0.046, suggesting that the chosen set of instruments are weak in predicting the growth rate of income. To overcome this problem, we re-estimate the same specifications as above, replacing the growth rate of income with the income lagged by one period. Under the null, the coefficient on this last should be zero: past income belongs to the individual information set. Results are reported in table 1.7.

The first two columns of table 1.7 estimate the baseline specification and find that the coefficient of past income is statistically different from zero, which is interpreted as evidence in favor of excess sensitivity. The next step is to augment the baseline specification with the change of the stock of vehicles. This is done in the last four columns of table 1.7. The third and the fourth compute the stock of vehicles as in table 1.5, the last two as in table 1.6. The results from both the experiments on the depreciation rate are consistent, but mixed, as far as the evidence on excess sensitivity is concerned. On one hand, the coefficient on lagged income drops, which would imply that, at least in part, the evidence of excess sensitivity can be attributed to the omission of the change of the stock of vehicles. On the other hand, the coefficient of the change of the stock is not statistically significant itself. This finding might be explained by the fact that the correlation between lagged income and

changes of the stock is not negligible and requires more investigation if the evidence on excess sensitivity is to be assessed.

1.5 Conclusions

The large majority of empirical studies testing the LC-PI model through the Euler equation do not include any measure of durable consumption among the conditioning variable. This omission can be partly explained by a general problem of measurement of the stocks from where households are assumed to derive utility. This study tries to fill this gap using a very rich source of information, the American Consumer Expenditure Survey. If non-durable and durable consumption are separable in utility, omitting the durable consumption from the estimation of the Euler equation does not lead to any bias. As long as this separability cannot be assumed (or the non-separability cannot be rejected), the omission of this durable good could potentially lead to a false rejection of the model.

The exercise performed here suggests that the non-separability between durable and non-durable consumption can be an issue for the evaluation of the theory. The coefficient of the interest rate is sensibly larger than in the case where durable goods are not conditioned upon. The coefficient of the stock of cars is statistically different than zero, which means that the durable and non-durable are potentially non-separable in utility. The evidence on excess sensitivity is, however, more mixed. The specification that include simultaneously lagged income and the change of the stock of vehicles find that the coefficients on both these variables are insignificant, while they are significant when they are included in turn. This is likely to be due to the fact that lagged income and changes of the stock are correlated and prompts for further investigation. Overall, this work suggests that, even though the exclusion of durable goods is not the sole responsible for the rejection of the theory, if any, there is stance for departing from the standard framework where the choices over non-durable are modeled independently of choices over durable goods.

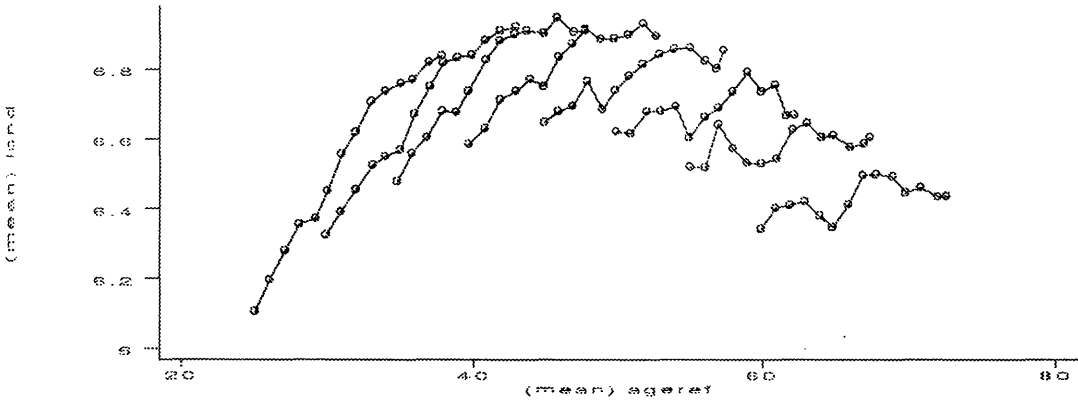


Figure 1.1: Household non-durable consumption

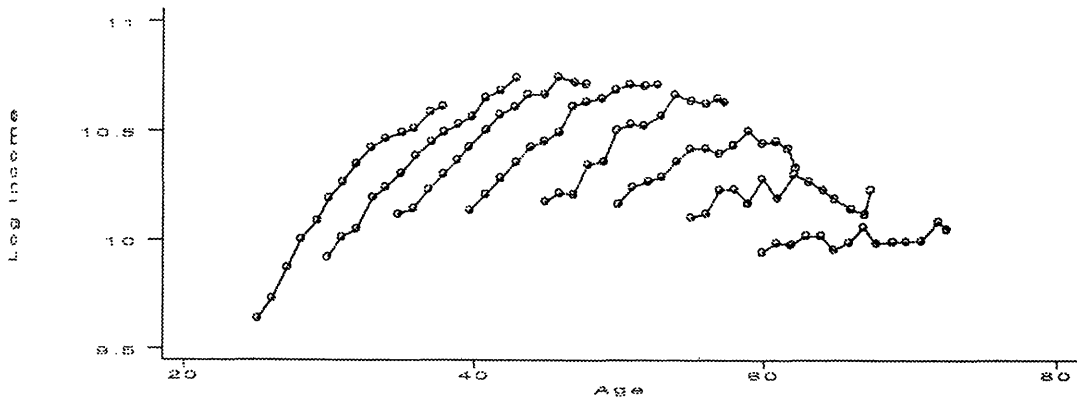


Figure 1.2: Household income after taxes

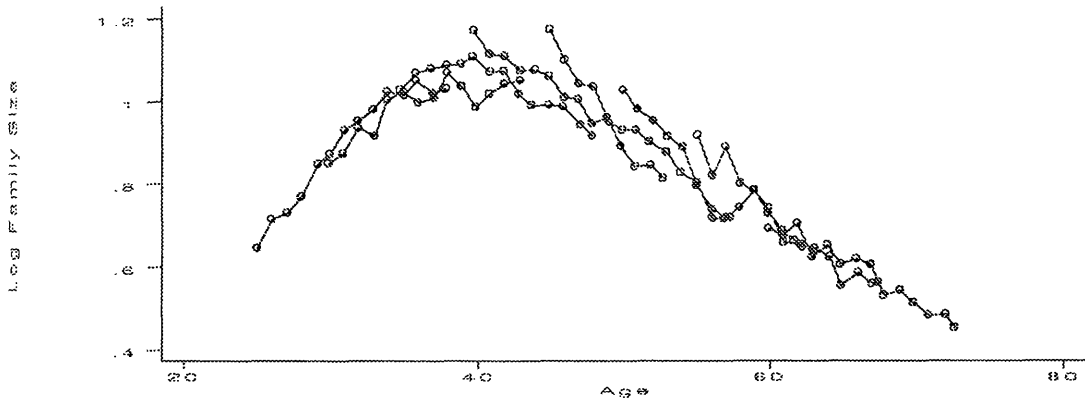


Figure 1.3: Household family-size

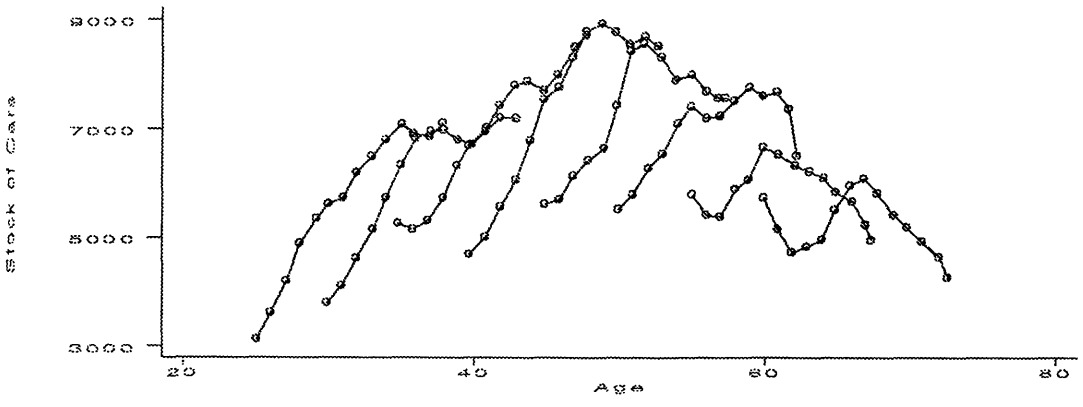


Figure 1.4: Household stock of cars

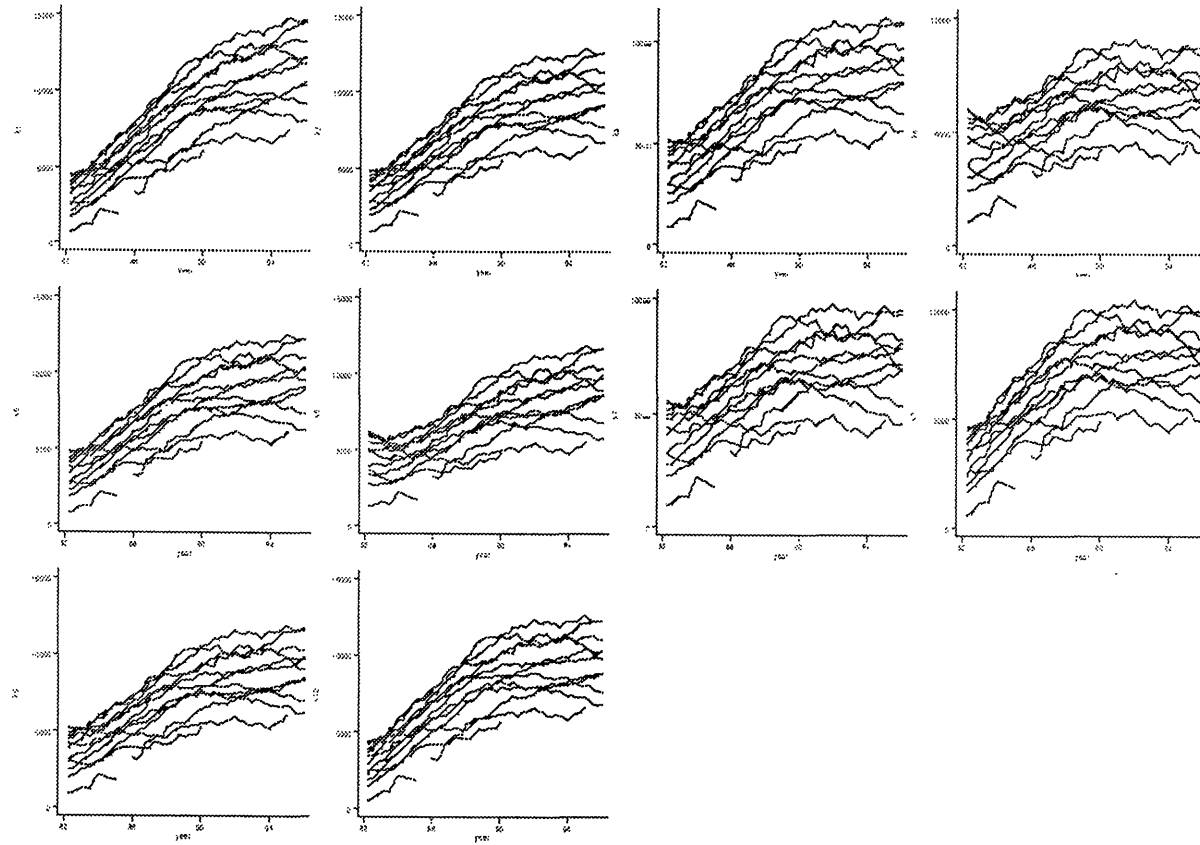


Figure 1.5: Stock of cars

Table 1.1: Cohort Definition

Cohort	Year of Birth	Age in 1982	Average Cell Size	U.E.
1	1909	73	31	no
2	1910-1914	68-72	190	no
3	1915-1919	63-67	230	no
4	1920-1924	58-62	263	yes
5	1925-1929	53-57	260	yes
6	1930-1934	48-52	246	yes
7	1935-1939	43-47	265	yes
8	1940-1944	38-42	327	yes
9	1945-1949	33-37	418	yes
10	1950-1954	28-32	468	yes
11	1955-1959	23-27	487	yes
12	1960-1966	16-22	564	no
13	≥ 1967	≤ 15	247	no

Note: In the first column is the cohort number, in the second the cohort definition, in the third the average age in 1982, in the fourth the average cell-size, while in the last column 'no' stands for not used in the estimation and 'yes' stands or used.

Table 1.2: Cell Size and Average Stock of Cars, 1984

Cohort	Cell Size	Average Stock of Cars
1	21	2098.333
2	157	3212.279
3	192	4473.213
4	229	4880.836
5	249	5249.038
6	224	6091.652
7	257	5795.866
8	291	5392.927
9	373	5044.728
10	400	4380.69
11	378	3941.405
12	214	3100.18

Note: In the first column is the cohort number. The oldest cohort is 1. The cell-size of each cohort in 1984 is in the second column . In the third column the average stock of cars is reported.

Table 1.3: Quarterly Depreciation Rate

Depreciation Rate	<i>I</i>	<i>II</i>	<i>III</i>	<i>IV</i>
1	.03			
2	.0375			
3	.045			
4	.06			
5		.0375	.045	.03
6		.06	.045	.03
7		.0525	.06	.045
8		.0375	.06	.045
9		.045	.0375	.05
10		.03	.0375	.05

Note: In the first column the number of the experiment is reported. Each row corresponds to the set of depreciation parameters indexing each experiment. Column I refers to the common depreciation rate, column II to the depreciation rate for the stock of cars in 1984, column III to the depreciation rate for new cars and column IV to the depreciation rate for old cars. Experiments labelled from 1 to 4 refer to the case where the same depreciation rate is assumed for both new and used cars. Experiments from 5 to 10 refer to the case where three different depreciation rate are assumed: for the stock of cars in 1984, for new cars and for old cars.

Table 1.4: Baseline Specification

	GMM	GMM	OLS	OLS
<i>Interest rate</i>	1.1554	1.0538	0.61028	0.5870
(0.4370)	(0.3991)**	(0.4460)*	(0.2295)**	(0.2288)*
<i>Growth rate of family size</i>	0.6447	0.6506	0.3491	0.3675
(0.0730)	(0.3090)*	(0.3246)*	(0.0798)**	(0.0799)**
<i>Change in number of earners</i>	0.2747	0.4284	0.1930	0.1460
(0.0830)	(0.2100)	(0.2168)*	(0.0431)**	(0.0478)**
<i>Growth rate of income</i>		-0.0659		0.0232
(0.0370)		(0.0610)		(0.0104)
Sargan	19.6927	13.6119		
p-value	0.2343	0.5551		

Note: Standard errors are in parentheses; * significant at 5% level; ** significant at 1% level. The dependent variable is the growth rate of non-durable consumption. In the first column is the right-hand variable name and in parentheses is the R^2 of the first stage regressions. The columns headed by GMM report the GMM estimates, those by OLS the OLS estimates. The instruments used are: the lag two and three of the growth rate of non-durable consumption and its square, the nominal interest rate, the inflation rate, the car expenditure; the lag two, three and four of the growth rate of the number of earners, the number of children and of the growth rate of the income. All the specifications include a constant and three seasonal dummies.

Table 1.5: $\delta = 0.0375$

	GMM	GMM	OLS	OLS
<i>Interest rate</i>	1.8678	1.8468	0.6094	0.5952
(0.4370)	(0.6058)**	(0.6785)**	(0.2312)**	(0.2302)
<i>Growth rate of family size</i>	0.5379	0.5318	0.3492	0.3662
(0.0730)	(0.3357)	(0.3398)	(0.0800)**	(0.0800)
<i>Change in number of earners</i>	0.3962	0.4383	0.1929	0.1453
(0.0830)	(0.2094)	(0.2309)	(0.0432)**	(0.0479)**
<i>Change in stock of vehicles</i>	-0.8244	-0.7842	0.0031	-0.0401
(0.2412)	(0.4106)*	(0.4689)	(0.1200)	(0.1200)
<i>Growth rate of income</i>		-0.0187		0.0239
(0.0370)		(0.0685)		(0.0106)
Sargan	12.7419	11.3182		
p-value	0.6222	0.6608		

Note: Standard errors are in parentheses; * significant at 5% level; ** significant at 1% level. The dependent variable is the growth rate of non-durable consumption. In the first column is the right-hand variable name and in parentheses is the R^2 of the first stage regressions. The columns headed by GMM report the GMM estimates, those by OLS the OLS estimates. The instruments used are: the lag two and three of the growth rate of non-durable consumption and its square, the nominal interest rate, the inflation rate, the car expenditure; the lag two, three and four of the growth rate of the number of earners, the number of children and of the growth rate of the income. All the specifications include a constant and three seasonal dummies. δ refers to the quarterly depreciation rate.

Table 1.6: $\delta_0 = 0.0525$, $\delta_n = 0.06$, $\delta_u = 0.045$

	GMM	GMM	OLS	OLS
<i>Interest rate</i>	1.7295	1.7079	0.6111	0.5945
(0.4370)	(0.5690)**	(0.6284)**	(0.2306)**	(0.2297)**
<i>Growth rate of family size</i>	0.5443	0.5355	0.3489	0.3662
(0.0730)	(0.3361)	(0.3407)	(0.0801)**	(0.0800)**
<i>Change in the number of earners</i>	0.3874	0.4343	0.1931	0.1452
(0.0830)	(0.2090)	(0.2318)	(0.0432)**	(0.0479)**
<i>Change in stock of vehicles</i>	-0.10041	-0.0947	-0.0010	-0.0050
(0.212)	(0.04887)**	(0.0559)	(0.0120)	(0.0131)
<i>Growth rate of income</i>		-0.0215		0.0240
(0.0370)		(0.0682)		(0.0106)
Sargan	12.5190	11.0552		
p-value	0.6394	0.6817		

Note: Standard errors are in parentheses; * significant at 5% level; ** significant at 1% level. The dependent variable is the growth rate of non-durable consumption. In the first column is the right-hand variable name and in parentheses is the R^2 of the first stage regressions. The columns headed by GMM report the GMM estimates, those by OLS the OLS estimates. The instruments used are: the lag two and three of the growth rate of non-durable consumption and its square, the nominal interest rate, the inflation rate, the car expenditure; the lag two, three and four of the growth rate of the number of earners, the number of children and of the growth rate of the income. All the specifications include a constant and three seasonal dummies. δ_0 refers to the depreciation rate for the initial stock of cars, δ_n to the depreciation rate for new cars and δ_u to the depreciation rate for used cars.

Table 1.7: Excess Sensitivity

	GMM	OLS	GMM	OLS	GMM	OLS
<i>Interest rate</i>	1.7177	0.6013	1.8892	0.6047	1.8372	0.6045
(0.4370)	(0.5339)**	(0.2304)**	(0.6260)**	(0.2316)**	(0.5852)**	(0.2311)**
<i>Growth rate of family size</i>	0.5738	0.3515	0.5313	0.3510	0.5275	0.3509
(0.0730)	(0.3303)	(0.0780)**	(0.3380)	(0.0802)**	(0.3376)	(0.0801)**
<i>Change in the number of earners</i>	0.4932	0.19038	0.4822	0.1904	0.4747	0.1904
(0.0830)	(0.2169)*	(0.0434)**	(0.2235)*	(0.0435)**	(0.2253)*	(0.0435)**
<i>Lagged income</i>	-0.0084	0.0005	-0.0051	0.0006	-0.0047	0.0006
(0.154)	(0.0035)**	(0.0010)	(0.0052)	(0.0010)	(0.0050)	(0.0010)
<i>Change in the stock of vehicles</i>			-0.0464	-0.0020	-0.0637	-0.0032
(0.246) (0.212)			(0.0586)	(0.0130)	(0.0663)	(0.0131)
Sargan	10.4305		10.5662		10.3490	
p-value	0.7918		0.7197		0.7362	

Note: Standard errors are in parentheses; * significant at 5% level; ** significant at 1% level. The dependent variable is the growth rate of non-durable consumption. In the first column is the right-hand variable name and in parentheses is the R^2 of the first stage regressions. The columns headed by GMM report the GMM estimates, those by OLS the OLS estimates. The instruments used are: the lag two and three of the growth rate of non-durable consumption and its square, the nominal interest rate, the inflation rate, the car expenditure; the lag two, three and four of the growth rate of the number of earners, the number of children and of the growth rate of the income. All the specifications include a constant and three seasonal dummies. The second and third columns host the baseline specification; in the third and in the fourth this is augmented with the change in the stock of vehicles computed with the same depreciation as in table 1.5 and in the fifth and the sixth with that in table 1.6.

Chapter 2

Stock of cars and (s, S) rules

2.1 Introduction

The number of empirical studies dealing with consumer durables is still small compared to that dealing with non-durables (see, for a survey, Attanasio [4] or Padula [50]). This is mainly due to the difficulty of measuring the stock of vehicles at the households level. Apart from few exceptions, as the Italian Survey of Households Income and Wealth, run by the Bank of Italy, households based surveys do not report measures of the stock of cars. In particular, they do not report the value of the stock of cars at each point in time, which is what economists are interested in.

This paper tries to fill this gap by devising a procedure to construct a households' level measure of the stock of vehicles. The procedure is flexible enough to be used also to construct other stock of durables, and has the virtue of feasibility in that it requires a limited amount of information. Namely, the methodology does not require to have a full set of second-hand prices, which may be a hard requirement to fulfill when the dimensionality of the problem is large. This, however, comes at the cost of imposing a few assumptions on the dynamics of prices, which will be clarified below. The quality of our measure of the stock of cars is checked for a few model, brand and vintages, for which second-hand prices are available.

The stock of cars so constructed is used to derive some stylized facts. We document the life-cycle and the business-cycle profile of the stock of cars. Owing to the lack of a households' level measure of the stock of cars the evidence on the life-cycle and the business-cycle profile of it is scarce. This is

particularly disappointing in view of the fact that the empirical evaluation of alternative models of durable consumption depends on the behavior of simple statistics that can be computed only if the a measure of stocks is available.

Moreover, the data set is used to test a (s,S) model. This is not novel. These rules, popularized by Grossman and Laroque [31], have been tested by a number of authors now, including Lam [44], Eberly [28] and Attanasio [5]. The evidence found is in line with that in Attanasio [5], who work on the same data-set, but on a shorter sample, and follows a different methodology to evaluate the stock of cars.

The paper is organized as follows. First, section 2 illustrates the methodology used to construct our measure of the stock of cars, presents the data and some descriptive statistics and checks. Section 3 documents the life-cycle and the business cycle profiles of the stock of cars. In this section we also derive the dynamic properties of the first and of higher moments of the cross-sectional distribution of the stock of cars divided by non-durable consumption. In section 4 we discuss an (s,S) model and some results. Section 5 concludes and points directions for future work.

2.2 Estimating the value of the stock of cars

This section discusses how we *estimate* the value of the stock of cars using a sample of micro-data drawn from the U.S. Consumer Expenditure Survey (CEX) and is made of three subsections. In the first, we discuss the main econometric issues and the methodology we use. Estimating the value of a car amounts to identify a single numerical index which measures its ‘quality’. This last depends on a number of features, including the year of production of the car, its age and the general level of prices. If the level of prices changes over time because of inflation, no identification strategy is available, which allows to distinguish among the three aforementioned effects. To get around this issue, we propose to use a set of cars characteristics to *proxy* for the year of production effect.

The use of micro-data is crucial if the value of cars has to be estimated at the households level, when second-hand car’s prices are not available. We use the CEX. This is a widely used survey in the empiric of consumption. However, the information referring to cars, which has been started to be recorded since 1984, have been much less used. Thus, the second subsection presents the sample of data used in the analysis.

The third subsection provides some descriptive statistics and the results. The descriptive statistics show that the data provide enough leverage for the value of the stock of cars to be estimated. We compare our results with some out-of-sample statistics, which provides evidence on the quality of our procedure. Overall, we can estimate the value of the stock of cars for around 160000 data-points (each data point corresponds to an household interviewed in a given quarter).

2.2.1 Econometric issues and methodology

In this section, we describe how to derive a measure of the stock of cars. Evaluating the stock of cars amounts to identify a single numerical index which measures the ‘quality’ of the stock. In other words, we need a number which measures the value of the stock in efficiency units. There are econometric issues to be dealt with when this number has to be inferred from the observed price. Next, we clarify and address these issues.

Suppose that we observe a car for V vintages. If we normalize to one the quality of, say, vintage v , the ratio:

$$\frac{P_{v+1,t}}{P_{v,t}} \tag{2.1}$$

measures the quality of the vintage $v + 1$ conditional on the time the two subsequent vintages are observed. If each vintage is observed for enough long time, averaging (2.1) over t gives a single numerical index which measures the value of the cars in efficiency unit.

Now, notice that the age of the cars whose price is involved in the computation of (2.1) is different, since, trivially, $a = t - v$. If the value of cars changes because of aging, which, indeed, seems to be the case, the ratio in (2.1) depends also on a pure age-effect. This age-effect is often assumed to be a consequence of the depreciation.

If more aged cars deliver ‘less’ services and, then, are valued less, we expect the depreciation pattern to be decreasing¹. The rate at which the car depreciates determines the concavity of the age-value profile. Comparing the price of cars at the same age but at different times might help to account for the age-effect. However, this comes at the cost of introducing a time-effect, which makes the price of cars to change only because of inflation.

¹It is worth noticing at this stage that it might happen that some cars are observed to appreciate, which means that their values increases with age.

To further illustrate this problem, suppose that the price data are arranged in a matrix. The value of a car is a function of age and time. For simplicity, we assume that the maximum age and the maximum time for which the prices are observed is 5. In the rows of this matrix, the age is constant while the time varies. Obviously, the opposite holds true for the columns.

The difference between the average of prices in the, say, second row and the average of prices in the first row would be a measure of how the price changes because of aging from age 1 to age 2. In the same way, the difference between the average of prices in the, say, second column and the average of prices in the first column would be a measure of how the price changes because of inflation from year 1 to year 2².

However, this procedure leads in general to biased estimate of the age and the time effect: the problem is that the prices of cars in a given row (or column) belongs to *different* cars, in that their vintage differs. Only moving along the diagonals we observe cars belonging to the same vintage.

Whether or not comparing cars belonging to different vintages to remove the age and the time effect is indeed a problem is an empirical matter. The main difficulty to assess the relative importance of the three effects (age, time and vintage) is related to the fact that they are not separately identifiable.

The literature offers two main strategies to deal with this problem. The first one amounts to normalize one of the three effects, say, the vintage effect, to zero. If the vintage effect proxies for the degree of technological progress embodied in the price of cars, this assumption sets to zero the net price change due to technological progress. In other words, this strategy does not allow to identify the trend in the degree of technological progress.

Alternatively, Hall [33], in a study which focuses on trucks, suggests using a set of characteristics, such as the Wheelbase, the Weight, the Ratio of Bore to Stroke, the Horsepower, the Torque, the Tire Width, to proxy for the vintage effect in an hedonic prices regression framework. The rationale is that this set of characteristics can be arranged in a vector which is a sufficient statistic for the vintage effect. If this is indeed the case, the identification problem is circumvented because these characteristic are chosen to be orthogonal to the age and the time-effect.

In what follows, we decide to pursue the second strategy. The main

²This procedure consists of computing a within-group average, where the group membership is first with respect to age and the with respect to time.

advantage of this strategy is to make possible the identification of all the three effects, the main disadvantage is to rely on the availability of a set of characteristic rich enough to be used as a proxy for the quality. Given that the ultimate goal of this work is to evaluate the stock of cars either strategy might be used. The choice of the second strategy is mainly based on empirical grounds.

The price of the cars at age a and time t can be written as:

$$p_{a,t} = \delta_a \tau_t \phi_v \quad (2.2)$$

where v is the vintage; δ_a is the age effect, τ_t is the time effect and ϕ_v is the vintage effect. From (2.2) it is clear that we cannot simultaneously identify the three effects. In order to achieve identification we replace ϕ_v by a set of characteristics.

If prices were not measured with error, the fitting of (2.2) to the data would be perfect. Alternatively, suppose that prices are measured with error and that the error enters (2.2) in a multiplicative fashion.

Being the model linear in the logs, the age, time and the vintage effects could be estimated through a linear regression. The issue here is what functional form to chose. To understand it, go back to table 2.1.

If in a matrix like table 2.1 there are not 'holes', which means that we observe at least one price for each age-time cell, an analysis of variance (ANOVA) model could be used. The prices of cars are regressed on a (restricted) set of age, time and vintage dummies.

If, instead, we do not observe a price for each age-time cell, we need to save on the number of parameters to be estimated. This might be accomplished by fitting to the price of cars a polynomial in age, time and vintage (abstracting for a while from the identification issues). Due to data constraints, we opt for this second model.

Needless to say, there is a mapping from the ANOVA to the polynomial model. For instance, the age dummies being all the same in the ANOVA model means that the depreciation pattern is exponential, i.e. the relation from age to price is linear in logs.

We conclude this section discussing the model we end up estimating. After some search, we find that a parsimonious but satisfactory representation of the log-price of a car i of age a observed at time t is:

$$\ln p_{i,a,t} = const + \tau_t + \delta_1 a_i + \delta_2 a_i^2 + \kappa_1 a_i * idn_i + \kappa_2 a_i^2 * area_i + x_i \phi' + \varepsilon_{it} \quad (2.3)$$

where the LHS variable is the log of the price, *const* stands for constant, τ_t is a time-dummy, i is the car index, a and t have the same meaning than before, idn_i is a make-model dummy, and $area_i$ indexes the area of production of the car, where three areas are identified: America, Far-East and Europe³; and x_i is a vector of car characteristics.

One of the main virtue of this representation is to allow for the age effect, i.e. the depreciation to be a function of the make-model and of the area of production of the car, which, in turn, allows for a great deal of heterogeneity in the value of the stock of cars⁴.

At this stage it is worth reporting the analytical representation of the age-effect, which comes out from differentiating (2.3) with respect to the age, i.e.:

$$Ageff = \delta_1 + 2 * \delta_2 a_i + \kappa_1 * idn_i + 2 * \kappa_2 a_i * area_i \quad (2.4)$$

Equation like (2.4) might be used to test a number of interesting hypothesis on the age-effect.

First, whether or not the car indeed depreciates depends of the sign of δ_1 . If this is negative, the price-age profile has a decreasing shape.

Instead, the convexity of the price-age profile depends of the sign of δ_2 . If this is positive, the profile exhibit a convex shape. It might well exhibit a convex shape even if this parameter is found to be equal to zero⁵. This last corresponds to the exponential depreciation case.

Finally, in this framework we may test if the parameters governing the age-price profile vary across make-models and area of production. If κ_1 is equal to zero, we cannot reject the hypothesis that the slope of the age-price profile is the same across different make-models, while κ_2 equal to zero means that the convexity does not differ across area of production.

2.2.2 The data

In what follows, we briefly describe the section of the Consumer Expenditure Survey (CEX), relevant to this work. For further details on the survey we refer to Attanasio and Weber [3].

³Resources limitation prevents to interact the second-order age term with the car make-model. After selection, we do observe about 500 different make-models.

⁴Estimating each separate regression for each make-model (about 500) is not feasible with these data.

⁵Remember that in the variable at LHS if the *log* of the price.

The CEX is a rotating panel which the Bureau of Labor Statistics (BLS) runs on a quarterly basis to construct commodity specific price indexes. These price indexes enter the computation of the U.S. Consumption Price Index (CPI). This should guarantee the representativeness of the sample and, partly, explains why the CEX is one of the most widely used survey in empirical consumption studies. Each quarter, about 7000 households (Consumption Units)⁶ are interviewed and 20% of them are replaced the following quarter by a new random group.

Each household is interviewed at most five times⁷ over a period of a year. After the fifth interview, households are replaced. Thus, the rotating nature of the sample. In the first interview, households are asked general information. This is a contact interview, which is not used in the estimation. From the 2nd to the 5th interview, households report detailed information on the expenditure made in the three months before the interview, while income information are collected at the 2nd and at the 5th interview.

A wide variety of expenditure categories are covered by the survey, which include non-durable, semi-durable, durable goods and services. The income data refer mainly to the family income before and after taxes, while a separate measure of income which quite closely mirrors the theoretical definition of salary is also available. Moreover, the survey records a number of variables which carry useful information on the family characteristics at the time of the interview. These information are collected at each interview, refer to the month of the interview and, typically, relate to demographics, work status, education, sex and race of the respondent and of the others family members.

The data on vehicles come from two files. The BLS starts to make publicly available these files since 1984. The first file (OVB), which refers to the vehicles owned by the household, records a full set of characteristic for the vehicles *present* in the Consumption Unit (CU) at the interview date. An incomplete list of these characteristics includes the type of the vehicle (car, truck, van, pick-up, motor-bike, boat and, eventually, airplane), the make and the model of the vehicle, the year and the month of purchase, the vintage, the number of cylinders, if the vehicle entered the consumption unit as new or used, if the vehicle is equipped with the air-conditioning, the automatic

⁶In what follows, Consumption Unit and household are used as synonymous. According to the BLS definition, the Consumption Unit consists of all members of a particular housing unit or other type of living quarters who are related by blood, marriage, adoption or some other legal arrangement, such as foster children.

⁷Some household drop from the sample after the first interview.

transmission, the power-brake, the power-steer, the radio, the sun-roof. The list also includes the purchasing price which contains two components. The net purchasing price, which turns out to be the cash out flow at the date of the purchase, and, if any, the trade-in allowance received.

Moreover, households are asked if they disposed a vehicle and, in case they did, they are asked when, how and a set of characteristics identifying the vehicle. These information are recorded in the second file (OVC) which refers to the vehicles disposed by the households. The way the household dispose the vehicle is particularly important to our purposes. Six alternatives are reported: Sold, Traded in, Given Away Outside the CU, Damaged beyond repair, Stolen and Other. The information we exploit here to estimate the price of the cars looking at their second hand market values relates to the price the CU receives for the selling the car. While the amount the CU received for trading-in the old car could have been used, the variables relating to the amount the consumption unit receive (or expect to) for theft or loss play no role at the present⁸.

In both the OVB and the OVC files a vehicle number is present, which identify the vehicle within the Consumption Unit and allows to merge the information contained in one file with those in the other.⁹

2.2.3 Descriptive statistics and results

This section reports descriptive statistics and results. We select in cars, trucks and vans. Trucks and vans enter the same category in the BLS definition. For brevity, cars, trucks and vans are termed as cars. A recent paper by Pickrell and Shimek [51], who use the data from the Nationwide Personal Transportation Survey (NPTS)¹⁰ documents the increasing role of the light trucks: the percentage of the light trucks of household vehicles was 26.7% in 1990, while reaching 32.8% in 1995. Hence, the decision to include vans and trucks in the definition of cars.

⁸Strictly speaking, these variable proxy the value of the cars only under much more restrictive conditions than the price they could have been sold.

⁹This is not entirely true, because the BLS stopped recording this variable in 1991. However, it is possible to compute the number identifying the vehicle when the household is interviewed more than once and when the households do not dispose off more than one vehicles at the same date.

¹⁰The NPTS is a survey run by the U.S. Department of Transportation. It is often used to study the trends of ownership and usage in the American fleet.

A direct way of evaluating the stock of cars at the household level would be to use the second-hand market prices. However, the entire history of these prices is not publicly available on electronic support. Resource limitations prevent using the paper support¹¹ as a source for the data.

In this work, we follow an alternative route. We use the price information contained in the survey to estimate the value of the stock of cars. In principle, if the number of the transactions observed in the sample is large enough, this method and the evaluation based on the second-hand market prices should lead to the same outcome. As we said above, in the sample we do observe households who buy and sells vehicles and, eventually, the price at which the vehicle is bought or sold. These prices provide the basis for the evaluation of the stock of cars.

The sample covers the years from 1984 to 1995. Around 422000 cars are present in the sample, the 58% of those are second-hand, while the number of make-models averages around 624 and the number of brands around 70. Around the 2.44% of cars are topcoded.¹² Around 78% of cars are domestic, while 16% have been produced in the Far-East and 5.37% in Europe.

The most frequent make-model is the Oldsmobile Cutlass. The unconditional probability of observing it is 0.0263 , while the unconditional probability of observing the most frequent brand, which is Chevrolet, is around 0.2.

The first vintage we observe includes cars whose year of production is before than 1969. The CEX does not deliver a point value for earlier vintages: for cars produced at earlier dates, the survey specifies an interval to which the year of production belongs. Consequently, we do not observe the 1970, 1971, 1973, 1974, 1975, 1976, 1978, 1979, 1980 vintages. We observe 8.62 vintages on average for each make-model, while the number of vintages observed on average for each brand is 11.6.

The CEX records the year and the month of purchase. This information is used to determine how 'old' is the car within the family. Most of cars are bought in the mid of the eighties (8.95% in 1985), while households buy cars mostly in June (12.63%).

Moreover, we use a set of cars' characteristics, such as whether the car has

¹¹In the CEX around 1000 make-models are present each year and for each make-model more than one vintage is present. With 12 years of data, it is immediate to realize that the measurement error arising from moving the data from a paper to an electronic support is potentially very large.

¹²For about 10000 cars neither the make-model nor the brand is observed.

automatic transmission or not, the number of cylinders, whether powerbrake or powersteer are present. It comes out that around 73% of cars in our sample has automatic transmission; the proportion of cars with 4, 6, and 8 cylinders is about the same and is equal to around 1/3; around 80% of cars has powersteer and the same amount has powerbrake. More importantly to our purposes, 75% of cars produced after 1985 are equipped with automatic transmission, while this number lowers down to 71% for cars produced before 1985; the proportion of cars with 4, 6, and 8 cylinders is 45%, 39% and 16% for those cars produced after 1985, while these numbers become 29%, 29% and 41% for those produced before 1985; moreover, 91% of cars produced after 1985 is equipped with powerbrake, while this number drops to 74% for those cars produced before 1985; finally, powersteer is installed in the 90% of cars produced after 1985, while for cars produced before 1985 the proportion is 74%.

Finally, the CEX reports the purchasing price, the trade-in allowances, if any, and the sales price. Those prices are observed for about the 40% of the cars sampled.

These numbers document that the CEX is a potentially very rich source of information for our purpose, which is to offer an *in-sample* measure of the value of the stock of cars. Next, we turn to the results from the main regressions and to some out-of-sample testing.

We estimate equation (2.3). The CEX reports if the cars entered the Consumption Unit as new or used. We sample only these last for the estimation of the value of the stock of the cars, while if the car entered the Consumption Unit as new, we assume that the value of the car coincides with its price at the date when the car has been purchased or sold. Then, the LHS of equation (2.3) is observed only when transactions take place.

We select out those vehicles for which the available information is not sufficient to give a reliable estimate of the price, i.e. those vehicles for which we do not know if they entered as new or used the consumption unit, the make-model, the brand, the area of production and those set of characteristics which are used to proxy for the vintage effect. This leaves us with around 340000 observations.

In table 2.2 we report the results of the estimation of equation (2.3) with quarterly data. The LHS of this regression is the log of prices. After some search, we assume that the time trend is exponential, which makes to include only a linear term in the log specification. We include a second-order polynomial in age. We cross the linear term in age with the make-model

of the car and the quadratic in age with the area of production fixed effect (see equation 2.4 above). To proxy for the vintage effect, we use a set of car characteristics, such as whether the transmission is automatic or not, the number of cylinders, and whether the car is equipped with powerbrake and powersteer.

In table 2.2 we report the analysis of variance for the model in equation 2.3. All the variables contribute at the standard levels to explain the overall variability of the price of cars. Interestingly, there is evidence of heterogeneity in the depreciation patterns of cars. This heterogeneity takes place along two dimensions: we cannot reject that the linear term in age is different across make-model nor we can reject that the quadratic term in age is different across area of production¹³

From table 2.3, where we report the results obtained estimating equation (2.3), it comes out that the age-profile is estimated to be decreasing and convex: the coefficient of the linear term is negative and that of the quadratic term is positive.¹⁴

As an indirect check of the quality of our procedure, we compare the prices so estimated with second-hand market prices observed for a selected sample of make-models. Those make-models are: Chevrolet Camaro, Chrysler New Yorker, Datsun-210, Ford T-Bird, Honda Civic, Oldsmobile Cutlass, Toyota Corolla, Volkswagen Rabbit, Volvo 240. Overall, these make-models cover around 10% of the sample.

In figure 2.1 we plot the estimated (smoothed lines) and the actual price-age profile for those make-models. Each segment represents a vintage¹⁵. Not surprisingly, the estimated profiles are closer to the actual ones for those make-models which are more frequent in the data (in decreasing order: Oldsmobile Cutlass, Toyota Corolla, Chevrolet Camaro, Honda Civic, Ford T-Bird) and while they depart in the tails of the age distribution.

¹³Resource limitation prevents us from crossing the quadratic term in age with the make-model

¹⁴Indeed, the price-age profiles depends also on the make-model and on the area of production of the cars in our specification (see equation 2.4).

¹⁵Because of the way data on vintages are recorded in the CEX, some vintages are not observed, see above.

2.3 A few stylized facts

This section briefly documents few stylized facts. We focus, first, on the life-cycle profile of the stock of cars. Then, we show how the aggregate stock of cars moves over time and compare that measure with the one reported by the Bureau of Economic Analysis (BEA). Furthermore, we focus on the first, the second, third and fourth moments of the cross-sectional distribution of the stock of cars.

The theory has various implications for the life-cycle pattern for the stock of cars. This is not surprising, the same happening with non-durable goods. Mankiw [47] derives and estimates a version of the Hall's model of consumption with the stock of durables, using aggregate data. With quadratic utility and no adjustment costs, the change in the stock of durable should follow a white noise. This implies that we should expect the life-cycle pattern of the stock of cars to be flat.

Bernanke [12] shows that if adjustment costs are convex, the change in the stock of vehicles should follow a AR(1) process, with the autoregressive coefficient depending on the speed at which the actual stock is adjusted to its long-run or equilibrium counterpart. If the AR(1) process is stationary, the stock of cars should be independent of age, which, again, means that an appropriate transformation of the stock of cars exhibit a flat life-cycle pattern.¹⁶

Model with non-convex adjustment costs deliver more complicated predictions on the life-cycle pattern of the stock of cars. Suppose, for instance, that the non-convex adjustment costs depend on age and that the probability of owning a car is zero for individuals aged less than, say, 20 years, but it increases afterwards. This means that the stock of cars should exhibit a step. Furthermore, if after some age, the probability of adjusting upward decreases (and/or that of adjusting downward increases), the dynamics of the stock of vehicles is driven by the depreciation. If this last is positive, the stock of cars should decrease with age. Aggregating, say, over heterogeneous individuals belonging to the same year of birth cohort, would give us a smooth hump-shaped function. This is what is shown in figure 2.2 that plots the life-cycle profile of the stock of cars for 13 year-of-birth cohorts.¹⁷

¹⁶If $\Delta k_{ht} = \rho \Delta k_{ht-1} + \varepsilon_{ht}$, $\rho < 1$, and ε_{ht} is a white noise, the variable $\Delta k_{ht} - \rho \Delta k_{ht-1}$ follows a white noise.

¹⁷Household's head born between 1909-1912 belongs to the first cohorts, those born between 1913-1917 to the second and so on.

Notice, however, that this pattern is not an exclusive feature of non-convex adjustment model, a similar pattern would arise if households were liquidity constrained at the early stage of their life, and not later on. Furthermore, the dynamic on car ownership, much more than that on car expenditure, is likely to be responsible for this pattern, as we can see in figure 2.3 where we plot the percentage of car owners for each year-of-birth cohort. The question of how to distinguish the life-cycle implications of models with non-convex adjustment costs from those of models with liquidity constraints is deferred to future work.

Figure 2.4 plot the aggregate stock of cars based on our household level measure and the aggregate measure derived by the BEA data. The two series match quite closely, except for the late eighties early nineties, when the series constructed using our measure is lower than that constructed using the BEA data. Namely, the CEX series start decreasing in 1988 and rises again in 1991, while the BEA series decreases between 1990 and 1991 in correspondence with the early nineties recession.

The rest of the section is devoted to investigate the business-cycle properties of the first four moments of the cross-sectional distribution of the stock of cars. Figure 2.5 plots the first moment. Its dynamic is similar to that of the aggregate shown in 2.4. Namely, it is seen to decrease in between 1989 and 1990. The standard deviation, which is shown in figure 2.6, drops in 1990, and the same happens to the skewness and the kurtosis, as one can see from figure 2.7 and figure 2.8. We speculate that this is related to the early nineties recession, but at the present stage we do not have a straightforward interpretation for these findings. Further investigation is required, possibly combining the properties of the cross-sectional distribution of the stock of cars with those of intermittent adjustment rule.

2.4 The econometric model and some evidence

This section describes the econometric model and provides some evidence from the estimation of a (s, S) type of rule and is made of two subsections, the first that deals with the econometrics and the second with the results.

The econometric specification follows closely Attanasio [5], to whom we refer for further details. The results are in line with the available evidence on the same data.

2.4.1 The econometric model

The model is specified in terms of a target point, a lower bound and an upper bound for the process z_{it} per i and t index respectively individuals and time. The target is given by:

$$z_{it}^d = \beta w_{it}^d + u_{it}^d \quad (2.5)$$

The lower bound is given by:

$$z_{it}^l = z_{it}^d - \exp(\theta_l w_{it}^b + u_{it}^b) \quad (2.6)$$

The upper bound by:

$$z_{it}^u = z_{it}^d + \exp(\theta_u w_{it}^b + u_{it}^b) \quad (2.7)$$

We assume that u_{it}^d and u_{it}^b are jointly distributed according to a bivariate normal. Moreover, in order to z^d being non-negative, u_{it}^d has to be greater or equal to $-\beta w_{it}^d$. Thus,

$$f(u_{it}^d, u_{it}^b) = \frac{\phi(\varepsilon_{it}^d \varepsilon_{it}^b)}{\Phi(A(\beta, \sigma^d, \rho, \varepsilon_{it}^b)) \sigma_d \sigma_b}$$

where:

$$A(\beta, \sigma^d, \rho, \varepsilon_{it}^b) = \frac{\beta w_{it}^d + \rho \varepsilon_{it}^b}{\sigma_d \sqrt{1 - \rho^2}}$$

$$\varepsilon_{it}^d = \frac{u_{it}^d}{\sigma_d}$$

$$\varepsilon_{it}^b = \frac{u_{it}^b}{\sigma_b}$$

We collect here a list of derivatives that will be useful in what follows.

$$\begin{aligned}
\frac{\partial \varepsilon_{it}^d}{\partial \beta} &= -\frac{w_{it}^d}{\sigma_d} \\
\frac{\partial \varepsilon_{it}^d}{\partial \sigma_d} &= -\frac{\varepsilon_{it}^d}{\sigma_d} \\
\frac{\partial \varepsilon_{it}^b}{\partial \theta^b} &= -\frac{w_{it}^b}{\sigma_b} \\
\frac{\partial \varepsilon_{it}^b}{\partial \sigma_b} &= -\frac{\varepsilon_{it}^b}{\sigma_b} \\
\frac{\partial \varepsilon_{it}^b}{\partial \theta^u} &= -\frac{w_{it}^b}{\sigma_b} \\
\frac{\partial \phi(\varepsilon_{it}^d, \varepsilon_{it}^b)}{\partial \varepsilon_{it}^d} &= -\frac{\varepsilon_{it}^d - \rho \varepsilon_{it}^b}{1 - \rho^2} \phi(\varepsilon_{it}^d, \varepsilon_{it}^b) \\
\frac{\partial \phi(\varepsilon_{it}^d, \varepsilon_{it}^b)}{\partial \varepsilon_{it}^b} &= -\frac{\varepsilon_{it}^b - \rho \varepsilon_{it}^d}{1 - \rho^2} \phi(\varepsilon_{it}^d, \varepsilon_{it}^b) \\
\frac{\partial A(\beta, \sigma^d, \rho, \varepsilon_{it}^b)}{\partial \beta} &= \frac{w_{it}^d}{\sigma_d \sqrt{1 - \rho^2}} \\
\frac{\partial A(\beta, \sigma^d, \rho, \varepsilon_{it}^b)}{\partial \sigma^d} &= -\frac{\beta w_{it}^d}{\sigma_d^2 \sqrt{1 - \rho^2}} \\
\frac{\partial A(\beta, \sigma^d, \rho, \varepsilon_{it}^b)}{\partial \rho} &= \frac{\varepsilon_{it}^b}{1 - \rho^2} \left(1 - \frac{\rho}{2\sqrt{1 - \rho^2}} \right) \\
\frac{\partial A(\beta, \sigma^d, \rho, \varepsilon_{it}^b)}{\partial \varepsilon_{it}^b} &= \frac{\rho}{\sqrt{1 - \rho^2}}
\end{aligned} \tag{2.8}$$

where:

$$\begin{aligned}
\phi(\varepsilon_{it}^d, \varepsilon_{it}^b) &= \frac{1}{2\pi\sqrt{1 - \rho^2}} e^{-q(\varepsilon_{it}^d, \varepsilon_{it}^b)} \\
q(\varepsilon_{it}^d, \varepsilon_{it}^b) &= \frac{\varepsilon_{it}^{d^2} + \varepsilon_{it}^{b^2} - 2\rho\varepsilon_{it}^d\varepsilon_{it}^b}{2(1 - \rho^2)}
\end{aligned}$$

The sampling protocol is the following. The target is observed when individuals “adjust” their process. If individuals upgrade, there are two relevant case. Either the process is continuous and, thus, the lower bound is observed or the process is discrete, which makes a lower bound of z_{it}^l to be observed. Thus, under observable bands:

$$\begin{aligned}
z_{it} &= z_{it}^d \\
z_{it}^- &= z_{it}^l \quad \text{if individuals upgrade} \\
z_{it}^- &= z_{it}^u \quad \text{if individuals downgrade}
\end{aligned}$$

where z_{it}^- is observed before the adjustment. If, instead, the bands are unobservable:

$$\begin{aligned}
z_{it} &= z_{it}^d \\
z_{it}^- &< z_{it}^l \quad \text{if individuals upgrade} \\
z_{it}^- &> z_{it}^u \quad \text{if individuals downgrade}
\end{aligned}$$

Observable bands

Individuals who upgrade

They contribute to the likelihood according to:

$$f(u_{it}^d u_{it}^b)$$

where:

$$\begin{aligned} u_{it}^d &= z_{it} - \beta w_{it}^d \\ u_{it}^b &= \ln(z_{it} - z_{it}^-) - \theta_l w_{it}^b \end{aligned}$$

After taking the logs:

$$\ln \phi(\varepsilon_{it}^d \varepsilon_{it}^b) - \ln \Phi(A(\varepsilon_{it}^b)) - \ln \sigma_d \sigma_b \quad (2.9)$$

where $A(\beta, \sigma^d, \rho, \varepsilon_{it}^b)$ is shortened to $A(\varepsilon_{it}^b)$. Differentiating (2.9) w.r.t. β and θ_l we obtain, respectively:

$$\begin{aligned} &\frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} \left[\frac{\varepsilon_{it}^d - \rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}} - \lambda(-A(\cdot)) \right] \\ &\frac{w_{it}^b}{\sigma_b \sqrt{1-\rho^2}} \left[\frac{\varepsilon_{it}^b - \rho \varepsilon_{it}^d}{\sqrt{1-\rho^2}} - \rho \lambda(-A(\cdot)) \right] \end{aligned}$$

Differentiating (2.9) w.r.t. σ_d , σ_b and ρ we obtain, respectively:

$$\begin{aligned} &\frac{1}{\sigma_d} \left(\varepsilon_{it}^d \frac{\varepsilon_{it}^d - \rho \varepsilon_{it}^b}{1-\rho^2} - \lambda(-A(\cdot)) \left(\frac{\rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}} - A(\beta, \sigma^d, \rho, \varepsilon_{it}^b) \right) - 1 \right) \\ &\frac{1}{\sigma_b} \left(\varepsilon_{it}^b \frac{\varepsilon_{it}^b - \rho \varepsilon_{it}^d}{1-\rho^2} + \lambda(-A(\cdot)) \frac{\rho \varepsilon_{it}^d}{\sqrt{1-\rho^2}} - 1 \right) \\ &-\lambda(A(\cdot)) A_\rho(\cdot) + 4\pi^2 \left(\rho - \frac{2}{\sqrt{1-\rho^2}} q(\varepsilon_{it}^d, \varepsilon_{it}^b) + \varepsilon_{it}^d \varepsilon_{it}^b \right) \end{aligned}$$

where:

$$\lambda(-A(\cdot)) = \frac{\phi(-A(\cdot))}{1 - \Phi(-A(\cdot))}$$

Individuals who downgrade

They contribute to the likelihood according to:

$$f(u_{it}^d u_{it}^b)$$

where:

$$\begin{aligned} u_{it}^d &= z_{it} - \beta w_{it}^d \\ u_{it}^b &= \ln(z_{it}^- - z_{it}) - \theta_u w_{it}^b \end{aligned}$$

Differentiating with respect $\beta, \theta_u, \sigma_d, \sigma_b$ and ρ we obtain the same as above.

Individuals with at least one car who do not do anything

They contribute to the likelihood according to:

$$\int_H^{+\infty} \int_{\psi_2(u_{it}^b)}^{\psi_1(u_{it}^b)} f(u_{it}^d u_{it}^b) du_{it}^d du_{it}^b + \\ + \int_{-\infty}^{-\beta w_{it}^d} \int_{\ln z_{it}^{max} - \theta_u w_{it}^b}^{+\infty} f(u_{it}^d u_{it}^b) du_{it}^d du_{it}^b$$

where:

$$H = \begin{cases} \log(z_{it}^{max} - z_{it}^{min}) - \log(e^{\theta_u w_{it}^b} + e^{\theta_l w_{it}^b}) & \text{if } z_{it}^{max} > z_{it}^{min} \\ -\infty & \text{if } z_{it}^{max} = z_{it}^{min} \end{cases}$$

and

$$\psi_1(u_{it}^b) = z_{it}^{min} + e^{\theta_l w_{it}^b + u_{it}^b} - \beta w_{it}^d \\ \psi_2(u_{it}^b) = \begin{cases} z_{it}^{max} - e^{\theta_u w_{it}^b + u_{it}^b} - \beta w_{it}^d & \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u_{it}^b} > 0 \\ -\beta w_{it}^d & \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u_{it}^b} \leq 0 \end{cases}$$

To the purpose of obtaining the first order conditions, notice that:

$$\frac{\partial H}{\partial \beta} = 0 \\ \frac{\partial H}{\partial \theta_l} = -\frac{w_{it}^b e^{\theta_l w_{it}^b}}{e^{\theta_u w_{it}^b} + e^{\theta_l w_{it}^b}} \\ \frac{\partial H}{\partial \theta_u} = -\frac{w_{it}^b e^{\theta_u w_{it}^b}}{e^{\theta_u w_{it}^b} + e^{\theta_l w_{it}^b}}$$

and that:

$$\frac{\partial \psi_1(u_{it}^b)}{\partial \beta} = \frac{\partial \psi_2(u_{it}^b)}{\partial \beta} = -w_{it}^d \\ \frac{\partial \psi_1(u_{it}^b)}{\partial \theta_l} = w_{it}^b e^{\theta_l w_{it}^b + u_{it}^b} \\ \frac{\partial \psi_2(u_{it}^b)}{\partial \theta_u} = \begin{cases} -w_{it}^b e^{\theta_u w_{it}^b + u_{it}^b} & \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u_{it}^b} > 0 \\ 0 & \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u_{it}^b} \leq 0 \end{cases} \\ \frac{\partial \psi_1(u_{it}^b)}{\partial \theta_u} = \frac{\partial \psi_2(u_{it}^b)}{\partial \theta_l} = 0$$

After some algebra and taking the logs, it becomes:

$$\ln\{\Delta_1(H, \beta, \theta_l, \sigma_d, \sigma_b, \rho) - \Delta_2(H, \beta, \theta_u, \sigma_d, \sigma_b, \rho) + \\ + \Gamma(\beta, \theta_u, \sigma_d, \sigma_b, \rho)\} \quad (2.10)$$

where:

$$\Delta_1(H, \beta, \theta_l, \sigma_d, \sigma_b, \rho) = \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \Phi\left(\frac{\frac{\psi_1(\sigma_b \varepsilon_{it}^b)}{\sigma_d} - \rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}}\right) d\varepsilon_{it}^b \quad (2.11)$$

$$\Delta_2(H, \beta, \theta_u, \sigma_d, \sigma_b, \rho) = \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \Phi\left(\frac{\frac{\psi_2(\sigma_b \varepsilon_{it}^b)}{\sigma_d} - \rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}}\right) d\varepsilon_{it}^b \quad (2.12)$$

$$\Gamma(\beta, \theta_u, \sigma_d, \sigma_b, \rho) = \int_{\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \Phi\left(-\frac{\frac{\beta w_{it}^d}{\sigma_d} + \rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}}\right) d\varepsilon_{it}^b \quad (2.13)$$

where:

$$\phi^*(\varepsilon_{it}^b) = \frac{\phi(\varepsilon_{it}^b)}{\Phi(A(\cdot))}$$

By definition, $\Delta_1(\infty, \beta, \theta_l, \sigma_d, \sigma_b, \rho) = \Delta_1(\beta, \theta_l, \sigma_d, \sigma_b, \rho)$ and $\Delta_2(\infty, \beta, \theta_u, \sigma_d, \sigma_b, \rho) = \Delta_2(\beta, \theta_u, \sigma_d, \sigma_b, \rho)$. To keep the expression as narrow as possible, we introduce further notation. Define:

$$B_1(\varepsilon_{it}^b) = \frac{\frac{\psi_1(\sigma_b \varepsilon_{it}^b)}{\sigma_d} - \rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}}$$

$$B_2(\varepsilon_{it}^b) = \frac{\frac{\psi_2(\sigma_b \varepsilon_{it}^b)}{\sigma_d} - \rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}}$$

Differentiating (2.11) w.r.t. β and θ_l respectively, we obtain:

$$\begin{aligned} & -\frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_1(\cdot)) \left[1 + \frac{\lambda(A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))}\right] d\varepsilon_{it}^b \\ & -\frac{w_{it}^b}{\sigma_b} \left\{ \frac{\phi^*\left(\frac{H}{\sigma_b}\right) \Phi\left(B_1\left(\frac{H}{\sigma_b}\right)\right)}{1 + e^{\theta_u w_{it}^b}} - \frac{1}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_1(\varepsilon_{it}^b)) \left[\frac{\sigma_b}{\sigma_d} e^{\theta_l w_{it}^b + \sigma_b \varepsilon_{it}^b} \right. \right. \\ & \left. \left. - \rho \frac{\lambda(A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))} d\varepsilon_{it}^b \right] \right\} \end{aligned}$$

Differentiating (2.11) w.r.t. σ_b , σ_d and ρ respectively, we obtain:

$$\begin{aligned} & \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_1(\varepsilon_{it}^b)) \left[\frac{\psi_1(\sigma_b \varepsilon_{it}^b)}{\sigma_d^2 \sqrt{1-\rho^2}} + A_{\sigma_d} \frac{\lambda(-A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \\ & -\frac{1}{\sigma_b} \left\{ \frac{\phi^*\left(\frac{H}{\sigma_b}\right) \Phi\left(B_1\left(\frac{H}{\sigma_b}\right)\right)}{\sigma_b} + \frac{\rho}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \frac{\varepsilon_{it}^b}{\sigma_b} \phi^*(\varepsilon_{it}^b) \phi(B_1(\varepsilon_{it}^b)) \left[1 + \frac{\lambda(-A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))}\right] d\varepsilon_{it}^b \right\} \\ & - \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_1(\varepsilon_{it}^b)) \left[\frac{B_1(\varepsilon_{it}^b)}{2(1-\rho^2)} + \frac{\lambda(-A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \end{aligned}$$

Differentiating (2.12) w.r.t. β and θ_u respectively, we obtain:

$$\begin{aligned}
& -\frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_2(\cdot)) \left[1 + \frac{\lambda(A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))}\right] d\varepsilon_{it}^b \\
& -\frac{w_{it}^b}{\sigma_b} \left\{ \frac{\phi^*\left(\frac{H}{\sigma_b}\right) \Phi\left(B_2\left(\frac{H}{\sigma_b}\right)\right)}{1+e^{\theta_u w_{it}^b}} - \frac{1}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_2(\varepsilon_{it}^b)) \left[\frac{\sigma_b}{\sigma_d} e^{\theta_u w_{it}^b + \sigma_b \varepsilon_{it}^b}\right. \right. \\
& \left. \left. - \rho \frac{\lambda(A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} d\varepsilon_{it}^b\right]\right\} \quad \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u} \\
& -\frac{w_{it}^b}{\sigma_b} \left[\frac{\phi^*\left(\frac{H}{\sigma_b}\right) \Phi\left(B_2\left(\frac{H}{\sigma_b}\right)\right)}{1+e^{\theta_l w_{it}^b}} + \frac{\rho}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_2(\varepsilon_{it}^b)) \frac{\lambda(A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} d\varepsilon_{it}^b \right] \quad \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u}
\end{aligned}$$

Differentiating (2.12) w.r.t. σ_b , σ_d and ρ respectively, we obtain:

$$\begin{aligned}
& \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_2(\varepsilon_{it}^b)) \left[\frac{\psi_1(\sigma_b \varepsilon_{it}^b)}{\sigma_d^2 \sqrt{1-\rho^2}} + A_{\sigma_d} \frac{\lambda(-A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \\
& -\frac{1}{\sigma_b} \left\{ \frac{\phi^*\left(\frac{H}{\sigma_b}\right) \Phi\left(B_2\left(\frac{H}{\sigma_b}\right)\right)}{\sigma_b} + \frac{\rho}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \frac{\varepsilon_{it}^b}{\sigma_b} \phi^*(\varepsilon_{it}^b) \phi(B_2(\varepsilon_{it}^b)) \left[1 + \frac{\lambda(-A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))}\right] d\varepsilon_{it}^b \right\} \\
& -\int_{\frac{H}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_2(\varepsilon_{it}^b)) \left[\frac{B_2(\varepsilon_{it}^b)}{2(1-\rho^2)} + \frac{\lambda(-A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b
\end{aligned}$$

Differentiating (2.13) w.r.t. β and θ_u respectively, we obtain:

$$\begin{aligned}
& -\frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} \int_{\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(-A(\cdot)) \left[1 - \frac{\lambda(-A(\cdot))}{\lambda(A(\cdot))}\right] d\varepsilon_{it}^b \\
& -\frac{w_{it}^b}{\sigma_b} \left[\phi\left(\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b}\right) \Phi\left(-\frac{\sigma_b \beta w_{it}^d + \rho \sigma_d (\ln z_{it}^{max} - \theta_u w_{it}^b)}{\sigma_d \sigma_b \sqrt{1-\rho^2}}\right) \right. \\
& \left. - \int_{\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \lambda(-A(\cdot)) \Phi(-A(\cdot)) d\varepsilon_{it}^b \right]
\end{aligned}$$

Differentiating (2.13) w.r.t. σ_b , σ_d and ρ respectively, we obtain:

$$\begin{aligned}
& -\frac{\beta w_{it}^d}{\sigma_d^2 \sqrt{1-\rho^2}} \int_{\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(-A(\cdot)) \left[1 - \frac{\lambda(-A(\cdot))}{\lambda(A(\cdot))}\right] d\varepsilon_{it}^b \\
& -\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b^2} \phi\left(\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b}\right) \Phi\left(-\frac{\sigma_b \beta w_{it}^d + \rho \sigma_d (\ln z_{it}^{max} - \theta_u w_{it}^b)}{\sigma_d \sigma_b \sqrt{1-\rho^2}}\right) + \\
& -\frac{\rho}{\sqrt{1-\rho^2}} \int_{\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b}}^{+\infty} \frac{\varepsilon_{it}^b}{\sigma_b} \phi^*(\varepsilon_{it}^b) \phi(-A(\cdot)) \left[1 + \frac{\lambda(-A(\cdot))}{\lambda(A(\cdot))}\right] d\varepsilon_{it}^b \\
& \left(1 - \frac{\rho}{\sqrt{1-\rho^2}}\right) \int_{\frac{\ln z_{it}^{max} - \theta_u w_{it}^b}{\sigma_b}}^{+\infty} \frac{\varepsilon_{it}^b}{1-\rho^2} \phi^*(\varepsilon_{it}^b) \phi(-A(\cdot)) \left[1 + \frac{\lambda(-A(\cdot))}{\lambda(A(\cdot))}\right] d\varepsilon_{it}^b
\end{aligned}$$

Individuals with no cars at the beginning of the period and at least one at the end

They contribute to the likelihood according to:

$$\int_{\ln z_{it} - \theta_l w_{it}^b}^{+\infty} f(u_{it}^d u_{it}^b) du_{it}^b$$

After some algebra it becomes:

$$\phi(\varepsilon_{it}^d) + \int_{\frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}}^{+\infty} \phi^*(\varepsilon_{it}^b) d\varepsilon_{it}^b \quad (2.14)$$

Differentiating (2.14) w.r.t. β , we obtain:

$$\frac{w_{it}^d}{\sigma_d} [\varepsilon_{it}^d \phi(\varepsilon_{it}^d) - \int_{\frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(-A(\varepsilon_{it}^b)) \lambda(-A(\varepsilon_{it}^b)) d\varepsilon_{it}^b]$$

Differentiating (2.14) w.r.t. θ_l , we obtain:

$$-\frac{w_{it}^b}{\sigma_b \sqrt{1 - \rho^2}} \left[\frac{\phi^*\left(\frac{\ln z_{it} - \theta_l w_{it}^b}{\sigma_b}\right)}{\sigma_b} + \rho \int_{\frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}}^{+\infty} \phi^*(\varepsilon_{it}^b) \lambda(-A(\varepsilon_{it}^b)) d\varepsilon_{it}^b \right]$$

Differentiating (2.14) w.r.t. σ_d , σ_b and ρ , we obtain, respectively:

$$\begin{aligned} & \frac{\phi(\varepsilon_{it}^d) \varepsilon_{it}^{d^2}}{\sigma_d} + \frac{\beta w_{it}^d}{\sigma_d^2 \sqrt{1 - \rho^2}} \int_{\frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}}^{+\infty} \phi^*(\varepsilon_{it}^b) \lambda(-A(\varepsilon_{it}^b)) d\varepsilon_{it}^b \\ & - \frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b^2 \sqrt{1 - \rho^2}} \phi^*\left(\frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}\right) - \frac{\rho}{\sigma_b \sqrt{1 - \rho^2}} \int_{\frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}}^{+\infty} \varepsilon_{it}^b \phi^*(\varepsilon_{it}^b) \lambda(-A(\varepsilon_{it}^b)) d\varepsilon_{it}^b \\ & 2\rho \frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b^2 \sqrt{1 - \rho^2}} \phi^*\left(\frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}\right) + \\ & - \frac{1}{1 - \rho^2} \left(1 - \frac{\rho}{2\sqrt{1 - \rho^2}}\right) \int_{\frac{\ln z_{it} - \theta_l w_{it}^b - \rho \sigma_b \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}}^{+\infty} \varepsilon_{it}^b \phi^*(\varepsilon_{it}^b) \lambda(-A(\varepsilon_{it}^b)) d\varepsilon_{it}^b \end{aligned}$$

Individuals with at least one car at the beginning of the period and no cars at the end

They contribute to the likelihood according to:

$$\int_{-\infty}^{-\beta w_{it}^d} f(u_{it}^d u_{it}^b) du_{it}^d$$

where:

$$u_{it}^b = \ln(z_{it}^- - z_{it}) - \theta_u w_{it}^b$$

After some algebra and taking the logs, it becomes:

$$\ln \phi(\varepsilon_{it}^b) + \ln \Phi(-A(\beta w_{it}^d, \sigma^d, \rho, \varepsilon_{it}^b)) - \ln \Phi(A(\beta w_{it}^d, \sigma^d, \rho, \varepsilon_{it}^b)) \quad (2.15)$$

Differentiating (2.15) w.r.t. β we obtain:

$$-\frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} [\lambda(A(\varepsilon_{it}^b)) + \lambda(A(\varepsilon_{it}^b))]$$

Differentiating (2.15) w.r.t. θ_u we obtain:

$$\varepsilon_{it}^b \left\{ w_{it}^b \sigma_b - \frac{\rho}{\sqrt{1-\rho^2}} [\lambda(-A(\varepsilon_{it}^b)) + \lambda(A(\varepsilon_{it}^b))] \right\}$$

Differentiating (2.15) w.r.t. σ_d , σ_b and ρ we obtain:

$$\begin{aligned} & -\frac{\beta w_{it}^d}{\sigma_d} [\lambda(-A(\varepsilon_{it}^b)) + \lambda(A(\varepsilon_{it}^b))] \\ & -\frac{\varepsilon_{it}^b}{\sigma_b} \left\{ \varepsilon_{it}^b + \frac{\rho}{\sqrt{1-\rho^2}} [\lambda(-A(\varepsilon_{it}^b)) + \lambda(A(\varepsilon_{it}^b))] \right\} \\ & -\frac{\varepsilon_{it}^b}{1-\rho^2} \left(1 - \frac{\rho}{2\sqrt{1-\rho^2}} \right) [\lambda(-A(\varepsilon_{it}^b)) + \lambda(A(\varepsilon_{it}^b))] \end{aligned}$$

Individuals with no cars throughout the sample period

They contribute to the likelihood with:

$$\begin{aligned} & \int_{-\infty}^{+\infty} \int_{\psi_2(u_{it}^b)}^{\psi_1(u_{it}^b)} f(u_{it}^d u_{it}^b) du_{it}^d du_{it}^b + \\ & + \int_{-\infty}^{-\beta w_{it}^d} f(u_{it}^d) du_{it}^d \end{aligned}$$

that after some algebra and taking logs becomes:

$$\begin{aligned} & \ln \{ \Delta_1(\beta, \theta_l, \sigma_d, \sigma_b, \rho) - \Delta_2(\beta, \theta_u, \sigma_d, \sigma_b, \rho) + \\ & + \Phi\left(-\frac{\beta w_{it}^d}{\sigma_d}\right) \} \quad (2.16) \end{aligned}$$

Differentiating $\Delta_1(\beta, \theta_l, \sigma_d, \sigma_b, \rho)$ w.r.t. β and θ_l respectively, we obtain:

$$\begin{aligned} & -\frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} \int_{-\infty}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_1(\cdot)) \left[1 + \frac{\lambda(A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \\ & -\frac{w_{it}^b}{\sigma_b \sqrt{1-\rho^2}} \int_{-\infty}^{+\infty} \phi^*(\varepsilon_{it}^b) \phi(B_1(\varepsilon_{it}^b)) \left[\frac{\sigma_b}{\sigma_d} e^{\theta_l w_{it}^b + \sigma_b \varepsilon_{it}^b} \right. \\ & \left. - \rho \frac{\lambda(A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))} d\varepsilon_{it}^b \right] \end{aligned}$$

Differentiating (2.11) w.r.t. σ_b , σ_d and ρ respectively, we obtain:

$$\begin{aligned} & \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^* (\varepsilon_{it}^b) \phi (B_1 (\varepsilon_{it}^b)) \left[\frac{\psi_1 (\sigma_b \varepsilon_{it}^b)}{\sigma_d^2 \sqrt{1-\rho^2}} + A_{\sigma_d} \frac{\lambda(-A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \\ & - \frac{1}{\sigma_b} \left\{ \frac{\phi^* \left(\frac{H}{\sigma_b} \right) \Phi \left(B_1 \left(\frac{H}{\sigma_b} \right) \right)}{\sigma_b} + \frac{\rho}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \frac{\varepsilon_{it}^b}{\sigma_b} \phi^* (\varepsilon_{it}^b) \phi (B_1 (\varepsilon_{it}^b)) \left[1 + \frac{\lambda(-A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \right\} \\ & - \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^* (\varepsilon_{it}^b) \phi (B_1 (\varepsilon_{it}^b)) \left[\frac{B_1 (\varepsilon_{it}^b)}{2(1-\rho^2)} + \frac{\lambda(-A(\cdot))}{\lambda(-B_1(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \end{aligned}$$

Differentiating (2.12) w.r.t. β and θ_u respectively, we obtain:

$$\begin{aligned} & - \frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^* (\varepsilon_{it}^b) \phi (B_2 (\cdot)) \left[1 + \frac{\lambda(A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \\ & - \frac{w_{it}^b}{\sigma_b} \left\{ \frac{\phi^* \left(\frac{H}{\sigma_b} \right) \Phi \left(B_2 \left(\frac{H}{\sigma_b} \right) \right)}{1+e^{\theta_u w_{it}^b}} - \frac{1}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^* (\varepsilon_{it}^b) \phi (B_2 (\varepsilon_{it}^b)) \left[\frac{\sigma_b}{\sigma_d} e^{\theta_u w_{it}^b + \sigma_b \varepsilon_{it}^b} \right. \right. \\ & \left. \left. - \rho \frac{\lambda(A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \right\} \quad \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u} \\ & - \frac{w_{it}^b}{\sigma_b} \left[\frac{\phi^* \left(\frac{H}{\sigma_b} \right) \Phi \left(B_2 \left(\frac{H}{\sigma_b} \right) \right)}{1+e^{\theta_l w_{it}^b}} + \frac{\rho}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^* (\varepsilon_{it}^b) \phi (B_2 (\varepsilon_{it}^b)) \frac{\lambda(A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \quad \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u} \end{aligned}$$

Differentiating (2.12) w.r.t. σ_b , σ_d and ρ respectively, we obtain:

$$\begin{aligned} & \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^* (\varepsilon_{it}^b) \phi (B_2 (\varepsilon_{it}^b)) \left[\frac{\psi_1 (\sigma_b \varepsilon_{it}^b)}{\sigma_d^2 \sqrt{1-\rho^2}} + A_{\sigma_d} \frac{\lambda(-A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \\ & - \frac{1}{\sigma_b} \left\{ \frac{\phi^* \left(\frac{H}{\sigma_b} \right) \Phi \left(B_2 \left(\frac{H}{\sigma_b} \right) \right)}{\sigma_b} + \frac{\rho}{\sqrt{1-\rho^2}} \int_{\frac{H}{\sigma_b}}^{+\infty} \frac{\varepsilon_{it}^b}{\sigma_b} \phi^* (\varepsilon_{it}^b) \phi (B_2 (\varepsilon_{it}^b)) \left[1 + \frac{\lambda(-A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \right\} \\ & - \int_{\frac{H}{\sigma_b}}^{+\infty} \phi^* (\varepsilon_{it}^b) \phi (B_2 (\varepsilon_{it}^b)) \left[\frac{B_2 (\varepsilon_{it}^b)}{2(1-\rho^2)} + \frac{\lambda(-A(\cdot))}{\lambda(-B_2(\varepsilon_{it}^b))} \right] d\varepsilon_{it}^b \end{aligned}$$

Differentiating $\Delta_1 (\beta, \theta_l, \sigma_d, \sigma_b, \rho)$ w.r.t. β and θ_l respectively, we obtain:

$$\begin{aligned} & - \frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} \int_{-\infty}^{+\infty} \phi (\varepsilon_{it}^b) \phi \left(\frac{\psi_1 (\sigma_b \varepsilon_{it}^b) - \rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}} \right) d\varepsilon_{it}^b \\ & - \frac{w_{it}^b e^{\theta_l w_{it}^b}}{\sigma_d \sqrt{1-\rho^2}} \int_{-\infty}^{+\infty} e^{\sigma_b \varepsilon_{it}^b} \phi (\varepsilon_{it}^b) \phi \left(\frac{\psi_1 (\sigma_b \varepsilon_{it}^b) - \rho \varepsilon_{it}^b}{\sqrt{1-\rho^2}} \right) d\varepsilon_{it}^b \end{aligned}$$

Differentiating $\Delta_2(\beta, \theta_u, \sigma_d, \sigma_b)$ w.r.t. β and θ_u respectively, we obtain:

$$\begin{aligned}
& -\frac{w_{it}^d}{\sigma_d \sqrt{1-\rho^2}} \int_{-\infty}^{+\infty} \phi(\varepsilon_{it}^b) \phi\left(\frac{\psi_2(\sigma_b \varepsilon_{it}^b) - \rho \varepsilon_{it}^b}{\sigma_d \sqrt{1-\rho^2}}\right) d\varepsilon_{it}^b \\
& -\frac{w_{it}^b e^{\theta_u w_{it}^b}}{\sigma_d \sqrt{1-\rho^2}} \int_{-\infty}^{+\infty} e^{\sigma_b \varepsilon_{it}^b} \phi(\varepsilon_{it}^b) \phi\left(\frac{\psi_2(\varepsilon_{it}^b) - \rho \varepsilon_{it}^b}{\sigma_d \sqrt{1-\rho^2}}\right) d\varepsilon_{it}^b \quad \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u_{it}^b} > 0 \\
& 0 \quad \quad \quad \text{if } z_{it}^{max} - e^{\theta_u w_{it}^b + u_{it}^b} \leq 0
\end{aligned}$$

Unobservable bands

If bands are unobservable, those individuals who up-grade, down-grade and down-grade to zero contribute to the likelihood in different way from above.

Individuals who upgrade

They contribute to the likelihood with:

$$\int_{-\infty}^{\ln(z_{it} - z_{it}^-) - \theta_l w_{it}^b} f(u_{it}^d, u_{it}^b) du_{it}^b$$

After some algebra and taking the logs, we obtain:

$$\ln \phi(\varepsilon_{it}^d) + \ln \Phi\left(\frac{\ln(z_{it} - z_{it}^-) - \theta_l w_{it}^b}{\sigma_b \sqrt{1-\rho^2}}\right) - \ln[1 - \Phi\left(-\frac{\beta w_{it}^d}{\sigma_d}\right)] \quad (2.17)$$

Differentiating (2.17) w.r.t. β and θ_l respectively, the following is obtained:

$$\begin{aligned}
& \frac{w_{it}^d}{\sigma_d} \left[\varepsilon_{it}^d + \frac{\rho}{\sqrt{1-\rho^2}} \lambda \left(\frac{\ln(z_{it} - z_{it}^-) - \theta_l w_{it}^b - \rho \varepsilon_{it}^d}{\sigma_b \sqrt{1-\rho^2}} \right) - \lambda \left(-\frac{\beta w_{it}^d}{\sigma_d} \right) \right] \\
& \frac{w_{it}^b}{\sigma_b \sqrt{1-\rho^2}} \lambda \left(\frac{\ln(z_{it} - z_{it}^-) - \theta_l w_{it}^b - \rho \varepsilon_{it}^d}{\sigma_b \sqrt{1-\rho^2}} \right)
\end{aligned}$$

Individuals who downgrade

They contribute to the likelihood with:

$$\int_{-\infty}^{\ln(z_{it}^- - z_{it}) - \theta_u w_{it}^b} f(u_{it}^d, u_{it}^b) du_{it}^b$$

After some algebra and taking the logs, we obtain:

$$\ln \phi(\varepsilon_{it}^d) + \ln \Phi\left(\frac{\ln(z_{it}^- - z_{it}) - \theta_u w_{it}^b}{\sigma_b \sqrt{1 - \rho^2}}\right) - \ln[1 - \Phi\left(-\frac{\beta w_{it}^d}{\sigma_d}\right)] \quad (2.18)$$

Differentiating (2.18) w.r.t. β and θ_u respectively, the following is obtained:

$$\begin{aligned} \frac{w_{it}^d}{\sigma_d} [\varepsilon_{it}^d + \frac{\rho}{\sqrt{1 - \rho^2}} \lambda\left(\frac{\ln(z_{it}^- - z_{it}) - \theta_u w_{it}^b - \rho \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}\right) - \lambda\left(-\frac{\beta w_{it}^d}{\sigma_d}\right)] \\ - \frac{w_{it}^b}{\sigma_b \sqrt{1 - \rho^2}} \lambda\left(\frac{\ln(z_{it}^- - z_{it}) - \theta_u w_{it}^b - \rho \varepsilon_{it}^d}{\sigma_b \sqrt{1 - \rho^2}}\right) \end{aligned}$$

Individuals with at least one car at the beginning of the period and no cars at the end

They contribute to the likelihood with:

$$\int_{-\infty}^{-\beta w_{it}^d} \int_{-\infty}^{\ln z_{it}^- - \theta_u w_{it}^b} f(u_{it}^d u_{it}^b) du_{it}^d du_{it}^b$$

After some algebra and taking the logs, we obtain:

$$\ln \int_{-\infty}^{\frac{\ln z_{it}^- - \theta_u w_{it}^b}{\sigma_b}} \phi(\varepsilon_{it}^b) \Phi\left(-\frac{\beta w_{it}^d + \rho \sigma_d \varepsilon_{it}^b}{\sigma_d \sqrt{1 - \rho^2}}\right) d\varepsilon_{it}^b - \ln[1 - \Phi\left(-\frac{\beta w_{it}^d}{\sigma_d}\right)] \quad (2.19)$$

Differentiating (2.19) w.r.t. β and θ_u we obtain, respectively:

$$\begin{aligned} -\frac{w_{it}^d}{\sigma_d} \left[\frac{\int_{-\infty}^{\frac{\ln z_{it}^- - \theta_u w_{it}^b}{\sigma_b}} \phi(\varepsilon_{it}^b) \phi\left(-\frac{\beta w_{it}^d + \rho \sigma_d \varepsilon_{it}^b}{\sigma_d \sqrt{1 - \rho^2}}\right) d\varepsilon_{it}^b}{\sqrt{1 - \rho^2} \left(\int_{-\infty}^{\frac{\ln z_{it}^- - \theta_u w_{it}^b}{\sigma_b}} \phi(\varepsilon_{it}^b) \Phi\left(-\frac{\beta w_{it}^d + \rho \sigma_d \varepsilon_{it}^b}{\sigma_d \sqrt{1 - \rho^2}}\right) d\varepsilon_{it}^b \right)} - \lambda\left(-\frac{\beta w_{it}^d}{\sigma_d}\right) \right] \\ - w_{it}^b \left(\frac{\phi\left(\frac{\ln z_{it}^- - \theta_u w_{it}^b}{\sigma_b}\right) \Phi\left(-\frac{\beta w_{it}^d + \rho \sigma_d (\ln z_{it}^- - \theta_u w_{it}^b)}{\sigma_d \sqrt{1 - \rho^2}}\right)}{\sigma_b \left(\int_{-\infty}^{\frac{\ln z_{it}^- - \theta_u w_{it}^b}{\sigma_b}} \phi(\varepsilon_{it}^b) \Phi\left(-\frac{\beta w_{it}^d + \rho \sigma_d \varepsilon_{it}^b}{\sigma_d \sqrt{1 - \rho^2}}\right) d\varepsilon_{it}^b \right)} \right) \end{aligned}$$

This concludes the description of the econometric model. We tried to show how each household in the sample contribute to the likelihood and what identifies the parameters of interest. Next, we provide some evidence and we test the econometric model on our new data.

2.4.2 Some evidence

Before discussing the results of the estimation of the (s,S) rules, we provide some preliminary evidence. Table 2.4 breaks down the sample by type of action: it reports the percentage of households with no cars, upgrading, upgrading from zero, downgrading, downgrading to zero and that of households who do not do anything. We find that around half of the sample does nothing, which is in favor of a model with non-convex adjustment cost. We also find a high percentage of households upgrading, around 21%, downgrading, around 10%.

We run a number of probits relating heterogeneity at the household's level to the probability of upgrading and downgrading. This is done in table 2.5. The first column of table 2.5 splits the sample in two parts, those who upgrade and those who not upgrade. The same does the second column of table 2.5 distinguishing between those who downgrade and those who do not. Given that most of households are inactive, i.e. do not actively modify their stock of cars (see table 2.4), the results could be interpreted taking those who do not do anything as a reference group.¹⁸ The probability of upgrading and that of downgrading are increasing and concave function of age, as the first two rows of table 2.5 show. The higher the number of males and females over 16, the higher is the probability of both upgrading and downgrading, which implies that households with bigger number of adults modify more actively their stock of cars. This is probably related to the effect of family-size mixed with that of the age structure of the household. On one hand, households with more adults need to upgrade, since bigger family need larger cars. On the other, as the family ages, it becomes more likely to downgrade. The results in the third row, where we control for the number of children between 3 and 15 years, go into this direction: the higher the number of children between 3 and 15 years, the higher the probability of upgrading, while the effect on the probability of downgrading is not statistically significant. This is probably due to the fact that households with children in schooling age need larger (or more) cars, a feature that is partially confirmed by the results in the fourth row, where the number of infants is found not to affect the probability of upgrading and downgrading. Households headed by a black are less likely both to upgrade and to downgrade. Those households are more likely to be

¹⁸Alternatively, we have run a multinomial logit in which we explicitly set as reference group those who do not actively modify their stock of cars. This did not lead to qualitatively different results.

inactive, even though they own at least a car, as we show below. Given that households headed by black come generally from poorer background, and are likely to be liquidity constrained, they probably delay the replacement of the old car. High school dropout are less likely to upgrade than college graduate. If education proxies for the permanent income, this result says that the probability of upgrading is positively affected by permanent income. The probability of downgrading, instead, behaves in the opposite way. It is negatively related to permanent income: the lower permanent income, the higher is the probability of downgrading. This is confirmed in the ninth row, where we relate the probability of downgrading to whether the household head is a high school graduate. However, the probability of upgrading is not affected by the head being a high school graduate, which suggests that the dependency of the probability of upgrading on the permanent income is not that strong.¹⁹ Households headed by single earners and those with a female head are less likely to be active, i.e. either to upgrade or to downgrade their stock of cars. These results are similar to that for households headed by a black and are interpreted in the same way. Finally, the probability of upgrading is lower, the higher is the stock of cars at the beginning of period, and the probability of downgrading is higher, the lower is the stock of cars at the beginning of period. This is in accordance with the intuition that action is more likely to take place, when the stock of cars is close to the borders of the inaction region and that the sign of the action depends on whether the stock of cars is closer to the minimum or to the maximum deviation from the target level.

The results reported in table 2.6 are specular to that in table 2.5. The first column refers to the probability of doing nothing and not owning cars, the second to the probability of doing nothing and owning at least one car. The probability of doing nothing is a decreasing and convex function of age. The coefficient on the number of males and females over 16 has a similar interpretation as in table 2.6. If the number of children increases the probability of doing nothing decreases if the household owns at least one car, but it increases if households do not own any car. The number of infants does not affect the probability of doing nothing. Households headed by a black are more likely to do nothing, if they do not own any car, but they are less likely to do nothing if they own at least one car. The same happens with high

¹⁹Possibly, the difference in permanent income between high school and college graduate affects the probability of downgrading, but not that of upgrading.

school drop out, high school graduate and households headed by females. On the contrary, single earners households are less likely to do nothing, if they do not own any car, and they are more likely do nothing if they own at least a car.

Table 2.7 estimates (s, S) rules assuming that the bands are observable. The first column refers to the target equation, the second to the upper bound and the third to the lower bound. We use the same control as in table 2.6 and we include a full set of year dummies in the target equation. We find that the target and the lower band are decreasing and convex function of age, while the upper band is increasing. This means that the inaction range is increasing with age and that households headed by older individuals adjust to lower stock of cars. Moreover, the higher the number of adults, the higher the target, and the lower are the two bands. In particular, if the number of males or females over 16 increases the upper band decreases more than the lower band, thus implying that the higher the number of adults, the smaller the inaction range. The number of children and infants reduces the target, the upper and the lower bands. Households headed by a black have (slightly) higher target, upper and lower band. The inaction range is, however, bigger for those household. High school drop out and high school graduate have a smaller target than college graduate. Furthermore, the upper band is higher and the lower band is lower, thus implying that college graduate have a smaller inaction range. The same interpretation applies to single earners households and to households headed by a female, who have lower target and bigger inaction range.

Table 2.8 estimates (s, S) rules assuming that the bands are unobservable. The results are qualitatively similar to those in table 2.7. Again the target and the bands are decreasing and convex function of age. The target increases with the number of adults, both males and females, and the inaction range roughly stay the same. The target also decreases with the number of children and the inaction range increases. On the other hand, the number of infants has a positive effect on the target and affect roughly in the same way the upper and the lower band. Households headed by black have a lower target and a bigger inaction range. High school drop out and graduate have lower target than college graduate, but smaller inaction range. Finally, single earner households and households headed by a female have lower target, higher upper and lower bands.

2.5 Conclusions

This paper is made of three part. First, it proposes a methodology to construct a household level measure of the stock of cars. The methodology is feasible and flexible. It can be easily extended to construct household level measure of the stock of other consumer durables, such as, white and black durables. We implement it on an American data set, the CEX.

Second, the paper documents some stylized facts. In particular, we derive the life-cycle and the business-cycle patterns of the stock of cars. We find that the life-cycle profile is hump-shaped, a finding that can be made consistent with a model with non-convex adjustment costs or with a model with liquidity constraints. As far as the business cycle properties, we find that the first moment of the cross-sectional distribution somewhat leads the recession and the higher moments, i.e. the standard deviation, the skewness and the kurtosis drop when the recession comes in. Furthermore, aggregating our measure of the stock of cars we find a profile similar to that obtained using the BEA data.

In the third part, we review and estimate a model similar to that in Attanasio [5]. This exercises is not novel and is done to check the ability of the model to fit these new data. Future work will use the estimated coefficient in the target and in the bands equation to construct theoretical moments to be matched against their population counterpart. This will be done in order to identify the missing piece of information, i.e. the dynamics in the innovation of the target and bands equation.

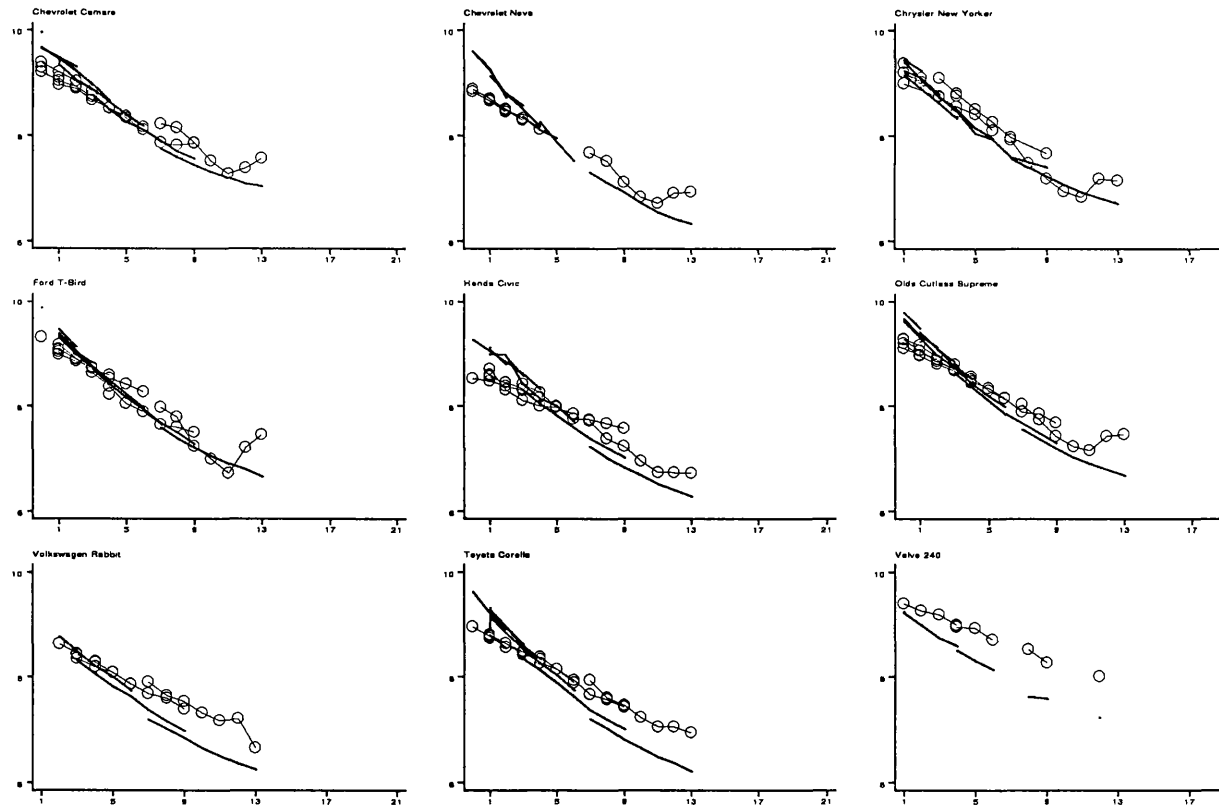


Figure 2.1: Actual versus estimated price-age profile for selected make-models



Figure 2.2: Life-cycle profile of the stock of cars

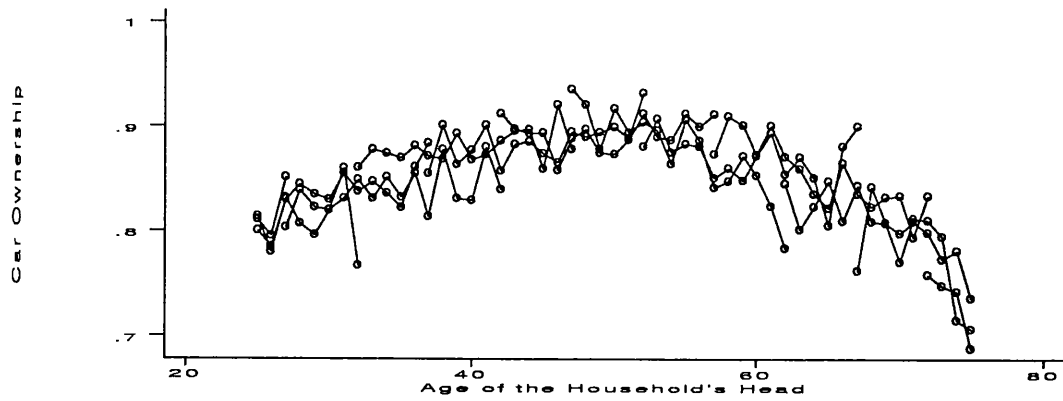


Figure 2.3: Life-cycle profile of cars ownership

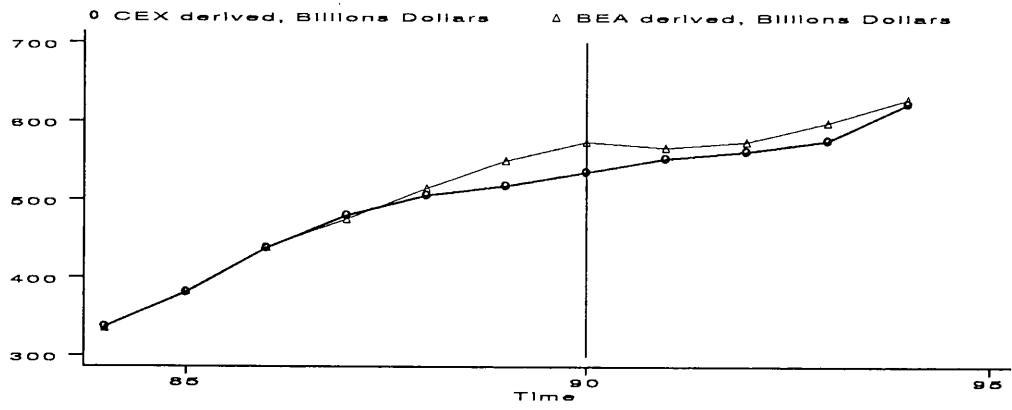


Figure 2.4: Aggregate stock of cars

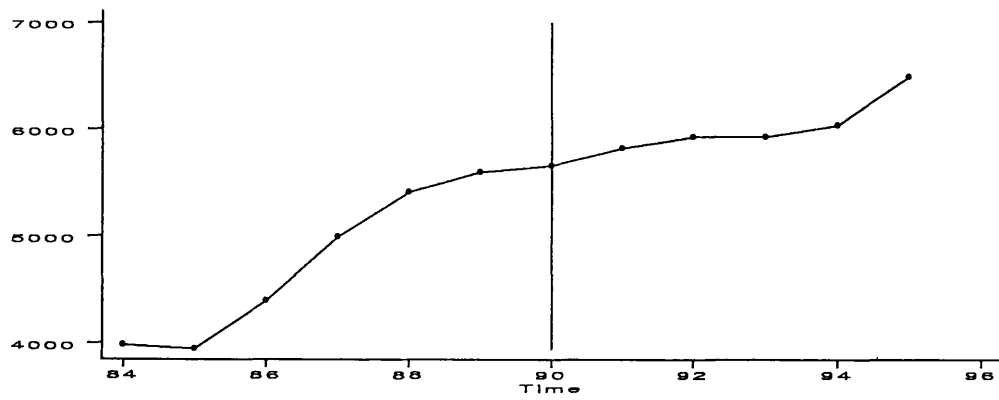


Figure 2.5: Mean of the stock of cars

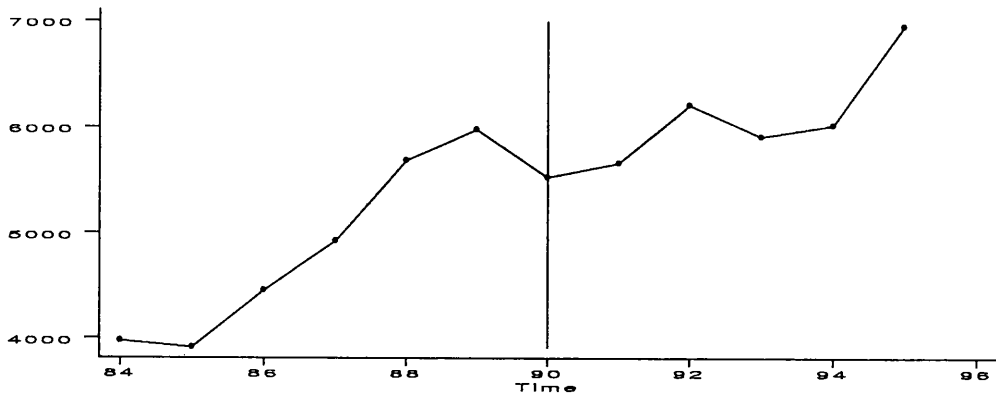


Figure 2.6: Standard deviation of the stock of cars

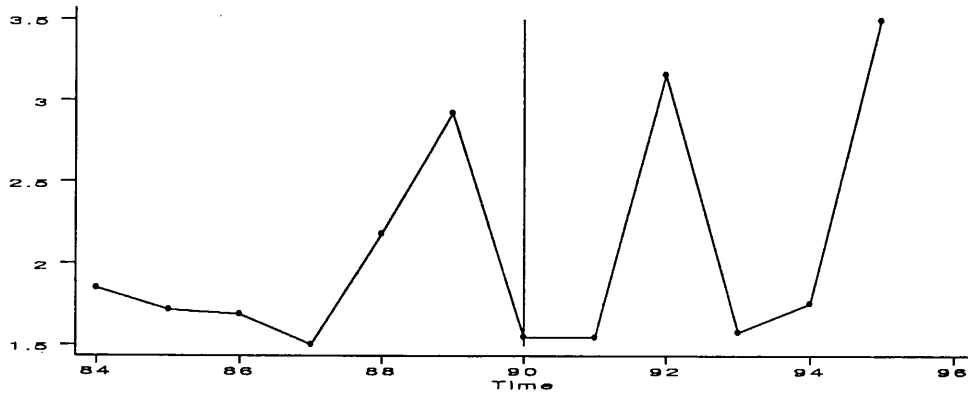


Figure 2.7: Skewness of the stock of cars

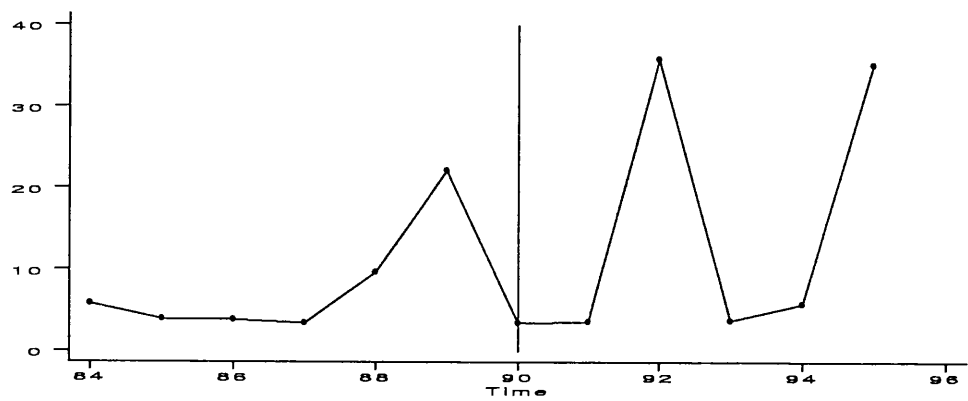


Figure 2.8: Kurtosis of the stock of cars

Table 2.1: The Age-Time Matrix

$(age, time)$	1	2	3	4	5
1	$p_{1,1}$	$p_{1,2}$	$p_{1,3}$	$p_{1,4}$	$p_{1,5}$
2	$p_{2,1}$	$p_{2,2}$	$p_{2,3}$	$p_{2,4}$	$p_{2,5}$
3	$p_{3,1}$	$p_{3,2}$	$p_{3,3}$	$p_{3,4}$	$p_{3,5}$
4	$p_{4,1}$	$p_{4,2}$	$p_{4,3}$	$p_{4,4}$	$p_{4,5}$
5	$p_{5,1}$	$p_{5,2}$	$p_{5,3}$	$p_{5,4}$	$p_{5,5}$

Note: Age is constant along the rows, while time is constant along the columns.

Table 2.2: Estimating the Value of Cars, Analysis of Variance

Source	Partial SS	DF	F	Prob> F
<i>Time</i>	131.7926	1	209.1202	0.0000
<i>Age</i>	1437.1335	1	2280.3345	0.0000
<i>Age</i> ²	248.6649	1	394.5617	0.0000
<i>Age * Mkm</i>	1600.2404	459	5.5324	0.0000
<i>Age</i> ² * <i>Area</i>	13.626992	2	10.8183	0.0000
<i>Autotran</i>	3.9042	1	6.1911	0.0128
<i>No. of Cylinders</i>	88.3837	2	70.1245	0.0000
<i>Powerbrake & Powersteer</i>	37.3028731	1	59.1932	0.0000

Note: This is the analysis of variance table. We report the variability accounted for by any variable in the model. In the first column, we report the name of the variable: *Mkm* stands for Make-Model and *Autotran* for automatic transmission, while *Powerbrake & Powersteer* is equal to one if the car is equipped with both powerbrake and powersteer. In the second column, the partial sum of squares is reported, while the third column contains the degrees of freedom and the fourth column the F-statistics and the fifth column the P-value of the F-statistics.

Table 2.3: Estimating the Value of Cars, Main Regression

Variable	Coefficient	Std. Error
<i>Time</i>	0.0034	0.0002
<i>Age</i>	-0.0985	0.0111
<i>Age</i> ²	0.0004	0.0001
<i>Autotran</i>	0.0502	0.0202
<i>Cylq</i> ₁	-0.3070	0.0261
<i>Cylq</i> ₂	-0.1620	0.0203
<i>Powerbrake & Powersteer</i>	-0.1682	0.0218
<i>R</i> ²	0.6446	

Note: In the last row, the adjusted R-square is reported. The first column refers to the variable used in the estimation, the second to the point estimates, while the third report standard errors. *Autotran* is equal to 1 if the car has automatic transmission *Cylq*₁ is equal to 1 if the engine is equipped with 4 cylinders; *Cylq*₂ is equal to 1 if the engine is equipped with 6 cylinders. Finally, *Powerbrake & Powersteer* is equal to one if the car is equipped with both powerbrake and powersteer. We do not report the coefficient of the age crossed with the make-model and of the age squared crossed with the area.

Table 2.4: Sample Composition

<i>No cars</i>	10.55
<i>Upgrading</i>	21.40
<i>Upgrading from zero</i>	3.91
<i>Downgrading</i>	9.87
<i>Downgrading to zero</i>	4.29
<i>Doing nothing</i>	49.99

Note: The first row reports the percentage of households with no cars throughout the sample. The second that of households who upgrade, the third that of households who upgrade from zero, the fourth those who downgrade, the sixth those who downrade to zero, the last those who do not do anything.

Table 2.5: Probability of Upgrading and of Downgrading

<i>Age of the household head</i>	0.030 (0.004)**	0.009 (0.005)*
<i>Age – square of the household head</i>	-0.391 (0.042)**	-0.124 (0.052)**
<i>Males over 16</i>	0.226 (0.012)**	0.201 (0.014)**
<i>Females over 16</i>	0.234 (0.012)**	0.090 (0.015)**
<i>Children 3 – 15</i>	0.017 (0.007)**	-0.003 (0.009)
<i>Children 0 – 2</i>	-0.038 (0.023)	0.005 (0.029)
<i>Black head</i>	-0.312 (0.024)**	-0.160 (0.031)**
<i>High school dropout</i>	-0.176 (0.022)**	0.126 (0.028)**
<i>High school graduates</i>	0.017 (0.016)	0.122 (0.021)**
<i>Single earner</i>	-0.125 (0.016)**	-0.065 (0.020)**
<i>Female head</i>	-0.229 (0.018)**	-0.001 (0.022)
<i>Stock of cars, beginning of the period</i>	-0.188 (0.015)**	0.542 (0.015)**
<i>Constant</i>	-1.604 (0.094)**	-2.219 (0.118)**
Observations	44349	44349

Note: Standard errors in parentheses. * significant at 5% level; ** significant at 1% level.
The first column refers to the probability of upgrading, the second to that of downgrading.

Table 2.6: Probability of Doing Nothing

<i>Age of the household head</i>	-0.019 (0.005)**	-0.010 (0.003)**
<i>Age – square of the household head</i>	0.215 (0.049)**	0.180 (0.035)**
<i>Males over 16</i>	-0.350 (0.019)**	-0.177 (0.011)**
<i>Females over 16</i>	-0.485 (0.019)**	-0.080 (0.011)**
<i>Children 3 – 15</i>	0.021 (0.010)*	-0.020 (0.007)**
<i>Children 0 – 2</i>	0.042 (0.033)	0.022 (0.021)
<i>Black head</i>	0.670 (0.023)**	-0.146 (0.019)**
<i>High school dropout</i>	0.750 (0.028)**	-0.339 (0.019)**
<i>High school graduates</i>	0.138 (0.024)**	-0.120 (0.014)**
<i>Single earner</i>	-0.081 (0.020)**	0.144 (0.014)**
<i>Female head</i>	0.554 (0.024)**	-0.138 (0.016)**
<i>Constant</i>	-0.745 (0.116)**	0.399 (0.081)**
Observations	44349	44349

Note: Standard errors in parentheses. * significant at 5% level; ** significant at 1% level. The first column refers to the probability of doing nothing and not owning cars, the second to the probability of doing nothing and owning at least one car.

Table 2.7: Observable Bands

<i>Age of the household head</i>	-0.2494 (0.1678)	0.0145 (0.0028)	-0.3131 (0.1337)
<i>Age – square of the household head</i>	0.1798 (0.0232)	0.0005 (0.0001)	0.1264 (0.0331)
<i>Males over 16</i>	0.0010 (0.0003)	-0.4925 (0.0849)	-0.1001 (0.0418)
<i>Females over 16</i>	0.0016 (0.0002)	-0.2566 (0.1631)	-0.0640 (0.0065)
<i>Children 3 – 15</i>	-0.0014 (0.0002)	-0.1881 (0.0222)	-0.1355 (0.0308)
<i>Children 0 – 2</i>	-0.0003 (0.0001)	-0.0044 (0.0009)	-0.0056 (0.0007)
<i>Black head</i>	0.0009 (0.0004)	0.1416 (0.0295)	0.0200 (0.0020)
<i>High school dropout</i>	-1.2222 (0.3425)	0.1740 (0.0240)	-0.2123 (0.1971)
<i>High school graduates</i>	-1.2232 (0.3422)	0.1943 (0.0215)	-0.2590 (0.1616)
<i>Single earner</i>	-0.0004 (0.0001)	0.1730 (0.0241)	-0.0014 (0.0002)
<i>Female head</i>	-0.0016 (0.0002)	-0.1195 (0.0350)	-0.0600 (0.0069)
<i>Constant</i>	-2.4085 (1.7381)	0.4051 (0.1033)	-1.1099 (0.3771)
σ_d	1.8162 (0.2304)		
σ_b	1.6735 (0.2501)		
ρ	-0.0006 (0.0001)		
Observations	44349	44349	44349

Note: Asymptotic standard errors in parentheses. The first column refers to the target equation, the second to the upper bound, the third to the lower. The target equation include a full set of year dummies.

Table 2.8: Unobservable Bands

<i>Age of the household head</i>	-0.4462	-0.0058	-0.3163
	(0.1110)	(0.0008)	(0.1565)
<i>Age – square of the household head</i>	0.1754	0.0008	0.1263
	(0.0282)	(0.0006)	(0.0392)
<i>Males over 16</i>	0.1065	0.1037	0.1113
	(0.0464)	(0.0477)	(0.0444)
<i>Females over 16</i>	0.0929	0.0144	0.0813
	(0.0533)	(0.0034)	(0.0609)
<i>Children 3 – 15</i>	-0.0366	0.1747	-0.0069
	(0.0135)	(0.0283)	(0.0007)
<i>Children 0 – 2</i>	0.0404	0.0769	0.0175
	(0.0122)	(0.0643)	(0.0028)
<i>Black head</i>	-0.1846	0.0451	0.0191
	(0.0268)	(0.0109)	(0.0025)
<i>High school dropout</i>	-0.2969	0.0126	0.0913
	(0.1668)	(0.0039)	(0.0542)
<i>High school graduates</i>	-0.5315	0.3727	0.6640
	(0.0931)	(0.1329)	(0.0746)
<i>Single earner</i>	-0.2709	0.2075	0.2788
	(0.1828)	(0.0238)	(0.1776)
<i>Female head</i>	-0.3712	0.1669	0.1529
	(0.1334)	(0.0296)	(0.0323)
<i>Constant</i>	-0.7474	0.4221	0.1168
	(0.6627)	(0.1173)	(0.0424)
σ_d	1.7780		
	(0.2786)		
σ_b	0.5892		
	(0.0840)		
ρ	-0.99		
	(0.5004)		
Observations	44349	44349	44349

Note: Asymptotic standard errors in parentheses. The first column refers to the target equation, the second to the upper bound, the third to the lower. The target equation include a full set of year dummies.

Chapter 3

Education, employment and wage risk

3.1 Introduction

Estimating the economic return to schooling is a popular and controversial exercise in labor economics (see Card, [21], for an exhaustive survey of the empirical literature). Many studies estimate the parameter of interest by running a simple OLS regression of log earnings on years of schooling, a polynomial in labor market experience, and other individual attributes. This is the celebrated Mincer equation. Instrumental variable estimation acknowledges the endogeneity of the schooling variable, although considerable controversy arises regarding the interpretation of the IV estimates (see the discussion in Heckman et al. [38]).

Here we abstract from such controversy and focus on a quite different issue: the introduction of uncertainty in lifetime income confronted by individuals with different levels of schooling. We compute the return to schooling using a procedure that accounts for unemployment and wage risk conditional on the schooling choice. We thus ignore the problem of why individuals with similar observable characteristics choose different levels of human capital investments, and focus instead on their post-schooling experience in the labor market.

The basic point of this work is that neglecting unemployment and wage risk in a world of incomplete markets may lead to underestimating the return to education if, say, more education gives access to less risky jobs and wage

profiles. Consider for instance unemployment risk. In each period individuals face a positive probability of being unemployed and getting zero earnings. Lifetime earnings are therefore lower in expected value than in the absence of unemployment risk. If unemployment risk were the same across schooling levels, there would be no difference with respect to the case of no uncertainty. However, if the more educated are less likely to face unemployment, then the return to schooling is higher and standard estimates of the return from schooling biased downward. If wage risk comes into the picture over and above unemployment risk, then the bias cannot be signed in general: it will depend on whether wage risk is lower among the more educated (which would reinforce the downward bias above), or higher (a fact that may be explained by a simple mean-variance scheme in which those facing high uncertainty are compensated by high earnings on average).

We are not the first to explore this issue. Lehvari and Weiss [45] present a two-period model of human capital investment with uncertainty, and show that an increase in uncertainty increases the level of investment for plausible assumptions concerning risk aversion and technology. Their simple model has been extended in a variety of directions (see the discussion in Snow and Warren, [53]). An empirical test of the main implication of their model is Kodde [42], who uses subjective expectations of future earnings reported by a sample of Dutch high-school graduates. The work that is closest in spirit to ours is Olson, White, and Shefrin [49], who allow for wage risk and estimate risk-adjusted and riskless rates of return to high school and college education using NLS data. They find that the difference between the risk-adjusted and the riskless rate is positive, higher for high school graduates, it increases with the amount borrowed to finance tuition costs, and it decreases with risk aversion. There are several differences between their work and ours. First, we extend the analysis to a longer sample period and consider both the US and Italy, so as to highlight the effect of risk on the rate of return to education in different institutional settings. Second, we allow for heterogeneity in the returns to education, assuming that people entering the labor market in different years face different returns to human capital investment. Third, we estimate age-earnings profiles for different cohorts using a non-parametric approach. Their approach ignores cohort effects. Finally, we consider both wage and employment risk, and show that the unemployment risk adjustment is as important as the wage risk adjustment, if not bigger. Moreover, we allow both wage and employment risk to vary over the life cycle, while they keep wage risk constant.

The plan of the chapter is as follows. We start in Section 2 by describing the problem and detailing the numerical solution method for estimating the return to schooling. Section 3 deals with the data. We focus on two countries, Italy and the US, which greatly differ in terms of labor market institutions. Our empirical analysis uses three microeconomic data sets: repeated cross-sections drawn from the 1984-1998 Bank of Italy Survey of Household Income and Wealth (hereafter, SHIW), the 1967-1991 Panel Study of Income Dynamics (hereafter, PSID), and the 1994-1998 Survey of Economic Expectations (hereafter, SEE). We allocate individuals in our sample to cohorts defined on the basis of year of birth and years of schooling. For each group we take actual earnings profiles and extrapolate back and forth over the missing ages. This gives us an estimate of the entire lifetime earnings profile that can be used to infer expected earnings over the life cycle. Wage and unemployment risk are obtained using the variability of individual earnings around the estimated earnings profile and perceived unemployment risk. For Italy, the latter is estimated using subjective unemployment probabilities available in the SHIW; for the US, we rely on those available in the SEE. We discuss the extrapolation technique in Section 4. The rate of return to schooling is obtained *via* numerical solutions under four different scenarios: no uncertainty, unemployment risk, wage risk, and both wage and unemployment risk. The results are reported in Section 5, while Section 6 concludes.

3.2 The return to education

An individual endowed with isoelastic preferences chooses years of schooling s to maximize the expected utility of lifetime consumption:

$$E_s \sum_{j=s}^T (1 + \rho)^{j-s} \frac{c_{ij}(s)^\gamma}{\gamma}$$

where $1 - \gamma$ is the coefficient of relative risk aversion, ρ the discount rate, E_s the expectation operator conditional on information available at time s (the school-leaving age), and T the expected age of retirement, which is known with certainty at the beginning of the life cycle.

Following the previous literature, we will focus on an incomplete markets case in which consumption equals income in each period, i.e. $c_{ij}(s) = y_{ij}(s)$ for all j and s . This is an extreme case in that both borrowing and savings

are not available; thus, self-insurance through savings is not allowed. The only form of insurance is, in fact, choosing a more stable earnings profile, i.e., selecting the schooling level that is associated with it. The extreme incomplete market case provides an upper bound of the amount of insurance provided by education.

Mincer-type earnings equations assume that there are no direct costs of human capital investments, an assumption that we also make. We assume for simplicity that retirement age is independent of schooling (and set $T = 65$ for all schooling choices), and that individuals live with their parents while in school, receiving a minimum consumption level at no cost. This should minimize the effect of institutional or demographics differences across countries that we do not model explicitly.

As far as these two assumptions are concerned, the following should be noticed. In Italy, workers are entitled to old age pensions (retirement age is 60 for males, 55 for females, recently raised to 65 and 60, respectively), or social security contributions pensions (set to 35 years for both males and females, with some exceptions in the public sector and for some worker categories), independently of education levels.¹ Furthermore, children tend to leave parental home later in life, and usually just before marriage (Becker, Bentolilla, and Ichino, [9]).

In the US, heterogeneity of retirement ages across education groups is less documented. On the other hand, student mobility at the college level is much higher than in Italy, which implies that the assumption that children live with their parents before the college completion may be less accurate. Our focus on the return to schooling gross of investment costs, however, should lessen this problem.

Individuals in this model confront two types of risk. First, they may be unemployed with positive probability. Second, conditioning on being employed, their earnings may be uncertain. The return to schooling level $s' > s$ is the implicit rate ρ^* that solves:

¹Social security contributions pensions obviously depend on the age of entry in the labor market, which in turn depends on school leaving age. However, pension legislation allows college graduates to make college years counting as working years *via* payment of additional contributions.

$$\sum_{j=s}^T (1 + \rho^*)^{j-s} \frac{\pi_{ij}(s) E_s [y_{ij}(s)^\gamma | e]}{\gamma} = \sum_{j=s'}^T (1 + \rho^*)^{j-s'} \frac{\pi_{ij}(s') E_s [y_{ij}(s')^\gamma | e]}{\gamma} \quad (3.1)$$

where $\pi_{ij}(s)$ is the probability of employment that individual i with schooling s faces at age j , and $E_s(\cdot | e)$ is an expectation that conditions on the information set available at time s and on the status of being employed, e .² To save on notation, from now on we remove the conditioning on the employment status e and leave it implicit.³

Individuals with schooling level s may choose to enter the labor market and earn $y_{ij}(s)$ or else invest in additional schooling ($s' - s$), which ensures earnings $y_{ij}(s')$. The discount rate ρ^* makes individuals indifferent between the two schooling choices s and s' . We estimate ρ^* as the numerical solution to (3.1), in the spirit of Becker [8], who defines the rate of return ρ^* to switching from education level 1 to education level 2 (with school-leaving ages of s and s' , respectively) as the value that equalizes the present discounted value of the age-earnings profiles calculated under the two schooling regimes.

To make (3.1) operational one should know expected earnings for an individual with schooling level s , expected earnings for the same individual had he chosen to invest in additional schooling ($s' - s$), and the preference parameter γ . Note also that what appears in (3.1) is the expectation of a non-linear function of y_{ij} .⁴

To avoid dealing with the expectation of a non-linear function of earnings, we use the following approximation based on a second-order Taylor expansion:

²We assume that in the case of unemployment people receive a subsistence level of utility independent of schooling and age. This term thus drops out from expression (3.1).

³The Mincer regression is a special case of (3.1), obtained assuming no uncertainty, and $\pi_{ij}(s) = \pi_{ij}(s') = 1$ for all i, j .

⁴In previous empirical work, the evaluation problem is solved by making two crucial assumptions. First, there is no selection based on unobservables. This will be violated if those who go to college would earn more than a representative high school graduate had they chosen not to go to college, due to the effect of unobserved ability traits. Second, there are no cohort effects. This implies that a 20-years old individual will earn at 30 what a 30-years old individual is earning today, at least on average. We remove the second assumption and account for the first, albeit imperfectly, by focussing on narrowly defined population subgroups.

$$\frac{E_s [y_{ij}^\gamma]}{\gamma} \cong \frac{[E_s (y_{ij})]^\gamma}{\gamma} + \frac{\gamma - 1}{2} var_s [y_{ij}] [E_s (y_{ij})]^{\gamma-2}$$

for all i, j , and schooling level. Note that under risk neutrality ($\gamma = 1$) higher moments of the conditional distribution of earnings do not affect utility. Individuals will choose schooling levels only on the basis of expected lifetime earnings.

The next step is to compute expectations and variances of earnings over the life-cycle. We estimate expected earnings with the average earnings of the individual's cohort. For example, an individual born in 1920 can choose to leave school at around 14 (less than high school), 19 (high school diploma), or 24 (college degree). We need to calculate average earnings over the working career for all individuals born in 1920, entering the labor market respectively in 1934, 1939, and 1944, and retiring in 1985. Estimation of the expected earnings variability is done in a similar way focusing on the variability of individual profiles around the cohort profile. More details are provided in the section that follows.

We estimate process in logs assuming log-normality (i.e., $\ln y_{ij} \sim N$) and substitute back using the formulae for the first and second moments of the exponential distribution, i.e.:

$$\begin{aligned} E_s [y_{ij}(s)] &= E_s [e^{\ln y_{ij}(s)}] = e^{E_s[\ln y_{ij}(s)] + 0.5 var_s[(\ln y_{ij}(s))]} \\ var_s [y_{ij}(s)] &= var_s [e^{\ln y_{ij}(s)}] = e^{2E_s[\ln y_{ij}(s)] + var_s[(\ln y_{ij}(s))]} (e^{var_s[(\ln y_{ij}(s))]} - 1) \end{aligned}$$

If log-normality is violated, these expressions should thus be seen as second order Taylor approximations to the true mean and variance.

3.3 Data

To perform the empirical exercise outlined in the previous section one needs microeconomic data. For this purpose we use the Bank of Italy SHIW, available for the years 1984, 1986, 1987, 1989, 1991, 1993, 1995 and 1998, and the PSID, available annually from 1967 to 1991. Our exercise also requires estimates of unemployment risk. We use subjective unemployment expectations available in the 1995-1998 SHIW (for Italy), and the 1994-1998 SEE (for the US). The three data-set are briefly described in turn.

3.3.1 The SHIW

The 1984-1998 SHIW contains measures of family income and consumption, demographic characteristics of households, and information on labor market status, labor supply and earnings for all labor income recipients in the household. In 1995 and 1998 respondents are also asked to provide perceived unemployment probabilities for the following 12 months.

The SHIW is conducted by the Bank of Italy that surveys a representative sample of the Italian resident population. Sampling is in two stages, first municipalities and then households. Municipalities are divided into 51 strata defined by 17 regions and 3 classes of population size (more than 40,000, 20,000 to 40,000, less than 20,000). Households are randomly selected from registry office records. From 1987 through 1995 the survey was conducted every other year and covered about 8,000 households, defined as groups of individuals related by blood, marriage or adoption and sharing the same dwelling. Ample details on sampling, response rates, processing of results and comparison of survey data with macroeconomic data are provided by Brandolini and Cannari [14].

3.3.2 The PSID

The PSID is a panel data set of US households and of their offsprings. It began in 1968 with a sample of approximately 5000 families drawn from the US non-institutional population. The PSID includes a variety of socio-economic characteristics, including age, education, labor supply, and income of family members. Families are interviewed annually and family members in the 1968 are followed through time if they form or join new families. This made the sample size to increase over time: around 18000 individuals were present in 1968 and around 30000 in 1992.

Three-fifths of the observations are drawn from a representative US sampling frame (the SRC sample). About two-fifths of the observations from a low-income sample (the SEO sample). The analysis below excludes SEO households. For a more detailed discussion of the PSID we refer to Hill [39].

3.3.3 The SEE

The SEE is run by the Survey Center at the University of Wisconsin as a periodic module of the WISCON Survey. It is a nationwide representative

survey consisting of daily telephone interviews that includes a set of constant core questions about people's experiences, attitudes, and their economic perspectives. A total of 5423 interview cover a time span of four years and are collected in 8 consecutive waves, 2 a year, one in the May-July and the other in the November-January interview period. Dominitz and Manski [27] offer a detailed description of the data.

3.4 Constructing life cycle profiles

In both the Italian and US samples we drop households where the head is self-employed and those with missing observation for at least one of the variables relevant to the analysis, i.e., age, education, and earnings. We group the resulting observations into ten year-of-birth cohorts. The first cohort (the oldest) includes individuals born between 1920 and 1924; the second cohort includes individuals born between 1925 and 1929, and so on. The youngest cohort includes individuals born between 1965 and 1969.

As a measure of earnings, we use labor income from employment before taxes for year-round employed. Real earnings are obtained by dividing nominal earnings by the CPI. For Italy the base year is 1991, and for the US 1982-1984. We split the sample on the basis of education, distinguishing between three groups: less than high school (which in Italy corresponds to 8 years of full-time schooling and in the US to 9-11 grades), high school degree (13 years and 12-15 grades, respectively), and college degree or more (between 18 and 21 years of full-time schooling in Italy, and at least 16 grades in the US).

Given the limited time span of our data set, we do not observe the entire life cycle profile of individual earnings. To estimate life cycle earnings profiles several alternatives are available, parametric and non-parametric. Parametric techniques of the type illustrated in Deaton and Paxson [26] impose strong restrictions on the effect of cohort, age, and time effects. We use a non-parametric approach. In particular, instead of assuming that aggregate shocks average out, we assume that cohorts of individuals born in adjacent years and choosing similar levels of schooling face similar aggregate shocks.

The non-parametric approach adopted here is similar to that used by Atanasio and Banks [6] in a very different context. It consists of extrapolating backward and forward the value of the variable of interest (in our specific

case, unobserved earnings at different points of the life cycle).

To see how the extrapolation technique works, consider figure 3.1, where we plot the actual age-earnings profile for each cohort/education group in the Italian data (figure 3.2 refers to the US). If there were no significant cohort or year effects, a cross-sectional graph could be interpreted as the life cycle of earnings for a representative individual. However, both cohort and time effects are likely to be present.

A complete life cycle earnings profile is unavailable because each cohort is observed only for a limited number of years: from 1984 to 1998 in Italy, and from 1967 to 1991 in the US. Thus, young cohorts are not observed when they age, while old cohorts are not observed when young. We extrapolate the unobserved values of the variable of interest using information available for adjacent cohorts. For simplicity of exposition, we illustrate the extrapolation technique with reference to the Italian data.

Suppose that the variable of interest is $x_{c,a}$, where c is a subscript for cohort and a for age. Let's assume that $c = 1, 2, \dots, C$, with C being the youngest cohort considered. Our problem is that for a young cohort we observe x from age 14 to age 25 (i.e., from 1991 to 1998), but not afterwards; similarly, for the adjacent cohort we observe x from age 14 to age 30 (i.e., from 1986 to 1998), and so forth. For the oldest cohort, we observe x from age 62 in 1984 to age 65 in 1987, but not before. Thus, we need to predict future values of x for the youngest cohorts, past values of x for the oldest cohorts, and both future and past the values of x for the intermediate cohorts. Note that almost at all ages values of x overlap for different cohorts. Formally, suppose that for a generic cohort c we have a series: $[x_{c,1}, x_{c,2}, \dots, x_{c,a}]$ of values for the variable x . The scope is to obtain an estimate of $x_{c,a+j}$ (with $1 < j < T - a$, with T being the maximum age, set to 65) from data available for older cohorts. Suppose there is just one such cohort, for which we have the series: $[x_{c+1,2}, x_{c+1,3}, \dots, x_{c+1,a+1}]$. Define the rate of growth: $g_{c,a,a+1} = \frac{x_{c,a+1}}{x_{c,a}} - 1$ (which is unobserved) and $g_{c+1,a,a+1} = \frac{x_{c+1,a+1}}{x_{c+1,a}} - 1$ (which is observed). Since $x_{c,a+1} = x_{c,a}(1 + g_{c,a,a+1})$, the knowledge of $g_{c,a,a+1}$ would provide us with the requested value for $x_{c,a+1}$.

The problem is that $g_{c,a,a+1}$ is unobserved. However, we can use as an estimate of $g_{c,a,a+1}$ the value of $g_{c+1,a,a+1}$ available for the older cohort. This amounts to assume that –between ages a and $a + 1$ – adjacent cohorts have a similar age profile for the variable of interest x . Clearly, when more cohorts are available, the estimate of g can be considerably refined (for instance,

through simple or weighted averages of the available growth rates). This has of course an element of arbitrariness, as weights must only satisfy the condition that they sum to one and that they should be larger as less distant is the available cohort's growth rate to the cohort of reference. In the end, we decided to weight each available growth rate by the squared value of the reciprocal of the distance between cohorts. So, the weights are chosen to be inversely proportional to the distance between the cohort of reference and the adjacent cohorts for which data are available: more adjacent cohorts thus receive more weight than more distant cohorts.

Figures 3.3 and 3.4 show, respectively, the Italy and US extrapolated and actual age-earnings profiles, separately for each education group. In this figure, the dotted lines represent the (forward and backward) extrapolated values, while the straight lines represent the original survey values. This technique reconstructs the entire life cycle earnings profile for a representative individual belonging to a given cohort. All profiles are concave as predicted by the human capital theory. Moreover, there is a negative correlation –across education– between the slope and the intercept of the earnings profile, another important implication of the human capital theory (see Ben-Porath, [10]; Hause [34]). This evidence is quite strong in the Italian case, much less clear in the US case.

We smooth the extrapolated profiles with a quartic in age, save the parameters, and use them to construct the expected earnings profile for an individual who is entering the labor market, conditional on his schooling choice.

We use a similar extrapolation technique to predict the variance of earnings at all ages for different cohort/schooling combinations. We first regress earnings on a quartic in age, and dummies for sex and time, separately by education. We take the squares of the residuals of these regressions, and average them for each age/cohort/schooling combination. We then apply the extrapolation technique described above. The age-variance profiles for Italy and the US are shown in figure 3.5 and 3.6. The variance profiles decline slightly at the beginning of the life cycle, and increase around age 30-35. In the US case, the increase is much stronger for the more educated and there appear to be some significant cohort effects. In the Italian case the evidence is similar, but the decrease at the beginning of the life cycle is much more pronounced and the increase at the end is less. The two figures show that the variance levels are generally higher in the US than in Italy. The most natural explanation for this is that it reflects tighter labor market regulations

and more generous welfare programs in Europe.

Finally, we estimate unemployment risk. To this purpose, we use subjective unemployment probabilities elicited in the 1995-98 SHIW and in the 1994-98 SEE. We take averages of subjective probabilities by age and schooling level (see figure 3.7 for Italy, and figure 3.8 for the US). Figure 3.7 shows that unemployment risk declines quite rapidly in the first few years after entering the labor market, it stabilizes around age 40, before increasing slightly towards the end of the life cycle, perhaps reflecting early retirement. Looking across education, two things are worth noting: (1) the more educated face less unemployment risk, and (2) the decline in unemployment probabilities at the start of the life cycle is much slower for the less educated. Figure 3.8 shows that unemployment risk declines over the life cycle for all education groups (apart from a slight increase at the beginning of the life cycle for those with high-school and beyond). The ordering of education groups in terms of unemployment is similar to that noticed above for Italy. Comparison across countries shows that Italian face slightly higher unemployment risk than the US counterparts regardless of education (an average of 22 percent in Italy *vis-à-vis* 14 percent in the US). Guiso, Jappelli, and Pistaferri [32] notice that the two distributions differ dramatically only at low levels of the probability of unemployment, with the fraction of individuals reporting no unemployment risk altogether being much higher in Italy than in the US.

Unemployment averages obviously neglect year and cohort effects. This is a strong assumption, but unfortunately the time span of unemployment probability data is too limited (two years in the SHIW, five in the SEE) to extend our extrapolation technique to unemployment risk.

3.5 Results

We use the estimates of the first two moments of the distribution of expected earnings (conditioning on employment) and the perceived unemployment probabilities to compute the rate of return to schooling in equation (3.1). We focus on four cases of interest: no uncertainty, unemployment risk, wage risk, and both unemployment and wage risk. We experiment with different values for the coefficient of relative risk aversion (RRA) ranging between 1 and 3.

The first two columns of table 3.1 display the return to high school (ρ_{12}) and college (ρ_{23}) when the coefficient of relative risk aversion is set to 1. In

these and other columns, Panel A refers to Italy, Panel B to the US.

Two main findings emerge: (1) the return to education is higher in the US than in Italy, at both the high school and college level, and (2) in both countries the return to college is higher than that for high school. These results are consistent with previous evidence. Brunello, Comi and Lucifora [20] find that the return to an additional year of education ranges between 5 and 7 percent in Italy. For the US, the return to an additional year of education ranges between 6 and 13 percent (see Card [21]).⁵

In Italy the return to high school declines almost monotonically with year of birth, while the return to college exhibits a distinctive U-shape: workers born in the 1940s and in the 1950s enjoy lower return to college than those born before or after these two decades.⁶ The U-shape for college education returns is the result of two contrasting forces. On the one hand, the supply of college graduates has increased relatively to that of high school graduates; on the other, the demand for college educated individuals has increased more rapidly than supply, due perhaps to skill biased technological changes. Moreover, the strong increase in the return to college education enjoyed by the youngest cohort is likely to reflect important institutional changes, such as the removal of the wage indexation mechanism (1985), which increased wage differentials after a long period of wage compression (see Manacorda [46]), and the decline in unionization rates and unions' power.

In the US the return to high school is virtually flat across cohorts, while the return to college is stable for the first six cohort and increases quite rapidly for the cohorts entering the labor market from the late 1970s onward (i.e., with the baby-boomers). This evidence is not novel, and it has been documented quite extensively elsewhere. The conventional view is that the skill biased technological change of the last two decades has dramatically increased the price of both observable (i.e., education) and unobservable skills (i.e., ability).

As remarked in Section 1, the return to education can be biased by the failure to account for higher moments of the distribution of earnings and for the risk of unemployment. We thus consider the introduction of uncertainty about employment status and future earnings.

⁵Averaging the return to education over different cohorts and levels of schooling and weighting by the cell size, we obtain a return of around 6 percent for Italy and 12 percent for the US.

⁶Consistently with these findings, Brunello, Comi and Lucifora [20] find that the return to education is flat in the 1980s and it rises in the 1990s.

The third column of table 3.1 reports estimates of the return to high school accounting only for employment uncertainty (ρ_{12}^{ur}). For all cohorts, the return is now higher than that in the absence of unemployment risk. In Italy, such increase is both higher and exhibits more heterogeneity than in the US (9-18 percent *vis-à-vis* 10-11 percent). This is due to the fact that high school graduates face less unemployment risk in the US than in Italy relatively to high school dropouts.

Column 4 repeats the same exercise for ρ_{23}^{ur} , the return to college education. Also in this case, the return increases (by anything between 7-19 percent in Italy, and by 6-7 percent in the US). Two remarks are in order. First, extra-returns are again higher and more disperse in Italy than in the US, mainly due to a *level* effect (unemployment risk is generally higher in Italy than in the US). Second, extra-returns to college are in both countries lower than extra-returns to high school education. The reason is that differences in unemployment risk between compulsory and high school educated individuals are stronger than those between high school and college educated individuals.

The fifth columns of table 3.1 deals with wage risk in isolation. One interesting finding is that in both countries the extra-return to high school due to wage risk is lower than the one due to unemployment risk. In Italy, the increase in the return to high school (ρ_{12}^{wr}) is higher than in the US (4-12 percent *vis-à-vis* 5-6 percent). Recall that our measure of wage risk reflects the uncertainty faced by those working full-time. This uncertainty varies across education group, but to a lower extent than unemployment risk. Furthermore, the variation across education groups is larger in Italy than in the US.

The sixth columns of table 3.1 reports estimates of the return to college that account for wage risk, ρ_{23}^{wr} . In both countries, the return to college increases, but less than the return to high school. In Italy, the increase is between 4 and 10 percent, in the US around 3 percent.

The last two columns of table 3.1 report the return to high school (ρ_{12}^{uwr}) and college education (ρ_{23}^{uwr}), jointly accounting for unemployment and wage risk. Overall, when both sources of risk are considered, the return to high school increases on average by 21 percent in Italy and 15 percent in the US. The increase in the return to college is lower than that to high school, and generally higher in Italy than in the US (13 percent *vis-à-vis* 9 percent). Perhaps more interestingly, the extra-return to high school and college education is quite stable over time in the US, while it is increasing until the end

of the 1970s in Italy and it declines afterwards, which, again, may be due to the changing institutional framework.

To check the robustness of our experiment, in table 3.2 we set the coefficient of relative risk aversion to 2. The results are similar to those reported in table 3.1. In both countries the effect of wage and unemployment risk on the return to schooling is larger than in table 3.1. This is because more risk averse individuals are willing to pay more for settling in less risky jobs. After accounting for wage and unemployment risk, the return to high school increases by around 84 percent in Italy and 45 percent in the US; that for college by 44 percent and 18 percent, respectively.

The main difference between table 3.1 and table 3.2 is in the balance between the extra-return due to unemployment risk and that due to wage risk. Comparing the third and the fifth column of table 3.2, one can notice that ρ_{12}^{ur} and ρ_{12}^{wr} are now very similar, as the increase in risk aversion magnifies the effect of wage risk on the return. The same holds true to the comparison between ρ_{23}^{ur} and ρ_{23}^{wr} .

In the US, the gap between the extra-return for unemployment risk and that for wage risk declines even more than in Italy, due to the fact that unemployment and wage risk vary across education groups in a similar fashion.

The general pattern of results is confirmed in table 3.3, where we set the coefficient of relative risk aversion to 3. Once we account for unemployment and wage risk, the return to high school increases by 82 percent in Italy and 47 percent in the US; that to college by 53 percent and 23 percent, respectively.

3.6 Conclusions

This work proposes a measure of the return to education that accounts for unemployment and wage risk. Individuals with different level of schooling are confronted with different levels (and types) of uncertainty. This should be taken into account when the return to each schooling choice is evaluated.

Intuitively, two schooling choices are pay-off equivalent if they give rise to the same pay-off. This pay-off depends potentially on the entire distribution of future earnings. We restrict this dependency to the first two moments. The second moment measures the amount of wage risk faced by human capital investors. Risk also arise from the possibility of facing unemployment spells over one's career. These two factors affect the pay-off of schooling choices

if different alternatives give rise to different levels of risk. We thus cast schooling choices in the framework of individual choices under uncertainty, following an early theoretical and empirical literature (see Lehvari and Weiss, [45]).

We measure the return to high school and college education allowing for heterogeneity across year of birth cohorts. Our methodology require the use of synthetic panel technique since individuals are not typically observed over the entire life cycle. Moreover, individuals belonging to different cohorts enter the labor market in different years and are likely to exhibit different level of productivity. These two factors interact and may affect quite dramatically the return to different types of education. Institutional factors are likely to influence the amount of unemployment and wage risk by which individuals are confronted. This prompts the use of samples drawn from Italy and the US, two countries that are very diverse in terms of labor market institutions.

For the sake of comparability, we concentrate on three schooling groups: high school dropout, high school graduate, and college graduate.

Some of our findings have been documented in previous empirical work, but some are novel. First, the return to both high school and college is, on average, higher in the US than in Italy. Furthermore, the return to high school declines with year of birth in Italy, while it remains about the same in the US. Conversely, in the US the return to college start increasing for individuals entering the labor market at the end of the 1970s, while in Italy it declines slightly in the 1970s and part of the 1980s and increases afterwards. The effect of skill biased technological change is common across countries, but it appears in Italy much later than in the US due to the effect of institutional constraints.

Second, accounting for risk increases the return to schooling in both countries. In particular, the extra-return is higher for high school graduate than for college graduates, and is higher for unemployment risk than for wage risk. Moreover, this extra-return increases with risk aversion.

There are some differences between Italy and the US, though. The first is related to the level of the extra-return, which is higher in Italy at any level of schooling, regardless of risk type. This suggests that in the US schooling choices are more risk-enhancing than in Italy. Moreover, as risk aversion increases, the gap between the extra-return for unemployment and that for wage risk shrinks more in the US than Italy. This reflects the fact that wage risk is in general higher in the US than in Italy.

Overall, this exercise suggests that failing to account for the uncertainty

that different schooling choices involve can bias downward the return to education. The size of the bias depends on investors' risk aversion and labor market characteristics. Future empirical work should attempt to correct Mincer regression estimates for this important factor.

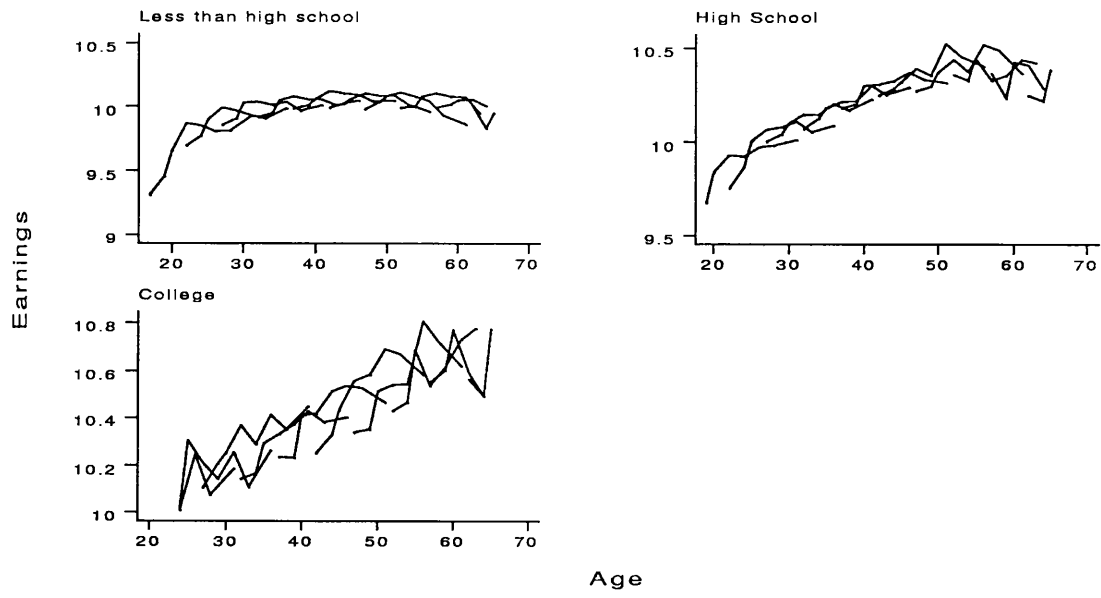


Figure 3.1: Actual age-earnings profile, by cohort and education group, Italy

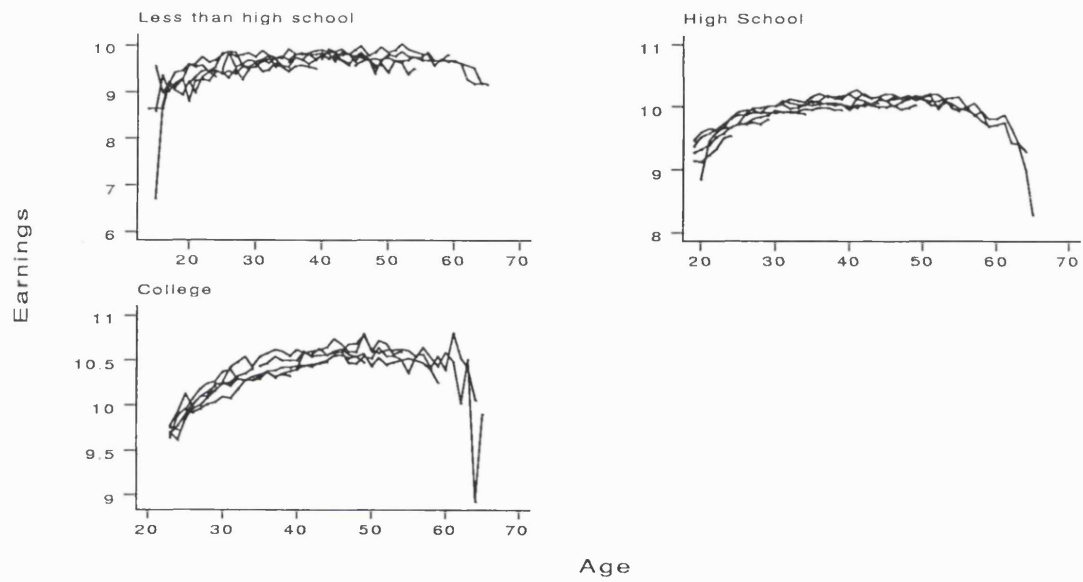


Figure 3.2: Actual age-earnings profile, by cohort and education group, US

- Actual values
- Extrapolated values, Forward

- Extrapolated values, Backward

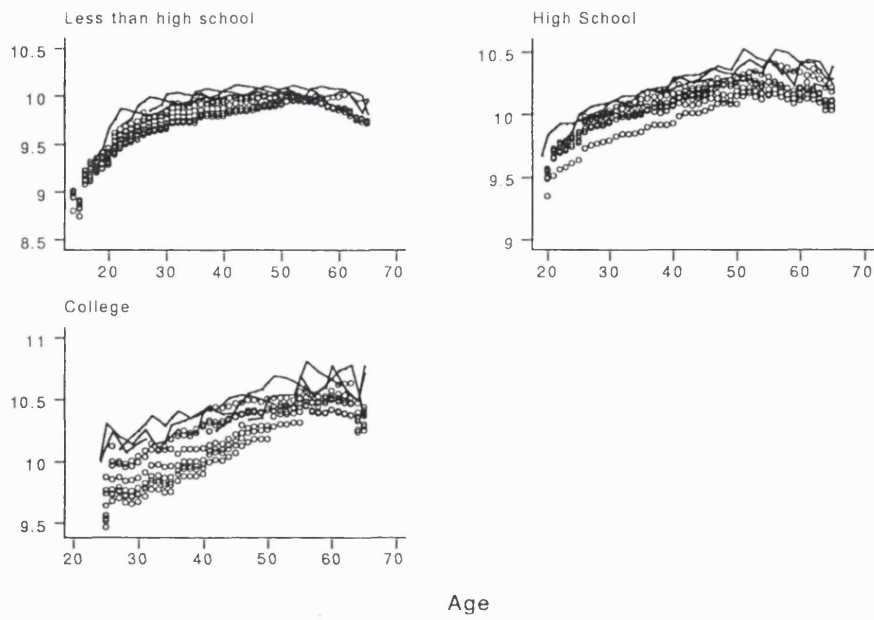


Figure 3.3: Extrapolated and actual age-earnings profile, mean, by cohort and education group, Italy

- Actual values
- Extrapolated values, Forward

- Extrapolated values, Backward

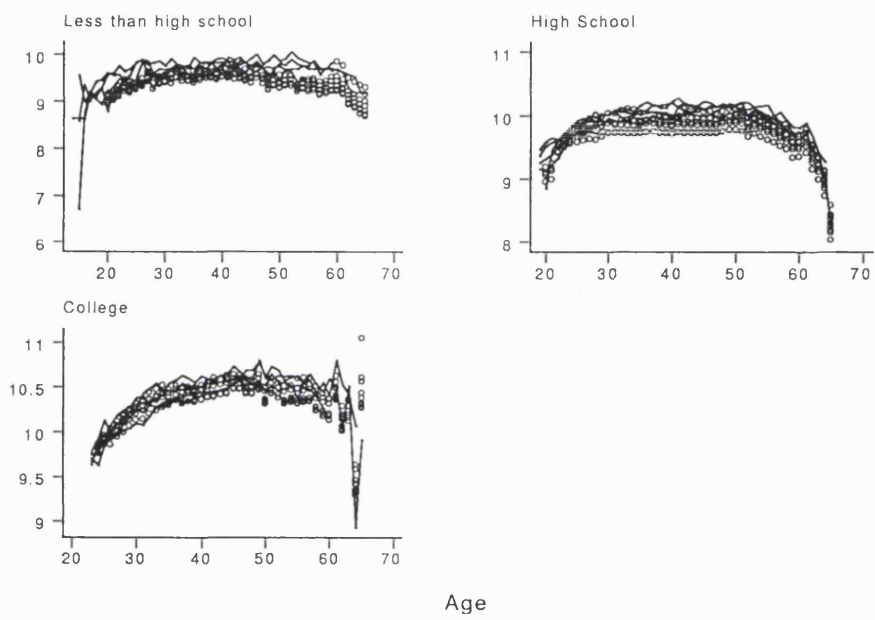


Figure 3.4: Extrapolated and actual age-earnings profile, mean, by cohort and education group, US

- Actual values
- Extrapolated values, Forward

- Extrapolated values, Backward

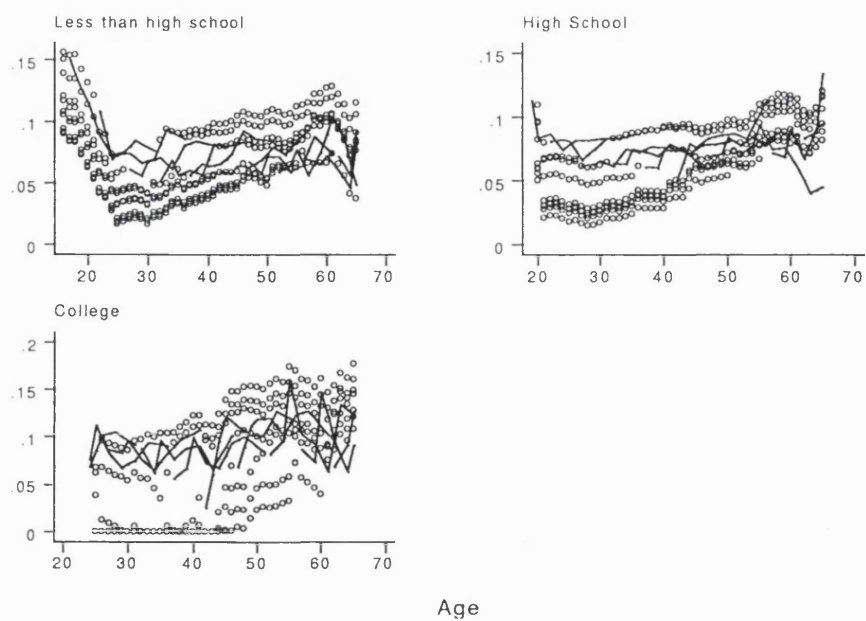


Figure 3.5: Extrapolated and actual age-earnings profile, variance, by cohort and education group, Italy

- Actual values
- Extrapolated values, Forward

- Extrapolated values, Backward

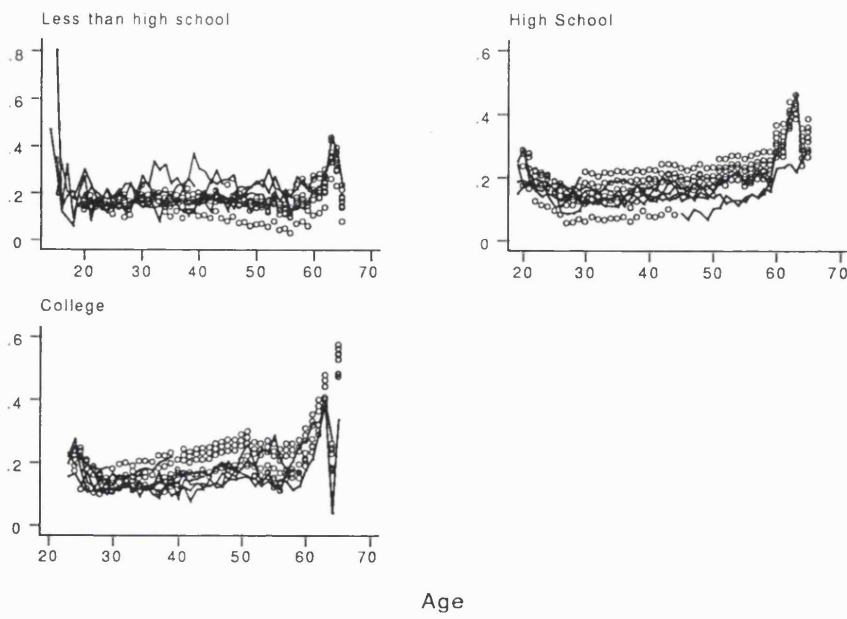


Figure 3.6: Extrapolated and actual age-earnings profile, variance, by cohort and education group, US

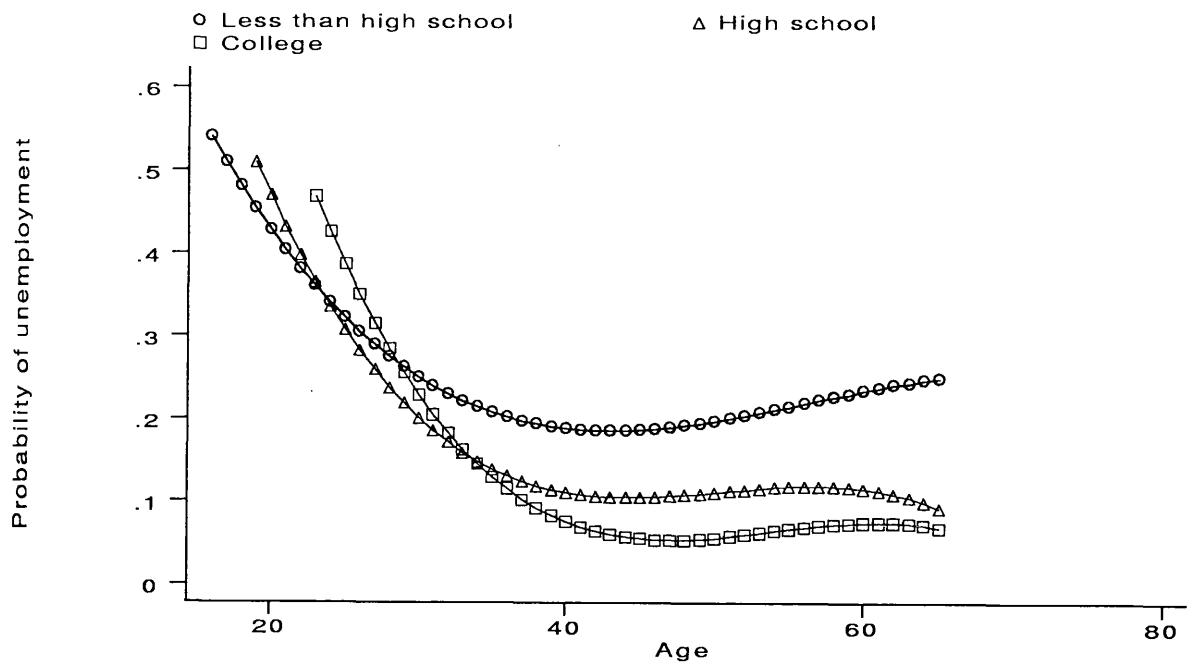


Figure 3.7: Probability of unemployment, by age and education group, Italy

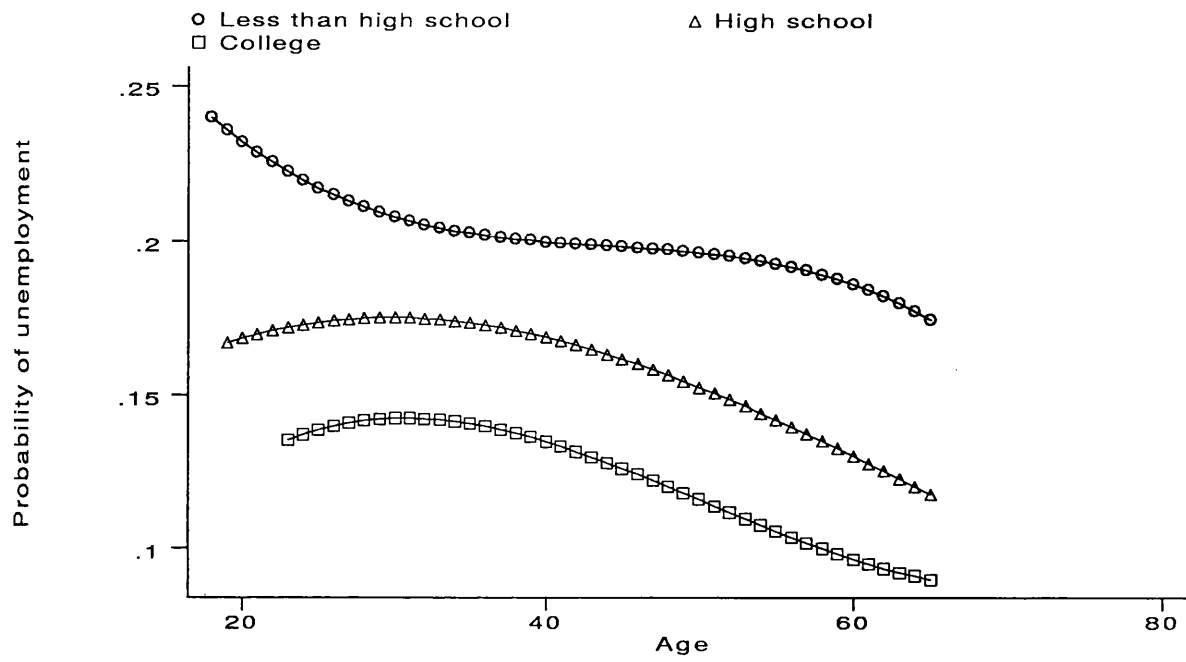


Figure 3.8: Probability of unemployment, by age and education group, US

Table 3.1: Return to education, $RRA = 1$

Cohort	ρ_{12}	ρ_{23}	ρ_{12}^{wr}	ρ_{23}^{wr}	ρ_{12}^{uw}	ρ_{23}^{uw}	ρ_{12}^{uw}	ρ_{23}^{uw}
Panel A: Italy								
1	0.1206	0.1507	0.1319	0.1624	0.12629	0.1565	0.1353	0.1659
2	0.1095	0.1442	0.1207	0.1558	0.11511	0.1500	0.1241	0.1593
3	0.0975	0.1315	0.1086	0.1429	0.10316	0.1371	0.1120	0.1464
4	0.0858	0.1190	0.0968	0.1303	0.09136	0.1246	0.1001	0.1337
5	0.0743	0.1067	0.0851	0.1179	0.07971	0.1123	0.0885	0.1213
6	0.0631	0.0946	0.0738	0.1058	0.06840	0.1003	0.0770	0.1092
7	0.0520	0.0604	0.0627	0.0710	0.05733	0.0657	0.0660	0.0743
8	0.0413	0.0548	0.0518	0.0655	0.04659	0.0601	0.0559	0.0687
9	0.0466	0.1116	0.0572	0.1228	0.05199	0.1171	0.0604	0.1262
10	0.0575	0.1165	0.0682	0.1278	0.06284	0.1221	0.0714	0.1312
Panel B: US								
1	0.1022	0.1567	0.1134	0.1684	0.1078	0.1626	0.1167	0.1720
2	0.0999	0.1606	0.1110	0.1723	0.1055	0.1664	0.1144	0.1759
3	0.0959	0.1631	0.1070	0.1749	0.1014	0.1690	0.1104	0.1784
4	0.0988	0.1651	0.1099	0.1768	0.1043	0.1709	0.1133	0.1804
5	0.0976	0.1664	0.1087	0.1781	0.1032	0.1722	0.1121	0.1817
6	0.0953	0.1657	0.1064	0.1775	0.1009	0.1716	0.1098	0.1811
7	0.0942	0.1696	0.1053	0.1814	0.0997	0.1755	0.1086	0.1850
8	0.0965	0.1894	0.1076	0.2014	0.1020	0.1954	0.1109	0.2051
9	0.0948	0.1921	0.1058	0.2041	0.1003	0.1981	0.1092	0.2078
10	0.0945	0.1962	0.1056	0.2083	0.1000	0.2022	0.1089	0.2119

Note: Each row refers to a different cohort. The cohort number is reported in the first column and is increasing with year of birth. The columns headed by ρ_{12} , ρ_{12}^{wr} , ρ_{12}^{uw} refer to the return to high school in the baseline case, accounting for unemployment risk, for wage risk and for the two risks together, respectively. The columns headed by ρ_{23} , ρ_{23}^{wr} , ρ_{23}^{uw} refer to the return to college.

Table 3.2: Return to education, $RRA = 2$

Cohort	ρ_{12}	ρ_{23}	ρ_{12}^{ur}	ρ_{23}^{ur}	ρ_{12}^{wr}	ρ_{23}^{wr}	ρ_{12}^{uwr}	ρ_{23}^{uwr}
Panel A: Italy								
1	0.0928	0.1251	0.1217	0.1548	0.1149	0.1478	0.1240	0.1572
2	0.0821	0.1188	0.1107	0.1483	0.1039	0.1414	0.1129	0.1507
3	0.0704	0.1063	0.0987	0.1355	0.0920	0.1286	0.1009	0.1378
4	0.0589	0.0940	0.0869	0.1229	0.0803	0.1161	0.0891	0.1252
5	0.0477	0.0821	0.0754	0.1107	0.0689	0.1039	0.0776	0.1129
6	0.0367	0.0704	0.0641	0.0987	0.0577	0.0920	0.0663	0.1009
7	0.0260	0.0367	0.0531	0.0641	0.0467	0.0577	0.0553	0.0663
8	0.0155	0.0313	0.0423	0.0586	0.0360	0.0521	0.0444	0.0608
9	0.0207	0.0868	0.0477	0.1155	0.0413	0.1088	0.0498	0.1178
10	0.0313	0.0916	0.0586	0.1205	0.0522	0.1137	0.0608	0.1227
Panel B: US								
1	0.0471	0.0989	0.0685	0.1213	0.0630	0.1156	0.0663	0.1190
2	0.0449	0.1025	0.0662	0.1250	0.0608	0.1193	0.0641	0.1227
3	0.0411	0.1050	0.0624	0.1275	0.0570	0.1218	0.0602	0.1252
4	0.0438	0.1068	0.0651	0.1294	0.0597	0.1237	0.0630	0.1271
5	0.0427	0.1080	0.0640	0.1306	0.0586	0.1249	0.0619	0.1283
6	0.0406	0.1074	0.0618	0.1300	0.0564	0.1243	0.0597	0.1277
7	0.0395	0.1111	0.0607	0.1338	0.0553	0.1280	0.0586	0.1315
8	0.0417	0.1299	0.0629	0.1530	0.0575	0.1472	0.0608	0.1507
9	0.0400	0.1325	0.0613	0.1556	0.0559	0.1497	0.0591	0.1533
10	0.0397	0.1364	0.0610	0.1596	0.0556	0.1537	0.0588	0.1572

Note: Each row refers to a different cohort. The cohort number is reported in the first column and is increasing with year of birth. The columns headed by ρ_{12} , ρ_{12}^{ur} , ρ_{12}^{wr} , ρ_{12}^{uwr} refer to the return to high school in the baseline case, accounting for unemployment risk, for wage risk and for the two risks together, respectively. The columns headed by ρ_{23} , ρ_{23}^{ur} , ρ_{23}^{wr} , ρ_{23}^{uwr} refer to the return to college.

Table 3.3: Return to education, $RRA = 3$

Cohort	ρ_{12}	ρ_{23}	ρ_{12}^{ur}	ρ_{23}^{ur}	ρ_{12}^{wr}	ρ_{23}^{wr}	ρ_{12}^{uwr}	ρ_{23}^{uwr}
Panel A: Italy								
1	0.1151	0.1480	0.1493	0.1832	0.1856	0.2206	0.1671	0.2016
2	0.1042	0.1416	0.1380	0.1765	0.1739	0.2137	0.1556	0.1948
3	0.0922	0.1288	0.1257	0.1634	0.1612	0.2001	0.1431	0.1815
4	0.0805	0.1164	0.1136	0.1505	0.1488	0.1869	0.1309	0.1684
5	0.0691	0.1042	0.1018	0.1380	0.1366	0.1739	0.1190	0.1556
6	0.0579	0.0922	0.0903	0.1256	0.1247	0.1612	0.1072	0.1431
7	0.0469	0.0579	0.0790	0.0902	0.1130	0.1247	0.0958	0.1072
8	0.0362	0.0524	0.0679	0.0846	0.1017	0.1189	0.0845	0.1015
9	0.0415	0.1090	0.0734	0.1429	0.1073	0.1790	0.0901	0.1607
10	0.0524	0.1139	0.0846	0.1480	0.1189	0.1842	0.1015	0.1658

Panel B: US

1	0.0577	0.1100	0.0848	0.1385	0.0793	0.1327	0.0826	0.1361
2	0.0555	0.1137	0.0825	0.1422	0.0770	0.1364	0.0803	0.1399
3	0.0516	0.1161	0.0786	0.1448	0.0731	0.1389	0.0764	0.1424
4	0.0543	0.1180	0.0814	0.1467	0.0759	0.1408	0.0792	0.1443
5	0.0533	0.1192	0.0803	0.1479	0.0748	0.1421	0.0781	0.1456
6	0.0512	0.1186	0.0780	0.1473	0.0725	0.1414	0.0758	0.1449
7	0.0500	0.1223	0.0770	0.1511	0.0714	0.1452	0.0747	0.1488
8	0.0522	0.1414	0.0792	0.1706	0.0737	0.1647	0.0770	0.1682
9	0.0505	0.1439	0.0774	0.1733	0.0719	0.1673	0.0753	0.1709
10	0.0503	0.1478	0.0772	0.1773	0.0717	0.1713	0.0750	0.1749

Note: Each row refers to a different cohort. The cohort number is reported in the first column and is increasing with year of birth. The columns headed by ρ_{12} , ρ_{12}^{ur} , ρ_{12}^{wr} , ρ_{12}^{uwr} refer to the return to high school in the baseline case, accounting for unemployment risk, for wage risk and for the two risks together, respectively. The columns headed by ρ_{23} , ρ_{23}^{ur} , ρ_{23}^{wr} , ρ_{23}^{uwr} refer to the return to college.

Chapter 4

Judicial costs and household debt

4.1 Introduction

In the last few years a new line of research started investigating the economic implications of different legal systems. The empirical research has provided strong evidence that both, the content of laws and the quality of legal enforcement of the investors' rights heavily affect the development of financial markets: Among others, La Porta, Lopez-de-Silanes, Shleifer and Vishny [43] show that countries which protect creditors better have a higher ratio of private debt in terms of GDP. Cristini, Moya and Powell [25] and Bianco, Jappelli and Pagano [13] find strong evidence about the relevance of the activity of the legal system respectively for the Argentinian and the Italian corporate credit market. In the United States, Meador [48] and Jaffee [40] find that mortgage interest rate were generally higher in states where the law extended the length and the expenses of the foreclosure process.

Only few papers have investigated the impact that different legal systems can have on the household credit market. The existing literature on this topic has provided evidence exclusively for the United State; moreover, it has focused on the differences in the content of laws. Gropp, Sholz and White [30] find that in the United States generous bankruptcy exemptions reduce the amount of credit available to low-asset households, conditioning on their observable characteristics (while the effect is the opposite for high-asset households), and increase the interest rate on automobile loans for

low-asset households.

Here, we focus our attention on the role of the legal enforcement rather than on the specific content of laws, trying to insulate the first aspect from the second one. To do so, we need to observe differences in the quality of legal enforcement, while holding *constant* the set of legal rules. For instance, the U.S. do not satisfy this requirement in that the set of rules varies across states. In Italy, instead, the set of rules regulating credit relationships is the same across regions or provinces, but the enforcement differs according to the performance of judicial districts. For that reason, Italy represents an useful, if not unique, natural experiment, which can be used to disentangle the effect of enforcement from that of rules on credit market relationship.

We model the legal enforcement as an exogenous variable that affects the credit relationships between banks and consumers, by assuming that the behavior of legal institutions affects the liquidation value of the asset pledged as collateral by the borrower. Focusing on this mechanism, we construct a simple model that outlines two main effects through which the allocation of credit is affected by the working of the judicial system. First, a badly functioning judicial system might cause households to be credit constrained. This happens because banks shelter their revenues by asking a minimum amount of collateral for the contract to be signed. Second, the working of justice can affect the amount of debt received by constrained and unconstrained consumers, through its impact on the cost of credit.

In order to test our theoretical predictions we perform two econometric exercises. First, we estimate a probit model to test the hypothesis that the probability that Italian households are credit constrained, depends not only on the characteristics of the family members, but also on the judicial costs, which are proxied by two sets of measures, based on the length of civil trials and on the stock of pending civil trials. Second, we estimate a tobit model for the amount of debt to investigate whether the level of liabilities held by the households who are not rationed is also sensitive to judicial costs.

We find that the probability that Italian households are credit constrained is negatively affected by the quality of the judicial enforcement, regardless of the different measures we use to proxy the misbehavior of judicial districts. At the same time, we find that the poorer is the quality of the judicial enforcement the lower is the level of debt received by the households who are not rationed.

The chapter is organized as follows. In section 2, we illustrate the theoretical benchmark to interpret our results. Section 3 describes the data

and discuss the measures used to proxy for the quality of the judicial system. In section 4, we present the results of the empirical analysis. Section 5 concludes.

4.2 Theoretical framework

We consider a market for mortgages or consumer credit where households represent the demand side and the banking industry the supply side.

Each consumer lives two periods. In the first period, he is endowed with a positive amount of illiquid asset, A_i . In the second period, he works and receives a stochastic wage. In the good state of nature, which occurs with probability equal to p , the consumer earns a positive wage denoted by w_i ; otherwise he earns a zero wage.

The utility depends on the consumption level and on the property of the asset in both periods. It is additive between the two periods: $U_i = [A_i + \lg(\varepsilon + c_{1i})] + \beta_i [A_i + \lg(\varepsilon + c_{2i})]$, where $\varepsilon > 0$. We assume that the intertemporal rate of substitution is the same across consumers ($\beta_i = \beta$). The consumer wants to smooth consumption over time. In order to finance the consumption in the first period, either he asks for a loan or he sells the asset. However, since we want to study how the judicial system affects the credit market, we assume that the unit selling price of A_i , denoted by α , is so low that it is always more convenient to keep the asset and eventually to use it as collateral in a credit contract, instead of selling it.

The credit is provided by a banking sector, in which there is free entry. For simplicity, we also assume that a fixed interest rate, denoted by $(1 + \bar{r})$ is paid on the deposits.¹

The consumer makes default in two circumstances. In case of negative shock to income, the consumer is not able to repay the loan (involuntary default). Alternatively, we also consider the case in which the consumer has incentives not to repay the loan even if he would be able to do so (strategic default). Thus, the only credible arrangement is a collateralized credit contract. The contract entitles the lender to the right of repossessing the asset pledged as collateral once the consumer does not repay.

The judicial system affects the credit contract relationships: the enforcement of the creditors rights is costly and this cost depends on the performance

¹Assuming that the supply of funds is increasing does not change the results.

of courts. These last set the time when the collateral is transferred from the borrower to the lender in case of default. The worse the performance of courts the more delayed is this time. From the lender's point of view, this time is a cost. The bank has to pay legal expenses proportionally to the length of the trial, the asset has a positive depreciation rate and holding funds in the collateral entails an opportunity cost. In any case, the liquidation value of the asset and therefore the total profits are lower the worse is the quality of judicial enforcement. If we denote it by g , where $0 < g < 1$, the liquidation value of each unit of collateral is equal to αg . From the consumer's point of view this time is a 'revenue' since he can enjoy the property of the asset until the judge orders its transfer to the lender. In particular, the utility that the consumer gets is $(1 - g)$ for each unit of collateral. As we will show, the degree of judicial enforcement will determine the decision to repay or not the loan.

4.2.1 The optimal credit contract

The optimal credit contract is a pair of debt and interest rate (B_i, r_i) , where B_i and r_i are maximizing the consumer's utility under this incentive compatibility constraint and the participation constraint of the bank. This is because, given the hypothesis of free entry in the banking industry, the rents generated by the transaction are kept by the consumer and the expected profits of the bank are zero. The consumer's problem is described by:

$$\max_{c_{1i}, c_{2i}} EU_i = [A_i + \lg(\varepsilon + c_{1i})] + \beta p [A_i + \lg(\varepsilon + c_{2Hi})] + \beta(1 - p) [A_i + \lg(\varepsilon + c_{2Li})]$$

$$c_{1i} = B_i \quad c_{2Hi} = w_i - B_i(1 + r_i) \quad c_{2Li} = 0 \quad (4.1)$$

$$B_i(1 + \bar{r}) \leq pB_i(1 + r_i) + \alpha(1 - p)gA_i \quad (4.2)$$

$$U_{Di} = [(1 - g)A_i + \lg(\varepsilon + w_i)] \leq [A_i + \lg(\varepsilon + w_i - (1 + r_i)B_i)] = U_{NDi} \quad (4.3)$$

where H and L stand for high and low state of the world; U_{Di} and U_{NDi} are the utility of making and not making default for consumer i . Since the credit is fully collateralized, the bank's expected return is given by the repayment

of the debt and the liquidation value of the collateral asset, which is affected by the quality of judicial enforcement through the parameter g .

The incentive compatibility condition of the borrower requires that the utility that the consumer gets by making strategic default (left hand side of condition 4.3) must be lower than the utility that he gets by repaying the loan (right hand side of condition 4.3). The constraint tells us that consumers with lower wealth endowment have a larger incentive to make strategic default, because the cost, which consists in losing the property on his asset, is lower for them. However, when the quality of judicial enforcement is very poor, the consumers are more tempted not to repay. Namely, if it takes long time before the transfer can occur, the consumer can longer enjoy the utility from the asset. If the incentive compatibility constraint were violated, the bank will make negative expected profit. This is because the consumer would have the incentive to default, even being able to repay the loan, and the lender would get the liquidation value of the collateral with a probability equal to one.

Let us assume, for simplicity that $\varepsilon = 0$. We introduce this assumption only to make more simple and intuitive the comparative static analysis but it is not necessary to derive our results.

If one neglects constraint (4.3), the optimal contract is characterized by the following level of debt and interest rate:

$$B_i^* = \frac{pw_i + \alpha(1-p)gA_i}{(1+\bar{r})\left(\beta + \frac{1}{p}\right)p} \quad (4.4)$$

$$(1+r_i)^* = (1+\bar{r}) \left[\frac{1}{p} - \frac{\alpha(1-p)gA_i\left(\beta + \frac{1}{p}\right)}{w_i p + \alpha(1-p)gA_i} \right] \quad (4.5)$$

This is the solution only if the consumer's incentive compatibility constraint is not binding, which means that the consumer has no incentive to do strategic default. We can check if this is the case, by substituting the two values into the incentive compatibility constraint of the consumer:

$$\exp(gA_i) [w_i p + \alpha(1-p)gA_i] \geq \frac{1}{\beta_i} + p \quad (4.6)$$

If this condition were not satisfied, then the amount of debt and the interest rate found before would not be the terms of an the optimal contract. In this

case, the consumer's incentive compatibility would be binding and the solution of the previous maximization problem would coincide with the solution of the system made by equations (4.2) and (4.3):

$$B_i^C = \frac{pw \left(1 - \frac{1}{\exp(gA_i)}\right) + \alpha(1-p)gA_i}{(1 + \bar{r})} \quad (4.7)$$

$$(1 + r_i)^C = \frac{(1 + \bar{r})}{p} \frac{pw \left(1 - \frac{1}{\exp(gA_i)}\right)}{pw \left(1 - \frac{1}{\exp(gA_i)}\right) + \alpha(1-p)gA_i} \quad (4.8)$$

If the selling price of the asset is sufficiently low ², the new amount of debt is lower than the previous one. Thus, we will define credit or liquidity constrained those consumers who receive the amount of credit given by equation (4.7).

4.2.2 A comparative static exercise

In this section, we derive some testable predictions about the role of the judicial enforcement for the household credit market. This is done by using a simple comparative static analysis. We are interested in investigating whether and in which direction a rise in the degree of judicial enforcement affects the amount of debt received by the consumers. Moreover, we also test whether the condition that establishes who will be credit constrained and who will not depends on the behavior of courts.

The partial derivative of B_i^* and B_i^C with respect to the parameter g are:

$$\begin{aligned} \frac{dB_i^*}{dg} &= \frac{pw + \alpha(1-p)A_i}{(1 + \bar{r}) \left(\beta + \frac{1}{p}\right) p} \\ \frac{dB_i^C}{dg} &= \frac{pwA_i\alpha(1-p) \left[A_i g \exp(gA_i) + \left(1 - \frac{1}{\exp(gA_i)}\right) \right]}{(1 + \bar{r})} \end{aligned}$$

They are both positive, which shows that if the quality of judicial enforcement increases, so does the amount of debt received by liquidity and non-liquidity constrained consumers in an unambiguous way. The intuition of this result is

²The selling price must satisfy this condition: $\alpha < \frac{w_i}{\beta \exp(A_i g) \alpha(1-p)gA_i}$

the following. If the consumer is not liquidity constrained, an increment in the legal parameter relaxes the participation constraint of the bank with the result that a larger amount of credit is provided. If he is liquidity constrained, a reduction of the legal costs not only relaxes the bank's participation constraint but also makes not binding the incentive compatibility constraint. Since both effects go into the same direction, they enlarges the set of feasible solutions of the transaction, which implies a larger availability of credit. In this explanation, we have implicitly assumed that the consumer were still constrained after the change in the degree of legal enforcement. Of course the opposite could also happen: the rise in the legal enforcement could completely eliminate the incentive to make strategic default. In this case, the consumer would be unconstrained after the change in the legal variable.

Finally, we may consider what happens to the condition that establishes whether a consumer will be credit constrained. Since the left hand side of inequality (4.6) increase monotonically as the wealth endowment increases, we can find a unique value of wealth such that consumers with a wealth endowment larger than that will not be credit constrained and viceversa. Moreover, by using the Implicit Function Theorem, we can easily show that, for each set of parameters of the model, this threshold value, denote by \tilde{A} , is decreasing in the legal variable:

$$\frac{d\tilde{A}}{dg} = -\frac{\tilde{A}}{g} < 0$$

This implies that an improvement in the degree of legal protection of the creditor's rights shifts down the collateral requirement asked by the bank and therefore reduces the share of people who will be credit constrained.

A similar exercise can be done for the parameter β . For each set of the parameters of the model, we can find a type $\tilde{\beta}$ such that individuals with β_i lower than this value are more likely to be rationed in the credit market, given that they have a demand of credit too large to be completely satisfied by the bank and viceversa. By using the Implicit Function Theorem, it is easily to show that also this threshold level is decreasing in the legal variable. Namely:

$$\frac{d\tilde{\beta}}{dg} = -\frac{A_i g \exp(gA_i) [pw + g(1-p)\alpha(1+gA_i)]}{\beta} < 0$$

This result is quite important for the empirical analysis we want to perform. Our data do not allow to know the β_i type of the borrower, but we can observe his wealth endowment. Then, for a given amount of wealth, if we assume that β is a random variable, it follows that the probability that a generic consumer is liquidity constrained is equal to the probability to be a β -type lower than the threshold type. Since we showed that the threshold shifts down when the degree of legal enforcement increases, it follows that also the probability to be liquidity constrained is decreasing in degree of legal enforcement.

The testable implications derived in the theoretical analysis are summarized in the following:

Proposition 1 *When the degree of legal enforcement improves, the amount of debt received by constrained and unconstrained consumers increases, while the probability to be liquidity constrained goes down.*

In the next section, we check if the empirical evidence is consistent with these two theoretical predictions.

4.3 Data

4.3.1 Households data

Households data come from the Survey of Household Income and Wealth (SHIW), that is ran by the Bank of Italy on a almost every other year basis. This is a national representative household survey that provides data on income, consumption and households' characteristics. We refer to Brandolini and Cannari [14] for a detailed description of the survey.

In this work we use data drawn from five waves: 1989, 1991, 1993, 1995 and 1998. The data used in this analysis are available for those waves only. Given that, pooling data coming from different waves of the SHIW is not without problems, since the sample design slightly changed from the 1989's wave to the last wave. All the statistics we present are thus computed using sample weights. Restricting our sample to the last five waves leaves 39833 observations.

This survey is an invaluable source of information for the issues investigated here. Data are provided on households assets and liabilities and enable

to identify credit constrained households. In the remaining of this section, we describe the data.

The survey distinguishes between real and financial assets, which is quite useful because the collateral that is pledged by the bank is likely to be a real asset.³

Real assets include houses, lands, valuables and the business, if any, owned by the households and average around 86175 1991's euro. Around 64% of the sample own the house of residence that is worth on average 79353 1991's euro. Financial assets include bonds and stocks held by the household and average around 13828 1991's euro.

Data on households' liabilities are quite detailed. They provide a breakdown by the usage of debt, which make it possible to identify the amount borrowed to finance the purchase of houses, real goods, such as valuables and jewelry, cars and other durable goods, such as furniture, white and black durable goods, but also the amount borrowed to finance non-durable consumption. Furthermore, in the 1989 and 1991's waves, the data distinguish between the debt towards bank held by the household at the beginning of the interview's year and that at the end of the interview's year, while in the 1993, 1995 and 1998's waves only the end of the year debt is surveyed. The amount borrowed to finance the house's purchase is 1640 1991's euros at the end of the year. This figure is computed using the whole sample, which includes all those households who are not indebted. Using only those who are actually indebted, the figure becomes 15633 1991's euros.

Conditional on those who are actually indebted, the amount borrowed to finance the valuables' purchase, the car's purchase and the purchase of other durable goods, such as furniture, white and black durable goods, and non-durable consumption, are, respectively, 3577, 4384, 2141, and 3245 1991's euros at the end of the year.

The proportions of households who are indebted to finance the house's purchase, valuables' purchase, the car's purchase and the purchase of other durable goods, such as furniture, white and black durable goods, and non-durable consumption, are, respectively, 10.97%, 0.24%, 6.21%, 2.98%, and 0.94% at the end of the year. These figures together show that households mostly borrow to finance the purchase of houses, cars, and other durable goods, such as furniture, white and black durable goods.

Furthermore, households are asked if they applied for a loan in the inter-

³Often mortgage contracts require the house to be used as collateral for the loan.

view's year and if their application has been accepted, rejected or partially rejected. They are also asked if they refrained from applying for a loan anticipating that their application could have been rejected. This allows to identify credit constrained households: they have been at least partially turned down from credit or they refrained from applying for loans feeling that their application could have been rejected. Using this definition,⁴ we obtain that around 3.55% of the households are credit constrained, going from around 5% in 1989 to 3% in 1998. This is admittedly a small figure also compared with what Jappelli [41] finds in the US, that is around 19%. Here, we can only claim that this figure is a lower bound for the percentage of credit constrained households in the population. Table 4.1 summarizes these statistics.

4.3.2 The quality of judicial enforcement

This section documents the differences across regions in the working of justice. Ideally, in order to assess the quality of judicial enforcement we should be able to estimate the parameters of the technology of each court and to relate them to the production frontier.

One possibility is to use a Data Envelopment Analysis approach, which, however, is not uncontroversial.⁵ In our case, lack of data prevents us to follow this route. In the impossibility of measuring the production frontier, any measure of 'efficiency' of the judicial system is somehow arbitrary.

We grossly follow Bianco, Jappelli and Pagano [13] in evaluating the working of justice by looking at a set of variables that approximate the cost that a lender would face to recover his loan in case the borrower goes bankrupt. These are the stock of pending civil trials and the length of civil trials. The first variable proxies for the degree of congestion of each judicial district variable, while the second gives an indication on how long is likely to take before the lender can repossess the collateral.

Before going into the detailed illustration of the differences across regions, it is worth devoting some space to the description of the judicial system in Italy.

⁴A similar definition appears in Jappelli [41] who uses an American survey, the Survey of Consumer Finances, with a structure similar to the SHIW to identify credit constrained household in the US.

⁵At the most, we could estimate the relative efficiency of different courts.

Italy is a civil-law country. This implies that the main attribute of the judicial system is that of enforcing the law. Italian law regulates separately the trials that deal with criminal offenses and those dealing with civil offenses. Correspondingly, different branches of the judicial system deal with criminal and civil offenses. This work concentrates on civil offenses. Those are the most relevant when households do not pay back their debts. Civil trials can undergo three degrees of judgment. The first degree, a second degree corresponding to the so-called appeal, and a third degree that can only deal with formal aspects of the summon issued in the former degrees. Readers familiar with the American system will recognize some similarities. Here we focus on civil trials in the first and in the second degree of judgment.

The data on trials come from a survey that is ran every year by the National Institute of Statistics (ISTAT), while the data on the number of judges and the size of the administrative staff assigned to each judicial district come from the Italian Ministry of Justice. The primary sample units are courts. Data are then aggregated by judicial district. Roughly, each district corresponds to a region. In few regions, such as Lombardia, Campania, Puglia, Calabria, Sicilia and Sardegna there are more than one judicial district.⁶ In the analysis, we aggregated judicial districts belonging to the same region. Furthermore, Valle d'Aosta and Piemonte belongs to the same judicial district, that we call Piemonte. We draw data from the 1992 to the 1998 surveys. The figures we present are obtained averaging the yearly data.

Figure 4.1 displays the average length of civil trials in days per region. This includes the length of both first and second degree of civil trials. We see that civil trials are longer in judicial districts corresponding to Southern regions, suggesting that the cost of repossessing the collateral is higher in these regions. A similar pattern arises in figure 4.2, that hosts the stock of pending trials. Lazio and Campania are ranked first and second.

It must be noticed that the stock of pending trials depends on the size of the judicial district and does not necessarily reflect a ill-functioning of it. In order to normalize the stock of pending trials, we use the number of judges, the administrative staff and the population of each judicial district. Those are plotted in figures 4.3,4.4 and 4.5.⁷ Inspecting those figures, we see that some of the judicial districts with high stock of pending trials are also big in

⁶About 30% of the Italian population resides in those regions.

⁷The data used in these figures come from the Department of Justice (Ministero di Grazia e Giustizia). Tullio Jappelli and Marco Pagano are gratefully acknowledged for providing us with the data.

terms of judges, staff and population. This is certainly the case of Lazio and at a less extent of Campania.

Next section presents the results of our empirical analysis. In order to proxy the ‘efficiency’ of the judicial system we use four variables. The first (see figure 4.6) is the stock of pending trials divided by the number of judges. The second (see figure 4.7) is the stock of pending trials divided by the number of judges and the staff. The third (see figure 4.8) is the stock of pending trials divided by the population. Finally, we use also the length of trials in days. These are not the only available proxies. Using proxies based on the stock of ended trials or on the stock of incoming trials does not lead to very different results, which are not discussed in the following.

4.4 Results

4.4.1 The working of the judicial system and credit constraints

In order to explore the relation between the working of judicial system and credit constraints, we rely on a variable that identifies credit constrained households. This variable allows us to split the sample in two groups: those who are and those who are not credit constrained. The two groups differ for a number of characteristics and we will try to relate these differences to the fact that some are credit constrained and some are not. This procedure has been successfully used by Jappelli [41] and Cox and Jappelli [24]. It is useful stressing, however, that the probability of being credit constrained depends both on the behavior of households and on that of banks. Thus, in the interpretation of the results, we will often refer to the procedure that banks uses to screen applications,⁸ even though this is not explicitly modeled. In that respect, we are following a reduced form approach.

We run a number of probit where the dependent variable is equal to one when households are credit constrained. In particular, we experiment on the different proxies of the efficiency of the judicial system to see how robust are

⁸This procedure is quite standard. Applicants are typically asked their age, their income, their occupation, few questions about the structure of the household, their parent’s income. Apparently, the education of the applicants does not enter the decision process of the bank. Notice that in Italy the market for loans to young individuals who wish to finance their study is virtually absent.

our results to the measures used. The results are reported in table 4.2.

Each column in table 4.2 refers to a different proxy for the *cost* of repossessing the collateral asset by the lender. In the second column, we use the stock of pending trial divided by the population. In the third column the stock of pending trials is divided by the number of judges. The same variable is divided by the number of judges plus the staff in the fourth column and by the number of incoming trials in the fifth column. Finally, in the sixth column the proxy used is the average length of trials.

The coefficients are all broadly significant at the standard levels. All the specifications include a set of year dummies, because households coming from different waves are pooled together. Furthermore, in order to avoid any potential bias coming from the fact that the sample design of the different waves is somewhat different, we use throughout the sample weights to compute our estimates. Standard errors are corrected for clustering and stratification.⁹

After some search,¹⁰ we find that the probability of being credit constrained increases with age but at a decreasing rate. The coefficient of age is positive in all the specifications, while the coefficient of the age squared term is negative. This is consistent with the evidence that income profiles are hump-shaped. When individuals are young, their income rises and it is at this stage that they are likely to be credit constrained, because they want to borrow against future income, while the bank is likely to decide on the basis of the current income. This effect is mitigated with age since the growth rate of income decreases.

Households headed by more educated individuals are more likely to be credit constrained. The positive coefficient of the variable *Years of schooling* points into this direction. This can be rationalized in a number of ways. First, more educated individuals face a steeper income profile, which is typically associated with credit constraints in the early part of the life cycle (typically, at the beginning of the career). Notice, however, that the coefficient of *Years of schooling* is not significant at 1%, which may suggest that the effect of

⁹The SHIW has a panel component and is sampled in 51 strata.

¹⁰Perhaps surprisingly, family income was not found to be statistically significant in most of the experiments. Specifications including also a set of dummies, for southern and northern regions, did not lead to results different from those reported here. Our data do not allow us to include a full set of regional dummies. We are aware that this might be a problem, which is partly lessened by the fact that the bulk of heterogeneity is between northern and southern regions, while northern regions, so as southern regions, are quite 'similar' among them.

schooling on the top of the age is not such strong. Second, our measure of credit constrained households might not sufficiently account for discouraged borrowers, who are likely to be less educated than those who apply for a loan.

Households who own the house of residence are less likely to be credit constrained, while to be self-employed increases the probability of being credit constrained. This two findings are in line with the intuition. It is likely to be the case that, when the loan finances the purchase of a house, the house itself is used as collateral. Banks are more likely to lend to those with collateral. On the other hand, self-employed earn much less stable income, which can cause the bank to be less willing to lend to them.

Married couples are more likely to be constrained. This might happen for a variety of reasons. First, single households are more likely to be wealthy than married couple. Second, households typically borrow to finance the purchase of a house and married couples are much more likely to purchase a house (this is apparent in the data).

Our specifications include also a variable to account for the size of the household's city of residence. The variable named *City size* is equal to one if the household is resident in a town with more than 20.000 inhabitants. We speculate that this variable might proxy for the severity of asymmetric information problems that plague credit relationship. The idea is that information is much more readily available in smaller than in bigger cities. This implies that the cost of screening for banks is smaller in less big cities. The positive coefficient of the *City size* variable is in accordance with the idea that more severe informational problems can cause individuals to be constrained.

We include also a variable that measures the degree of concentration of the banking sector at the regional level.¹¹ Households facing less competitive bank industry are more likely to be credit constrained. This seems reasonable. Experimenting with other variables, such as the number of employees divided by the GDP, led to a very similar evidence.

The variable called *Justice* is proxying for the judicial costs that the lender has to pay to recover his credit in case of borrower's default. One can notice that in all the specifications, the coefficient is positive and significant. This implies that the higher judicial costs the more likely households are

¹¹This and the other variables that refer to the bank industry have been kindly provided by Tullio Jappelli.

credit constrained. In order to appreciate the importance of judicial costs we compute by how much the probability of being credit constrained increases for an 'average' household that moves from a low-cost judicial district to an high-cost one. This is done in table 4.3, which is a double entry matrix: the columns are the judicial districts from where and the rows are those to that the household moves.¹² Each entry of the matrix is computed as 1 minus the ratio between the probability of being credit constrained for the average household living in the column's judicial district and that for the same household living in the row's judicial district. A positive entry means that moving from the column's to the row's judicial district decreases the probability of being credit constrained. For instance, the entry in the Campania's column and the Lombardia's row is 0.4659, which means that moving from Campania to Lombardia lowers the probability of being credit constrained by around 47%.

The general pattern arising from table 4.3 is that moving from northern judicial district generally increases the probability of being credit constrained. The case of Trentino A.A is emblematic: moving to any other district increases the probability of being credit constrained.

The effect of judicial costs on the probability of being credit constrained is not the only welfare implication of the quality of judicial enforcement. Indeed, there might be a welfare effect also for those who are not credit constrained. This might happen because banks require more collateral in those judicial districts where the quality of enforcement is poorer. In other words, it might be the case that a bad functioning of the judicial system reduces the shadow value of the collateral. If this is indeed the case, the bank compensates this lack of value of the collateral by increasing the interest rate. Thus, if the quality of the judicial enforcement improves, the interest rate should decrease, other things being the same and the demand for debt should increase, as shown in section 2. Next section deals with those questions.

¹²This table is computed using the stock of pending trials divided by the population as proxy for judicial costs. The figures obtained using the other proxies are similar and, thus, are not reported.

4.4.2 The role of collateral and the quality of the judicial enforcement

In this section, we study how the relation between household's debt capacity and collateral is mediated by the quality of the judicial enforcement. Banks use collateral to shelter their revenues from the event of borrower's default. In case of default, they repossess the collateral at a cost that crucially depends on the quality of judicial enforcement. Namely, the poorer is the quality of the judicial enforcement, the higher is the cost the bank has to face to repossess the collateral. This lowers the shadow value of collateral since, other things being equal, the bank will ask for more collateral anticipating that recovering losses in case of borrower's default will be more costly. On the other hand, for a given amount of collateral, that must exceed a certain threshold beyond that the borrower is not given credit, the poorer is the quality of judicial enforcement the lower is the amount of debt received by the borrower, i.e. the lower is his debt capacity. Thus, we expect to find a negative relationship between the cost of repossessing the collateral and the amount of debt that we observe for the households who are not credit constrained.

We estimate a tobit model with a term that corrects for endogenous selection.¹³ The use of a tobit model is required by the fact that we are

¹³If households are not credit constrained the observed amount of debt is given by:

$$D_i = x_{1i}\beta + u_{1i} \quad (4.9)$$

while for credit constrained households it holds:

$$I[x_{2i}\beta + u_{2i} > 0] \quad (4.10)$$

where $I[\cdot]$ is a binary indicator equal to one when the relation within brackets is true and to zero otherwise. We assume that u_{1i} and u_{2i} come from a double-truncated normal with full variance-covariance matrix.

Selecting only those households who are constrained induces bias if the probability of being credit constrained depends upon a same set of factors upon which the amount of debt depends and these factors cannot be controlled for, i.e. when u_{1i} is not independent of u_{2i} . This is the well known bias coming from non-random selection (see Gronau [29] and Heckman [37]). The textbook version of the so-called Heckman selection model deals with estimating a model such as that in equations (4.9)-(4.10), but under the assumption that before selection u_{1i} is normal. Our case is slightly more special in that u_{1i} comes from a truncated normal also before selection. This happens because the amount of debt is not allowed to be negative.

matching the mean of a left-truncated distribution. The endogenous selection term comes from the fact that we exclude the households who are constrained and that the probability of being credit constrained and the amount of debt are affected by the same set of unobservable factors.

The selection term is computed using the estimates in the previous section. We rely on two exclusion restrictions to identify the model. Namely, we assume that the size of the city of residence and the degree of concentration of the banking industry at a regional level affect the probability of being credit constrained, but do not affect the amount of debt for those who are not constrained.

For those exclusion restrictions to be valid two conditions need to be satisfied. First, we need assuming that the household's tastes for debt do not depend on either the size of the city of residence or on the degree of concentration of the banking industry in the region where the borrower resides. This is a relatively safe assumption. Second, we have to assume that for those who are given credit the price of the loan, which is the combination of interest and collateral, does not depend on the city size and on the degree of concentration of the banking sector. This is a much stronger claim, that is mitigated by the fact that we control for other variables in the regressions. Thus, we need requiring *only* a conditional independence. Given that we control in the regression for a number of households characteristics and that the price of the loan is likely to depend on those, we believe that this assumption is not so dramatic after all.

In table 4.4 we report a first set of results. These are obtained using as a proxy for the quality of judicial enforcement the stock of pending trials divided by the population. Using the other proxies for judicial costs leads to very similar results, which are not reported here.¹⁴ Columns differ for the measure of collateral used. In the first column, we use as a measure of collateral the stock of real wealth, that includes land, houses and, eventually, the business ran by the households. In the second column, we restrict the measure of collateral to land and houses. The third column proxies the collateral by the value of the house of residence, while the fourth excludes from the stock of land and houses the house of residence. The use of different

¹⁴These proxies are: the stock of pending trials divided by the number of judges, the stock of pending trials divided by the judges and staff, the stock of pending trials divided the number of incoming trials and the length of trials. For reference, we report also table 4.5, where judicial costs are proxied by the stock of pending trials divided by the number of judges.

measures of collateral comes from the fact that the collateral that is actually pledged by the bank is unobservable to us.

The coefficients are well determined. The relation between the amount of debt held by unconstrained households and the age of the head is hump-shaped. This arises from the positive sign of the age term and the negative sign of the age squared term and it is in line with the results from other studies, as for example the one by Cox and Jappelli [24]. Households headed by more educated individuals held more debt. Education is a likely proxy of the permanent income. Then, it would be tempting to attribute this positive coefficient to the relation between permanent income and debt. However, the correct assessment of this relation depends on the nature of transitory shocks, that are typically unobservable. On the other hand, a positive coefficient of the education variable may signal that borrower with higher education has high credit scores and thus may receive credit at better conditions.

Owning the house of residence raises the amount of debt. Notice that the coefficient is only marginal significant in the second and in the third column where the measure of collateral used is closer to the value of the house of residence (in the third column it is indeed the value of the house of residence). This may depend on two factors: the house of residence can be used as collateral and its purchase might have been financed by a mortgage.

Being self-employed reduces the amount of debt. This may happen for two reasons. First, self-employed and employed may be given loans of different size. It might be that banks discriminate on the size and are more willing to give big loans, typically mortgages, to those who are not self-employed and earn a more stable stream of income. In our data, however, most of the households borrow to finance the house purchase. Second, being self-employed may reduce the credit scores used by the banks. A similar interpretation applies for married couples who hold more debt.

The coefficient of the collateral is positive. This is in line with the theory and with the intuition. Banks are more willing to lend to borrowers endowed with more collateral.

The coefficient of the quality of judicial enforcement is negative. Recalling that we are measuring the cost of a badly functioning judicial system, the negative coefficient means that if the quality of the judicial enforcement gets worse, the debt held by unconstrained households decreases. This is the effect we were expecting from the theory and it suggests that poorer quality of judicial enforcement is associated with higher cost of the debt for the households. We might try also to quantify this effect.

Table 4.6 shows how much the household's debt capacity increases as judicial costs fall, other things being equal. Columns differ for the measure of collateral used in the estimation, as described above. Rows differ for the proxies of judicial costs: the stock of pending trials divided by population in the first row, the stock of pending trials divided by the number of judges in the second, the stock of pending trials divided by the judges and staff in the third, the stock of pending trials divided the number of incoming trials in the fourth and the length of trials in the fifth.

The first thing to notice is that the effect of judicial costs on the household's debt capacity is less than one to one: it is at most around 70%, which means that less than 3/4 of a percentage increase of judicial costs is passed through the household's debt capacity. Secondly, the effect of judicial costs does not much vary for different measures of collateral, while it does when different proxies of judicial costs are adopted. For instance, when judicial costs are proxied by the stock of pending trials divided by the population, the effect averages around 33%, which means that if the stock of pending trials increases by 6250 units (which is around the 5% of the national average) the household's debt capacity decreases by 170 1991's euro. On the other hand, when judicial costs are proxied by the length of trials, the effect averages around 70%, which means that if the length of trials increases by 111 days (which is around the 5% of the national average) the household's debt capacity decreases by 382 1991's euro. Given that the median debt is around 5.000 1991's euro, these effects do not seem to be small. Moreover, given that the debt is very unevenly distributed and skewed to the left, these effects greatly differ across households. Not surprisingly, households holding less debt are going to be more affected by the increase in judicial costs.

Taken together, these results suggests that judicial costs affect the average household's debt capacity and that the effect varies across different definition of judicial costs.

4.5 Conclusions

This chapter analyzes the relation between the quality of judicial enforcement and the allocation of credit to households at a theoretical and empirical level. The theoretical analysis provides a benchmark to interpret the empirical results. We derive a simple model that outlines two main effects through which the allocation of credit is affected by the working of the judicial system.

First, a badly functioning judicial system might cause households to be credit constrained. This happens because banks shelter their revenues by asking a minimum amount of collateral for the contract to be signed. This minimum amount of collateral increases if banks operate in a more ‘risky’ environment, that in our case means that the cost of repossessing the collateral in case of borrower’s default is higher. Through this channel, badly functioning institutions can have relevant welfare costs.

Second, the working of justice mediates the relation between collateral and debt also for the households who are *not* constrained. The cost of debt for the households is at a large extent an endogenous variable. It is likely to depend on a number of factors, including household characteristics and environmental variables. Among those, we focus on the quality of the judicial enforcement. Typically, for a given amount of collateral, the interest rate asked by banks is higher the higher is the cost of repossessing the collateral. A badly working judicial system raises this cost.

The empirical analysis uses a sample drawn from an Italian survey, the Survey of Households Income and Wealth and suggests that these two effects take place.

To perform the analysis we use a self-reported measure of credit constrained. We are aware of the limitation of the self-reported measure. Mainly, they may be affected by severe measurement errors, which might also be the case for all the other measures elicited from household surveys. The main advantage, however, is to prevent using incredible identification restrictions in order to distinguish those who are credit constrained from those who are not.

We find that the working of justice affects the probability of being credit constrained: households who live in more efficient judicial districts tend to have a lower probability to be turn down from the loan. It arises that, other things being equal, moving from low-costs (typically, in northern Italy) to high-costs judicial districts reduces the probability of being credit constrained by around 35%.

In the second part of the empirical analysis, we focus only on the households who are unconstrained. This is done by correcting for endogenous selection, given that the probability of being credit constrained and the amount of debt received by each household are likely to depend upon the same set of factors which we cannot control for. We find that the amount of debt of non-rationed households decreases if the quality of judicial enforcement worsen in the area of residence. This implies that the household’s debt capacity is

higher the lower are judicial costs. We interpret this result as evidence of the fact that, other things being equal, the cost of debt is lower where the justice works better. The magnitude of this effect varies according to how judicial costs are measured: it ranges from 22% to 70%. We find that the median and most of the households are going to be affected by judicial costs in a non-negligible way.

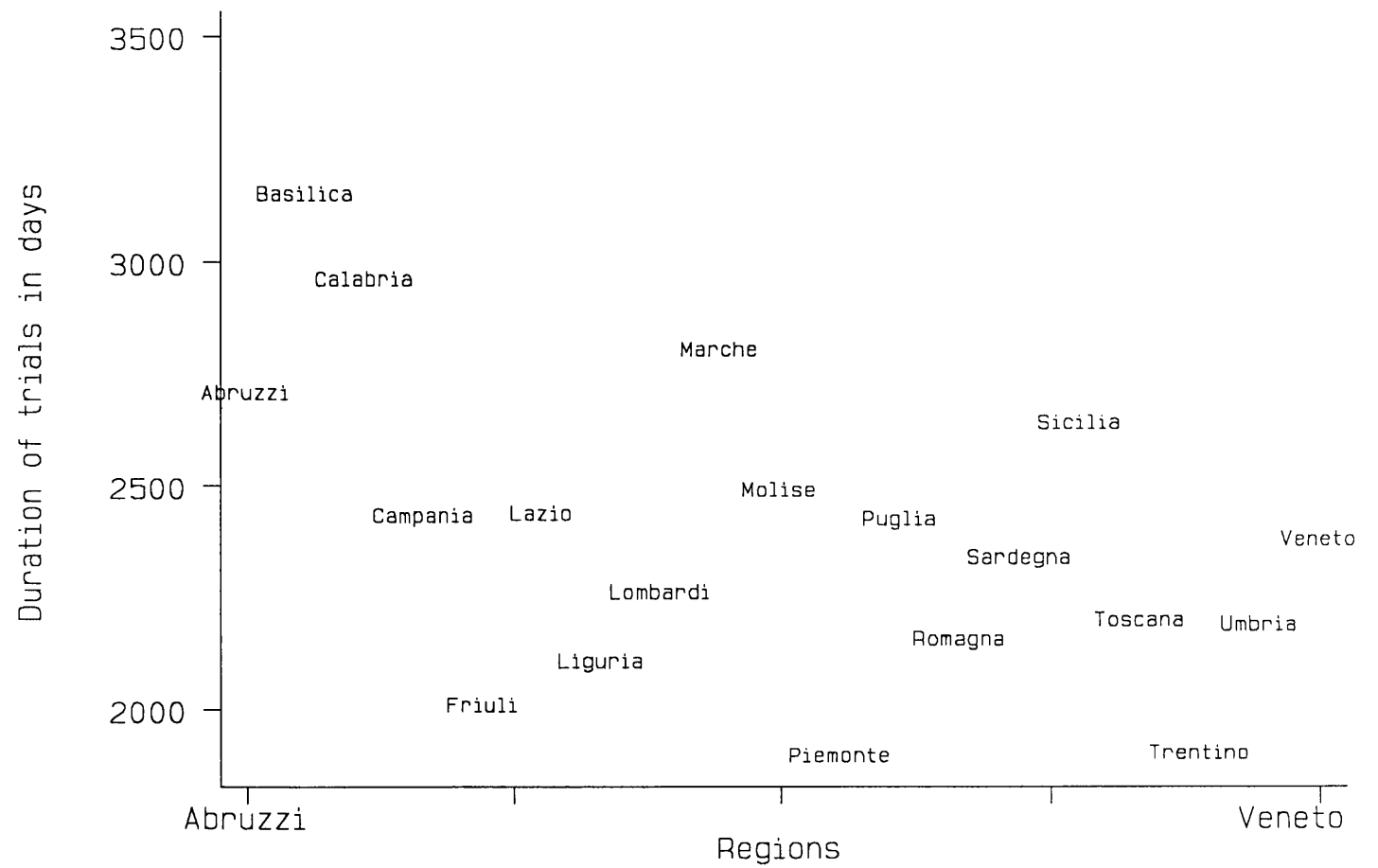


Figure 4.1: Average length of trials in days

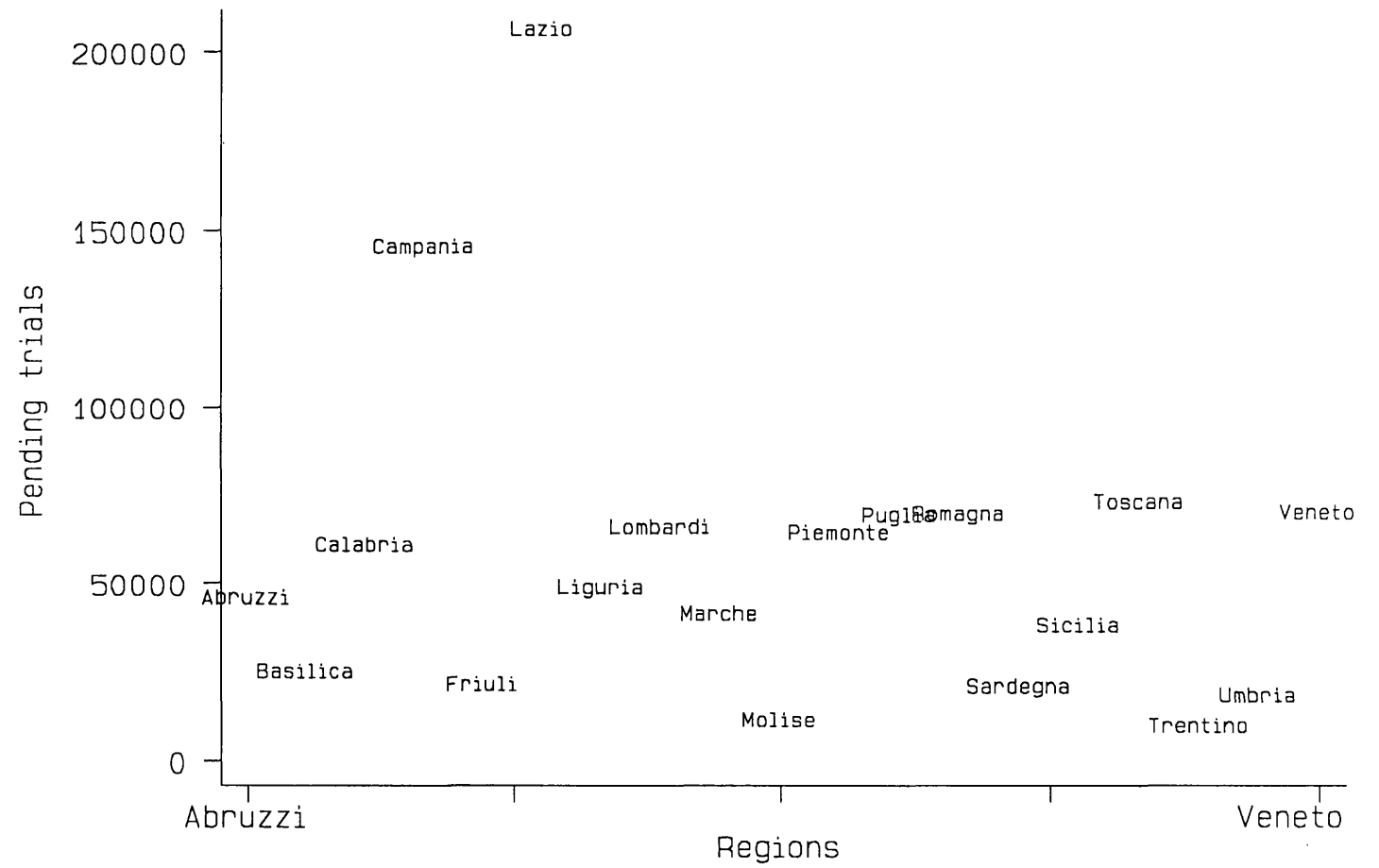


Figure 4.2: Stock of pending trials

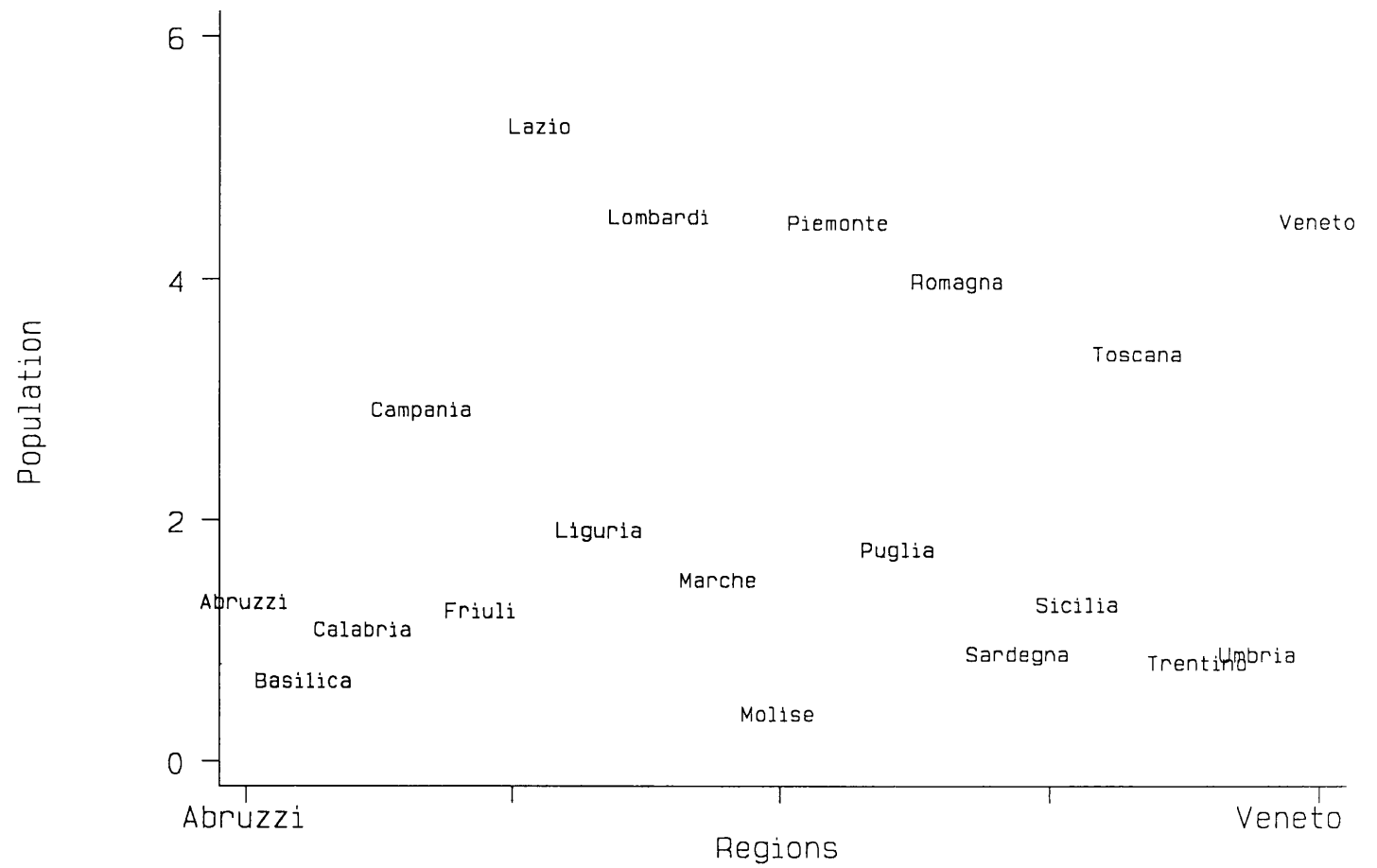


Figure 4.3: Population per judicial district

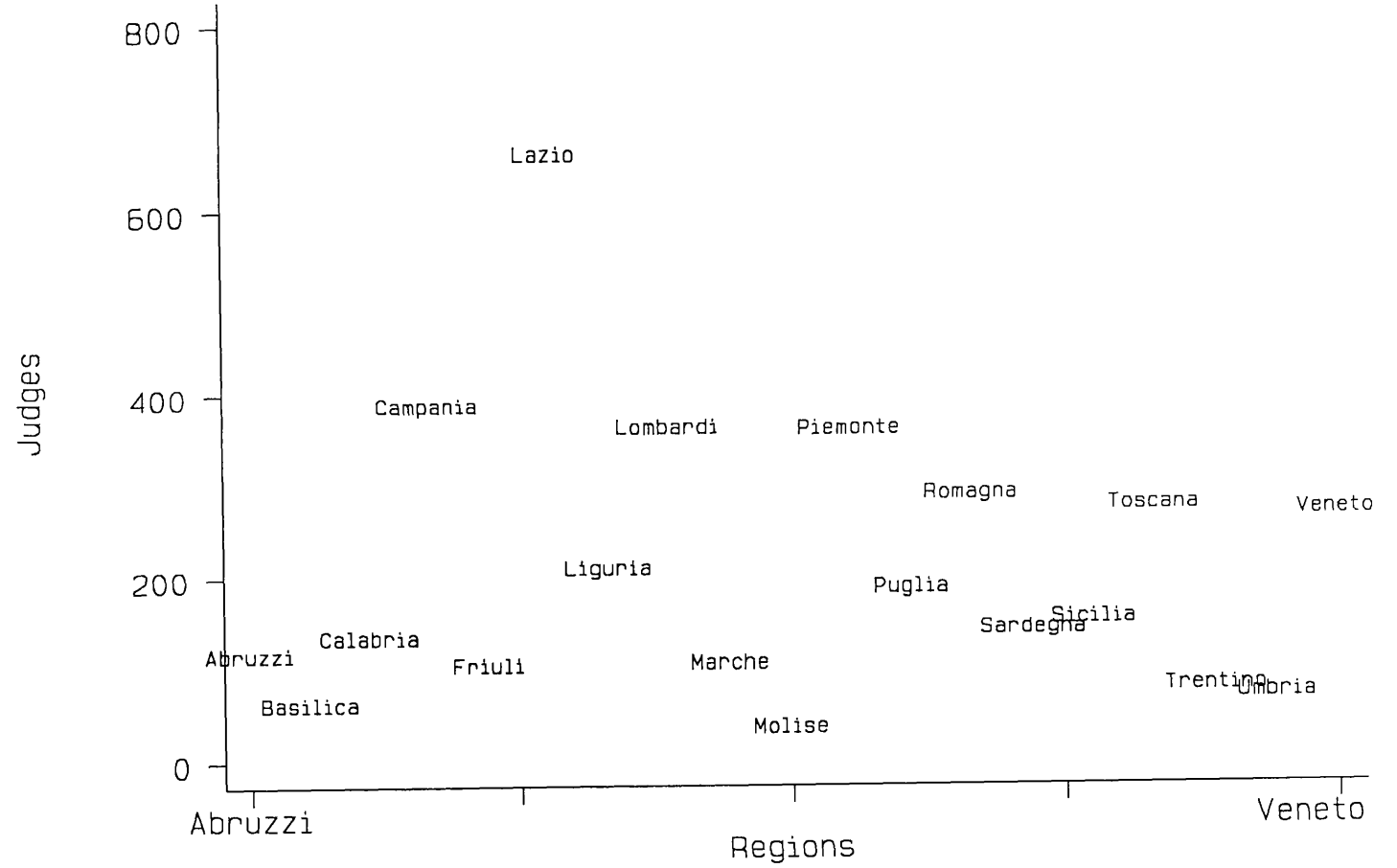


Figure 4.4: Judges per judicial district

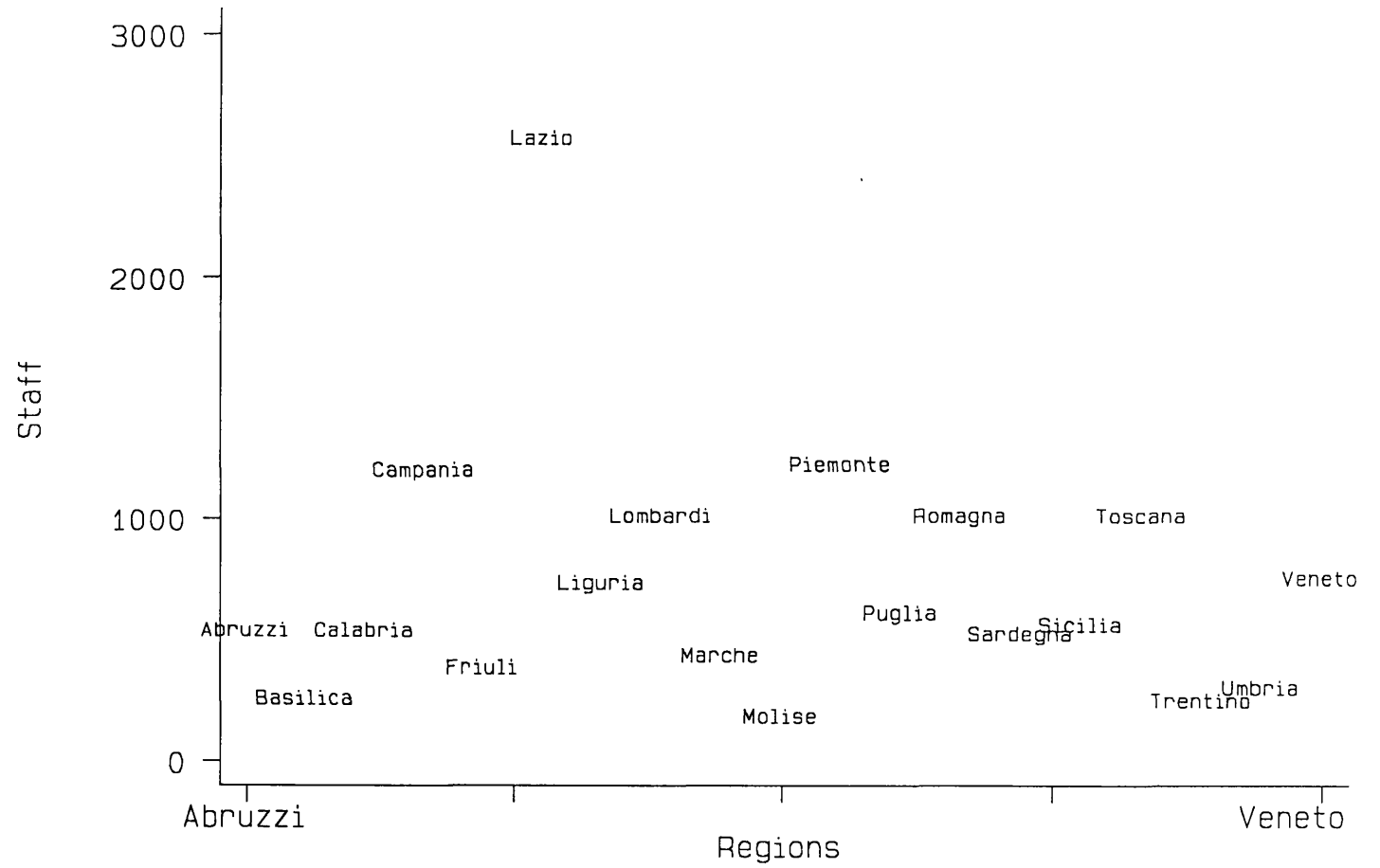


Figure 4.5: Staff per judicial district

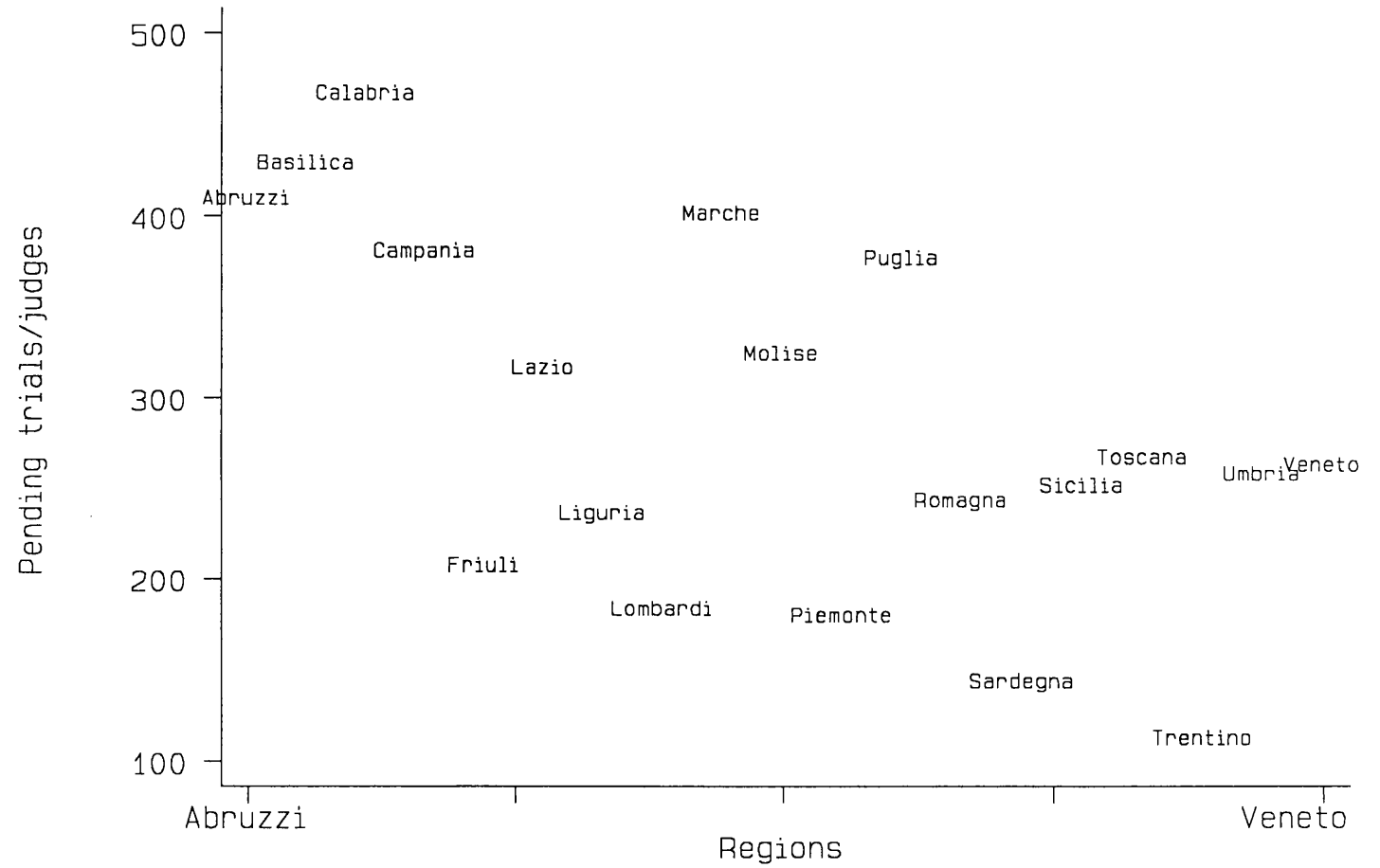


Figure 4.6: Sock of pending trials divided by judges

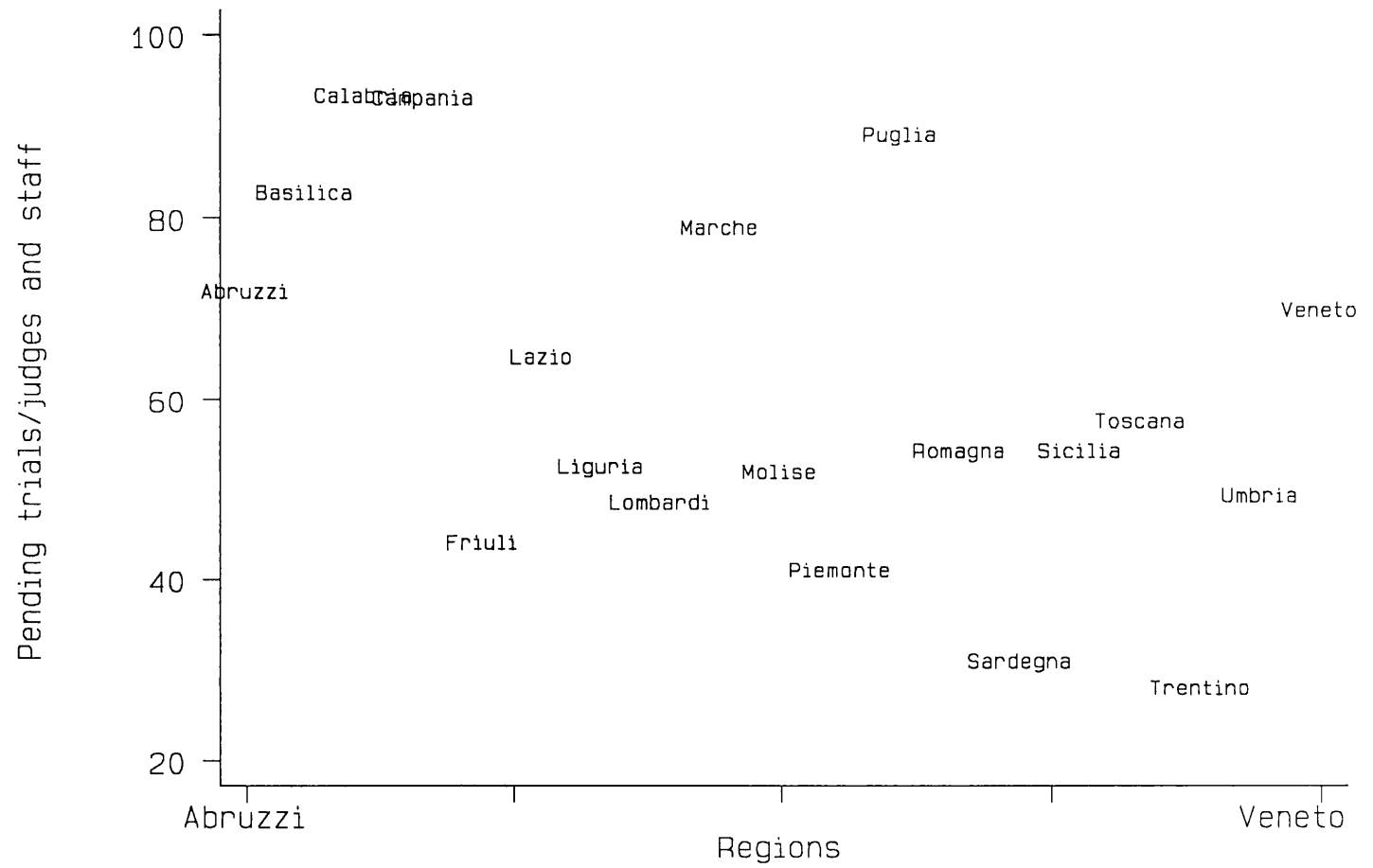


Figure 4.7: Sock of pending trials divided by judges and staff

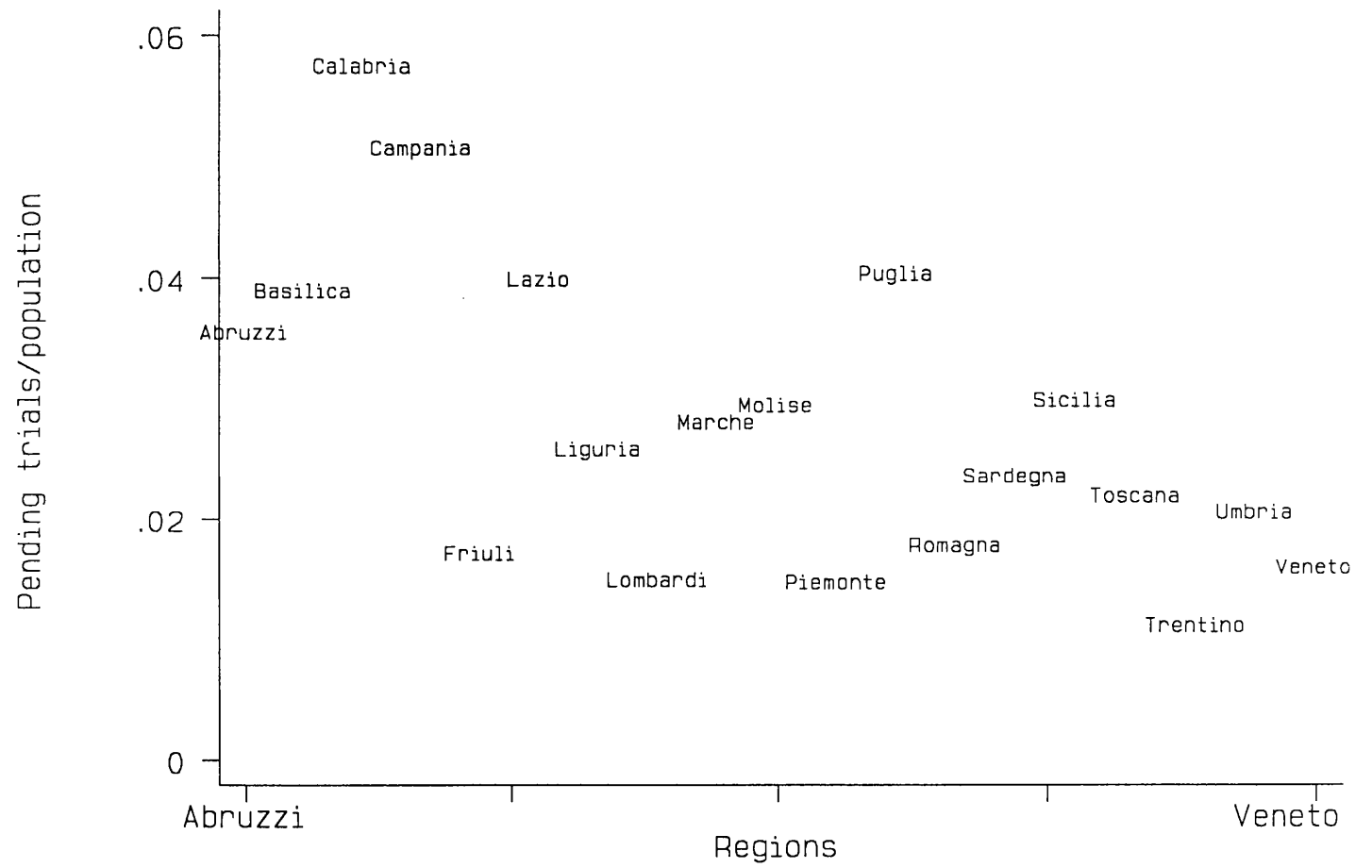


Figure 4.8: Sock of pending trials divided by population

Table 4.1: Summary Statistics

	<i>Mean</i>	<i>Standard deviation</i>
<i>Real assets</i>	86174.87	1229.396
<i>House of residence</i>	79352.56	804.2228
<i>Percentage of home-owners</i>	0.6369	
<i>Financial assets</i>	13828.12	301.0069
<i>Debt for house's purchase</i>	15632.86	406.7867
<i>Debt for valuables' purchase</i>	3577.391	1028.172
<i>Debt for car's purchase</i>	4383.83	146.2216
<i>Debt for other durables' purchase</i>	2140.59	184.8629
<i>Debt for non-durable consumption</i>	3245.226	517.7559
<i>Percentage of households holding debt for house's purchase</i>	8.50	
<i>Percentage of households holding debt for valuables' purchase</i>	0.24	
<i>Percentage of households holding debt for car's purchase</i>	6.21	
<i>Percentage of households holding debt for other durables' purchase</i>	2.98	
<i>Percentage of households holding debt for non-durables consumption</i>	0.94	
<i>Percentage of credit constrained households</i>	3.55	

Figures are in 1991's Euros except for those that are explicitly referred to be in percentage. Debt is measured as the amount of end of the year households' liabilities. The figures for debt are computed including only those households who are actually indebted. The inverse of the inclusion probability has been used as sample weights.

Table 4.2: Credit constraints and the quality of judicial enforcement

<i>Age of the household's head</i>	0.0307 (0.0102)**	0.0311 (0.0102)**	0.0310 (0.0102)**	0.0312 (0.0102)**	0.0315 (0.0102)**
<i>Age squared of the household's head</i>	-0.0466 (0.0106)**	-0.0471 (0.0106)**	-0.0470 (0.0106)**	-0.0472 (0.0106)**	-0.0474 (0.0105)**
<i>Years of schooling</i>	0.0082 (0.0041)*	0.0078 (0.0041)*	0.0081 (0.0041)*	0.0077 (0.0041)*	0.0073 (0.0041)*
<i>Home-ownership</i>	-0.2532 (0.0347)**	-0.2579 (0.0348)**	-0.2554 (0.0347)**	-0.2635 (0.0347)**	-0.2617 (0.0346)**
<i>Employee</i>	-0.0952 (0.0401)**	-0.0926 (0.0401)*	-0.0920 (0.0401)*	-0.0918 (0.0400)*	-0.0924 (0.0401)*
<i>Marital status</i>	0.0930 (0.0453)*	0.0958 (0.0454)*	0.0946 (0.0453)*	0.0967 (0.0452)*	0.1038 (0.0450)*
<i>City size</i>	0.1366 (0.0424)**	0.1471 (0.0426)**	0.1464 (0.0425)**	0.1352 (0.0425)**	0.1567 (0.0424)**
<i>Herfindal Index</i>	0.0087 (0.0037)*	0.0113 (0.0039)**	0.0134 (0.0039)**	0.0071 (0.0035)*	0.0109 (0.0036)**
<i>Justice</i>	0.6502 (0.1031)**	1.0260 (0.1632)**	0.4719 (0.0743)**	2.0865 (0.3369)**	0.2269 (0.0573)**
<i>Constant</i>	-2.5397 (0.2475)**	-2.6841 (0.2503)**	-2.7152 (0.2487)**	-2.8717 (0.2649)**	-2.9310 (0.2911)**
<i>No. of observations</i>	39833	39833	39833	39833	39833

Standard errors robust to unknown form of heteroskedasticity and corrected for the cluster effect are reported in parentheses; * significant at 5% level; ** significant at 1% level. In the second column, we use the stock of pending trials divided by the population as a proxy for the cost of repossessing the collaterals. In the third column the stock of pending trials is divided by the number of judges, in the fourth column the stock of pending trials is divided by the number of judges plus the staff, in the fifth column the stock of pending trials is divided by the number of incoming trials, in the sixth column the length of trials. All the specifications include a full set of years dummies.

Table 4.3: Credit constraints and the quality of judicial enforcement, transitions

	Abruzzi	Basilicata	Calabria	Campania	Emilia R.	Friuli V.G.	Lazio	Liguria	Lombardia	Marche	Molise	Piemonte	Puglia	Sardegna	Sicilia	Toscana	Trentino A. A.	Umbria
Basilicata	-.1869																	
Calabria	-.6679	-.4053																
Campania	-.3084	-.1024	.2155															
Emilia R.	.2602	.3767	.5565	.4346														
Friuli	.2804	.3937	.5685	.4500	.0272													
Lazio	-.0433	.121	.3745	.2026	-.4103	-.4498												
Liguria	.147	.2813	.4886	.348	-.1531	-.1854	.1824											
Lombardia	.3012	.4112	.581	.4659	.0553	.0289	.3302	.1808										
Marche	.1052	.2461	.4635	.3162	-.2095	-.2434	.1424	-.0489	-.2804									
Molise	.0885	.232	.4535	.3033	-.2322	-.2667	.1263	-.0686	-.3044	-.0187								
Piemonte	.3072	.4163	.5846	.4705	.0635	.0373	.336	.1878	.0086	.2257	.2399							
Puglia	-.1109	.064	.3339	.1509	-.5017	-.5438	-.0648	-.3023	-.5897	-.2416	-.2188	-.6035						
Sardegna	.1704	.301	.5026	.3659	-.1215	-.1529	.2048	.0274	-.1872	.0728	.0898	-.1975	.2532					
Sicilia	.0797	.2246	.4482	.2967	-.244	-.2788	.1179	-.0788	-.3169	-.0285	-.0096	-.3283	.1716	-.1093				
Toscana	.2106	.3349	.5267	.3967	-.0671	-.0969	.2434	.0746	-.1296	.1178	.134	-.1394	.2895	.0485	.1423			
Trentino AA	.3373	.4417	.6027	.4936	.1042	.0792	.3649	.2232	.0518	.2594	.273	.0435	.4035	.2013	.28	.1605		
Umbria	.2209	.3436	.5329	.4045	-.0532	-.0827	.2532	.0866	-.1149	.1292	.1452	-.1246	.2987	.0609	.1534	.013	-.1758	
Veneto	.2815	.3947	.5692	.4509	.0288	.0016	.3114	.1577	-.0281	.1970	.2118	-.037	.3533	.134	.2193	.0898	-.0842	.0778

Note: Households move from the column's to the row's judicial district. Each entry of the matrix is computed as 1 minus the ratio between the probability of being credit constrained for the average household living in the column's judicial district and that for the same household living in the row's judicial district.

Table 4.4: The interplay between collateral and quality of judicial enforcement for unconstrained households, Stock of pending trials divided by population

<i>Age of the household's head</i>	0.6812 (0.0910)**	0.6866 (0.0910)**	0.6542 (0.0907)**	0.7165 (0.0911)**
<i>Age squared of the household's head</i>	-1.0396 (0.0949)**	-1.0508 (0.0949)**	-1.0273 (0.0946)**	-1.0751 (0.0951)**
<i>Years of schooling</i>	0.3056 (0.0448)**	0.2921 (0.0451)**	0.2395 (0.0452)**	0.3454 (0.0446)**
<i>Home-ownership</i>	9.2472 (0.6378)**	9.0565 (0.6405)**	7.0247 (0.6697)**	9.8582 (0.6342)**
<i>Employee</i>	4.0310 (0.4347)**	3.8702 (0.4322)**	3.8384 (0.4301)**	3.7221 (0.4328)**
<i>Marital status</i>	5.1646 (0.4809)**	5.1905 (0.4807)**	5.0685 (0.4794)**	5.3225 (0.4814)**
<i>Collateral</i>	0.0064 (0.0008)**	0.0083 (0.0010)**	0.0312 (0.0025)**	0.0046 (0.0012)**
<i>Justice</i>	-12.6026 (1.7528)**	-12.5180 (1.7532)**	-11.4304 (1.7509)**	-13.0178 (1.7555)**
<i>Mill's ratio</i>	-45.0621 (11.2524)**	-44.8385 (11.2542)**	-42.1832 (11.2187)**	-45.2386 (11.2790)**
<i>Constant</i>	-40.3429 (2.5292)**	-40.1052 (2.5306)**	-38.4586 (2.5226)**	-41.2841 (2.5344)**
<i>No. of observations</i>	38419	38419	38419	38419

Note: Standard errors robust to unknown form of heteroskedasticity and corrected for the cluster effect are reported in parentheses. In the second column the collateral is proxied by the amount of real asset held by the household, in the third by the stock of land and houses, in the fourth by the value of the house of residence and the fifth by the stock of land and houses minus the value of the house of residence. * significant at 5% level; ** significant at 1% level.

Table 4.5: The interplay between collateral and quality of judicial enforcement for unconstrained households, Stock of pending trials divided by judges

<i>Age of the household's head</i>	0.6738 (0.0909)**	0.6792 (0.0909)**	0.6451 (0.0906)**	0.7103 (0.0911)**
<i>Age squared of the household's head</i>	-1.0278 (0.0945)**	-1.0389 (0.0944)**	-1.0101 (0.0941)**	-1.0659 (0.0946)**
<i>Years of schooling</i>	0.3037 (0.0443)**	0.2899 (0.0445)**	0.2334 (0.0447)**	0.3456 (0.0440)**
<i>Home-ownership</i>	9.4422 (0.6166)**	9.2555 (0.6192)**	7.2789 (0.6471)**	10.0343 (0.6133)**
<i>Employee</i>	4.0344 (0.4287)**	3.8727 (0.4262)**	3.8704 (0.4241)**	3.7090 (0.4266)**
<i>Marital status</i>	5.1124 (0.4784)**	5.1378 (0.4781)**	4.9968 (0.4768)**	5.2791 (0.4788)**
<i>Collateral</i>	0.0065 (0.0008)**	0.0084 (0.0010)**	0.0316 (0.0025)**	0.0047 (0.0012)**
<i>Justice</i>	-19.8998 (2.4122)**	-19.8046 (2.4128)**	-18.7807 (2.4092)**	-20.2437 (2.4165)**
<i>Mill's ratio</i>	-45.9998 (10.3655)**	-45.9120 (10.3675)**	-45.1649 (10.3364)**	-45.4365 (10.3890)**
<i>Constant</i>	-38.5701 (2.4683)**	-38.3511 (2.4696)**	-36.8926 (2.4610)**	-39.4628 (2.4740)**
<i>No. of observations</i>	38419	38419	38419	38419

Note: Standard errors robust to unknown form of heteroskedasticity and corrected for the cluster effect are reported in parentheses. In the second column the collateral is proxied by the amount of real asset held by the household, in the third by the stock of land and houses, in the fourth by the value of the house of residence and the fifth by the stock of land and houses minus the value of the house of residence. * significant at 5% level; ** significant at 1% level.

Table 4.6: The effect of judicial costs on household's debt capacity

	(1)	(2)	(3)	(4)
<i>Stock of pending trials/Population</i>	-.3034	-.3088	-.3518	-.2844
<i>Stock of pending trials/Judges</i>	-.5523	-.5571	-.5754	-.5462
<i>Stock of pending trials/(Judges+Staff)</i>	-.7193	-.7233	-.7364	-.714
<i>Stock of pending trials/Incoming trials</i>	-.2282	-.2301	-.2292	-.2284
<i>Length of trials</i>	-.6936	-.6907	-.6382	-.7085

Note: In the column (1) the collateral is proxied by the amount of real asset held by the household, in (2) by the stock of land and houses, in (3) by the value of the house of residence and (4) by the stock of land and houses minus the value of the house of residence. In the second row, we use the stock of pending trials divided by the population as a proxy for the cost of repossessing the collaterals. In the third the stock of pending trials is divided by the number of judges, in the fourth the stock of pending trials is divided by the number of judges plus the staff, in the fifth column the stock of pending trials is divided by the number of incoming trials, in the sixth column the length of trials.

Conclusions

Here, we draw some conclusions and point some directions for future work. We will discuss the four chapters in turn.

The first chapter has been prompted by the idea that preferences misspecification can matter in the empirical evaluation of the model, even in its simplest version. In particular, assuming non-separability between non-durable and durable consumption can be crucial in the empirical assessment of the theory. This is mainly because durable goods deliver services over more than one period, which is not a vacuous point because the standard testing of the theory assumes that the consumption today does not influence the marginal utility of consumption tomorrow. We use as reference model the life-cycle/permanent income model and the main goal is to establish if some of its empirical failures can be reconciled with the theory when a broader definition of consumption is taken. We find that durable and non-durable goods are non-separable, which means that the properties of durable goods spill over that of non-durable (and vice-versa). Our approach is conditional, in that we do not model the choice of durable consumption, but rather we take the stock of cars as given. This is perhaps a limitation of our present approach and future work plan to study the interaction between durable and non-durable consumption in a fully unconditional model.

Something is done in the second chapter, where we provide a measure of stock of cars, a methodology to evaluate stock of durables, a few stylized facts and evidence on an infrequent adjustment model. The second chapter can be extended in a number of ways. First, we want better explore the life-cycle implication of models of infrequent adjustment, in view of the fact that the life-cycle profile of stock of cars is hump-shaped. Second, we plan to study the dynamics of the cross-sectional distribution of the stock of cars, which should allow to better interpret the stylized facts. The way the cross-sectional distribution of the stock of cars evolves depends on what is the

relevant model of households behavior. If it is that of infrequent adjustment, a prominent role is played by the function that describes the ‘probability’ of adjusting. Third, and related, we wish to allow for some dynamics in the innovation to the target and the bands equation in the (s,S) model. This is not trivial due to the modest panel dimension of the sample used in the estimation.

The third chapter looks at the interaction between uncertainty and educational choices. It proposes a measure of return to education that accounts for different aspects of the future wages distribution. We estimate the entire life-cycle profile for a typical individual using an extrapolation technique and we numerically determine the rate of return under different assumption: no uncertainty, unemployment and wage risk. We find that there is an extra-return due to uncertainty, since, typically, more educated individuals face, also, lower probability of unemployment. This extra-return is bigger in Italy than in the US, which is probably an effect of the different degree of protection in the two labor markets. The rate of return is computed adopting a baseline setup, which could be enriched in future work. Moreover, we plan to apply the procedure to other countries.

The fourth chapter complements the available literature on law and finance and focuses on household secured debt. The data set allows to identify liquidity constrained households in a simple way and to insulate the effect of law from that of judicial districts performance. We find that the effect of the quality of judicial enforcement on debt market outcomes is present and not negligible. The approach used heavily relies on the data, and it is probably not easy to extend. One possible extension is to look at the effect on outcomes in firms debt market, to see whether those firm living in districts where the quality of judicial enforcement is poorer, are more likely to be liquidity constrained or held less debt. This could be done using Italian data.

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