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Chapter 1

Introduction

The present thesis collects four papers that aim at contributing to different fields of economics. The analyses encompass intertemporal consumption, industrial organization, and the economics of migration. Nothwithstanding this diversity, all papers have three elements in common:

i. a strong emphasis on clean and credible research design;

ii. an effort to develop simple but general theoretical models that can guide the empirical research;

iii. the use of highly detailed (and novel) micro-data.

As effectively put forward by Angrist and Pischke in their provocative article on "*the credibility revolution in empirical economics*" [5], what makes an empirical analysis credible is a clean research design in which the identification assumptions (i.e., the conditions that must be met for the assignment to the treatment to be considered random with respect to any non-ignorable confounding factor) are crystal clear. Although identification assumptions are, in most of the cases, not directly testable, the researcher should defend them on the basis of sound theoretical reasoning, indirect evidence, and (last but not least) basic reasonability. It is ultimately on the basis of this defense (along with formal statistical tests whenever they are possible) that the soundness of any empirical strategy must be evaluated.

It is really a non-contentious fact that this approach that emphasizes the development and defense of credible research design has become the prevailing one in most of the empirical literature over the past two decades (Angrist and Pischke [5]). This movement, however, has not come without critics. In their recent contribution to the Handbook of Econometrics, Heckman and Vytlacil [33] argue that the emphasis on the identification of treatment effects has favored simplicity in estimation to the cost of "obscurity in interpretation". In short, they claim that researchers have tended to overlook the link between theory and empirical analyses, up to the point that the relationship between estimated effects and theoretical structural parameters has blurred. Using the terminology of Holland [35], while the treatment effect literature has been able to understanding the "effects of causes", it has become less and less able to identify the "causes of effects".

In the researches collected in this volume, I tried to partially take charge of this critical point: in all the papers there is a fairly general theoretical model which informs me about what the empirical analysis allows me to identify. In contrast to the more structural approach supported by Heckman and Vytlacil, however, I do not necessarily claim that the theoretical model identifies *all* the set of counterfactuals and *all* the set of confounding factors that can be rationalized, nor that the resulting equations (or, better, their stochastic counterparts) must be directly estimated. Indeed, *no* theoretical model gives a complete picture of the reality: it solely highlights some of the aspects that are mostly prominent. From this consideration, the central role of checking the robustness of the findings to alternative (non-modelled but still reasonable) explanations emerges: it is a core element of any treatment effect analysis. Moreover, in several cases the theoretical model is too simple to be directly estimated, although it does help the researcher in understanding *what* he is estimating, and in defining the correct research design.[1]

[1] As a partial exception, see Chapter 3, where I obtain a linearized equation that can be directly estimated. Even in that case, however, robustness checks are fundamental to assess whether other non-modelled explanations are responsible for the estimated effect. Although the result is robust to these explanations in terms of significance, I obviously cannot rule out that they play a role in defining the strength of the

Finally, all empirical analyses in this volume exploit large panel datasets, usually characterized by a big-N x big-T structure. In all cases, data come from big consultancy firms and were originally collected for marketing purposes. The use of this type of real-life data, which has been increasingly collected over the last fifteen years thanks to the development of ICT in both private and public organizations, represents a fundamental improvement for empirical capabilities in economics. However, although availability of millions of observations has the virtue of placing the researcher in the realm of Asymptopia, it does not make causal identification much easier. Indeed, identifying sources of exogenous variation in relevant regressors is still largely a matter of creativity, wit, and knowledge of econometric tools. I hope that the reader will find in these essays some evidence of all three of them.

The volume is structured as follows. In Chapter 2, I present the first paper that deals with identifying monthly cycle in consumption and shopping behaviors linked to paydays. The paper presents a critical analysis of previous literature and, as a novel contribution, identifies the shopping cycle (i.e., the fact that consumers tend to shop for food in larger groceries at payday and in smaller shops in the rest of the month). It shows both theoretically and empirically that the shopping cycle represents a relevant confounding factor for identifying intertemporal preferences using high-frequency expenditure data.

In Chapter 3, I build on these findings and develop a test for the joint identification of liquidity constraints and time-inconsistency using data on daily expenditures from a large sample of households observed both before and during the current economic crisis. The idea is to look at how consumers that face a drop in available resources smooth consumption between monthly paydays. Theory predicts that time-consistency and/or perfect access to capital markets would result in a constant growth rate of consumption over the month. Empirical identification exploits the rich data available using a triple-differences model that controls for the confounding factors via fixed-effects.

In Chapter 4, I study the effect of an inflow of less informed consumers in a market of retail

estimated effect. Thus, any attempt to calibrate this (as *any*) model is bound to fail.

goods on the expected equilibrium price and quantity, and assess how competition affects this effect. Theory predicts that such an inflow should raise the equilibrium price, as firms can extract a rent from lack of information by consumers. However, this "rent extraction effect" should be reduced by competition, due to the countervailing incentive to increase market share. In the paper, co-authored with Giacomo Calzolari, Andrea Ichino, and Viki Nellas, we gather data from a large sample of Italian pharmacies and their monthly sold quantity and price charged on a basket of child hygiene products over the period 2007-2010. We study the effect of an increase in the monthly number of newborns on the equilibrium price and quantity, under the assumption that parents of newborns are new consumers and, thus, more likely to be imperfectly informed on the market prices. Consistently with the theory, we find that a raise in newborns at the municipal level increases the average expected price in the City for this basket of goods. We identify a set of thresholds (based on the municipal population) set by the Law to define the number of pharmacies allowed to enter the market. We exploit them using a Regression Discontinuity framework. Thanks to this identification strategy, we find that a larger number of competitors has a negative effect on the elasticity of price to changes in newborns, consistently with the theoretical predictions. Finally, Chapter 5 reports the preliminary findings from a study of the effect of an inflow of immigrants on the distribution of prices within cities that I am conducting with Antonio Accetturo, Sauro Mocetti, and Elisabetta Olivieri. We develop a spatial equilibrium model that shows how immigration shock to a neighborhood propagates to the rest of the city through changes in local amenities and local prices. On the empirical side, we collect data at the neighbourhood level for a sample of main Italian cities and we analyze the impact of immigration on natives' residential choice and house price dynamics. We find that there is a negative relationship between changes in native population and changes in immigrant population across neighbourhoods; we also find some evidence that price growth is lower than the average in those neighbourhoods where immigrants settle. Second, we extend the analysis to all Italian municipalities and we investigate the impact of immigration on indicators of city price distribution. We find that immigration causes an increase in the average price. This effect, however, is driven by the upper two deciles of the price distribution: the effect on immigration on lower prices is never statistically different from zero.

Chapter 2

The Monthly Cycle of Consumption and the Role of Shopping Costs

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Abstract

Recent studies documented that consumption of poor households falls markedly between paydays (a phenomenon called 'paycycle'), and considered this finding as a rejection of the permanent income hypothesis (PIH) and evidence of liquidity constraints and time inconsistency (modelled with hyperbolic preferences). In this paper, I criticize and extend previous analyses of the paycycle, arguing that standard tests may have omitted a crucial confounding factor that may have biased the results toward the rejection of the PIH. I show theoretically that when households change the shopping regime over the month in a cyclical (and rational) way a paycycle may emerge even if the households are time consistent. I test my results using a panel dataset that provides daily information on food expenditures from a large sample of Italian households. This is the first analysis of the monthly cycle in expenditures and consumption outside the US and UK. Results show that households display a monthly cycle in shopping behavior: the probability of performing a shopping trip in a larger supermarket is higher at payday and decrease afterward. The paycycle appears to be driven by this shopping cycle, while the pure effect of time preferences result in a flat pattern of consumption between paydays.

2.1 Introduction

Several recent studies have documented that household food consumption responds to the monthly inflow of income. Notably, food consumption has been found to fall steepely in the period between paydays (Stephens Jr. [62] [63], Shapiro [61]), a phenomenon which has been called 'paycycle' of consumption (Mastrobuoni and Weinberg [51]). Since monthly income is predictable, transitory, and exogenous, the paycycle represents a clear rejection of the rational expectations-permanent income hypothesis (RE-PIH, henceforth).

Previous analyses focused on the US or UK: as a first contribution, this paper extends the analysis to Italy. I use a unique panel dataset that collects information on daily food expenditures from a large sample of households to provide evidence of the paycycle among Italian consumers. Results are consistent with previous analyses showing that the cycle is particularly strong among liquidity constrained households (as identified by age or education of the household head). Total food expenditures decrease by more than 10% between paydays for this subgroup, while quantities purchased of fruits and vegetables (i.e. highly perishable food for which expenditures and consumption are more likely to coincide) decrease by 5 to 6%.

All previous studies have explained the paycycle with the existence of self-control problems. According to this view, liquidity constrained individuals do not resist temptation and over-consume when they receive their monthly income: as a result, they fall short of cash-on-hands at the end of the month and are forced to reduce consumption. This time-inconsistent behavior has been formalized using hyperbolic discounting functions (Strotz [65], Phelps and Pollak [55], and Laibson [45]), or other modelling techniques (e.g. Gul and Pesendorfer [30]). On this regard, as a second original contribution, I point to a relevant confounding factor that could not be controlled for by previous studies and may have biased their results toward the rejection of the null-hypothesis of time-*consistency*. In my theoretical framework, the paycycle emerges because liquidity constrained households shop in bigger/farther supermarkets when they receive the monthly payment, in order to rebuild stocks of food, while they go to smaller/nearer shops during the rest of the month to continue purchasing more perishable food (such as fruits and vegetables, milk, etc.). Since prices are higher in smaller shops than in bigger supermarkets, this cycle in shopping behavior generates a fall in quantities of perishable food consumed over the month, i.e. a paycycle. Thus, the paycycle may be determined by the combined effects of different perishability in food categories (some being stockable for larger periods while others are not), implicit or explicit liquidity constraints (that induce preference for rebuilding food stocks at paydays), and the structure of grocery market, in which there is a trade-off between proximity and convenience (i.e. between fixed costs of travel and marginal price differentials).

I provide evidence of this phenomenon for Italy thanks to a rich dataset that provides information on the type of shop in which each purchase has been performed. Several theoretical predicitons are confirmed. First, liquidity constrained households display a shopping cycle: the probability of performing a trip to a supermarket or a hyperstore declines markedly between paydays. This effect is particularly prominent for liquidity constrained households. Second, once I control for the effect of the shopping cycle, the paycycle disappears, and the pattern of intra-monthly consumption is ultimately flat both for liquidity constrained and unconstrained households, showing no evidence of time-inconsistency.

The paper is structured as follows. Section 2.2 reports a critical review of the studies that have analysed the paycycle. I present the dataset used for the empirical exercises in Section 2.3. Section 2.4 replicates the analyses performed by previous literature and shows that my findings are ultimately consistent with it. Section 2.5 sketches a simple theoretical model to show how a paycycle may emerge even if the consumer is perfectly rational and discounts future utility exponentially. Section 2.6 presents the first estimate of the shopping cycle, and shows that it is consistent with the implications of the theoretical model. Section 2.7 studies the paycycle controlling for the effect of the shopping cycle, and shows that no significant fall is present: households seem to smooth consumption exponentially between paydays. Robustness checks of this finding are provided in Section 2.8. Finally, Section 2.9 concludes.

2.2 Previous empirical findings and their interpretation

The analysis of the paycycle is a relatively new issue in the consumption literature.

The earliest contribution is attributable to Melvin Stephens Jr. [62], who uses data on daily expenditures from the US Consumer Expenditure Survey (CES). In order to identify the effect of the distance from payday on expenditure, he focuses on households receiving at least 70% of their income from Social Security benefits. These benefits are paid in all the US on the 3rd of the month: the distance from payday is then identified in the data as the difference between the interview date and the 3rd of the month. This strategy has an additional positive by-product: since the interview date is arguably random with respect to any observable or unobservable household characteristic, it is possible to obtain unbiased estimate of the paycycle. A problematic issue, shared even by the present paper, emerges for what regards the identification of consumption: since the CES collects information on *expenditures*, to study the cycle in consumption Stephens Jr. has to focus on those food categories that cannot be stockpiled.

His results are at odds with the standard predictions of the RE-PIH. He finds that expenditure on instant consumption goods are 20% higher right after payday with respect to the rest of the month. For fresh fruits and vegetables, the peak at payday is at around 9% and significant. He does not perform any analysis of the causes of such a rejection of the RE-PIH.

Stephens Jr. [63] replicates and extends the analysis using the UK Family Expenditure Survey (FES). He improves on his previous study in two dimensions. First, the dataset provides direct information on the payday of each household and this allows him to extend the analysis to households that do not receive Social Security benefits, and to control for possible day-of-the-calendar-month effect. Second, since each household is observed for two weeks, the author can control for household unobserved heterogeneity. The results are consistent with those obtained for the US, although the paycycle seems less strong: expenditure on instant consumption goods and services peaks by 6% at payday with respect to the rest of the month. In addition, the paper reports some evidence of the role of liquidity constraints (as proxied by low wealth or low age) in explaining the paycycle.

Jesse Shapiro [61] focuses on household participating in the US food stamps project. He exploits the Continuing Survey on Food Intake by Individuals (CSFII) that collects information on daily food intake. Thus, he is able to overcome the problem of identifying consumption. However, data limitations do not allow him to control for day-of-the-month effect and household unobserved heterogeneity. In addition, in the econometric specification he imposes a linear trend on the effect of distance from payday on (log)caloric intake, a rather strong assumption that is rejected by subsequent studies.

Nothwithstanding these limitations, this study has been particularly influential, since it is the first to point to time-inconsistency as a possible explanation of the paycycle. To maintain this thesis, Shapiro calibrates an exponential and a quasi-hyperbolic model of intertemporal consumption, using the results of his econometric exercise. He shows that the exponential model results in either implausibly low estimate of the discount factor, or in too high estimate of the elasticity of intertemporal substitution, while the quasi-hyperbolic model yields results of the δ and the ρ parameters that are in line with the standard results of the consumption literature, and a β at around 0.96.

A similar calibration exercise is performed by Huffman and Barenstein [36], who use the FES to provide additional insights in the behavior of UK households. They show that the paycycle is particularly prominent for expenditures out of cash on hand, while purchases performed via credit card are generally flatter: they interpret this finding as evidence of mental accounting (Thaler [67]). The result of their calibration again points to quasi-hyperbolic discounting as a better hypothesis to model household consumption behavior with respect to exponential discounting.

Mastrobuoni and Weinberg [51] use the CSFII to study the behavior of Social Security recipients. They find a fundamental heterogeneity between the behavior of high and low wealth households: the former display a flat consumption pattern over the month, while the latter show strong evidence of a paycycle. They explain the cycle as the product of time-inconsistency. They study the consumption pattern of an agent who has to consume all his resources within one month, and show that this differs according to the type of discount function assumed: an exponential agent would display a constant declinig consumption pattern, while a quasi-hyperbolic discount function would result in a concave declining path. They provide evidence that the consumption of the low-wealth Social Security recipients follow the lattern pattern.

Although the evidence on the existence of a paycycle reported by Stephens Jr., Shapiro, Huffman and Barenstein, and Mastrobuoni and Weinberg are robust, time-inconsistency may not be the sole factor explaining it. Indeed, the theoretical model used by previous authors to sustain the case of time-inconsistency is the standard one, usually used to explain monthly or quarterly consumption behavior. The application of it to high frequency settings, however, may not be so immediate. At daily or weekly frequencies there may be important confounding factors that explain the monthly cycle in consumption without any need of time-inconsistency. In the next section I point to one of these possible alternative explanations.

2.3 Data and identification issues

To investigate the linkage between consumption and monthly payment receipt I use the 2007 ACNielsen Homescan Panel (henceforth, Homescan). The Homescan is a nationally representative panel of 6,655 households that provide daily information on expenditure on grocery goods (food, housecare, and healthcare goods). A portable scanner is provided to the household head, and he/she is asked to scan the barcode of each good purchased. This information is sent weekly to ACNielsen. The multinational firm, then, matches the codebars with the corresponding price paid thanks to a dataset of grocery prices called ScanTrack. For goods lacking barcodes, households are asked to fill a daily diary that includes information on prices and quantities of each product purchased as well as the place in which it has been bought.[2]

For each household, I obtained the following information: geographic area (province level), household size (five groups), household head age (five groups), education of the household head (threee groups: elementary, upper secondary, and tertiary), and income. For what regards income, ACNielsen calculates for each household the income per adult equivalent, using the OECD equivalence scale.[3] It then groups households according to whether they belong to the first two deciles of the income distribution, the third to fifth deciles, the sixth to eight deciles, or the upper two deciles.

To identify payday, an ad hoc questionnaire was administered in which each household member was asked whether he/she receives income in a fixed date of the calendar month, whether this fixed income is a wage or a pension benefit, and in which period of the month it is received. The calendar month was divided into 10 periods of three days each (henceforth, triplets), so that detail of paydays is available at the triplet level.[4] Around 64% of households received the questionnaire, the remaining share was no longer participating to Homescan in 2009 and could not be contacted. The response rate was 63.2% among these households, and among the households who responded 90.5% provided at least one payday. Thus, I have information on paydays for 2,123 households. Table 2.1 shows descriptive statistics of all households in the Homescan panel and of the subsample of those households who answered the 2009 questionnaire. Differences by socio-demographic characteristics are usually not statistically significant, the exceptions are represented by a lower share of larger households (5 components or more), and a lower share of very-low income families among those who

[2]Einav et al. [24] tested the reliability of this system of data collection and found that errors present in the Homescan dataset are of the same order of magnitude of those present in standard datasets on earning and employment. See the Appendix for a parallel test, that documents that the Italian Homescan data yields results which are in line with those obtained from the consumption survey of the Italian National Statistical Institute (ISTAT).

[3]All adults except the household head have weight equal to 0.7, children under 16 have weight equal to 0.5.

[4]Obviously the tenth triplet varies in length between 1 day (in Febrary) to 4 days, depending on the month. By calculating the average daily consumption for each triplet, I overcome this problem.

provided information on paydays.

Figure 2.1 shows the distribution of paydays over the calendar month. There are three main modes: one at the beginning of the month (the first triplet of calendar days), a second one (smaller) at the fourth triplet (between the 10th and the 12th of the month), and the last one at the ninth triplet. In Figure 2.2 I distinguish between wage and pension earners. Pension receipts are strongly concentrated at the beginning of the month, a fact that has been used for the US case by Stephens Jr. [62] and Mastrobuoni and Weinberg [51] to identify the payday. Wage receipts are, instead, more uniformly spread over the calendar month, although the modes at the fourth and the ninth triplets persist. Such a good degree of variation in paydays allows me to control for the effect of the calendar day of the month in our estimate of the paycycle: this was not possible in most previous studies that concentrated solely on pension earners or food-stamps receivers.

An additional identification issue emerges for households reporting more than one payday. To obtain a clear picture of the paycycle, I focus on those households whose paydays are concentrated in two adjacent triplets at most: this leaves me with 1,365 households for the analysis. I consider different thresholds for the definition of a payday in the section on robustness checks.

From ACNielsen, I obtained three daily time series for each household: total grocery expenditure, expenditure on fresh fruits and vegetables, and average price paid per kilo of fresh fruits and vegetables purchased. The first category, that practically coincide with total food expenditures, is commonly used for consumption analyses at monthly or quarterly frequency (e.g. with the PSID or the CEX datasets). However, at higher frequency, most food categories do not perish immediately: they can be purchased, stored, and they release their services as durables over one month. Thus, total grocery expenditure cannot be used to infer consumption at high frequency. I, therefore, focus on fresh fruits and vegetables, as a food category for which expenditure and consumption are more likely to coincide. I use the price vector to identify quantities consumed. In addition, I aggregate data from each month in five groups of six days each, starting with the payday, and calculate the average daily consumption in each of these periods. The main identifying hypothesis, then, is that at this six-days level of aggregation, expenditure and consumption coincide for fresh fruits and vegetables.

I define the month that follows a payday as the "paymonth" and, with a small semantic slide, the six-days groups in which it is parted as "payweeks".

Crucially, ACNielsen provided information on where each purchasing event took place, distinguishing between supermarkets and small shops.[5] For each triplet of days, I define a dummy equal to 1 if some food expenditure was performed in a supermarket, and zero otherwise. I consider it a proxy of whether the household has incurred in the fixed cost sketched in the model of Section 2.5. This proxy is somehow conservative, since many supermarket chains have smaller stores in the city centers, and purchases in these smaller supermarkets may entail lower fixed costs. This fact, however, should bias our estimate toward the rejection of any relationship between the shopping regime chosen and the distance from payday.

2.4 The paycycle among Italian households

Using the afore-mentioned identification hypotheses, it is possible to study the paycycle in Italy with the Homescan panel. The analysis is similar to the one performed by Stephens Jr. [63] for UK: heterogeneity in paydays allows me to control for day-of-the-month effects, while the availability of a panel dimension permits the use of a fixed-effect estimator. In addition, by aggregating observations at a six-days interval, I overcome the problem of censoring in the dependent variable that would be otherwise present.

The baseline econometric specification to study the percentage change in weekly expenditures

[5] The supermarket category includes even hyperstores, wholesalers, etc.

and consumption of household i at time t is:

$$\log C_{it} = \sum_{k=2}^{5} \beta_k PWEEK_k + \phi_{it} + a_i + \epsilon_{it} \tag{2.1}$$

with

$$\phi_{it} = DOM_{it} + DOW_{it} + MONTH_{it} + Hol_{it} + PHol_{it}$$

where C_{it} can be alternatively total weekly expenditures on grocery goods or weekly quantities of fruits and vegetables consumed, $PWEEK_k$ are dummies for the payweeks 2-5, ϕ_{it} is a vector of calendar effects, a_i is household unobserved heterogeneity, and ϵ_{it} is an i.i.d. error term. Among the calendar effects, DOM stands for day of the month, DOW for day of the week, $MONTH$ is a calendar month fixed effect, Hol and $PHol$ are dummies equal to 1 if there is a holiday or a pre-holiday (respectively) within the payweek.

Table 2.2 reports results of the estimate of (2.1) omitting the calendar effects (specifications 1 and 3) or including them (specifications 2 and 4). In both cases the paycycle is significant: total expenditures drop by 6.1% in the second payweek, and remains ultimately constant for the rest of the month, slightly increasing in the fifth payweek to -4.9% with respect to the first week of the paymonth. The left panel of the Table focus on quantities of fresh fruits and vegetables, as a food category for which consumption and expenditures are likely to coincide at the payweek level. The drop is particularly significant in the second payweek of the month (-4.2%). Weekly consumption raises a bit in the subsequent payweeks reaching -2.9% with respect to payday.

As previously argued, past researches have shown that the paycycle is particularly prominent among low income/low wealth households (e.g. liquidity constrained households, pensioners with no wealth, food-stamps receivers, etc.). It is important, then, to investigate whether there are evidence of heterogeneity in consumption smoothing among the sample. I consider two different measures of liquidity constraints. First, age has been recognized as a good predictor of difficulties in accessing credit (Jappelli [40]) so I split the sample between households whose head is under 45 and those whose head is 45 or older. Younger households are expected to be more likely to be liquidity constrained, since they have lower savings and would like to borrow against future increases in labor income. Forty percent of the household in the sample belongs to the first group, while 60% have an old head. Alternatively, I split the sample according to the education level of the household head. Evidence from the Italian Survey on Household Income and Wealth show that a low education level of the head is positively correlated with the probability of being liquidity constrained (Magri [48], Guiso et al. [29]).[6] Thus, I distinguish between households whose head has a primary or lower secondary education (30.4% of the sample), and those whose head has an upper secondary or tertiary education.

Estimate are then replicated controlling for possible different effects of the distance from payday between the two subgroups. The model used for the estimate is:

$$\log C_{it} = \sum_{k=2}^{5} \beta_k PWEEK_k + \sum_{h=2}^{5} \delta_h PWEEK_h * UNCONST_i + \phi_{it} + a_i + \epsilon_{it} \tag{2.2}$$

with

$$\phi_{it} = DOM_{it} + DOW_{it} + MONTH_{it} + Hol_{it} + PHol_{it}$$

When I use household head's age as a proxy for liquidity constrained $UNCONST_i$ is a dummy equal to 1 if the head is aged 45 or more. Alternatively, when the sample is splitted by education level, it is a dummy equal to 1 if the head has at least an upper secondary education. Results of estimating (2.2) for total grocery expenditures and weekly consumption of fresh fruits and vegetables are reported in Table 2.3.

The left panel splits the panel by age. The paycycle in total grocery expenditures looks significant in both young and old headed households: the monthly fall reaches slightly more than 6%. Looking at weekly consumption of fruits and vegetables, instead, shows a more

[6]Here, obviously, causality goes in both directions, since lower education reduces labor income and thus increases the probability of living at the substitance level; if households do not access the credit market, on the contrary, they may be less likely to invest in education.

strong difference between the young and the elderly: while consumption drops by 5% since the third payweek, for the latter the consumption pattern is flat over the month. Stronger discrepancies are highlighted if I split the sample according to the education level of the household head. The cycle in total grocery expenditures is significant both for low and high education households, but it is much more pronounced among the former: weekly expenditures among the lower educated drop by more than 10% after the third payweek, reaching -13.1% in the fourth and -11.5% in the last one. For what regards higher educated households, instead, the monthly peak is reached in the second payweek (+2.1% with respect to payday), and then expenditures decline at around -5.7% (-3.8% with respect to the first payweek). Thus, using any of the two proxies for liquidity constraints, the paycycle in weekly consumption of fresh fruits and vegetables is significant only among those which are more likely to be liquidity constrained.

These results are consistent with those obtained by Melvin Stephens Jr. [63], although the paycycle seems remarkably less strong for the Italian case: for UK, Stephens Jr. found that total food expenditures drop by 12.6% between the first and the last week of the paymonth, and consumption of fresh food drops by 5.4%. Focusing on liquidity constrained households (as proxied with asset income) furtherly increase the strength of the paycycle: the drop in total food expenditures and in fresh food consumption reach -15.7% and -10.5%, respectively. Other estimate by Stephens Jr. [62], Shapiro [61], Huffman and Barenstein [36], and Mastrobuoni and Weinberg [51] are more difficult to compare to my findings, since they focus on smaller subsamples of the population (as discussed in Section 2.2). Nonetheless, their qualitative results are similar to mine. All previous studies have considered the paycycle as an evidence of self-control problems, as modelled with hyperbolic discounting preferences. In the next Section, however, I suggest a different explanation based on liquidity constraints and heterogeneity in the shopping behavior chosen by consumers.

2.5 Shopping and price regimes: a model

At low frequency, food consumption is not subject to substantial trade-offs: individuals have to feed themselves and this need can hardly be compensated by other goods. At high frequency, however, the utility obtained from consuming according to a smooth pattern can be limited by the existence of other types of needs or costs. One of these is represented by shopping costs.

Going shopping for food entails a fixed cost in terms of time spent and travel costs that is paid for each trip. It is widely recognized that the price of food a consumer faces is subjected to a huge heterogeneity with respect to the place in which it is purchased (Fox [25]). The literature documents that the nearest a place is to residential areas the higher is the price charged by groceries (Bell et al. [7]). Shopping in the neighborhood, however, entails a significant lower cost in terms of time. Thus, anytime a consumer has to purchase food, she has to trade-off marginal price gains with fixed costs of shopping.

A large part of the food categories that are consumed daily, in addition, are characterized by short perishability, so that they must be purchased several times in a month. The interplay between shopping costs and food perishability has important implications for the paycycle. To show this consider the following stylized problem of intertemporal shopping and consumption.[7] A consumer has to allocate its monthly income I to the consumption of two types of food: one that can be stored for one month ('non-perishable', NP, e.g. pasta and cereals, beverages, meat, etc.) and one that rots in less than one month ('perishable', P, e.g. milk, fruits and vegetables, etc.). No borrowing and no saving is possible from outside the month, so that she has to rely on I for her consumption. Assume, for simplicity, that preferences are weakly separable between the two goods.[8] Let the month be divided into two equally spaced periods, $t \in \{1, 2\}$: the NP food rots completely in two periods, while

[7] The model can be considered a two-periods adaptation of Moffitt's [53] model of social stigma, for an early application of it to the food-stamps cycle see Wilde and Ranney [69].

[8] As long as the goods are not *perfect* substitutes, the result remains qualitatively unchanged.

the P food lasts only one period and, thus, must be purchased twice per month.[9]

Shopping can be done into two types of grocery: a supermarket (S), where marginal prices are p_i, $i \in \{P, NP\}$, and a small shop (D), where prices are higher, $q_i > p_i$. Shopping in the supermarket, however, entails a fixed cost $\theta > 0$ in terms of utility. This cost represents the value of proximity of the grocery to the consumer, and is useful to identify the aforementioned trade-off. Besides the consumption decision, the agent has an additional control variable, s_t, which is a dummy equal to 1 if she chooses to shop in S at time t.

Let the utility function for this two-periods problem be:

$$U(c_{NP,t}, c_{P,t}, I) = u(c_{NP,1}) + u(c_{P,1}) + \theta s_1 + \delta \left[u(c_{NP,2}) + u(c_{P,2}) + \theta s_2 \right] \tag{2.3}$$

At time $t = 1$, the consumer chooses to shop in S if the utility gain from being charged a lower price is larger than the fixed cost θ:

$$\begin{aligned} &\overbrace{u(c^*_{NP,1}|s_1 = 1) + \delta u(c^*_{NP,2}|s_1 = 1) - u(c^*_{NP,1}|s_1 = 0) - \delta u(c^*_{NP,2}|s_1 = 0)}^{\text{Gain from NP food}} \\ &\qquad\qquad + \overbrace{u(c^*_{P,1}|s_1 = 1) - u(c^*_{P,1}|s_1 = 0)}^{\text{Gain from P food}} > \theta \end{aligned} \tag{2.4}$$

where the asterisks signal the (conditional) optimal choices.

In the second period, instead, the consumer chooses the S shop if

$$u(c^*_{P,2}|s_2 = 1) - u(c^*_{P,2}|s_2 = 0) > \theta \tag{2.5}$$

These two conditions imply that it is always suboptimal to go shopping first in the small shop at time $t = 1$ and then in the supermarket at $t = 2$. To see this, notice that the gains from shopping in the supermarket for the NP food in (2.4) are always weakly positive, since $p_{NP} < q_{NP}$. In addition, as long as $\delta \leq 1$, and for any well-behaved utility function, the gains from shopping in the supermarket for the P food in (2.4) are always weakly larger

[9] Using explicit depreciation rates does not change the qualitative results of the model.

than the LHS of (2.5). Thus, the LHS of (2.4) is always weakly larger than the LHS of (2.5) and it will be optimal for the consumer either to purchase in the same type of shop in both periods, or to switch from the supermarket to the small shop overtime, *tertium non datur*.
It is useful to compare how consumption declines over the month in these different situations. To do this, let us assume that the instantaneous utility function is of the CRRA type: $u(\bullet) = \bullet^{1-\rho}/(1-\rho)$. The rate of decline in consumption of the P food, if the consumer *does not* change the shopping place over the month (i.e. always shops either in S or in D) is $\delta^{\frac{1}{\rho}} - 1$. If, instead, the consumer switches from S to D in the second period, the resulting rate of change in consumption between the two periods is $(\delta p_P/q_P)^{\frac{1}{\rho}} - 1$, which is smaller that the previous one for all $q_P > p_P$: consumption would then fall at a higher rate over the month. To sum up, at high frequencies, the switch between different shopping regimes may generate a significant drop in consumption of perishable goods, even if the consumer does not suffer from self-control problems (i.e. she is an exponential discounter).
A couple of considerations can be made on this result. First, it crucially relies on the existence of implicit or explicit liquidity constraints, since otherwise there would be no reason to stockpile the non-perishable food at payday, rather than in other days of the month. Second, the change in the shopping regimes over the month represents a confounding factor with respect to the identification of time preferences in consumption.
To see this, let assume to observe an heterogenous population which is randomly assigned among the two periods of the month. The presence of consumers that switch between S and D from the first to the second period of the month, then, results in a much lower average fall in consumption between the two periods with respect to what would be if no shopping choice was possible. If an analyst does not control for such a change in the shopping regime, her estimate of the exponential discount factor may be downward biased. If, as Shapiro [61] has done, the analyst tries to calibrate a hyperbolic ($\beta\delta$) discount function, she may obtain a more plausible result, but only because she is confounding the price ratio p/q with the short-term discount factor β. For instance, calibrating the $\beta\delta$ model assuming log-utility

($\rho = 1$), Shapiro obtains $\beta = 0.9$ which is remarkably similar to the average ratio between grocery and mass-merchandisers food prices reported by Fox [25].

Looking at a concave declining pattern, such as the one highlighted by Mastrobuoni and Weinberg [51], seems a more robust identification strategy. However, the estimate of the rate of change between different periods may still be biased downward. In addition, for any $\rho > 1$, the condition to choose between one shopping regime or the other is highly non-linear. If the perishable food must be purchased more than twice per month, then, the resulting consumption pattern may be non-linear, and eventually concave.

Summing up, this simple and stylized model has two main empirical implications: first, liquidity constrained households should display a monthly cycle in shopping behavior, going in larger/farther shops at payday and in smaller/nearer shops afterwards; second, the shopping cycle may explain part of the drop in consumption over the month identified by empirical analyses. In the next Section, I bring the first prediction to the data.

2.6 Does the probability of shopping in a supermarket display a monthly cycle?

To test the prediction of the theoretical model concerning the shopping behavior of liquidity constrained consumers, I exploit information available for Homescan families on the place in which each purchase has been performed. ACNielsen distinguishes between two main types of shop: large supermarkets (and hyperstores) and small grocery shops. I define a dummy equal to 1 if the household has performed at least one purchase in a supermarket in that payweek. Most of the 67,250 payweeks in the sample (71%) have at least one purchase performed in the supermarket/hyperstore, 36.36% of the paymonths have all five dummies equal to 1, and 2.55% have all equal to zero. Thanks to this relatively large variability, it is possible to study whether there exist a cycle in shopping behavior and, in particular, whether the probability of shopping in larger supermarkets is significantly larger at the beginning of the month, as the model predicts.

Table 2.4 reports the results of several probability models. Specification 9 uses a linear fixed-effect model, which controls for calendar effects and household unobserved heterogeneity; specification 10 is a simple probit model, with standard errors clustered at the household level, and controls for calendar effects and household socio-demographic characteristics; coefficients from a fixed effect logit estimate are reported in specification 11; results of a random effect probit are reported in the last column. In all the possible specifications, there is a significant drop in the probability of shopping in a supermarket/hyperstore after the first week of the paymonth.

The model in the previous Section attributes this drop to the presence of liquidity constraints, that induces household to prefer paydays for rebuilding their stocks, since at that time they have more cash-on-hands. It must be stressed, that such behavior may not only be produced by explicit constraints, such as the inability to borrow against future income, but even by *implicit* constraints, such as those produced by precautionary savings. Indeed, in the presence of uncertainty over future disposable income (due to uncertainty over income inflows, or over future compulsory expenditures) consumers may prefer to use cash rather than credit to perform their monthly purchases.

For these reasons, I split the sample between liquidity constrained and unconstrained households (using one of the proxies considered in Section 2.4). Table 2.5 reports results of four linear probability models applied to the young, old, less educated, and more educated households, respectively. Consistently with the predictions of the model, the drop is much more prominent among household whose head is under 45 (-5% between the first and the last payweek) with respect to the older ones (-1.6%), and among households whose head has lower education (-6%) with respect to the more educated ones (-1.7%).

Since the price differentials between the two types of shops is significant (average price per kilo for fresh fruits and vegetables is 10.2% lower in supermarkets than in small shops), this shopping behavior may contribute to explain the paycycle in consumption. Thus, in the next Section, I try to estimate the paycycle *net* of the effect of the shopping cycle, to see whether the results remain consistent with those obtained by previous studies.

2.7 Evidence of time-inconsistency?

I now test whether the 'pure' effect of time-preferences (controlling for the effect of the shopping cycle) induces a significant drop in weekly consumption. This task is complicated by the fact that it is reasonable to assume that choices of where to shop and of how much to purchase are simultannous. Hence, simply adding the shopping dummy to models (2.1) and (2.2) would yield biased results.

As an instrument for shopping decision, I use the price ratio between supermarkets and small shops. For each household, I compute an estimate of the price faced in each type of shop using the average price paid by households belonging to its province in that type of shop. Formally the price faced by individual i belonging to province h in shop $k = \{supermarket, smallshop\}$ in paymonth t is defined as:

$$P^k_{iht} = E\left(P^k_{jt} | j \in h, j \neq i\right) \tag{2.6}$$

The exogeneity of the resulting price ratio $R_{it} = P^{Super}_{iht}/P^{Small}_{iht}$ relies on the assumption that there are neither social interactions between sampled households belonging to the same province. To obtain more precise estimates of (2.6), I focus on provinces where there are at least thirty sampled households.

Table 2.6 reports the results of the reduced form estimates in which I inserted the log of R_{it} directly as a control variable. Specification 17 estimates model (2.1) on all sample. The ratio has a negative and highly significant effect: a 1% increase in the relative price of supermarkets decreases consumption by 0.24%. After controlling for this effect, however, consumption is flatter over the month with respect to what was estimated before. Controlling for the price ratio in model (2.2) yields similar results (estimates 18 and 19).

Table 2.7 shows the 2SLS results on the effect of distance from payday net of the effect of the shopping cycle. The shopping dummy has been instrumented using the price ratio. The shopping dummy has a positive and significant effect on consumption: when the household shops in a supermarket, its weekly consumption of fruits and vegetables increases by 37.6 percent with respect to when it shops only in small groceries. All the Payweek dummies have very small coefficients which are not statistically different from zero at any conventional level. Results are similar if I split the sample according to household head's age and education (columns 21 and 22, respectively): the paycycle is not present in any of the subgroups. These findings can be considered at odds with the interpretation of the paycycle given by previous studies. In the Italian Homescan sample, households do experience a significant drop in consumption between paydays, consistently with results from US and UK, but this fall is explained by the intra-monthly drop in the probability of shopping in the supermarket/hyperstore and by the price differentials between this type of shop and small groceries.

2.8 Robustness checks

There may still be alternative explanations for the results provided. First, supermarket and groceries may anticipate the cyclical behavior of consumers and implement an ad hoc pricing strategy. Note, however, that what would be the resulting cycle in prices is not clear ex ante. Standard models of perfect competition predict that price increases when demand peaks, so that the prices would be pro-cyclical; however, existing evidence on grocery prices show that they tend to *decrease* at seasonal peaks of demand, consistently with a 'loss-leader' model of retail competition (Chevalier et al. [16]). A counter-cyclical price strategy would induce a strengthening of the paycycle: since I do *not* find any intra-monhtly fall in consumption (once I control for the shopping cycle), my result would be robust. On the contrary, a standard pro-cyclical pricing would reduce the paycycle and may explain the flat consumption pattern found. Finally, notice that paydays may be hard to infer, given the variance in paycheque receipts highlighted in Section 2.3. Be as it may, an endogenous pricing strategy would ultimately make it impossible to identify time preferences, thus weakening the interpretation given to previous findings. To test for the existence of any strategic pricing by retailers, I study the intra-monthly cycle in price-per-kilo of fruits and vegetables purchased by the households in the sample. It is important to stress that if retailers would implement a cyclical pricing strategy, and if this strategy would have *any* effect on consumers' behavior, then we would observed changes in the price *paid*. Note, in addition, that prices analised are *effective*, since they are net of any discount or sale, as stressed in Section 2.3. Specifications 23 and 24 of Table 2.8 show results of the estimate of the effect of distance since payday on price-per-kilo, separately between small groceries and supermarkets/hyperstores. The fixed-effect strategy controls for household unobserved heterogeneity and calendar effects, as usual. For small shops, the mild reductions reported in the second and fourth payweeks are not statistically significant, while for supermarkets even the point-estimate show an absolutely flat pattern. I conclude that there are no evidence of strategic pricing by grocery shops and supermarkets.

By focusing on paydays distributed over six days (i.e. the first payweek) I may have reduced the precision of the estimate of the distance since the last income receipt. Specification 25 in Table 2.8 reports results of the model (2.1) on the sample of households whose paydays are gathered in a single triplet of days: no significant paycycle emerges, after controlling for the change in the shopping regime over the month.[10]

Finally, the analyses have focused on *quantities* of fresh fruits and vegetables, since this represents the correct measure to identify consumption. Given that the paycycle emerges as the effect of the price differentials, the model predicts that looking at weekly *volumes* of fresh fruits and vegetables (i.e. quantity timed price) we would observe a flat pattern even without controlling for the shopping cycle. Indeed, exponential consumers would increase quantities purchased when they shop at the supermarket, so to maintain expenditures constant over the month. I, therefore, study the effect of distance from payday on weekly volumes of fresh

[10]Similar results are obtained even splitting the sample between liquidity constrained and unconstrained households.

fruits and vegetables, estimating equation (2.1) without adding the shopping dummy. The result, summarized in specification 26 of Table 2.8 is consistent with the model predictions, showing no significant drop in expenditures between paydays.

2.9 Conclusions

Recent studies have produced evidence of a paycycle in intra-monthly consumption, and have argued that this represents evidence of self-control problems among consumers. In this paper, I have replicated previous results using a rich dataset collecting weekly data on food expenditures and consumption. Consumption of highly perishable food significantly drops by 3% between the beginning and the end of the paymonth. This effect is reinforced if we look more closely at liquidity constrained households (as proxied by age or education of the household head). Contrary to previous results, however, I show that this drop is largely explained by the intra-monthly change in shopping behavior: households that are liquidity constrained or have some degree of preference for purchasing out of cash rather than out of credit, are more likely to shop in farther/cheaper stores at the beginning of the paymonth to rebuild food stocks. The price differentials between these supermarkets and nearer/more expensive shops where households continue to buy perishable food for the rest of the paymonth determines a drop in the quantities purchased of this food category. This effect could not be controlled for by previous analyses and may have biased previous estimates of time-preferences toward the rejection of standard exponential discounting models. Consistenly with this explanation, no paycycle emerges once I control for the change in the shopping behavior. Robustness checks show no sign of strategic pricing and other confounding factors that may have hampered my results.

2.10 Tables and Figures

Table 2.1: Descriptive statistics

	All Sample	With Fixed PDay Income
No. of Components		
1 Comp.	7.73	8.43
	(.60)	(.60)
2 Comp.	21.28	22.23
	(.90)	(.90)
3 Comp.	28.79	29.76
	(.99)	(.99)
4 Comp.	32.68	31.84
	(1.01)	(1.01)
5 or more.	9.48	7.72
	(.57)	(.57)
Income		
Deciles 1-2	22.39	18.69
	(.84)	(.84)
Deciles 3-5	30.30	29.76
	(.99)	(.99)
Deciles 6-8	31.12	33.72
	(1.02)	(1.02)
Deciles 9-10	16.18	17.80
	(.83)	(.83)
Head Age		
Under 35	7.10	8.10
	(.59)	(.59)
35-44	31.51	33.58
	(1.02)	(1.02)
45-54	27.86	25.24
	(.94)	(.94)
55-64	22.48	22.09
	(.90)	(.90)
65 or more	11.02	10.97
	(.67)	(.67)
Education		
Primary	6.64	5.88
	(.51)	(.51)
Secondary	25.41	24.11
	(.92)	(.92)
Tertiary	67.94	69.99
	(.99)	(.99)
Monthly Exp.		
Tot. Grocery	368.7	375.29
	(1.10)	(1.80)
Fruits & Veg.	39.45	42.16
	(.16)	(.26)
No. of HHs	6,655	2,123

Notes: Standard error in parentheses. a: includes Sardinia.

Table 2.2: Effect of distance from payday on total weekly expenditures on grocery and fruits & vegetables - all sample

	Total Grocery Exp.		Fruits & Vegetables	
	(1)	(2)	(3)	(4)
PayWeek 2	-0.001	0.003	0.008	0.011
	(0.008)	(0.009)	(0.009)	(0.010)
PayWeek 3	-0.072	-0.061	-0.038	-0.042
	(0.008)***	(0.009)***	(0.009)***	(0.011)***
PayWeek 4	-0.077	-0.063	-0.028	-0.024
	(0.008)***	(0.009)***	(0.010)***	(0.011)**
PayWeek 5	-0.073	-0.049	-0.032	-0.029
	(0.008)***	(0.009)***	(0.009)***	(0.011)**
HH Fixed Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Obs.	58589	58589	58589	58589
HHs.	2123	2123	2123	2123
Overall R^2	.12	.22	.10	.25
ρ	.39	.40	.51	.53

Notes: Heteroskedasticity-robust standard error in parentheses. Controls include calendar month, day of the week, day of the month, holiday, and preholiday.

Table 2.3: Effect of distance from payday on total weekly expenditures on grocery and fruits & vegetables - proxies of liquidity constraints

	Young / Old			Low / High Education		
		Tot. Grocery Expenditures (5)	Fruits & Vegetables (6)		Tot. Grocery Expenditures (7)	Fruits & Vegetables (8)
	Young			Low Ed.		
PayWeek 2		0.008	0.004		-0.032	-0.011
		(0.011)	(0.013)		(0.014)**	(0.017)
PayWeek 3		-0.059	-0.053		-0.108	-0.074
		(0.011)***	(0.013)***		(0.014)***	(0.017)***
PayWeek 4		-0.064	-0.050		-0.131	-0.055
		(0.011)***	(0.014)***		(0.015)***	(0.018)***
PayWeek 5		-0.050	-0.053		-0.115	-0.062
		(0.011)***	(0.014)***		(0.014)***	(0.018)***
	Old			High Ed.		
PayWeek 2		-0.001	0.026		0.021	0.022
		(0.014)	(0.016)		(0.011)**	(0.012)*
PayWeek 3		-0.062	-0.022		-0.038	-0.026
		(0.014)***	(0.016)		(0.010)***	(0.017)**
PayWeek 4		-0.062	0.016		-0.031	-0.010
		(0.014)***	(0.017)		(0.011)***	(0.013)
PayWeek 5		-0.049	0.007		-0.020	-0.014
		(0.013)***	(0.017)		(0.011)**	(0.013)
HH FE & Controls		Yes	Yes		Yes	Yes
Obs.		58589	58589		58589	58589
HHs.		2123	2123		2123	2123
Overall R^2		.12	.22		.10	.25
ρ		.39	.40		.51	.53

Notes: Heteroskedasticity-robust standard error in parentheses. Controls include calendar month, day of the week, day of the month, holiday, and preholiday.

Table 2.4: Effect of the distance from payday on the probability of shopping in the supermarket - all sample

	Linear (9)	Probit (10)	FE Logit (11)	RE Probit (12)
PayWeek 2	-0.012	-0.041	-0.081	-0.045
	(0.005)**	(0.016)**	(0.034)**	(0.020)**
PayWeek 3	-0.039	-0.124	-0.252	-0.148
	(0.006)***	(0.018)***	(0.035)***	(0.020)***
PayWeek 4	-0.034	-0.105	-0.218	-0.125
	(0.006)***	(0.018)***	(0.035)***	(0.020)***
PayWeek 5	-0.034	-0.105	-0.216	-0.127
	(0.005)***	(0.017)***	(0.034)***	(0.020)***
Household FE	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes
Obs.	58589	58589	50681	58589
HHs.	2123		1987	2123
Log-Likelihood	–30410.30	–34427.44	–26785.03	–31670.79

Notes: Standard error in parentheses. For the fixed effect specifications, controls include calendar month, day of the week, day of the month, holiday, and preholiday. For the probit and random effect probit, the following controls are added: household size, residential area, income group, head's age and education.

Table 2.5: Effect of the distance from payday on the probability of shopping in the supermarket - linear prob. models

	By Age		By Education	
	Under 45 (13)	45 or More (14)	Low (15)	High (16)
PayWeek 2	0.003	-0.008	0.001	0.012
	(0.007)	(0.008)	(0.010)	(0.007)*
PayWeek 3	-0.047	-0.019	-0.072	-0.012
	(0.007)***	(0.009)**	(0.010)***	(0.006)**
PayWeek 4	-0.040	-0.022	-0.046	-0.022
	(0.007)***	(0.009)**	(0.010)***	(0.006)***
PayWeek 5	-0.051	-0.016	-0.060	-0.017
	(0.006)***	(0.009)*	(0.010)***	(0.006)***
HH FE & Controls	Yes	Yes	Yes	Yes
Obs.	25295	41956	20435	46815
HHs.	820	1303	680	1443
Overall R^2	0.16	0.18	0.16	0.19

Notes: Robust standard errors in parentheses. Controls include calendar month, day of the week, day of the month, holiday, preholiday, as well as household unobserved heterogeneity.

Table 2.6: Effect of distance from payday on total weekly expenditures on fruits & vegetables - controlling for the price ratio

	All Sample (17)	Young / Old (18)	Low / High Education (19)
		Young	Low Ed.
PayWeek 2	0.012	-0.001	0.004
	(0.010)	(0.013)	(0.017)
PayWeek 3	-0.013	-0.002	-0.013
	(0.009)	(0.013)	(0.016)
PayWeek 4	-0.005	-0.014	-0.016
	(0.010)	(0.014)	(0.017)
PayWeek 5	-0.020	-0.026	-0.033
	(0.011)*	(0.013)*	(0.017)*
Log Price	-0.237	-0.351	-0.257
Ratio	(0.106)***	(0.157)***	(0.124)**
		Old	High Ed.
PayWeek 2		0.004	0.011
		(0.016)	(0.015)
PayWeek 3		0.019	-0.020
		(0.015)	(0.015)
PayWeek 4		-0.008	-0.014
		(0.016)	(0.017)
PayWeek 5		-0.011	-0.016
		(0.017)	(0.015)
Log Price		-0.214	-0.195
Ratio		(0.102)**	(0.095)***
HH FE & Controls	Yes	Yes	Yes
Obs.	55611	55611	55611
HHs.	1978	1978	1978
Overall R^2	.17	.21	.18
ρ	.32	.41	.42

Notes: Heteroskedasticity-robust standard errors in parentheses. Controls include calendar month, day of the week, day of the month, holiday, and preholiday.

Table 2.7: Effect of distance from payday on total weekly expenditures on fruits & vegetables - controlling for the instrumented shopping decision

	All Sample	Young / Old	Low / High Education
	(20)	(21)	(22)
		Young	Low Ed.
PayWeek 2	0.002	-0.005	-0.019
	(0.013)	(0.016)	(0.018)
PayWeek 3	-0.011	0.000	0.007
	(0.012)	(0.015)	(0.018)
PayWeek 4	0.006	0.010	0.022
	(0.015)	(0.015)	(0.017)
PayWeek 5	-0.002	-0.013	-0.021
	(0.016)*	(0.015)	(0.018)
Shopping	0.376	0.443	0.399
in Supermkt	(0.183)**	(0.210)**	(0.191)**
		Old	High Ed.
PayWeek 2		-0.001	0.028
		(0.018)	(0.021)
PayWeek 3		0.012	-0.006
		(0.017)	(0.020)
PayWeek 4		0.010	-0.028
		(0.018)	(0.017)
PayWeek 5		-0.015	-0.000
		(0.014)	(0.019)
Shopping		0.303	0.340
in Supermkt		(0.154)*	(0.175)*
HH FE & Controls	Yes	Yes	Yes
Obs.	55611	55611	55611
HHs.	1978	1978	1978
Overall R^2	.18	.19	.20
ρ	.23	.27	.25
F-stat. of excl. instr.	13.62	11.01	10.5

Notes: Heteroskedasticity-robust standard errors in parentheses. Controls include calendar month, day of the week, day of the month, holiday, and preholiday.

Table 2.8: Robustness checks: effect on prices; effect on quantities consumed using HHs with one payday; effect on volumes of fruits and vegetables

	Prices		Fruits and Vegetables	
	Small Shops	Supermarkets	Payday in 1 Triplet	Volumes
	(23)	(24)	(25)	(26)
PayWeek 2	-0.038	-0.002	0.020	0.020
	(0.034)	(0.007)	(0.025)	(0.015)
PayWeek 3	-0.003	0.000	-0.023	-0.008
	(0.034)	(0.007)	(0.027)	(0.015)
PayWeek 4	-0.036	0.010	-0.005	-0.012
	(0.035)	(0.008)	(0.027)	(0.016)
PayWeek 5	0.003	0.011	-0.019	-0.014
	(0.035)	(0.008)	(0.029)	(0.016)
Shopping in Supermkt			0.341	
			(0.141)***	
HH FE & Controls	Yes	Yes	Yes	Yes
Obs.	2443	36366	29510	38809
HHs.	672	1510	1095	1515
Overall R^2	0.09	0.04	0.21	0.20
ρ	.62	.42	.41	.47
F-stat. of excl. instr.			12.10	

Notes: Robust standard errors in parentheses. Controls include calendar month, day of the week, day of the month, holiday, preholiday, as well as household unobserved heterogeneity.

Figure 2.1: Distribution of payday over the month

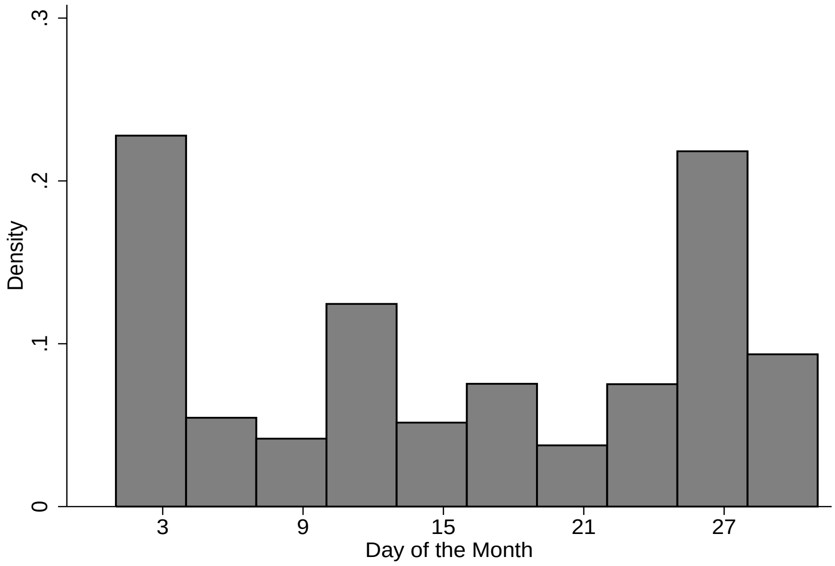
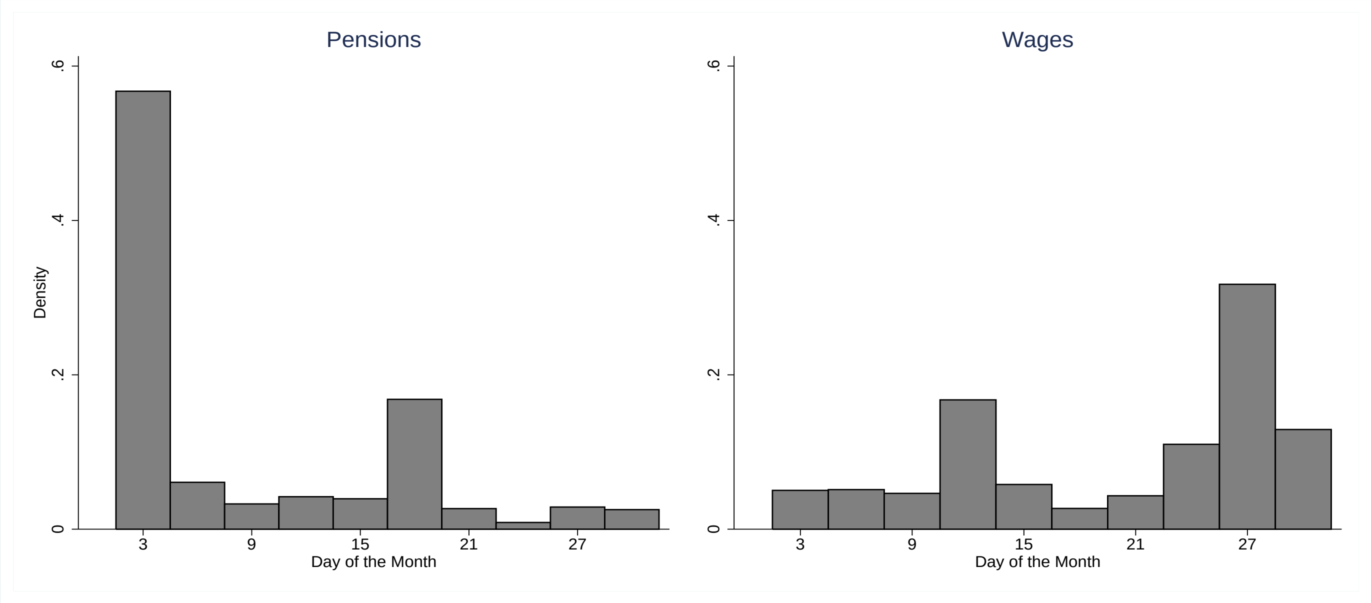


Figure 2.2: Distribution of payday over the month, by type of income



Chapter 3

Consumption during Recession.

Evidence of Liquidity Constraints and Time Inconsistency

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[1]Earlier versions of this paper were circulated under the title 'The impact of the 2008 recession on intra-monthly consumption: clean evidence of time-inconsistency'. This paper benefited from several discussions with Erich Battistin, Renata Bottazzi, Christopher Carroll, Andrea Ichino, David K. Levine, Carlos Lamarche, Andrew Leicester, Giovanni Mastrobuoni, Matthew Wakefield, seminar participants at Bologna (DSE) and Florence (EUI), as well as participants at the following conferences: AIEL-CHILD (Turin), PSPE (Prague), ESPE (Essen), EALE-SOLE (London), SAEe (Madrid), ICEEE (Pisa), RES (London).

Abstract

I develop a test for the joint presence of liquidity constraints and time inconsistency. These phenomena can be identified by looking at how households smooth their consumption between paydays when hit by a drop in available resources. Based on a large panel of Italian households observed daily both before and during the crisis of 2008/09, I show that households whose resources dropped in 2009 experienced a significant decline in the growth rate of consumption since the fourth week after income receipt. This decline is stronger for younger and less educated households. A generalized model of consumption shows that differential changes in the intra-monthly growth rate of instantaneous consumption is evidence of the presence of both liquidity constraints and self-control problems among Italian households.

3.1 Introduction

The Great Recession of 2008/09 represents an unprecedented collective shock to household welfare in most industrialized countries. In Europe in particular, households were hit by the collapse of the real estate and financial markets, the tightening of bank loan policies, and an increase in unemployment rates. Some first estimates for the UK show that the combined effects of all these channels may sum up to an astounding loss of around 37,000 euros per household,[2] and estimates for Germany that consider only the loss of financial assets have yielded an average loss of 4,000 euros per household.[3] Although these figures are still highly preliminary and should be taken with caution, it is clear that the recession has resulted into a sudden negative shock to household resources.

I used this unique shock to jointly identify evidence of liquidity constraints and time inconsistency among consumers, by looking at how the crisis has changed the ability of households to smooth their consumption in the period that separates two paydays (a "paymonth").

Theory predicts that a time-consistent consumer will always display a constant growth rate of consumption over a paymonth. Similar results are obtained for a time-inconsistent consumer who has perfect access to capital markets. However, the combination of time inconsistency and liquidity constraints results in a declining growth rate within the paymonth when the consumer faces a drop in cash-on-hand. Thus, a significant drop in the growth rate of consumption at the end of the paymonth signals the joint presence of binding liquidity constraints and time inconsistency.

To implement such a test, I exploited the ACNielsen Homescan panel, which collects information on daily food expenditures from a large sample of Italian households. The same households are observed for several paymonths, both in 2007 and in the period of October 2008 to August 2009. Thus, it is possible to compare each household's behavior before and during the crisis. To study consumption using expenditure data, I focused on food categories

[2]Estimate by Halifax bank, cited by BBC '*How every household lost 31,000 GBP*', September 10, 2009. Note that the large part of this loss is driven by the cut in the market value of all residential properties.

[3]'*Krise kostete Durchschnitts-Haushalt 4000 Euro*', Die Welt Online, May 11, 2009.

characterized by high perishability (fresh fruits and vegetables) and aggregate observations at the weekly level. The impact of the recession on household income and assets is proxied by the year-on-year monthly change in total real grocery expenditures between 2007 and 2009. Proxying drop in cash-on-hand with drops in total expenditures on grocery goods is necessary because ACNielsen does not collect any reliable monthly measure of household income and wealth. To the extent that the elasticity of grocery expenditures with respect to income shocks is lower than one, however, this proxy is conservative.

I tested for the effect of a drop in household resources by estimating a triple differences model, which controls for all confounding factors via fixed effects. I found that households hit by a drop in total expenditures displayed a significant decline in the growth rate of consumption of around 4.3% at the end of the paymonth. I looked for heterogeneity in the sample by splitting it according to the head of the household's age and education level. Younger and less educated households displayed stronger declines when hit by the drop. In the latter group, for example, the week-to-week growth rate in consumption was -8.3% in the last week of the paymonth. This result may not be surprising, given that previous literature has found these subgroups to be more likely to be liquidity constrained (Jappelli and Pistaferri [42]), and that there is scattered laboratory evidence showing that time inconsistency is negatively correlated with age and education (Tanaka et al [66]). Therefore, I built on this finding and constructed a proxy of liquidity constraint: the probability of having difficulties in accessing the credit market conditional on the full set of a household's observed characteristics. To construct such a proxy, I used the Bank of Italy Survey on Household Income and Wealth (SHIW), which directly asks a representative sample of the Italian population a set of questions concerning their access to the credit market. Statistical matching between the SHIW and the Homescan panel was then used to identify households that are likely to be liquidity constrained.

I found that households belonging to the upper two deciles of this conditional probability distribution displayed increasing difficulties in smoothing consumption between paydays when

they face a reduction in cash-on-hand. On average, when total monthly expenditures decrease by 10% or more, consumption of perishable food fell by 18% between the first and the last week of the paymonth (i.e. the month between two paydays). Households that are less likely to be liquidity constrained displayed no similar pattern. Thus, conditional on being liquidity constrained, I was able to identify time inconsistency among Italian households.
Finally, I extended the test by considering the drop in total grocery expenditures as a continuous treatment and estimating the dose-response function by means of the Generalized Propensity Score technique developed by Hirano and Imbens [34]. I checked the robustness of my finding by considering the following alternative explanations: strategic pricing by grocery stores, cyclical shopping behavior, changes in household composition, and intra-household competition for resources can be either ruled out or controlled for.
This research is connected to several strands in the literature and represents an improvement over them in several respects. First, it connects to the huge empirical literature on excess sensitivity of consumption to income shocks (see Browning and Lusardi [10] and Jappelli and Pistaferri [42] for extensive reviews). Despite tests of excess sensitivity having been performed for more than thirty years to date, results in this area are still mixed (Alegre and Pou [3]). One of the main empirical challenges that must be faced is the identification of clearly predictable, transitory, and exogenous income inflows. The present research improves on the existing literature by looking at the monthly payday, which is a perfect candidate in this respect (Stephens Jr. [62]).
Second, I used field evidence to contribute to the growing empirical literature documenting the existence of self-control problems in intertemporal choices (DellaVigna [22]). Some recent empirical works have tried to identify rejections of the rational expectations-permanent income hypothesis (RE-PIH) using daily or weekly consumption data. Stephens Jr. [62] was among the first of these. He used information from the 1986-1996 US Consumer Expenditure Survey (CEX) to identify a monthly cycle in daily expenditures on instant-consumption goods (e.g., leisure, food out of home, fresh fruits and vegetables, milk) for Social Security

recipients (who, at the time, were paid on the 3rd of the month). He found that purchases of this category of goods peaks significantly right after payday.[4] Mastrobuoni and Weinberg [52] repeated his analysis using data from the 1997-2007 CEX (when the timing of Social Security receipts changed) and found no sizeable monthly peak in expenditures, however. Shapiro [61] studied the behavior of food stamps recipients and showed that their caloric intake decreases markedly after the food stamps arrive. Calibrating an exponential and a quasi-hyperbolic model of intra-monthly consumption, he showed that the latter fits the data better. Mastrobuoni and Weinberg [51] focused on Social Security recipients and showed that low-wealth individuals display a concave declining pattern in intra-monthly consumption. Using a model that studies consumption allocation within one single month, they showed that such a cycle linked to paydays (which they called a *paycycle*) can be explained by the introduction of quasi-hyperbolic preferences. These studies suffer from two shortcomings, however.

First, the theoretical model used to distinguish between exponential and hyperbolic discounting considers only the allocation within one month; the agent receives income at the beginning of the month and has to consume everything by the end of it. This not only implies liquidity constraints, but also rules out the possibility of the consumer saving from one month to the other. As shall be seen later, relaxing this hypothesis yields different predictions. Second, and most important, in Manaresi [49] I demonstrated that there may have been a relevant confounding factor that biased all of the previous results toward the rejection of exponential discounting. In short, liquidity constrained households may display a cycle in shopping behavior; they may shop in larger supermarkets right after payday to rebuild stocks of food and in smaller/nearer stores during the rest of the month to purchase perishable food. In this case, any estimate of the discount factor that does not control for the price differential between these two types of shops may have been biased downward, and the

[4]Stephens [63] extends this analysis to the UK case and confirms his previous results.

existence of the paycycle may have been erroneously attributed to hyperbolic discounting.[5] The present research overcomes both these shortcomings: the theoretical model provides a more realistic treatment of exponential and hyperbolic discounting at high-frequencies, and the empirical estimate controls for intra-monthly shopping behavior.

The remainder of the paper is structured as follows. Section 3.2 introduces a simple theoretical model of intertemporal consumption in discrete-time that allows me to pinpoint the main differences between exponential and hyperbolic consumers at high-frequency and the role of liquidity constraints. Section 3.3 sets out the empirical framework. Section 3.4 presents the dataset used and the strategies adopted to identify consumption, paydays, and drops in cash-on-hand. Section 3.5 presents the main econometric analysis and its main results, as well as robustness checks. Section 3.6 presents two extensions of the main econometric model: a continuous treatment analysis and a test of time-consistency *conditional* on being liquidity constrained. Section 3.7 concludes.

3.2 A simple theory of consumption between paydays

Consider the problem faced by a consumer who receives a stochastic income $y_t \sim F(y)$ every four periods (i.e. every four weeks) and has to allocate that income to maximize her intertemporal utility function.[6]

$$\max_{c_t \in C} U(t) = u(c_t) + \sum_{\tau=1}^{T-t} D(\tau) u(c_{t+\tau}) \tag{3.1}$$

s.th.

$$y_t = \begin{cases} f(y) & \text{if } t = 4k+1 \qquad k \in N \\ 0 & \text{otherwise} \end{cases}$$

[5]The shopping cycle may represent a more significant confounding factor for studies based on food expenditures, [52] [62] [63], rather than on caloric intake [51] [61]. I thank Giovanni Mastrobuoni for raising this point.

[6]Here, I assume that, in the short term, monthly income is constant up to a white noise multiplicative transitory shock. A more general case, in which the income process has both permanent and transitory shocks is considered in the appendix.

$$A_t = R(A_{t-1} - c_{t-1} + y_{t-1})$$

where A_t is a perfectly liquid asset in week t and R is the gross interest rate, which is assumed to be constant overtime. Cash-on-hand is defined as the sum of assets and the present income flow: $X_t = A_t + y_t$, and lifetime wealth is the sum of cash-on-hand and the discounted value of future income flows: $W_t = X_t + \sum_{\tau=1}^{T-t} R^{-\tau} E_t y_{t+\tau}$. Define a shock to resources S_t as the difference between the actual realization of income and its expected value: $S_t = y_t - E(y_t)$. Finally, let $T \to \infty$, to avoid end-of-time effects.

In the problem depicted in (3.1), no assumptions have been made on the instantaneous budget constraint, C, and the discount function, $D(t)$. I use this general specification to obtain four possible cases: the consumer can be liquidity constrained or unconstrained, and she can be time-consistent or inconsistent.

If the consumer has perfect access to capital markets, then $C = [0, W_t]$ (Hall [31]). If, instead, she is liquidity constrained, then $C = [0, X_t]$ (Deaton [18]). Time-consistency is obtained by assuming that the discount function is exponential: $D(\tau) = \delta^\tau$. Finally, I model time inconsistency by assuming that the discount function is quasi-hyperbolic (Laibson [45]):[7]

$$D(\tau) = \begin{cases} 1 & \text{if } \tau = 0 \\ \beta\delta^\tau & \text{if } \tau > 0 \end{cases}$$

Interest relies on the consumption pattern between paydays, i.e. between $4k + 1$ and $4k + 5$. Here, I focus on a simple case that assumes $\delta = R = 1$, a CRRA utility function of the type $u(\bullet) = \bullet^{1-\rho}/(1-\rho)$, and a normally distributed income process ($y_t \sim N(\mu, \sigma^2)$). A general analysis of this model is provided in the online appendix:[8] the qualitative results remain unchanged even in more complex settings.

Consider a month of life for with infinite lifespan. The subscript $w = \{1, \ldots, 4\}$ is now used, instead of t, to signal the four weeks of the month. At the beginning of the month, $w = 1$,

[7]Other models of self-control problems, such as Gul and Pesendorfer [30] or Fudenberg and Levine [26] yield results that are qualitatively identical.

[8]Available at http://www2.dse.unibo.it/francesco.manaresi/LiqConsTestApp1.pdf.

the consumer has assets at their long-term expected value. I study the effect of two possible transitory shocks: a weakly positive and a negative one ($S_1 \geq 0$ and $S_1 < 0$).

Case 1: Perfect access to capital markets and time-consistency

These assumptions define the standard RE-PIH case. Temporary shocks in income are perfectly smoothed out by accessing capital markets. Thus, consumption stays constant within the month both when $S_1 \geq 0$ and when $S_1 < 0$.

Case 2: Perfect access to capital markets and time inconsistency

This case, which corresponds to the Laibson [45] model without illiquid assets, results in consumption following the Euler equation:

$$u'(c_w) = E_w \left[1 + (\beta - 1) \frac{\partial c_{w+1}}{\partial W_{w+1}} \right] u'(c_{w+1}) \tag{3.2}$$

It is straightforward that even in this case consumption should not react to any transitory income shock. Indeed, for T large enough (i.e., if the end-of-time is not near), the discount factor is constant overtime because the effect of the temporary shock on total lifetime resources becomes negligible. Formally, $\partial W_t / \partial S_t \to 0$ as $T - t \to \infty$, and thus the rate of change in consumption is constant over time. Note, however, that while in the time-consistent case the pattern was flat, here the pattern is declining at a constant rate for any $\beta < 1$.

Case 3: Liquidity constraints and time-consistency

The consumer can only smooth out transitory shocks by dissaving A_w. Thus, income fluctuations between months are partially tracked by consumption. In particular, when the negative shock is strong enough to let liquidity constraints bind, the optimal strategy is to dissave all resources and consume them all within the end of the month (i.e., $\sum_{w=1}^{4} c_w^* = X_1$, where the asterisk signals the optimal consumption level at week w). In these four periods time-consistency assures that the consumption pattern is constant and (given the parameter assumptions) perfectly flat. Thus, no paycycle emerges both in case $S_1 \geq 0$ and $S_1 < 0$.

Case 4: Liquidity constraints and time inconsistency

Between paydays, consumption follows the Generalized Euler equation (Harris and Laibson [32]):

$$u'(c_w) = E_w \left[1 + (\beta - 1) \frac{\partial c_{w+1}}{\partial X_{w+1}} \right] u'(c_{w+1}) \ . \tag{3.3}$$

In the appendix, I show that for nonbinding liquidity constraints, $\frac{\partial c_{w+1}}{\partial X_{w+1}}$ is ultimately constant, and thus the discount factor is expected to be constant within the month for $S_1 \geq 0$. Now consider the case of a negative shock, $S_1 < 0$, such that the liquidity constraint is binding. In this case, it is optimal to set $\sum_{w=1}^{4} c_w^* = X_1$. Defining the optimal consumption in each week $c_w^* = \alpha_w X_w$ (with $\alpha_4 = 1$) and using (3.3), it is easy to obtain the following:

$$c_w^* = \frac{\alpha_{w+1}}{(1 + (\beta - 1)\alpha_{w+1})^{\frac{1}{\rho}} + \alpha_{w+1}} X_w \tag{3.4}$$

Inserting the condition for $w = 4$ and solving backward we obtain the following:

$$c_w^* = \frac{\prod_{s=2}^{w} (4 - s + 1)\beta^{\frac{1}{\rho}}}{\prod_{s=1}^{w} \left[1 + \beta^{\frac{1}{\rho}} (4 - s) \right]} X_1 \tag{3.5}$$

Taking logs and differencing between week $w - 1$ and week w, we obtain the growth rate of consumption:

$$\gamma_w \equiv \Delta \ln c_w^* = \frac{1}{\rho} \ln \beta - \frac{1}{4 - w + 1} + \frac{1}{(4 - w) + \beta^{-\frac{1}{\rho}}} \tag{3.6}$$

which is the result obtained by Huffman and Barenstein [36] and Mastrobuoni and Weinberg [51]. It is easy to see that, for any $\beta < 1$, $\partial \gamma_w / \Delta w < 0$ (i.e., that the growth rate decreases over the month).

The four results obtained are summarized in Figure 3.1. It simulates the within-month consumption pattern of an infinite-lifespan agent in two cases: (i) no shocks and resources equal to their expected value, and (ii) a negative shock in income that reduces initial resources by two standard deviations of their long-term expected value. In the upper-left panel, the consumer has perfect access to capital and is time-consistent (Case 1); in such a setting, the two consumption patterns are identical and constant over the paymonth. The upper-right figure represents Case 2, with time-consistency and liquidity constraints. Consumption is reduced by the negative shock, but the intra-monthly growth rate of consumption remains constant. The lower-left panel assumes time inconsistency and no liquidity constraints (Case 3); the overall pattern is declining (because the discount factor is now equal to $\beta < 1$) but constant. Finally, in the last figure, liquidity constraints and time inconsistency are both present (Case 4); the shock results in both a drop in monthly consumption and a change in the intra-monthly shape of the curve, which now is concave and declining, following (3.6). Thus, if we are able to identify the growth rate of consumption between paydays in the presence of an income shock, we may identify the *joint* presence of liquidity constraints and time inconsistency by testing the null of $\gamma_{w-1} = \gamma_w$. The empirical strategy for doing so is outlined in the next section.

3.3 Empirical model

Consider a random sample of consumers, indexed by $i = \{1, \ldots, N\}$, whose weekly consumption is observed for two years $y = \{2007, 2009\}$ and for $m_{it} = \{1, \ldots, M\}$ paymonths in each year. $\Delta_w \log c_{iwmy}$ is the growth rate of consumption in week w of paymonth m in year y for individual i. In 2009, a subset of households faces a drop in cash-on-hand X_{imy} in some paymonths. Let $S_{im} = 1\left(\ln X_{im2} - \ln E(X_{im}) < 0\right)$ be a dummy equal to 1 if the consumer i has been affected by this drop in paymonth m. The effect of S_{im} on the weekly growth rate of consumption can be estimated using the following triple-differences model:

$$\Delta_w \log c_{iwmy} = a_{iwm} + S_{im}\boldsymbol{Week\beta} + d_{2009}\boldsymbol{Week\pi} + d_{2009}S_{im}\boldsymbol{Week\gamma} + d_{2009}g_i + \varepsilon_{iwmy} \quad (3.7)$$

where a_{iwm} is a consumer-week-paymonth specific fixed effect that encompasses individual unobserved time-preferences, $\boldsymbol{Week}$ is a vector of payweek dummies, d_{2009} is a dummy that takes value 1 in 2009, g_i is a household specific change in the weekly growth rate of consumption between 2007 and 2009, and ε_{iwmy} is the error term.

Note that the parameters of interest are the vector $\boldsymbol{\gamma}$, which represent the effect of a drop in cash-on-hand on the growth rate of consumption, defined by equation (3.6). The three differences in model (3.7) are: the one between paymonths affected and not affected by a drop in resources, the one between 2007 and 2009, and finally the household specific trend between the two years g_i.

Alternatively, one may impose $g_i = g$ for all i, to obtain a standard difference-in-differences estimate. However, the common trend assumption (Angrist and Pischke [4]) necessary for causal identification in a diff-in-diff model may not hold in this case: households affected and not affected by the crisis may not display the same counter-factual change in $\log c_{iwm}$ between 2007 and year 2009. First, changes in time preferences may be correlated with exposure to a drop in cash-on-hand; consumers who have become more impatient, for example, may have dissaved resources, thus being more likely to become liquidity constrained. Second, there may be unobserved changes in household characteristics that affect both intertemporal consumption and the propensity to be hit by the crisis. Third, there may be changes in intertemporal prices at the local level that correlate with the exposure to the crisis. For instance, the effective interest rate faced by consumers may increase more than proportionally in areas negatively affected by the crisis.

Allowing for a household-specific change in the growth rate over the years overcomes all these possible confounding factors, and allows me to test (i) whether changes in the growth rate of consumption in week w have been affected by the shock (using the null-hypothesis: $\pi_w = \gamma_w$), and (ii) if the effect of the drop S_{im} increases over the paymonth (with the null: $\gamma_h = \gamma_j$ for $h \neq j$).

3.4 Data and identification strategies

The ACNielsen Homescan panel collects daily information on expenditures on grocery goods from a representative sample of Italian households.[9] Households are equipped with a portable scanner with which they are asked to scan the barcode of each grocery packaged good purchased. Barcodes are then matched by ACNielsen with a dataset of retail store prices called ScanTrack. As a result, ACNielsen collects information on the quantity and quality of each good purchased, as well as its effective price (i.e. price paid net of eventual discounts due to promotions, sales, or coupons). For goods that do not have a barcode, households must compile a daily diary in which they report both the quantity and the price paid. Households provide some demographic information: their size, their province of residence, and the household head's age and education.[10]

Data was provided by ACNielsen for two different periods: January-December 2007 and October 2008-August 2009. The former corresponds to a pre-crisis period, while the latter (which for convenience will be named simply "2009") spans from the financial collapse of late 2008 to the core of the recession in 2009.

The panel dimension of the Homescan dataset is large: out of 6,655 households participating in 2007, 64.1% (4,266) were participating even in 2009.

3.4.1 Identification of payday

To identify paydays, a questionnaire was administered on April 2009 by ACNielsen, asking each individual in a household whether he or she receives a monthly wage or pension and if so in which day of the calendar month. The latter information was obtained with three-days detail (i.e., available answers were "from the 1st to the 3rd of the month", "from the

[9] Representativeness is guaranteed by the use of sample weights. Since these weights have not been disclosed by ACNielsen, I prepared an ex-post weighting based on the SHIW dataset, to obtain national representativeness.

[10] There is even an income measure but its use is problematic. First, it is coarse (a 4-values categorical variable); second, it is a measure of relative income, updated periodically; third, some robustness checks have been performed (such as correlations with education or age groups) and have questioned its reliability.

4th to the 6th", ..., and "from the 28th to the 30th/31st").[11] For a thorough discussion of the distribution of paydays over the month, see Manaresi [49]. Among the households that participated both in 2007 and 2009, the response rate for the payday questionnaire was 63.2%, and 90.5% of the households who responded provided at least one payday. Thus, I had information on paydays for 2,705 households who provided information both in 2007 and 2009.

I divided each paymonth into five groups of six days each, which I call 'payweeks'. A paymonth was thus composed of five payweeks, from the first (which contained the payday) to the fifth (which preceded the subsequent payday).[12]

Although the vast majority of households (65.95%) had paydays concentrated in a single triplet of days, there are as many as 921 households whose paydays were spread in more than one triplet. To precisely identify the paycycle, however, I restricted my attention to households whose paydays were, at best, spread among two subsequent triplets (that is, within one payweek). This restriction reduced my sample to 2,034 households. Households usually do not participate for all twelve months of the year; sometimes, for holidays or other reasons, they stop sending information to ACNielsen. Since my goal was to compare expenditure behaviors for the same households in the same weeks of the year between 2007 and 2009, I focused on paymonths for which the household provided information both in 2007 *and* in 2009. This restriction excluded 10 additional households. Finally, to control for the household-specific trend of model (3.7) I had to restrict the sample to household who had been both treated and untreated. The resulting sample is composed of 1,832 households and a total of 14,572 paymonths.

Table 3.1 shows the descriptive statistics for the overall sample of 2007 and for the subsample on which I performed the econometric analysis, using ex-post sampling weights as described

[11] This restriction was the result of space availability in the questionnaire and of the way in which information was collected: the families had to use the portable scanner to 'scan' their desired answer. As a result, each possible answer had a specific barcode, and this increased the space needed. ACNielsen considered the three-day aggregation to be the only feasible solution.

[12] Aggregation at the payweek level was used to identify consumption: see next paragraph.

in note 9. In the subsample, there are fewer households from southern Italy, and more from the northeastern regions. Single households are over-represented, and households whose head is age 65 or older are under-represented.

3.4.2 Identification of consumption

The Homescan panel collects information on purchases, but this paper focuses on the analysis of household consumption. The difference between the two can be substantial (Aguiar and Hurst [1]), particularly at high frequencies. Indeed, most of the items that are part of the consumption basket can be bought once and stored for several days or weeks. Thus, a peak in food expenditures may not signal any self-control problem, assuming that households shop at the beginning of the month and then smooth consumption at home. To overcome this problem and identify consumption through data on purchases, I used two strategies. First, I focused on a food category characterized by high perishability: fresh fruits and vegetables. Second, I aggregated data at the payweek level. The assumption, then, is that in an interval of six days, consumption and expenditure practically coincide for this kind of perishable good.

3.4.3 Identification of drops in cash-on-hand

An additional problem that must be addressed is the identification of drops in cash-on-hand similar to those outlined in the theoretical model. Ideally, we would like to observe income received and assets owned in 2007 and 2009 for each paymonth. Unfortunately, there is no reliable measure of income in the Homescan dataset, and ACNielsen does not collect any data on household wealth. What I did have, however, was the monthly total expenditure on grocery goods (i.e., food, beverages, and home-care goods). To the extent that this aggregate correlates with total resources available, I could calculate the paymonth-on-paymonth percentage change in grocery expenditures from 2007 to 2009 and use it as a proxy of drops in cash-on-hands.[13]

Figure 3.3 shows the distribution of real drops in total grocery expenditure for each paymonth and for each household in the weighted sample between 2007 and 2009. The mean value is 0.012, with a variance of .17. The distribution is moderately right-skewed with fat tails (sample skewness and kurtosis are .38 and 2.91, respectively). Some additional remarks are needed here.

First, the vast empirical literature on Engel's law shows that a correlation between total financial resources (income and wealth) and food expenditures indeed exists. However, the variance in food expenditures is usually less pronounced than that of income because marginal utility gains from food consumption are decreasing in overall resources. As a result, my measure of resources drop can be considered conservative. This conservatism should ultimately bias the result toward the rejection of any sizable effect.

Second, a variation in total food expenditure can be due to other confounding factors, such as a change in household characteristics and composition or a change in residential area. These confounding factors are relevant because they may even change the shape of consumption within the paymonth (for example, an increase in household size may change the optimal intertemporal consumption pattern markedly). In a standard difference-in-differences approach, one could control for these changes by including observable sociodemographic characteristics provided by ACNielsen among the regressors. In the model (3.7), instead, the additional household fixed-effect wipes out these possible confounding factors.

3.5 Empirical analysis

In this section, I estimate the effect of a drop in cash-on-hand on the weekly growth rate of consumption γ_w. I first start with full sample estimate of (3.7). The results show a significant negative effect in the last two payweeks of the paymonth. I then analyze the heterogeneity

[13]Total expenditures have been adjusted with the regional CPA index calculated for similar aggregates by the National Statistical Institute.

of the effect, splitting the sample by age and by education of the household head. The drop appears to be particularly strong among younger and less educated households. Since the test allows for the joint identification of liquidity constraints and time inconsistency, the results can be considered consistent with the previous literature, which has traditionally considered these subgroups to be more likely to be liquidity constrained. Finally, I test the robustness of my findings against several possible alternative explanations and reject all of them.

3.5.1 Baseline regression

For each payweek of the paymonth, I estimated the model (3.7). The estimates controlled for calendar effects via appropriate dummies. The dummies included the day of the calendar month and the day of the calendar week in which the payweek starts, calendar month dummies, and dummies controlling for whether there has been a holiday or a pre-holiday in the payweek.

Results are summarized in Table 3.2. The standard errors are clustered at the household level. The π parameters represent the change in weekly growth rate of consumption experienced between 2007 and 2009 in paymonths not characterized by a drop in resources (the control group). None of these coefficients are statistically different from zero, showing that the consumption pattern has ultimately remained constant. The γ parameters, instead, represent the difference between paymonths affected by a drop in resources and the control group. When total expenditures on grocery goods drop, the growth rate of consumption declines in the first payweek by 4.6% (i.e., consumption drops with respect to the previous paymonth). In payweeks 2 and 3, instead, there is no significant effect of a drop in resources. Finally, for payweeks 4 and 5 there is a significant drop in the growth rate, of a similar magnitude with respect to the effect on payweek 1.

Figure 3.2 depicts the consumption patterns implied by results of model (3.7). The drop in resources clearly generates both a decline in the level of consumption and a change in the within-paymonth consumption pattern.

These first results represent evidence of the joint presence of liquidity constraints and time inconsistency in the sample. An estimate of β out of γ crucially relies on some assumptions about the CRRA coefficient ρ. For example, if we allow $\rho = 1$ (log-utility), using (3.6) we obtain an estimated short-term discount factor β slightly lower than 0.97. This result is however an upper bound, because it implicitly relies on the assumption that all households for which a drop in total expenditures is observed are both time-inconsistent and liquidity constrained. This assumption may not hold, however, and time-preferences and liquidity constraints may be heterogeneous in the population.

3.5.2 Heterogeneity and liquidity constraints

In general, access to credit markets can be expected to be highly heterogeneous among the population. The availability of collateral is usually correlated with sociodemographic characteristics, and the desire to access credit markets usually depends on one's expectations about future income streams. Indeed, a large empirical literature has shown that liquidity constraints are usually negatively correlated with household wealth, age, and education level (Jappelli [40], Browning and Lusardi [10], Jappelli and Pistaferri [42]).

In addition, more recent evidence has shown that low wealth is correlated with myopic behaviors in intertemporal consumption (Aguiar and Hurst [1], Mastrobuoni and Weinberg [51]). Although in this case the direction of causality cannot be easily identified ex ante,[14] this correlation represents an additional factor pointing to the existence of possible heterogeneous effects behind the full sample estimate.

On the basis of the previous literature and the data availability, I stratify the estimate of the change between 2007 and 2009 for treated and control paymonths by age, interacting the payweek dummies with a group dummy for households younger than 45 years old, and by education level, interacting with a dummy =1 if the household's head has no more than

[14] Indeed, on one hand time inconsistency may result in lower saving rates (Laibson et al. [46]), while on the other hand lower wealth may allow time inconsistency to be better identified, as was previously discussed.

a lower secondary education.

The results for splitting based on the head's age are summarized in Table 3.3. For younger households, the estimated γ_w is usually lower, particularly in the 1st, 4th and 5th payweeks. Specifically, when the household is hit by a drop in resources, consumption drops by 5.7% in the first payweek, by 3.7% between the 3rd and the 4th payweek and by 6.7% between the 4th and the 5th. For households whose head is 45 or older, instead, the drop is significant only for the 5th payweek (at which time it is 3.9%).

Splitting by the head's education (Table 3.4) yields more marked differences; for less educated households, the drop is 6.1% in the first payweek (with respect to the fifth payweek of the previous paymonth), 3.2% at the third payweek (but it is significant only at the 10% level), and increases in the fourth and fifth payweek to 4.6% and 8.9%, respectively. Households with upper secondary education or more, by contrast, do not display any significant drop when they experience a drop in monthly resources.

3.5.3 Robustness checks

I now consider possible alternative explanations for the results obtained.

First, the decline in consumption within the paymonth may be explained by the shopping cycle. Indeed, as discussed in Manaresi [49], households display a shopping cycle over the paymonth: going to larger/cheaper stores when they receive income and in smaller and more expensive ones later in the month. This cycle can be explained by the trade-off between proximity and convenience (Bell et al. [7]). Since a change in the marginal price can result in a drop in the quantities of highly perishable food consumed between paydays, the shopping cycle represents a relevant confounding factor in any estimate of time-preferences using consumption data at high frequency. In the present analysis, in particular, the relevance of the shopping cycle stems from the fact that a reduction in available resources may affect the decision about *where* to shop inasmuch as *how much* to eat. To control for this confounding factor, I exploit two strategies.

First, I compute the ratio between prices paid in the supermarkets and prices paid in smaller shops for each household i, paymonth m, year y: $R_{imy} = P_{imy}^{Super}/P_{imy}^{Small}$ (using the average price paid in both types of shops by households sampled in the same province of i, see Manaresi [49]). This ratio is then interacted with the payweek dummies and with the year dummy:

$$\begin{aligned}\Delta_w \log c_{iwmy} = a_{iwm} + S_{im}\boldsymbol{Week\beta} + d_{2009}\boldsymbol{Week\pi} + d_{2009}S_{im}\boldsymbol{Week\gamma} \\ + R_{im,2007}\boldsymbol{Week\delta_1} + d_{2009}R_{im,2009}\boldsymbol{Week\delta_2} + d_{2009}g_i + \varepsilon_{iwmy}\end{aligned} \tag{3.8}$$

the resulting γ parameters can be thought of as estimating the effect of a drop in resources S_{im} on the weekly growth rate of consumption *net* of the potential effect of switching between different types of shops (i.e., the effect of the price gain/loss incurred by switching from supermarket to smaller shop or vice-versa). As a second strategy, I use the interactions between the price ratio R_{imy} and the payweek dummies as instruments for the decision to shop in a supermarket rather than in a small shop in each payweek (defined by a dummy S_{iwmy} equal to 1 if the household has performed at least one trip to a supermarket/hyperstore in payweek w of paymonth m in year y, and equal to zero otherwise).

Panel A of Table 3.5 summarizes the result of controlling for the price ratio directly, while Panel B shows the estimated π and γ coefficients when I controlled for the decision to shop in a supermarket vis-à-vis a small shop. Because I need to observe several households in the same province in order to compute the price ratio (I consider 30 households as the threshold), the sample is further reduced to 1,480 households for which we observe a total of 10,672 complete paymonths both in 2007 and in 2009. The estimates become slightly less precise, due to the combined effect of a smaller sample and a larger number of regressors. Nonetheless, the effect of a drop in cash-on-hand remains significant and negative in the fifth payweek of the month.

An alternative possible explanation of declining consumption within the paymonth is intra-household competition for resources (Shapiro [61], Mastrobuoni and Weinberg [51]). If household members compete for the same resources non-cooperatively, then they have an incentive to consume all they can when resources are first available. This strategic behavior can result in a declining consumption profile at the household level, even if its members are exponential discounters. Moreover, the struggle within the household is likely to become stronger as resources get scarcer, and this may explain the effect of the negative drop. However, this effect should vanish among single households, so we can check whether the previous results hold even among that subgroup. The upper panel of Table 3.5 reports the results of estimating (3.7) for single households only. Since the sample size decreases markedly, the coefficient estimates become less precise. Nonetheless, there is still a significant fall in the consumption slope in the last two payweeks which cannot be explained by intra-household competition.

The declining consumption profile may signal the effect of unexpected increases in payments at the end of the month. If the household cannot borrow to honor such payments, it may have to decrease consumption in response. This effect can generate both a reduction in total monthly expenditure and an intra-monthly fall in consumption, even if the consumer is time-consistent. To exclude this possible alternative explanation, I focused on the drops in total grocery expenditure in the first two payweeks of the paymonth. Panel B of Table 3.5 reports estimate of the model in (3.7) with deciles computed over the distribution of drops in total expenditures in the first two weeks of the paymonth. The resulting pattern is very similar to the one in Table 3.2, showing that the role of intra-monthly shocks in resources is negligible.

Finally, drops in consumption of highly perishable food may result from cyclical pricing by groceries. Indeed, if groceries increase prices at the end of the paymonth, and consumers are not able to identify this pricing strategy, they may end up decreasing their consumption at the end of the month. Panels C and D look at the growth rate of the price per kilo of fruits and vegetables paid by the consumers, distinguishing between supermarket/hypermarkets and small groceries. None of these rates are significantly different from zero, a result which is inconsistent with the existence of cyclical pricing.

3.6 Extensions

In this section I consider two extensions to the empirical analysis performed. First, I develop a direct measure of the probability of being liquidity constrained, conditional on observed household characteristics, and test whether there is evidence of time inconsistency among households that are more likely to have difficulties in accessing credit markets. Second, I consider the drop in cash-on-hand as a continuous treatment and estimate the dose-response functions for each payweek.

3.6.1 Testing for the effect of the drop among liquidity constrained households

While the test in the previous section allowed for the joint identification of liquidity constraints and time inconsistency, I now identify the latter conditioning on the former. In order to identify liquidity constraints, I followed Guiso et al. [29] and used a survey in which difficulties in accessing credit markets are directly elicited from the questionnaire. I then calculated the conditional probability of being liquidity- constrained based on a set of covariates and performed statistical matching between the survey and the Homescan dataset. To calculate the conditional probability of being liquidity constrained, I used the 2006 Bank of Italy Survey on Household Income and Wealth (SHIW). The SHIW identifies liquidity constrained households among a representative sample of the Italian population using a set of precise questions. Households are asked whether they have been denied credit or discouraged from borrowing.[15] Out of 7,768 households in the sample, 308 (3.96%) can be considered liquidity constrained, which corresponds, using sample weights, to 5.4% of

[15]The questions are: 'C48. During 2006, did you or your family apply for a loan?' If yes ⇒ 'C49. Was your application accepted?' If no ⇒ 'C51. Did you consider applying for a loan but then changed your mind, since you expected it to be denied?'. See Jappelli [40] for a discussion on the use of direct questions to identify liquidity constrained consumers.

the Italian population. On the basis of this information, I estimated the probability that households are liquidity constrained conditional on a vector of household characteristics, $Pr(d_L = 1|Z_i = z)$. I then used this estimate, to attribute a probability of being liquidity constrained to the households that are part of the Homescan dataset, conditional on their sociodemographic characteristics. This procedure is valid as long as the SHIW estimate can be considered representative of the Italian situation and as long as the characteristics of the credit-constrained households did not vary substantially in Italy between 2006 and 2009.[16]
Table 3.6 reports the results of the probit model used to estimate the conditional probability of being liquidity constrained. All of the coefficients have signs consistent with similar reports in the literature (Jappelli et al. [41]); liquidity constraints are more common among younger households and those whose head is less educated and increase with household size. All the other covariates (e.g., being headed by a male or having an unemployed household head) have the expected sign, although they are not statistically significant.
Conditional probabilities for the Homescan households were then calculated by using the probit coefficients. The resulting distribution of $Pr(d_L = 1|Z_i = z)$ is depicted in Figure 3.4. I considered the deciles of this distribution and interacted the payweek dummies in the baseline DDD model with deciles dummies. Therefore, it was possible to obtain, for each week of the paymonth, estimates of the effects of the drop in cash-on-hand on the growth rates of consumption for households belonging to each decile of the distribution. The results of this exercise are summarized in Table 3.7. The drop has a significant and negative effect only for households belonging to the ninth and tenth deciles (that is, the 20% who are more likely to be liquidity constrained). For the highest decile, in particular, consumption drops by 8.1 percentage points in the fifth payweek, and by 4.6 in the fourth. To the extent that the proxy for liquidity constraints correctly identifies difficulties in accessing credit markets, the liquidity constrained households present clean evidence of time inconsistency.

[16]The period 2000-2006 was characterised by an increase in financial depth, while the global crisis has created a tightening in credit policies. If anything, the share of households that were liquidity constrained in 2006 is a lower bound with respect to the level in 2009.

3.6.2 Continuous treatment

So far, the treatment variable has been dichotomous: equal to 1 if there was a negative growth rate in real grocery expenditure between the same paymonths of 2007 and 2009 and 0 otherwise. As a final assessment, I studied the effect of the growth rate of real grocery expenditure as a continuous treatment. The theoretical support of a growth rate is $[-1, \infty)$; in practice, as shown in Figure 3.3, the empirical support of the treatment is $[-1, 1.5]$, and the distribution is highly concentrated over the median. Let S^C_{iwm} be the continuous treatment variable. To estimate the dose-response function for each value of the treatment, I used the Generalized Propensity Score. I modified the original methodology developed by Hirano and Imbens [34], to take into account the panel dimension of the dataset. Estimation is based on the following sequential steps, applied to each payweek separately:

i. Both the growth rate of consumption, the treatment variable, and the covariates are de-meaned at the household level;

ii. The conditional distribution of S^C_{iwm} given the covariates is estimated by maximum likelihood, assuming a normal distribution for the error term;[17]

iii. The GPS, which is the conditional density of the treatment given the covariates, is estimated;

iv. The balancing property is tested for all covariates;

v. The conditional expectation of the dependent variable is estimated parametrically with a second-order polynomial function in both the treatment and the GPS, with standard errors clustered at the household level;

vi. Finally, the dose-response function at a particular value of the treatment is estimated by averaging the conditional expectation over the GPS at that value of the treatment.

[17] I followed Bia and Mattei [8] and used a Box-Cox transformation of S^C_{iwm} for which the null of normality is rejected with $p > 0.56$ using a Kolmogorov-Smirnov test. The variance-covariance matrix is allowed to be clustered at the household level.

Figure 3.5 depicts the dose-response functions for payweeks $2, \ldots, 5$, along with bootstrapped confidence intervals. Dose-response functions have been calculated for deciles 1-9 of the treatment distribution, and linear interpolation is applied between them. Consistent with the prior analysis, the effect of the drop on the growth rate of consumption has been labeled γ on the vertical axis. This effect is never statistically different from zero for payweeks 2 and 3. For payweek 4, it is around -5% and is significant only for shocks larger than -50%. Finally, in payweek 5, it is around -7.5% and statistically significant for any drop lower than about -10%.

3.7 Conclusions

In this paper, I developed a test for the joint identification of liquidity constraints and time inconsistency in food consumption using real-life data on daily expenditures from a large panel of Italian households.

Theory predicts that time-inconsistent, liquidity constrained households will not be able to maintain a constant growth rate of consumption between paydays if they face a sudden negative shock to cash-on-hand. Assuming either time-consistency or perfect access to capital markets, by contrast, theory predicts that households are always able to perfectly smooth consumption within the paymonth. By implementing a triple differences estimate, I showed that a large sample of Italian households facing a drop in total expenditures on grocery goods between 2007 and 2009 experienced a significant intra-monthly decline in consumption of fresh fruits and vegetables, particularly among younger and less educated households. This decline seems not to be driven by intra-household strategic motives, strategic pricing, or unexpected negative resources shocks at the end of the paymonth.

The empirical results, which are at odds with consumption models that assume time-consistency, are robust to several confounding factors that may have biased previous results toward the rejection of the standard RE-PIH model. They point to a new, high-frequency dimension of welfare analysis, in which cognitive abilities and psychological tracts may become particularly important and standard assumptions of the RE-PIH model less salient.

3.8 Tables and Figures

Table 3.1: Descriptive statistics

	All Sample	With Fixed Payday
Geog. Area		
North-West	25.97	24.92
	(0.17)	(0.36)
North-East	21.12	27.26
	(0.15)	(0.36)
Center[a]	24.89	24.22
	(0.17)	(0.35)
South	28.02	23.60
	(0.17)	(0.36)
No. of Components		
1 Comp.	24.58	30.53
	(0.16)	(0.36)
2 Comp.	30.11	25.52
	(0.17)	(0.36)
3 Comp.	21.14	22.33
	(0.15)	(0.35)
4 Comp.	17.81	17.95
	(0.14)	(0.30)
5 or more	6.35	3.67
	(0.09)	(0.37)
Age		
Until 34	8.08	8.26
	(0.15)	(0.28)
35-44	18.11	19.21
	(0.15)	(0.31)
45-54	19.91	20.99
	(0.16)	(0.33)
55-64	19.04	20.65
	(0.15)	(0.32)
65 or more	34.60	30.89
	(0.18)	(0.32)
Education		
Primary	29.98	27.97
	(0.17)	(0.36)
Lower Secondary	28.71	29.11
	(0.72)	(0.37)
Up. Sec. and Tertiary	41.31	42.92
	(0.19)	(0.30)
No. HH	6,655	1,832

Notes: Standard error in parentheses. All results use sample weights. a: includes Sardinia.

Table 3.2: Effect of a negative shock in total monthly expenditure on the growth rate of consumption

	PayWeek 1	PayWeek 2	PayWeek 3	PayWeek 4	PayWeek 5
Drop (γ_w)	-0.046	0.004	0.012	-0.034	-0.043
	(0.016)***	(0.016)	(0.015)	(0.17)**	(0.016)**
Control (π_w)	0.012	-0.010	-0.002	-0.010	-0.008
	(0.014)	(0.014)	(0.013)	(0.015)	(0.014)

Notes: No. obs.: 14,572 observations. No. HH: 1,832. For each Payweek w, except for Payweek 1, the coefficients reported are the sum of the baseline coefficient (either pi_1 or γ_1) and the corresponding coefficient (pi_w and γ_w, respectively). Controls include day of the calendar week, day of the calendar month, holiday, pre-holiday, calendar month, and household fixed-effects. Heteroskedasticity-robust standard errors are clustered at the household level.

Table 3.3: Effect of a negative shock to total monthly expenditure - by age of the HH head

	Payweek 1	PayWeek 2	PayWeek 3	PayWeek 4	PayWeek 5
	Panel A: DDD estimate for household with head < 45				
Drop (γ_w)	-0.057	-0.002	0.010	-0.037	-0.067
	(0.018)***	(0.017)	(0.018)	(0.018)**	(0.015)***
Control (π_w)	0.020	-0.020	0.016	-0.007	-0.028
	(0.016)	(0.017)	(0.016)	(0.015)	(0.016)
	Panel B: DDD estimate for household with head ≥ 45				
Drop (γ_w)	-0.028	-0.004	0.011	-0.010	**-0.039**
	(0.017)	(0.014)	(0.015)	(0.15)	(0.016)***
Control (π_w)	0.009	0.012	0.0020	-0.017	-0.008
	(0.013)	(0.014)	(0.015)	(0.014)	(0.013)

Notes: No. obs.: 14,572 observations. No. HH: 1,832. For each Payweek w, except for Payweek 1, the coefficients reported are the sum of the baseline coefficient (either pi_1 or γ_1) and the corresponding coefficient (pi_w and γ_w, respectively). Controls include day of the calendar week, day of the calendar month, holiday, pre-holiday, calendar month, and household fixed-effects. Heteroskedasticity-robust standard errors are clustered at the household level.

Table 3.4: Effect of a negative shock to total monthly expenditure - by education group

	PayWeek 1	PayWeek 2	PayWeek 3	PayWeek 4	PayWeek 5
	Panel A: DDD estimate for low educated households				
Drop (γ_w)	-0.061	0.013	-0.032	-0.046	-0.089
	(0.017)***	(0.018)	(0.016)*	(0.017)***	(0.018)***
Control (π_w)	0.003	0.007	0.004	-0.015	-0.022
	(0.015)*	(0.016)	(0.014)	(0.015)	(0.014)
	Panel B: DDD estimate for high educated households				
Drop (γ_w)	-0.016	-0.016	0.023	-0.026	-0.028
	(0.017)	(0.018)	(0.017)	(0.17)	(0.018)
Control (π_w)	0.027	-0.015	0.003	0.010	-0.025
	(0.014)*	(0.015)	(0.014)	(0.016)	(0.016)

Notes: No. obs.: 14,572 observations. No. HH: 1,832. For each Payweek w, except for Payweek 1, the coefficients reported are the sum of the baseline coefficient (either pi_1 or γ_1) and the corresponding coefficient (pi_w and γ_w, respectively). Controls include day of the calendar week, day of the calendar month, holiday, pre-holiday, calendar month, and household fixed-effects. Heteroskedasticity-robust standard errors are clustered at the household level.

Table 3.5: Robustness checks

	PayWeek 2	PayWeek 3	PayWeek 4	PayWeek 5
	Panel A: market price differential as regressor			
Drop	-0.000	0.004	-0.030	-0.042
$(\gamma_1 + \gamma_w)$	(0.018)	(0.017)	(0.017)	(0.018)**
Control	-0.003	0.001	0.004	-0.009
$(\pi_1 + \pi_w)$	(0.017)	(0.017)	(0.016)	(0.017)
	Panel B: market price differential as instrument			
Drop	0.014	0.010	-0.040	-0.044
$(\gamma_1 + \gamma_w)$	(0.021)	(0.020)	(0.22)*	(0.021)**
Control	-0.010	-0.002	-0.010	0.018
$(\pi_1 + \pi_w)$	(0.016)	(0.019)	(0.017)	(0.018)
	Panel C: drop at the beginning of the month			
Drop	-0.004	-0.018	-0.030	-0.047
$(\gamma_1 + \gamma_w)$	(0.016)	(0.015)	(0.14)**	(0.016)***
Control	-0.013	-0.001	-0.008	0.003
$(\pi_1 + \pi_w)$	(0.014)	(0.015)	(0.014)	(0.015)
	Panel D: single households only			
Drop	-0.009	-0.032	-0.045	-0.061
$(\gamma_1 + \gamma_w)$	(0.024)	(0.026)	(0.024)*	(0.026)**
Control	-0.023	0.021	0.011	-0.004
$(\pi_1 + \pi_w)$	(0.022)	(0.020)	(0.021)	(0.022)
	Panel E: dep.var. price in supermarkets/hyperstores			
Drop	0.002	0.012	-0.005	-0.020
$(\gamma_1 + \gamma_w)$	(0.018)	(0.017)	(0.018)	(0.018)
Control	0.004	0.000	0.019	-0.010
$(\pi_1 + \pi_w)$	(0.015)	(0.015)	(0.015)	(0.016)
	Panel F: dep.var. price in small groceries			
Drop	-0.013	0.008	-0.014	-0.007
	(0.021)	(0.020)	(0.20)	(0.020)
Control	0.003	-0.013	0.008	0.006
	(0.019)	(0.019)	(0.018)	(0.019)

Notes: Controls include calendar effects and household fixed-effects. Heteroskedasticity-robust standard errors are clustered at the household level.

Table 3.6: Probability of being liquidity constrained: probit results and sample means.

Variable	Coefficient	Unconstrained HH Variable Mean	Constrained HH Variable Mean
Age	-.011	57.9	49.9
	(.003)***		
Male	-.099	63.1	59.1
	(.083)		
Primary Education	.378	60.4	56.2
	(.143)***		
Secondary Education	.307	30.6	37.7
	(.144)**		
Unemployed	.209	2.7	5.2
	(.229)		
Pensioner	-.103	36.7	22.1
	(.126)		
Household Size	.073	2.5	2.8
	(.034)**		
Number of Earners	-.048	1.7	1.7
	(.058)		
Constant	-.688		
	(.248)***		
Number of Obs.	7768	7460	308
F	7.954		

Notes: Standard errors in parentheses. Omitted variables are: female headed household, tertiary education, being employed. The probit specification includes a set of 18 regional dummies (Val d'Aosta is included in Piedmont, Molise is included in Abruzzi) whose coefficient is not included here for the sake of brevity. All results used sampling weights provided by the Bank of Italy.

Source: Author's elaborations on 2006 SHIW.

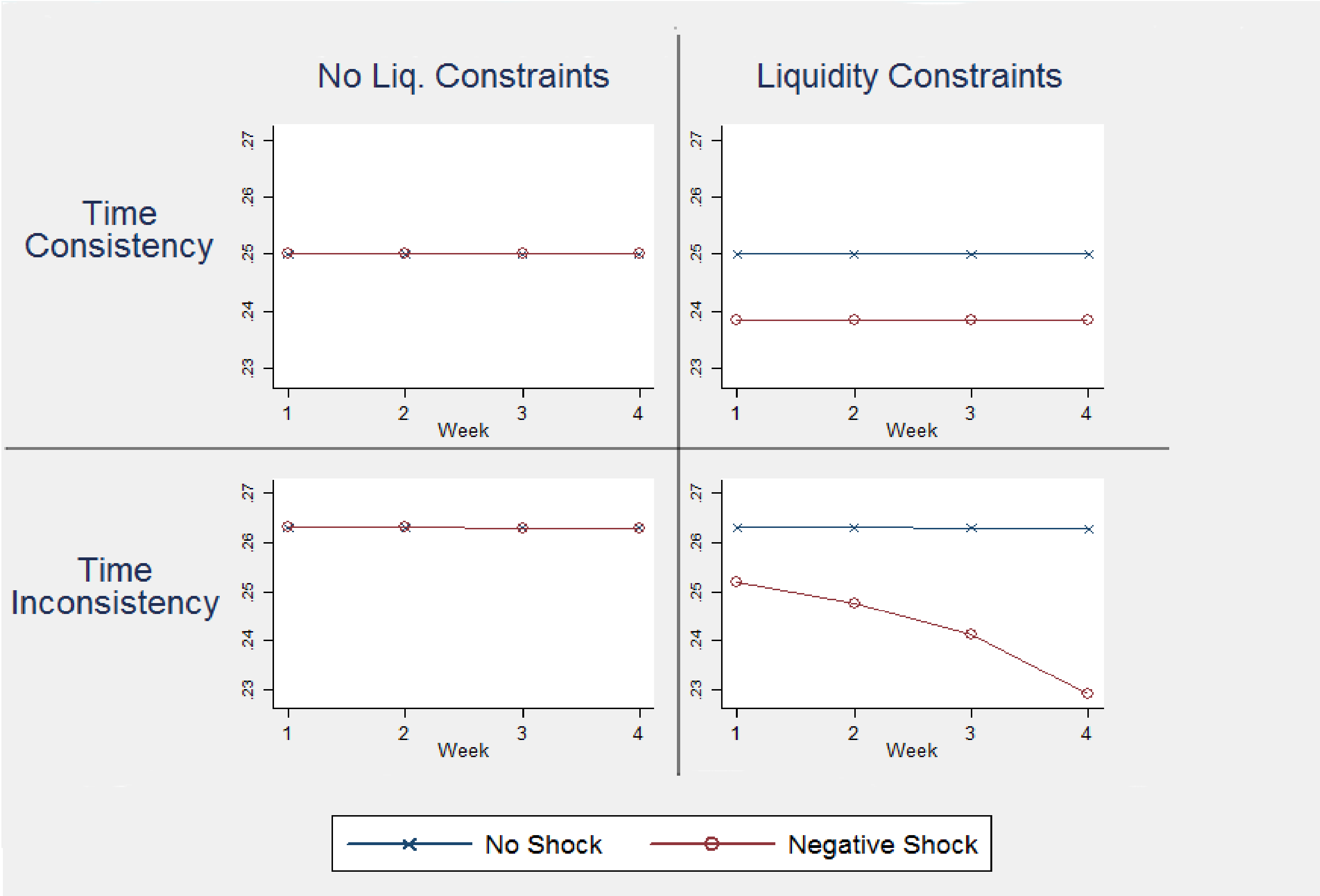
Table 3.7: Effect of a negative shock to total monthly expenditure - by deciles of the liquidity constraint dummy

	PayWeek 2	PayWeek 3	PayWeek 4	PayWeek 5
Decile 1				
Drop ($\gamma_1 + \gamma_w$)	0.000	0.008	-0.002	0.017
	(0.017)	(0.016)	(0.18)	(0.017)
Control	-0.009	-0.002	-0.009	0.010
	(0.014)	(0.014)	(0.014)	(0.015)
Decile 2				
Drop ($\gamma_1 + \gamma_w$)	-0.016	0.022	-0.003	-0.015
	(0.014)	(0.015)	(0.13)	(0.016)
Control	-0.010	-0.002	-0.013	0.015
	(0.013)	(0.014)	(0.014)	(0.014)
Decile 3				
Drop ($\gamma_1 + \gamma_w$)	0.007	-0.021	-0.018	-0.016
	(0.016)	(0.015)	(0.017)	(0.016)
Control	-0.012	-0.020	-0.006	-0.020
	(0.014)	(0.013)	(0.015)	(0.014)
Decile 4				
Drop ($\gamma_1 + \gamma_w$)	0.011	0.008	-0.005	0.008
	(0.015)	(0.014)	(0.015)	(0.013)
Control	0.005	0.006	0.013	-0.017
	(0.011)	(0.013)	(0.011)	(0.012)
Decile 5				
Drop ($\gamma_1 + \gamma_w$)	0.005	-0.017	0.006	-0.001
	(0.013)	(0.013)	(0.014)	(0.013)
Control	0.0009	0.006	0.013	-0.015
	(0.012)	(0.011)	(0.012)	(0.011)
Decile 6				
Drop ($\gamma_1 + \gamma_w$)	-0.012	0.019	-0.007	0.003
	(0.015)	(0.017)	(0.16)	(0.018)
Control	-0.013	-0.004	-0.012	0.006
	(0.016)	(0.013)	(0.014)	(0.014)
Decile 7				
Drop ($\gamma_1 + \gamma_w$)	0.000	0.018	-0.004	0.009
	(0.017)	(0.016)	(0.18)	(0.017)
Control	-0.009	-0.002	-0.009	0.010
	(0.014)	(0.014)	(0.014)	(0.015)
Decile 8				
Drop ($\gamma_1 + \gamma_w$)	-0.006	0.011	-0.013	-0.017
	(0.014)	(0.015)	(0.13)	(0.016)
Control	-0.010	-0.002	-0.013	0.015
	(0.013)	(0.014)	(0.014)	(0.014)
Decile 9				
Drop ($\gamma_1 + \gamma_w$)	0.006	0.013	-0.030	-0.045
	(0.016)	(0.015)	(0.017)*	(0.016)**
Control	-0.012	-0.020	-0.006	-0.020
	(0.014)	(0.013)	(0.015)	(0.014)
Decile 10				
Drop ($\gamma_1 + \gamma_w$)	-0.008	-0.012	-0.046	-0.081
	(0.012)	(0.014)	(0.013)***	(0.014)***
Control	0.005	0.006	0.013	-0.017
	(0.011)	(0.013)	(0.011)	(0.012)

Notes: Controls include calendar effects, shopping behavior, and household fixed-effects. Heteroskedasticity-robust standard errors are clustered at the household level.

Source: Author's elaborations on ACNielsen Homescan.

Figure 3.1: Liquidity constraints, time inconsistency, and intra-monthly consumption patterns



Notes: the figure simulates intra-monthly consumption patterns in different settings. Parameter values commont to all specifications: $\delta = \rho = R = 1$, $y_t = N(1, 0.1)$ for $t = 4k + 1$. Time-inconsistency discount factor: $\beta = 0.95$. A negative shock is a drop in resources available at the beginning of the month of two-times the standard deviations. The simulation code, prepared for Mathematica 5.0, is available upon request.

Figure 3.2: Consumption within the paymonth - predicted pattern

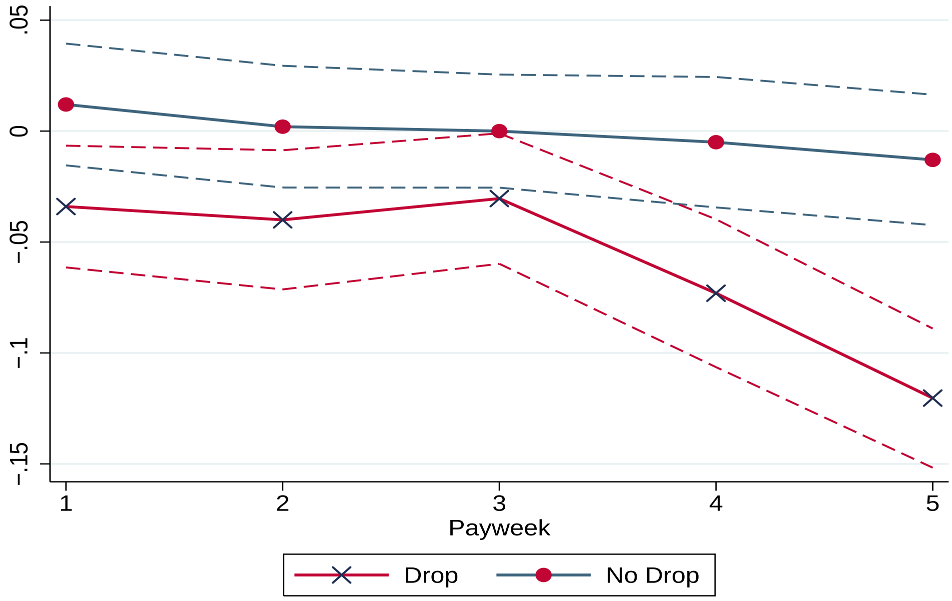
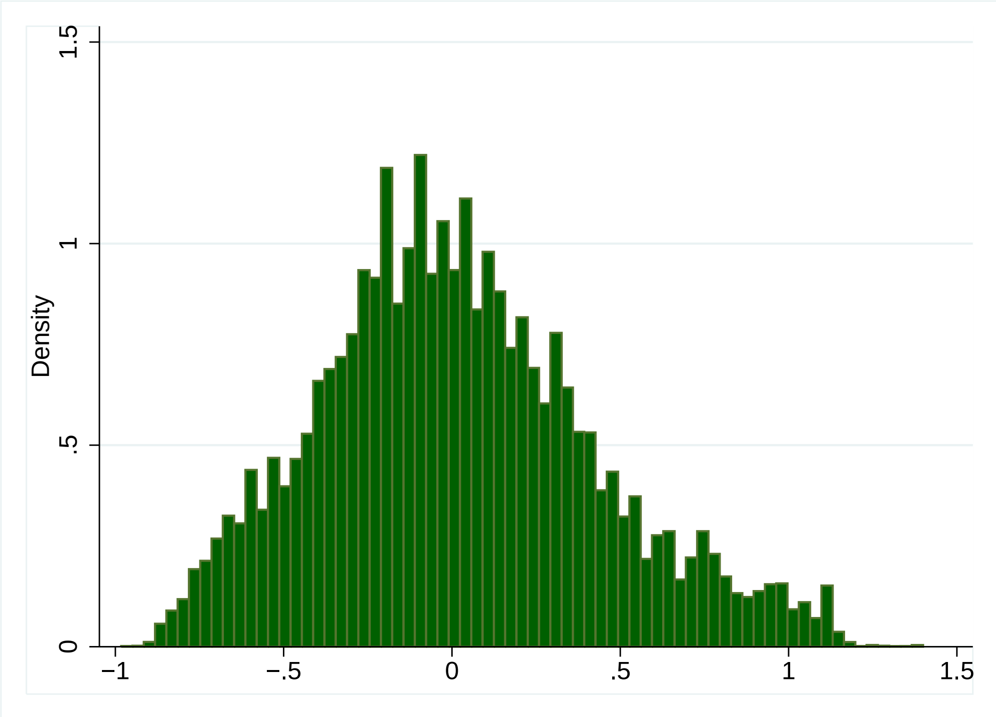


Figure 3.3: Distribution of shocks in total monthly expenditure on grocery goods between 2007 and 2009.



Notes: The graph plots the distribution of the rate of change in total monthly real expenditures for each paymonth of each household between 2007 and 2009.

Figure 3.4: Distribution of the conditional probability of being liquidity constrained in the Homescan dataset

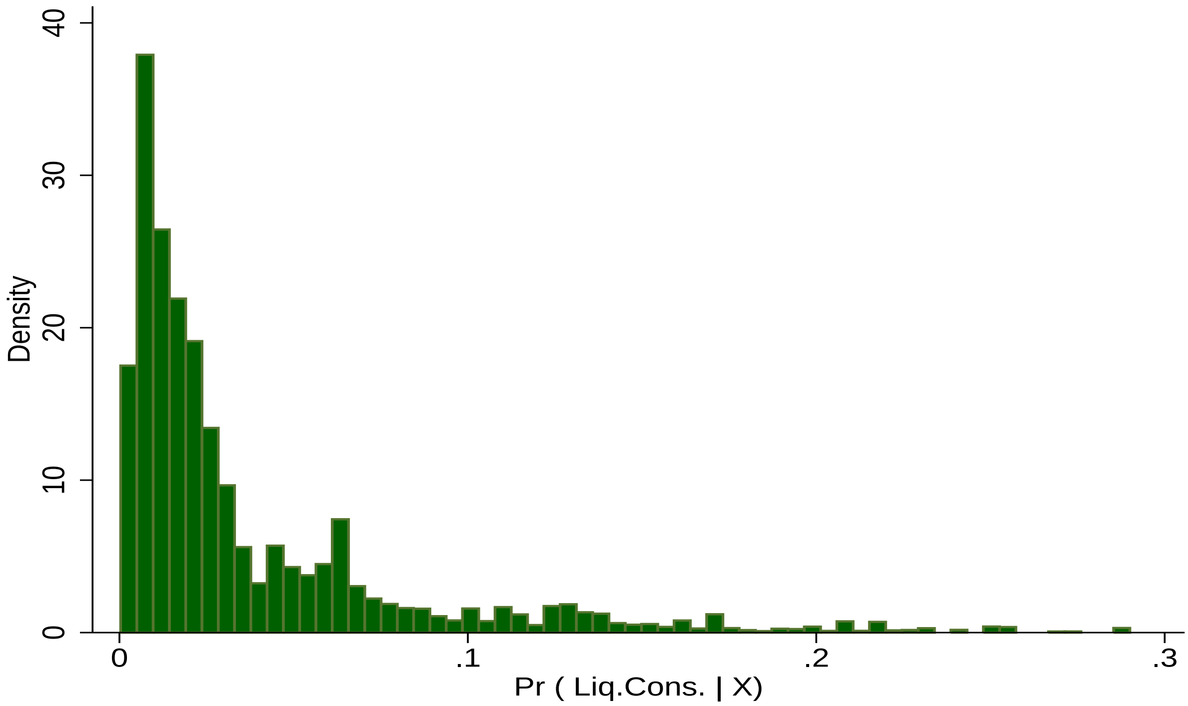
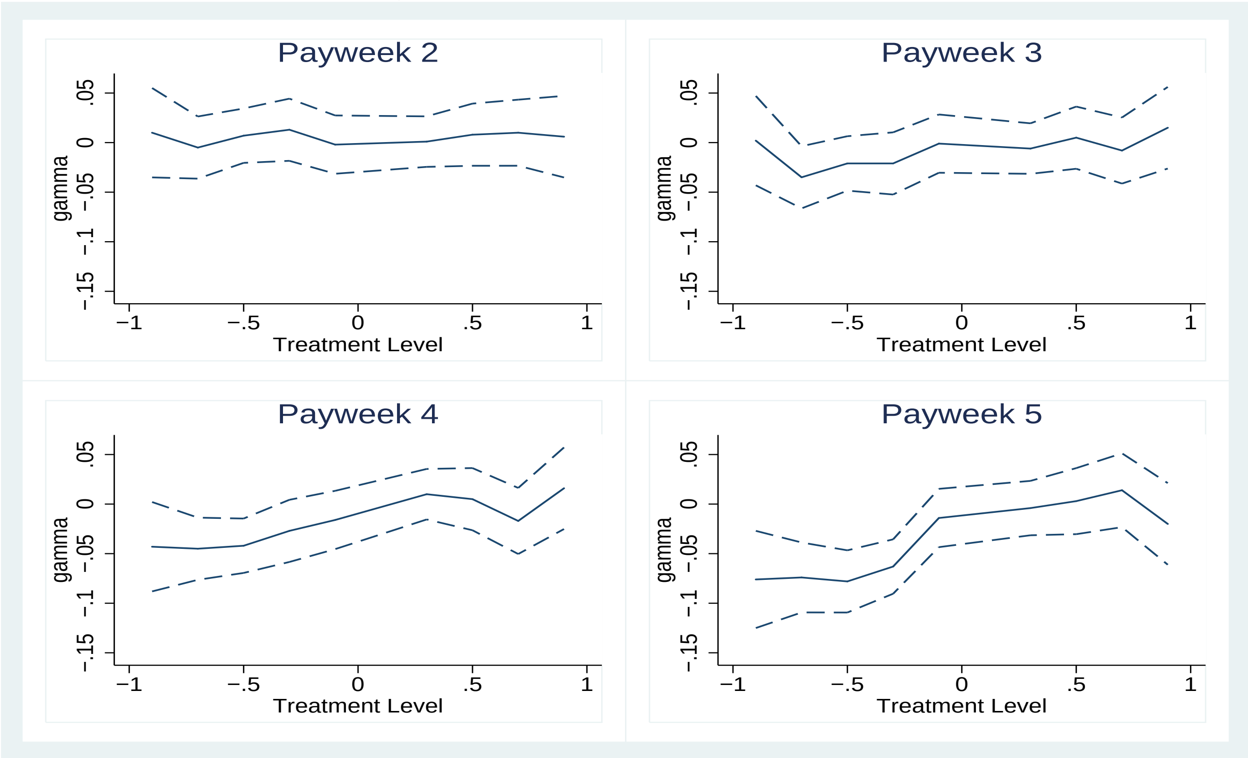


Figure 3.5: Dose-Response Functions



3.9 Appendix: a general model of intertemporal consumption with paydays

3.9.1 The Model

The consumer has to allocate resources in order to maximize her intertemporal utility function $U(t) = u(c_t) + \sum_{\tau=1}^{T-t} D(\tau)u(c_{t+\tau})$, where $u(c_t)$ is a CRRA utility function, and $D(t)$ is a generic discount function. Each period t corresponds to one week, and income is received every four periods. Without loss of generality, let us assume that income is received in periods $4k+1$ for $k \in Z$. The end-of-time T is conveniently set sufficiently far away, by assuming $T \to \infty$.

We assume that in the short-run, permanent income p_t is constant, while multiplicative transitory income shocks (v_t) follow a stationary, mean one process.

The problem faced by the consumer is then:

$$\max_{c_t \in C} U(t) \tag{3.9}$$

s.th.

$$y_t = \begin{cases} p \cdot v_t & \text{if } t = 4k+1 \qquad k \in Z \\ 0 & \text{otherwise} \end{cases}$$

$$A_t = R(A_{t-1} - c_{t-1} + y_{t-1})$$

where C is a generic instantaneous budget constraint, R is the gross interest rate, assumed to be constant over time, and A_t is a perfectly liquid asset.

Finally, let us define cash-on-hand as $X_t \equiv A_t + y_t$; lifetime wealth as $W_t \equiv X_t + \sum_{\tau=1}^{T-t} R^{-\tau} E_t y_{t+\tau}$, and a transitory shock as $S_t \equiv y_t - E(y_t)$.

We are interested in studying the *intra-monthly* growth rate of consumption under two different assumptions on C and two assumptions on $D(t)$. In particular:

- assumptions on the budget constraint: if $C = [0, W_t]$ the consumer is liquidity unconstrained, if $C = [0, X_t]$ she is liquidity constrained;
- assumptions on the discount function: if $D(t) = \delta^t$ the consumer is time-consistent, if $D(t) = 1$ for $t = 0$, and $D(t) = \beta\delta^t$ for $t > 0$ she is time-inconsistent.

We distinguish between liquidity constrained and unconstrained consumers, first, and within each case discuss the role of time-consistency and inconsistency.

3.9.2 Liquidity unconstrained consumers

As long as the end-of-time is sufficiently far away, and the consumer has perfect access to capital market and no precautionary saving motives that prevents her to access it, both time-consistency and time-inconsistency will yield a similar consumption pattern, with constant growth rate of consumption between income receipts. To show this, consider the Euler equation obtained assuming no liquidity constraints and time-inconsistency (Laibson [45]):

$$u'(c_t) = RE_t \left[\beta\delta \left(\frac{\partial c_{t+1}}{\partial W_{t+1}} \right) + \delta \left(1 - \frac{\partial c_{t+1}}{\partial W_{t+1}} \right) \right] u'(c_{t+1}) \tag{3.10}$$

The standard time-consistent case is obtained by assuming $\beta = 1$. The discount factor between present and future marginal utility of consumption is a weighted average between the short-term factor ($\beta\delta$) and the long-term one (δ), with weights equal to the future marginal propensity to consume and marginal propensity to save, respectively. The growth rate is, thus, constant as long as the weights remain constant overtime. It is straightforward to see that

$$\frac{\partial c_t}{\partial W_t} \to \frac{\partial c_{t+1}}{\partial W_{t+1}} \text{ as } T - t \to \infty$$

Similarly, shocks to income at the beginning of the month do not have any effect on the intra-monthly consumption pattern, since $\partial W_t / \partial S_t \to 0$ as $T - t \to \infty$.

3.9.3 Liquidity constraints

If consumers are prevented to borrow, due to explicit or implicit liquidity constraints, then it can be shown (Harris and Laibson [32]) that consumption follows the Generalized Euler relationship:

$$u'(c_t) = RE_t\left[\beta\delta\left(\frac{\partial c_{t+1}}{\partial X_{t+1}}\right) + \delta\left(1 - \frac{\partial c_{t+1}}{\partial X_{t+1}}\right)\right]u'(c_{t+1}) \tag{3.11}$$

which is very similar to the previous one, with the exception that the marginal propensity to consume is now calculated out of future cash-on-hand, not wealth. To study the intra-monthly consumption pattern in this case, we can follow Deaton [18] and Carroll [13], and simulate the behavior of a liquidity constrained consumer and calculate the long-term consumption functions for each period of the month. An additional assumption needed here is that consumer must be 'relatively impatience', i.e. $(R\beta\delta)^{\frac{1}{\rho}}/R \leq 1$.[18]

Simulation

To obtain the long-term consumption functions in this discrete-time intertemporal optimization model with finite time, we must start from the end-of-the-time, when the optimal rule is simply to consume all available resources: $c_T = x_T$, and then go backward using (3.11). The consumption function is obtained by inverting the utility functions. For all $t = 4k$, the optimal consumption function has to consider the future stochastic inflow of income, which will increase future available resources.[19]

I perform a simple simulation exercise to compare the case in which $\beta < 1$ to the case in which $\beta = 1$. I assume that the consumer faces a constant weekly interest factor $R = 1.0011$ (which, again, corresponds to an annual discount rate of slightly less than 5%), income is a stationary, normally distributed process with $\mu = 100$ and $\sigma^2 = 30$, the coefficient of relative risk aversion is $\rho = 5$, the long-term weekly discount factor is $\delta = 0.99$ (slightly less

[18] This is what Carroll [14] calls the 'return impatience condition': the consumer must not be so patient that an increase in available resources does not increase spending.

[19] Instead of numerically integrate all possible solutions to obtain the expected value, I follow Carroll [14] and discretize the distribution of future income, obtaining a faster and accurate estimate of the optimal consumption function.

than 0.99345, which corresponds to Deaton's [18] yearly discount rate of 0.9090), and the short-term discount factor is $\beta = 0.9$ for the quasi-hyperbolic case. I set $T = 100$, assume that $t = 1$ is the first week of the first paymonth, and calculate the consumption function for each t.

As it has been shown by Deaton [18], as long as the consumer is sufficiently impatient, the finite-time consumption function should converge as we move backward from the end-of-time to the beginning. However, in this case, there is a slight complication due to the fact that income shocks arrive every four periods. Indeed, each of the four weeks within a paymonth have a different distance with respect to the next income shock and this generates four different converged consumption functions: one for $t = 4k + 1$ (the week in which there is a payday), one for $t = 4k + 2$ (the second week of the paymonth), one for $t = 4k + 3$ (the third week), and one for $t = 4k$ (the last week of the paymonth). Figure 3.6 shows the convergence of each type of consumption function. Consider the top-left figure: it plots the consumption functions of the first weeks of several paymonths. The straight line is, thus, the first week of the last paymonth in life (the 25th in our case): at that time the rule is simply to consume a fixed share of cash-on-hand, and leave the rest to the last three weeks. The line below it corresponds to the first week of the 24th month: if resources are sufficiently low with respect to their expected value, then the rule is again to consume that fixed share and leave remaining resources for the next weeks of the paymonth. However, as resources increase, a first discontinuity appears, and the marginal propensity to consume (MPC) out of cash-on-hand is reduced. The subsequent lines correspond to the first week of, from above to below, the 22nd, the 20th, the 15th, and the 5th paymonth. The distance between them rapidly shrinks: consumption functions converge.

A similar analysis can be done for the second week of the paymonth (top-right), the third (bottom-left), and the fourth one (bottom-right). What must be noticed, however, is that the slope of the straight line tends to increase as we move forward in the paymonth. Actually, in the fourth week, the slope of the line is 45 degrees, so that when liquidity constraints bind, the consumer will simply set $c_t = x_t$.

For the simulation, I restrict my interest to the converged consumption functions, which corresponds to the infinite-horizon case (Carroll [13]). Figure 3.7 compares the four converged consumption functions in the quasi-hyperbolic case (left) to those in the exponential case (right). As it can be seen, the two figures seem visually very similar, so that one could conclude that there are no fundamental differences in consumption behavior between sophisticated quasi-hyperbolic and exponential agents, apart from a relatively larger MPC (the curves on the left figure are steeper than those on the right one). In fact, only pertains to the values of X_t such that liquidity constraints are not binding.

Figure 3.8 shows the simulated income, saving and consumption patterns for 200 out of a total of 400 simulated weeks. I use the converged consumption functions, so that the consumer is not expected to die after the 400th week. In addition, I trim the first half of the weeks, since in the simulation the consumer starts with no saving and I want her to build up her long-term level of assets before analysing her behavior. The top panel shows the income receipts (the dots) which are distributed around their average value (the solid line) placed at 100. The middle and the bottom panel show, respectively, savings and consumption for an exponential consumer (solid line) and a hyperbolic one (dashed line). Savings spike at each payday, and decrease afterward. Those of the quasi-hyperbolic consumer are everywhere weakly lower than those of the exponential consumer, since the former values current consumption more than the latter. Consequently, consumption of the hyperbolic consumer has a larger variance and reacts more to positive and negative temporary shocks in income. The overall path of consumption does not seem to be significantly different, however. The most important differences come out right after $t = 300$, when consumers face a series of low income shocks that decrease their cash-on-hands. I focus on consumption patterns around that period in Figure 3.9 and look at the intra-monthly consumption behavior of both types of consumer. Before the negative shocks, when liquidity constraints do not bind, the within-month rate of reduction in consumption is constant both for exponential and quasi-hyperbolic consumers, albeit for the latter it is higher. However, after $t = 300$, income shocks are such that liquidity constraints start binding and the behavior of the two consumers differ. Indeed, the rate of decline for the quasi-hyperbolic consumer becomes increasing within the month (as it can be seen by the concave declining pattern lasting four weeks, followed by a peak at the subsequent payday), while for the exponential agent it is still constant. In short, when liquidity constraint binds time-inconsistent agents are no longer able to maintain a smooth consumption pattern within the paymonth, since the cost of self-control becomes unsustainable as the marginal gain from consuming today increases. To have a clearer picture of what is happening we can return to the consumption functions analysis. Let's consider the growth rate of consumption from week $t-1$ to t: $\frac{c_t - c_{t-1}}{c_t}$. Another way of interpreting the previous finding is that this rate is a function of available resources, and decreases markedly when liquidity constraint binds. Define X_1 as the resources available in the first week of the paymonth, i.e. saving from previous month plus the new income inflow. We are interested in how the weekly growth rate of consumption changes as a function of X_1. That is, we are interested in studying the functions

$$\chi(X_1) = \frac{c_\tau(X_1) - c_{\tau-1}(X_1)}{c_{\tau-1}(X_1)} \qquad \text{for } \tau \in \{2, 3, 4\} \tag{3.12}$$

Figure 3.10 plots these functions for the exponential and the quasi-hyperbolic cases. The exponential consumer has the same discount rate for all weeks of the paymonth and for all possible levels of cash-on-hands at payday, and it is (in this simulation) at around -0.035. The quasi-hyperbolic consumer, instead, presents sharp differences. When liquidity constraint binds, i.e. when cash-on-hands at payday is sufficiently below its expected value, the rate of decline between weeks is higher at the end of the month with respect to the beginning of the month. As cash-on-hands increases the different decline rates tend to converge at the same level, which is nonetheless lower than the exponential one.

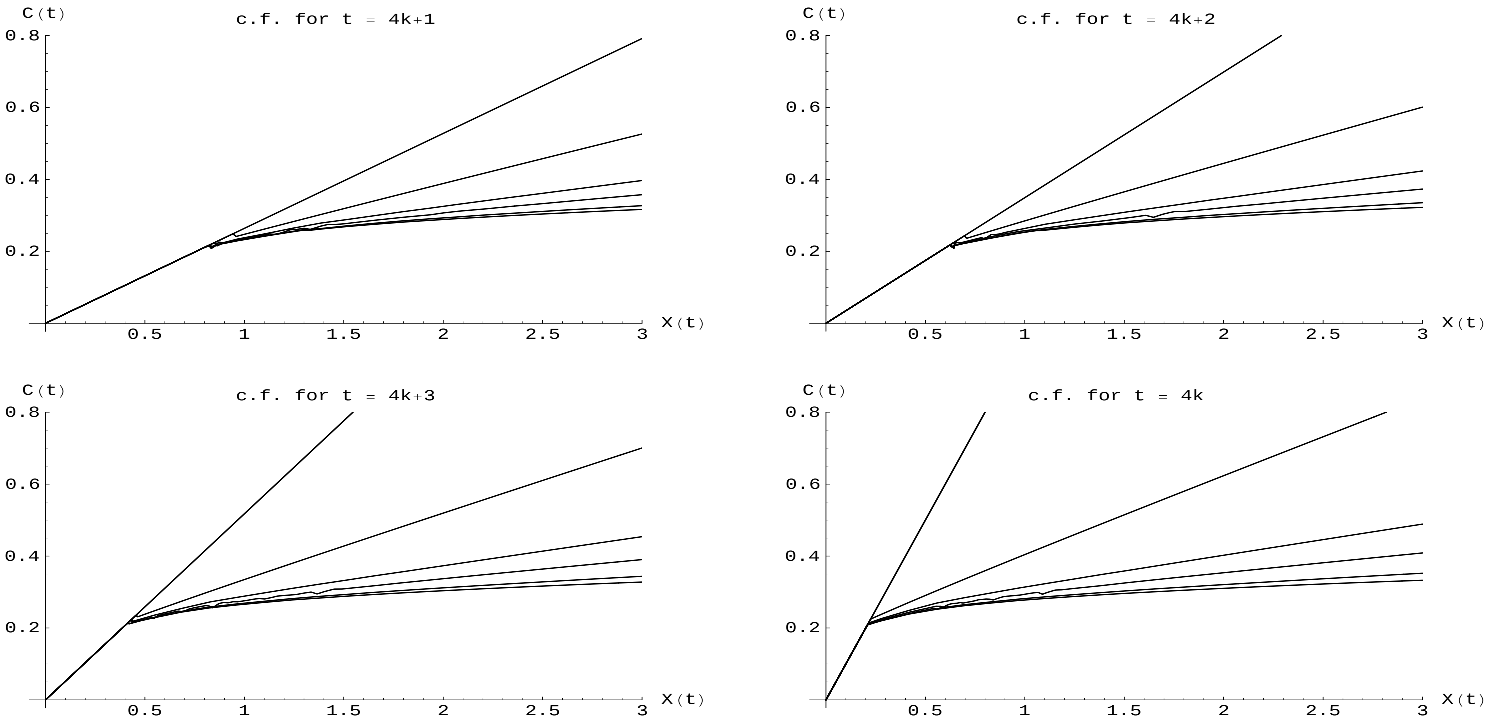
Why does the intra-monthly growth rate differs so sharply depending on the level of cash-on-hand? When liquidity contraints bind, it is easy to show that the pattern is concave declining over the month (see the paper). When, instead, liquidity constraints are present but not binding, time-inconsistent agents at the beginning of the month must trade-off the utility of anticipating consumption today over the disutility of a discontinuity in consumption between the end of the month and the beginning of the next one. Such a disutility reduces present consumption vis-à-vis future consumption and effectively constraints short-term impatience. Thus, the consumer will try to maintain a constant consumption pattern over the month, whenever he is able to (i.e. if liquidity constraints are not binding).

3.9.4 Conclusions

This short appendix analyses the intra-monthly growth rate of consumption for an agent that receives income once per month. It is shown that neither liquidity constraints nor time-inconsistency per se result in a change in the growth rate of consumption over the month. Indeed, only the joint presence of both yields a declining growth rate as we move from one income receipt to the other.

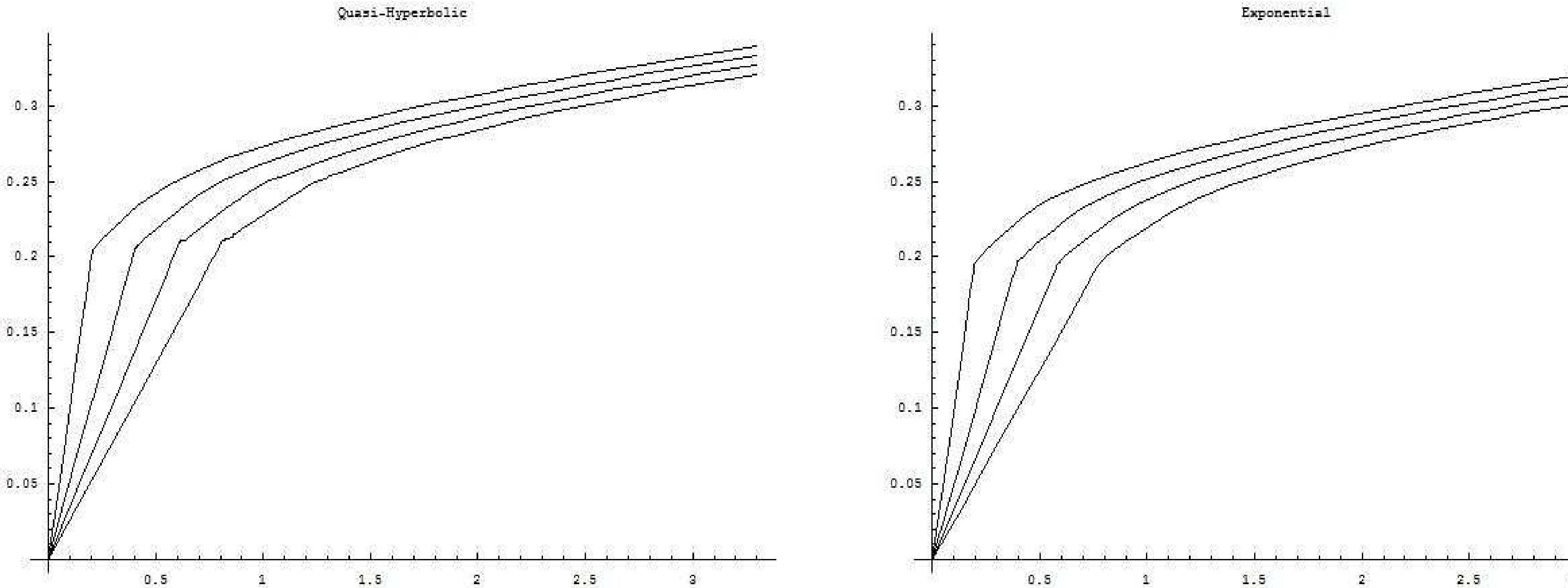
3.10 Figures

Figure 3.6: Convergence of consumption functions



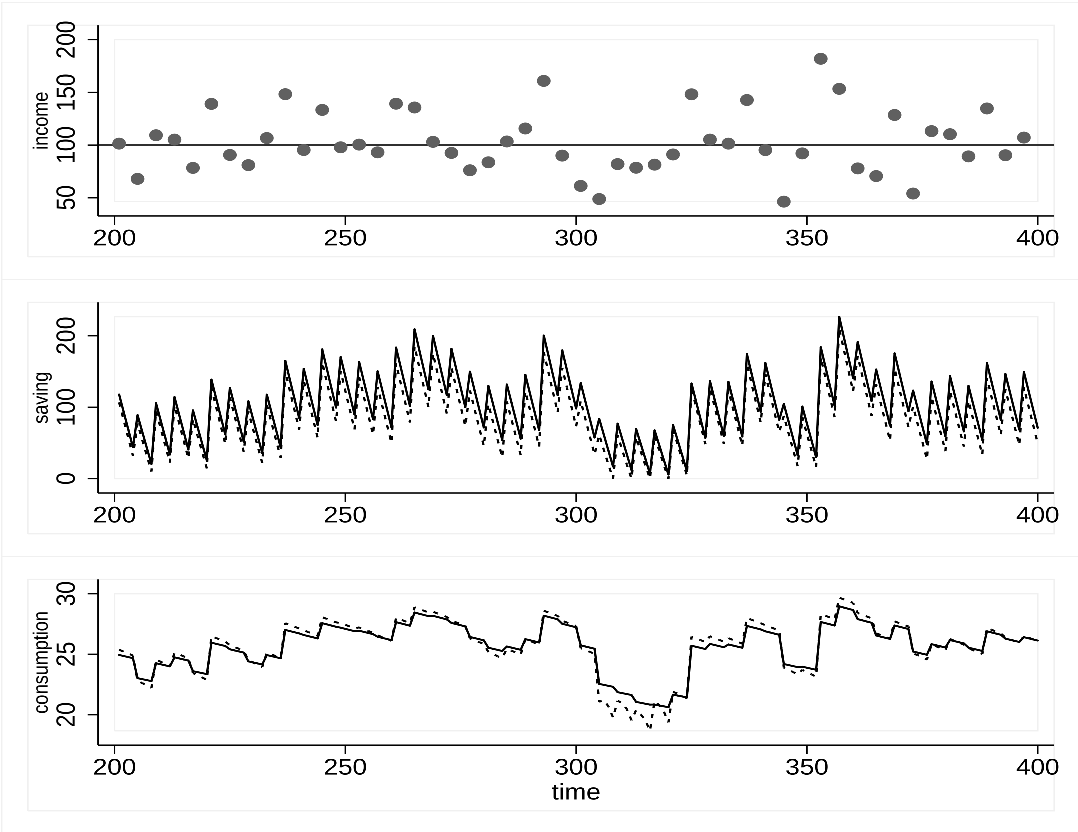
Notes: Convergence of consumption functions for each week of the paymonth. In each figure lines correspond, from the upper to the lower, to the last paymonth, to the first-to-last, to the third-to-last, to the fifth-to-last, to tenth-to-last, and to the first paymonth. T=100, $R = 1.0011$, $Y_t = 1$, $\rho = 5$, $\delta = 0.99$, $\beta = 0.94$

Figure 3.7: Converged consumption functions for quasi-hyperbolic and exponential consumers



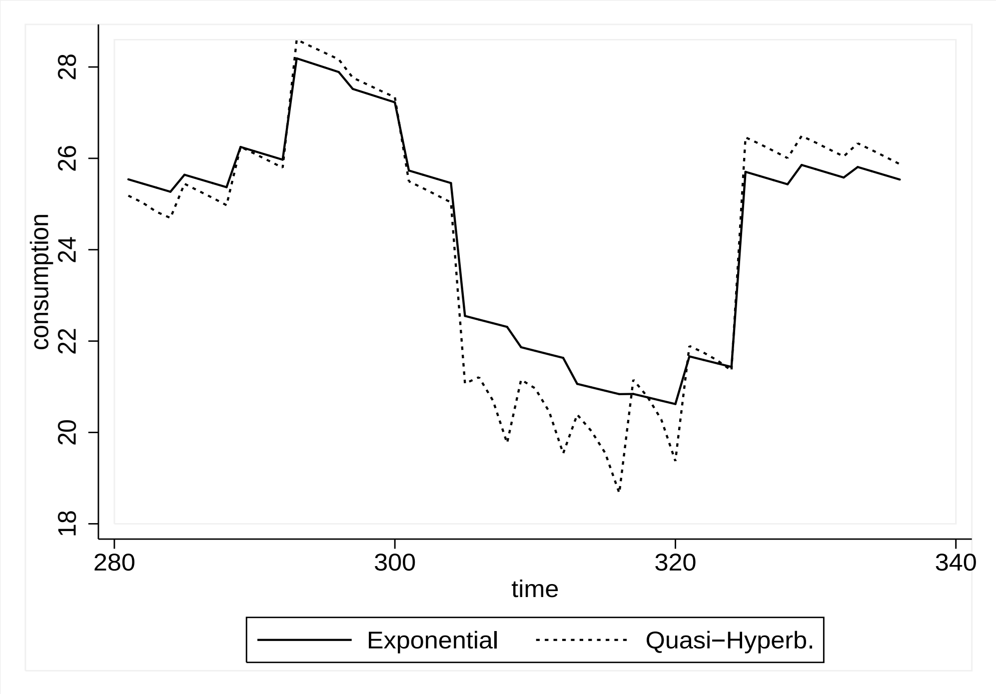
Notes: The figure plots infinite-horizon consumption functions for (respectively, from bottom to top) the first, second, third, and fourth week since payday, for quasi-hyperbolic (left) and exponential (right) consumers. T=400, $R = 1.0011$, $Y_t = 1$, $\rho = 5$, $\delta = 0.99$, $\beta = 0.94$

Figure 3.8: Simulation of income, saving, and consumption for exponential (solid line) and quasi-hyperbolic (dashed) consumers



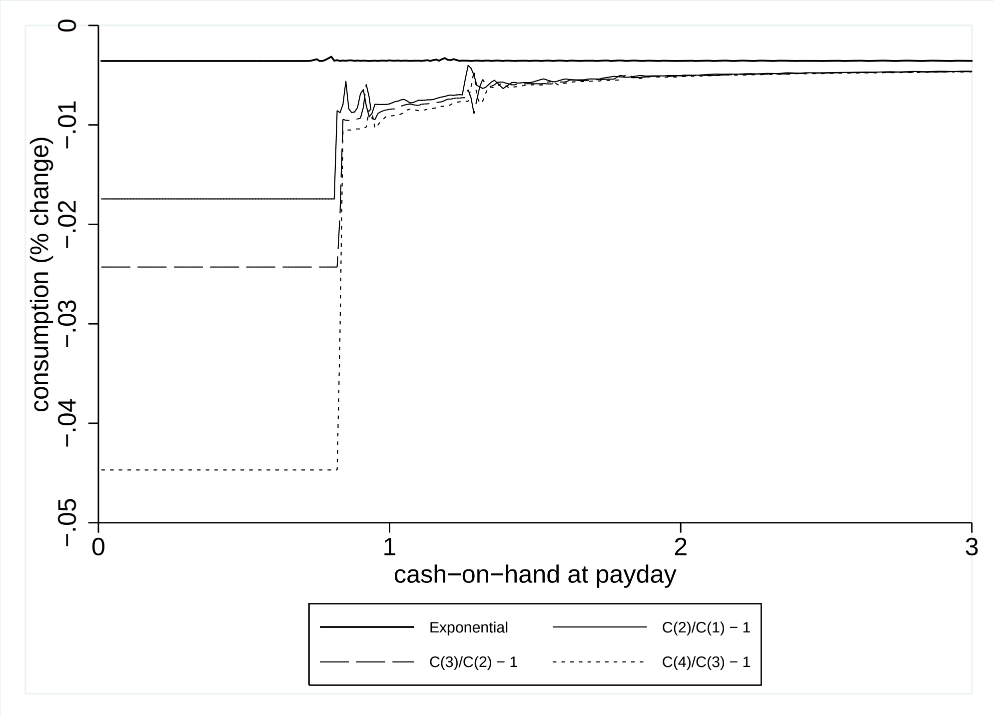
Notes: The converged (infinite-horizon) consumption functions are used. The first 200 weeks are trimmed. Parameters used: $r = 0.0011$, $Y \sim N(100, 30)$, $\rho = 5$, $\delta = 0.99$, $\beta = 0.9$

Figure 3.9: Simulation of income, saving, and consumption: focus on consumption around a series of low-income shocks



Notes: $r = 0.0011$, $Y \sim N(100, 30)$, $\rho = 5$, $\delta = 0.99$, $\beta = 0.9$

Figure 3.10: Rate of decline of consumption between weeks, as a function of cash-on-hand at the beginning of the month: exp. and q-h sophisticated



Notes: The converged (infinite-horizon) consumption functions are used. Parameter values: $r = 0.0011$, $Y \sim N(1, 0.3)$, $\rho = 5$, $\delta = 0.99$, $\beta = 0.9$

Chapter 4

When the baby cries at night.

Uninformed and hurried buyers in non-competitive markets[1]

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Francesco Manaresi, Viki Nellas

First draft: May 2011

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All authors are at the University of Bologna. Giacomo Calzolari is Fellow of CEPR, Andrea Ichino is Fellow of CEPR, IZA and CESifo

Abstract

We study both theoretically and empirically what happens when waves of less informed consumers enter a retail market. The theoretical model shows that firms may react by increasing price in order to extract surplus from less informed consumers. This effect, however, should decline as the degree of competition in the market increases. We gather data from a large sample of Italian pharmacies and identify the effect of an increase in newborns on the average price charged for a basket of child hygiene products at the municipal level, under the assumption that parents of newborns that just entered the market are less informed consumers. Consistently with the model, we find a positive effect of newborns on average price. We study the effect of competition on the elasticity of price to newborns by exploiting the Italian legislative framework, which defines a threshold based on resident population to define the number of pharmacies allowed to enter the market. Identification uses the fuzzy RD design set by the law. We find that an increase in competition has a significant and negative effect on the elasticity of price to changes in less informed consumers.

4.1 Introduction

Starting from the seminal work of Hal Varian [68], the role of consumers' information on market prices has been the object of a vast theoretical literature in industrial organization. On the empirical side, however, economists have only recently started to identify the effects of search costs and incomplete information in markets. The existing literature has focused on identifying evidence of mixed strategy in firm's pricing,[2] and on estimating the effect of competition on price dispersion.[3] Both results have been considered evidence of imperfect information among consumers.

In this paper, we provide a novel identification strategy, testing a new set of theoretical implications of models with imperfect consumers' information. We study what happens to the expected price and quantity when waves of uninformed buyers enter a market. In addition, we estimate how the effect of an increase in the share of uninformed buyers is affected by an exogenous increase in the degree of competition.

Our analysis rests on the assumption that immediately after child birth, parents suddenly enter as buyers in the market of the goods that are necessary to raise their baby, but are relatively less informed than other consumers of those products. They are also more likely to be under pressure (... when the kid cries!), since they are less able to evaluate the urgency of children's needs and claims.

We show theoretically that an increase in the number of less informed consumers should raise the average price in the market, and that this effect should be declining in the number of competitors. Both results can be obtained assuming either perfectly or imperfectly substitutability of the products of different shops in the market.

For each of the 8,092 Italian municipalities (henceforth, Cities), we have data on the number of newborn babies at the monthly frequency between 2006 and June 2010. We have also identified a set of hygiene products specifically designed for small babies and we are able to

[2]Lach [43], DeCicca et al. [20], Martin-Oliver et al. [50].

[3]Gerardi and Shapiro [27], Lewis [47], and Lach and Moraga-Gonzalez [44].

access monthly data on the quantities of these goods sold by a large number of pharmacies in these Cities, together with charged prices. Thanks to these unique sets of data, under relatively mild assumptions[4] we are able to estimate the elasticity of the equilibrium price and of the equilibrium quantity with respect to a shock in the monthly number of newborns. Consistently with the theoretical predictions, we find that a percentage increase in the number of newborns significantly raises the average price at the City level. There are other possible interpretations for this result (most notably increasing marginal costs) but none of these alternative interpretations is consistent with the other available pieces of evidence. We even find that sold quantities increase, which is the straightforward result of a demand shock.

The insights of the theoretical model invites us to search for exogenous sources of variation in the number of sellers. We find these sources by concentrating the analysis on cities whose maximum population during the last 45 years is in a neighborhood of the 7500 units threshold. Indeed, the Italian law prescribes that cities with a population lower than this threshold should have only one pharmacy, while an additional pharmacy should be opened in Cities above the threshold. With respect to current population, there is substantial non-compliance with this rule, partly because of geographic reasons[5], but more importantly because during the post-war period, when population grew above the threshold, pharmacies were opened but later they were not closed if population declined under the threshold. However, precisely for this reason, the maximum population size reached historically by cities generates a partially fuzzy assignment mechanism for the current number of pharmacies. We exploit this assignment mechanism within a Regression Discontinuity Design to study how the number of sellers influences the effect of an increase in the share of less informed consumers.

Using this identification strategy we show that Cities immediately above the thresholds (in terms of maximum historical population) have, on average, a larger number of pharmacies

[4]Controlling for City and time fixed effects, the variation in newborns at the monthly frequency is arguably random.

[5]The presence of remote areas or valleys within the City boundaries is the most commong motivation for being allowed to have more pharmacies than what the Law would prescribe.

than cities immediately below. As a consequence, where the number of competing pharmacies is larger for this exogenous reason, the elasticity of equilibrium prices to newborns is close to zero, while it is instead positive and significant when the number of pharmacies is lower. We interpret this finding as evidence that in less competitive environments sellers can exploit to their advantage increases of demand originating from less informed consumers, as the model predicts. The rest of the paper is organized as follows. Section 4.2 provides the theoretical background that drives our empirical exercise. Section 4.3 present the empirical strategy while section 4.4 introduces the data and provides descriptive statistics. The effect of newborns on equilibrium price and quantity is estimated in Section 4.5. In Section 4.6 we present the RD design, that we use in Section 4.7 to study the effect of increasing the number of competitors on the average price and quantity, and in Section 4.8 to estimate the effect of the number of competitors on the elasticity of price and quantity to a shock in newborns. Section 4.9 discusses alternative explanations and performs robustness checks. Section 4.10 concludes.

4.2 Less informed buyers and the number of sellers: the theoretical insight

In a market for a good there are S shops and two groups of consumers. A first group is composed of N_t^I "regular" consumers who are fully informed about prices available in period t. The individual demand of each one of these consumers for the good purchased at shop i is $q_i^I(p, S)$ where $p = (p_i, p_{-i})$, p_i is the prices of shop i and p_{-i} the vector of prices of all other shops.

There are also N_t^U consumers who just entered the market and may be also in a hurry when they decide to buy, so that they express a possibly different demand $q_i^U(\tilde{p}, \tilde{S})$ for the good at shop i, where $\tilde{p}$ and $\tilde{S}$ respectively indicate with compact notation the information consumers have about prices and shops. There are many explanations for why

q_i^U may differ from q_i^I. In our case, for instance, we consider child hygiene products. These type of goods are consumed both by newborns and by other non-child consumers[6]. While the latter use them continuously over time and thus have the opportunity to substantial learning, parents of newborns are normally very pressed and may be completely new to the market of childcare products (especially when they are having their first child). In this case we may expect that they are much less attentive and informed about prices in the market, which implies that the demand of uninformed and hurried parents of newborns q_i^U is less elastic with respect to price p_i than the demand q_i^I of the other informed consumers.

For brevity we will indicate the N_t^U consumers as the uninformed, although they may be simply less informed than the informed consumers.

At any period t, we assume that there is an inflow of uninformed which is IID over time and, for simplicity, we assume that they remain in the market only for 1 period. In general, although we do not explicitly model this possibility, N_t^I may also depend on uninformed inflows of periods preceding date t.After some periods of purchase some uninformed consumers may learn enough information and thus enter the group of N_t^I informed consumers. Although we do not allow for this possibility, we will test it with our empirical analysis. See below for a discussion.

We also assume that shops cannot discriminate the two groups of consumers and thus set a single price.

The profit of shop i can be written as

$$\pi_i = (p_i - c_i)\left[q_i^I(p,S)N_t^I + q_i^U(\tilde{p},\tilde{S})N_t^U\right], \tag{4.1}$$

where c_i is the constant marginal cost (see later for a discussion of non-constant marginal

[6] Ointments for child skin protection are largely used by sportsmen; shampoos, bath foams, and barrier creams for children are extensively used by adults aswell.

costs). For given price of competitors, the first order condition for own price is thus simply

$$\left[q_i^I + (p_i - c_i)\frac{\partial q_i^I}{\partial p_i}\right] N_t^I + \left[q_i^U + (p_i - c_i)\frac{\partial q_i^U}{\partial p_i}\right] N_t^U = 0 \tag{4.2}$$

We can then derive the following simple observation.

Remark 1. *If the individual demand of all types of consumers is the same, then for given number of shops, the equilibrium price of any shop is independent of the number of consumers.*

This is a simple consequence of the fact that when the demand of both types of consumers is the same $q_i(p, S)$, then the previous optimality condition becomes

$$\left[q_i + (p_i - c_i)\frac{\partial q_i}{\partial p_i}\right] (N_t^I + N_t^U) = 0 \tag{4.3}$$

and the total number of consumers $N_t^I + N_t^U$ cancels out.

This is not the case, instead, when demands are different. In particular, and as argued above, we may well expect that for given prices, uninformed consumers are less responsive to price changes than informed ones. To investigate this possibility we develop two approaches as for the degree of substitutability of the goods of the different shops for the informed consumers. These models lead to different conclusions in terms of pure and mixed strategies for equilibrium pricing and for some comparative statics which we will then investigate with our empirical analysis.

4.2.1 Perfect substitutable products.

Since Varian [68], it is well known that when uninformed consumers do not react to price changes and goods are perfect substitutes for the informed ones, then there are no equilibria in pure strategies. The reason is that shops face the trade-off to extract the maximal rent from uninformed consumers, thus increasing price (the rent extraction effect), but at the same time they would like to reduce their price in order to sell to all informed consumers (the business stealing effect).

Let uninformed consumers be price-insensitive, i.e. $\partial q_i^U \backslash \partial p_i = 0$, and each of them buys randomizing among the S shops. Furthermore, with perfect substitutability, we have that $q_i^I(p)$ is nil whenever $p_i > p_{-i}$. To simplify exposition we assume unitary demand for any type of consumer, with a value v for the good and common marginal cost c.

We can then consider symmetric equilibria in which the probability that each shop j sets a price lower than p is $G(p)$. The profit of shop i is then

$$\pi_i = (p_i - c)\left[(1 - G(p_i))^{S-1} N_t^I + \frac{N_t^U}{S}\right]. \tag{4.4}$$

The first term in the squared parenthesis is the demand of informed consumers and $(1 - G(p_i))^{S-1}$ is the probability that price p_i is actually the lowest price among all firms. The second term refers to the fraction of uninformed consumers who randomly enter shop i.

The symmetric equilibrium is (for details see Janssen and Moraga-Gonzalez [39], among others)

$$G(p) = 1 - \left[\frac{v - p}{S(p - c)} \frac{N_t^U}{N_t^I}\right]^{\frac{1}{S-1}} \quad \text{on} \quad [p_0, v] \tag{4.5}$$

where

$$p_0 = c + (v - c)\frac{N_t^U}{N_t^U + SN_t^I} \tag{4.6}$$

is the lowest price in the support of the mix strategy G.

The comparative statics of G with respect to S is ambiguous. In fact, a larger number of competitors does not induce a first order stochastic dominance change in G: a higher S strengthens the business stealing effect thus inducing a lower p_0, but at the same time it increases the rent extraction effect (shops respond with a higher price to a lower fraction of uniformed due to more shops sharing these consumers).

However, one can derive the following result.

Remark 2 (Janssen and Moraga-Gonzalez [39], Proposition 1). *The expected price*

$$E[p] = \int_{p_0}^{v} \frac{v}{S(S-1)(p-c)} \frac{N_t^U}{N_t^I} \left[\frac{v-p}{S(p-c)} \frac{N_t^U}{N_t^I} \right]^{\frac{2-S}{S-1}} dp \tag{4.7}$$

$$\left(\frac{N_t^U}{N_t^I} \right)^{\frac{1}{S-1}} \int_{p_0}^{v} \frac{v}{S(S-1)(p-c)} \left[\frac{v-p}{S(p-c)} \right]^{\frac{2-S}{S-1}} dp \tag{4.8}$$

is increasing in S and in N_t^U (and decreasing in N_t^I).

The quoted paper also shows that when also uninformed consumers optimally randomize between buying or not buying (which requires that the number of shops is sufficiently large), then taking this effect into account $E[p]$ does not vary with S.

4.2.2 Imperfect substitutes

Here we model imperfect substitute goods for informed consumers with a simple analysis based on a Salop model. The S shops are evenly distributed on a unitary circle so as consumers of both types. Thus, each consumer can be defined by her position $x_i \in [0,1]$ in the circle. Let τ be the consumer's transport cost.

Decision of informed is as follows. The consumer indifferent between shops i and $i+1$ is at

$$p_i + \tau(x_{i,i+1}^I - \frac{i}{S}) = p_{i+1} + \tau(\frac{i+1}{S} - x_{i,i+1}^I) \tag{4.9}$$

from which

$$x_{i,i+1}^I = \frac{p_{i+1} - p_i}{2\tau} + \frac{1+2i}{2S} \tag{4.10}$$

By analogy we can identify the consumer indifferent between shop i and shop $i-1$ at

$$x_{i,i-1}^I = \frac{p_i - p_{i-1}}{2\tau} + \frac{2i-1}{2S} \tag{4.11}$$

Setting $p_{i-1} = p_{i+1} = p$ as in a symmetric equilibrium, the demand of informed consumers is

$$N_t^I(x_{i,i+1}^I - x_{i,i-1}^I) = N_t^I(\frac{1}{S} + \frac{p - p_i}{\tau}) \tag{4.12}$$

Consider now uninformed. The consumer indifferent between shop i and $i+1$ is at

$$x_{i,i+1}^U = \frac{p_{i+1}^e - p_i^e}{2\tau} + \frac{1+2i}{2S} \tag{4.13}$$

where p_k^e is expectation of price k for uninformed consumers. The one indifferent between shop i and $i-1$ is at

$$x_{i,i-1}^U = \frac{p_i^e - p_{i-1}^e}{2\tau} + \frac{2i-1}{2S} \tag{4.14}$$

Hence the total demand for uninformed for shop i is

$$N_t^U(x_{i,i+1}^U - x_{i,i-1}^U) = N_t^U(\frac{1}{S} + \frac{p^e - p_i^e}{\tau}) \tag{4.15}$$

Notice that the demand of uninformed is based on their expectation on prices and is thus not responsive on actual price, although we will impose rational expectations so that in equilibrium p^e is equal to the (symmetric) equilibrium price.

The profit of firm i is then

$$\pi_i = (p_i - c_i)[N_t^I(\frac{1}{S} + \frac{p - p_i}{\tau}) + N_t^U(\frac{1}{S} + \frac{p^e - p_i^e}{\tau})]. \tag{4.16}$$

Solving for the optimal price and imposing symmetry

$$p^* = c + \frac{\tau}{S}\frac{N_t^I + N_t^U}{N_t^I} \tag{4.17}$$

which is decreasing in N_t^I and increasing in N_t^U. It is also decreasing in S.

Remark 3. *The equilibrium price with differentiated good is increasing in N_t^U and decreasing in S (and in N_t^I). The cross effect of S and N_t^U is negative: $\partial^2 p^*/\partial N_t^U \partial S < 0$*

4.3 Empirical strategy

To test the predictions of the theoretical model, we study how the equilibrium price and quantity are affected by a demand shock deriving from a change in the number of less informed consumers in the market. We argue that a measure of this kind of shock is represented by changes at the monthly frequency in the number of newborns in the City where the pharmacy is located. The choice of this measure needs to be justified on two grounds.

First, it must be true that the parents of newborns are less informed. As it will be apparent in the next section, we are going to focus on a subgroup of products that must be bought *after* birth and that are used extensively during the first years of life of the child. Thus, the need for this products emerge only after the birth of the baby. In addition, gathering information on prices of these products is likely to be costly, because it is mostly obtained by performing trips to pharmacies.[7] All in all, it is plausible to assume that parents of newborns do not have perfect information on the distribution of prices among pharmacies. Noteworthy, some child hygiene products, like after diaper change ointments, are largely consumed by runners and bikers to prevent skin rash. This suggests that in this market there is also a stock of other consumers that are, to the contrary of newborns' parents, informed. The stock of informed buyers is a specific characteristic of each municipality. Our identification strategy relies on the fact that there is not a substantial correlation between changes in uninformed consumers and changes in informed ones (conditioning on a set of municipality and time fixed effects). In Section 4.9 we present substantial evidence in favor of this hypothesis.

Second, a change in the number of newborns should be a random event, i.e. it should not be correlated with any non-ignorable characteristic. Since in our analysis we will always control for city and time fixed effects, we will be using as a shock the time variation in the number of newborns from month to month, net of any possible seasonality or aggregate-trend effects. Given the randomness in the actual dates of delivery of newborns, we feel confident that this

[7] In principle, consumers may even use the internet to learn the expected price. However, even the acquisition of information from the internet is far from being costless.

identifying assumption is satisfied.

In order to estimate the effect of an increase in the number of competitors S, we need to identify an exogenous source of variation in the number of pharmacies in the market. Here, the legislative features of the Italian pharmacy market come at hand. In Italy, entry and exit in the pharmacy market are regulated by the Law 475/1968. The Law establishes the so-called 'demographic criterion' for defining the number of pharmacies in each City: for Cities under 12,500 inhabitants, there must be one pharmacy every 5,000 inhabitants; for Cities above 12,500 inhabitants, there must be one pharmacy every 4,000 inhabitants. The thresholds for allowing an additional pharmacy to enter are placed in the middle of any multiple of 4,000 or 5,000 inhabitants. Thus, Cities right below 7,500 inhabitants should have one pharmacy, while those right above it should have two. Further discussions on the fuzzy regression discontinuity design provided by this legislative framework are left to Section 4.6. Given these identification strategies, the following empirical model can be considered.

For each City $c \in \{1, \ldots, C\}$ at month $t \in \{1, \ldots, T\}$, we observe the average quantity sold q_{ct} and price charged p_{ct} by the S_c pharmacies present. In addition, in each month we observe newborns at the city level N_{ct}. Given the previous theoretical analysis, we consider the following linear model for each of the dependent variables $Y_{ct} = \{q_{ct}, p_{ct}\}$:

$$Y_{ct} = \alpha + \beta S_c + \delta N_{ct} + \lambda S_c \times N_{ct} + \phi_c + \mu_t + \varepsilon_{ct} \tag{4.18}$$

where ϕ_c and μ_t are, respectively, City and time fixed-effects, and ε_{ct} is an error term, which we allow to display both heteroskedasticity and serial correlation at the City level. We are going to exploit this framework with three empirical exercises.

Model A

We exploit within City variation in newborns in a standard fixed-effect model, and estimate the following:

$$Y_{ct} = a + dN_{ct} + h_c + g_t + u_{ct} \tag{4.19}$$

the resulting coefficient d is the effect of N_{ct} averaged over different levels of competition S_c. That is, $d = \delta + \lambda E(S_c)$. Note that N_{ct} is uncorrelated with the idiosyncratic error term u_{ct}. If parents of newborns are indeed less informed consumers, we shall expect a positive d for price. If instead, they are as informed as other consumers, the effect on price should be weakly negative.[8] In both cases, the increase in demand should raise sold quantities.

Model B

Each variable X_{ct} in model (4.18) is integrated over time, to obtain $\bar{X}_c = E(X_{ct}|c)$. Thus, from the original model, we obtain the following:

$$\bar{Y}_c = a + b\bar{S}_c + l\bar{S}_c \times \bar{N}_c + e_c \tag{4.20}$$

Notice that $\bar{S}_c = S_c$, since the number of pharmacies in a municipality remain constant over time.[9]

OLS estimates of b and l are likely to be biased due to several possible unobserved factors that affect the number of competitors, the average number of newborns, and the expected value of the outcome variables.[10]

In order to overcome this problem, we exploit the afore-mentioned 7,500 threshold to study the effect of moving from one to two pharmacies in the City. Let Pop_c denote the reference population in City c, and κ be the threshold value.[11]

[8] This holds if we assume constant or declining marginal costs for the pharmacy, as in the model. Given the features of the pharmacy market, we are quite confident in ruling out that pharmacists face increasing marginal costs for the products used in this study. Further discussion on this point is left to Section 4.9.

[9] In our sample, this holds for more than 90% of municipalities.

[10] For instance, Cities where there is a larger willingness-to-pay are likely to display higher number of competitors, higher quantities, and higher prices. If willingness-to-pay is correlated with wealth, age, or other socioeconomic variables, then endogeneity of newborns is plausible aswell.

[11] In general, the assignment variable Pop_c should be measured *before* the treatment period (i.e. 2007-2010). Discussion on the choice of Pop_c is left to Section 4.6.

The RD design has two important implications. First, it is necessary to include a polynomial in the assignment variable (i.e., resident population) stratified according to the side of the threshold (Imbens and Lemieux [37]). Second, in this model is no longer possible to estimate the effect of $\bar{S}_c \times \bar{N}_c$. This is because the RD design is such that the assignment to treatment $\bar{S}_c$ should be unconfounded with respect to newborns around the threshold, and thus the interaction term should be perfectly collinear with the treatment variable.[12]

The RD regression function is then:

$$Y_c = a + bS_c + f(|Pop_c - \kappa|) + e_c \tag{4.21}$$

Where $f(\cdot)$ is a polynomial function. Given unconfoundedness around the threshold, we have $b = \beta$.

In general, we may expect average sold quantity to decline as the number of competitors increase. For what regards the price, however, the model does not yield a clear prediction on the sign of b: with perfectly substitutable goods, it should be positive. If, instead, the goods are not perfect substitutes, it should be negative.

Model C

In our final and more ambitious exercise, we estimate the interaction effect of competition and inflows of less informed consumers, exploiting both the City level variability in N_{ct} and the RD design for instrumenting S_c.

For this, we use an algorithm made of three steps:

i. we regress prices, quantities, and newborns on City and time fixed effects to obtain the demeaned values, i.e. we consider the following model for dependent variables $H_{ct} = \{N_{ct}, q_{ct}, p_{ct}\}$:

$$H_{ct} = \phi_c + \mu_t + \eta_{ct} \tag{4.22}$$

[12] Formally, $\lim_{Pop \to \kappa^-} E(\bar{N}_c) = \lim_{Pop \to \kappa^+} E(\bar{N}_c)$. This hypothesis is statistically tested and confirmed in Section 4.6.

demeaned values of each variables are simply the error term: $\tilde{H}_{ct} = \eta^{H}_{ct}$.

ii. for each City separately, we regress demeaned prices and quantities on demeaned newborns. That is, we run a total of C regressions:

$$\tilde{Y}_{ct} = a_c + d_c \tilde{N}_{ct} + u_{ct} \tag{4.23}$$

each regression yields $d_c = \delta + \lambda_c S + \gamma Q_c$, where Q_c is some unobserved city characteristic affecting the elasticity of outcome variables to newborns. This missing variable prevents us from naively comparing Cities with different number of pharmacies.

iii. we can overcome the problem posed by Q_c by exploiting the RD design. Indeed, given the unconfoundnedness assumption, around the threshold κ we have $\lim_{Pop\to\kappa^-} E(\bar{Q}_c) = \lim_{Pop\to\kappa^+} E(\bar{Q}_c)$.

We then estimate the final model:

$$\hat{d}^{Y}_{c} = a + lS_c + f(|Pop_c - \kappa|) + v_c \tag{4.24}$$

where $\hat{d}^{Y}_{c}$ is the estimated value of d obtained from regressing price and quantity as in model (4.23).

The coefficient l in model (4.24) is a consistent estimate of λ.

According to the theoretical model, we may expect a negative value for this interaction term with respect to the average price: an increase in the number of competitors should reduce the ability of pharmacies to extract surplus from lack of information by consumers.

In the next Section, we discuss the data we use to perform these three exercises and provide some descriptive statistics of them.

4.4 Data and descriptive statistics

To test the predictions of the previous models, we use information from a large sample of Italian pharmacies, collected by the consulting firm Newline. Newline is an IT company that in the period considered (from January 2007 to July 2010: 2007-2010, henceforth) has produced software for pharmacies. With the consent of its clients we were given access to the details of every item sold by each pharmacy in the Newline data base. During the period of interest, Newline collected data from 3,331 Italian pharmacies (i.e., around 18.6% of the reference universe). For 60% of them, we have complete information for all years; for 28.7% of the sample we have information starting from January 2009; and for the remaining 11.26% of the sample data is available only for the period January 2007-December 2008. Sampled pharmacies belong to almost all the Italian regions (with the exception of Basilicata). However, they are typically concentrated in the North, since the company is located near Milan.[13]

Among the products sold by pharmacies, we selected a category that is potentially of specific interest for parents of newborn babies: child hygiene products.[14] The category includes the following types of products: bath foams and shampoos for babies; cleansers for babies; cold and barrier creams and oils for babies; baby wipes; talcum and other after-bath products for babies. Table 4.11 describes a sample of items in this basket: the upper panel shows the five products sold in largest quantity during the period 2007-2010, while the lower panel shows products which reported the highest unit price over the same period.

For each item, we obtained from Newline the quantity sold by each pharmacy in each month and the price charged.[15]

[13]There are 19% of the Newline pharmacies in the norht east of Italy, 45% in the north west, 9% in the center, 16% in the south and 11% in the islands.

[14]We considered even other categories: notably, powder milk and diapers. Powder milk does not have enough variability in prices. For diapers, results are qualitatively similar to those obtained with hygiene products.

[15]For items which have not been sold for an entire month, the price imputed is simply the price announced by the pharmacy. For items which have a positive sold quantity, the monthly price imputed by Newline is the weighted average between the (possibly) different prices charged over the month, with weights equal to the number of items sold at each price level.

To create an aggregated product, we construct Laspeyres indexes for the price and the quantity of the basket of hygiene goods (hereafter, the price and the quantity). Let $h \in 1, \ldots, H$ indicate each product of the basket, then price and quantity indexes for pharmacy i in month t are defined by:

$$p_{it} = \frac{\sum_h p_{iht}\bar{q}_h}{\sum_h \bar{p}_h \bar{q}_h} \tag{4.25}$$

$$q_{it} = \frac{\sum_h \bar{p}_h q_{iht}}{\sum_h \bar{p}_h \bar{q}_h} \tag{4.26}$$

where $\bar{q}_h$ and $\bar{p}_h$ are, respectively, the average monthly sold quantity and the average price charged for product h in all months by all pharmacies.

Trends of these two indexes are plotted in the left panels of Figure 4.1. As it can be seen, sold quantities are characterized by seasonality (with the most relevant peaks during summer) and a somehow downward trend. Conversely, prices are characterized by a more robust upward trend, topping 1.02 in February 2010. In our empirical strategy, we are going to exploit within pharmacy variance in both variables. The right panels shows that both quantity and price change subtantially at the intra-pharmacy level. The two figures plot the residuals of a regression of (log) quantity and (log) price on pharmacy and time fixed effects. Although the variance of quantities is bigger, there is substantial variability even in prices.

Data on monthly newborns are obtained at the City level from the National Statistical Office. They are plotted in the left panel of Figure 4.2. As it can be seen there is a significant seasonality in newborns: the most important peaks are during summer, while lowest levels are reached during spring. Finally, the residuals of a regression of (log) newborns on pharmacy and time fixed effects are plotted in the right panel of the figure: the presence of within-pharmacy/within-month variance in newborns can be appreciated.

Ideally we would like to measure monthly newborns in some neighborhood of the pharmacy, but we can only measure it at the level of a city. Therefore in the empirical analysis we aggregate the Newline pharmacies in each City and consider as a unit of observation the average price index and the average quantity index of all the newline pharmacies in each

City. Descriptive statistics for these and the other variables used in the econometric analyses are described in Table 4.2.

Obviously, we do not observe the quantity and the price of the non-sampled pharmacies within each city and in nearby cities. These are potential confounding factor and we will discuss the extent to which they may affect our results in the robustness section of the paper. We will also produce results restricted to the cities in which we observe all the pharmacies, to show that our conclusions hold also in that case.

4.5 Model A: the effect of newborns on equilibrium quantities and prices

We start by estimating model A using the fixed-effects within-estimator. Table 4.4 shows the results using different temporal aggregates for the (log) newborns. In Panel A we regress quantity and price measured at time t on newborns measured at time t. We find a positive and highly significant effect on both dependent variables. In particular, a 10% increase in the number of newborns causes a 0.2% increase in the quantity index and a 0.005% increase in the price charged. Alternatively, simple calculation shows that an increase of 1 standard deviation in log-newborns increases log-price by 0.2 standard deviations. Measuring newborns within a larger window marginally reinforces our findings: in Panel B we consider births at time t and $t-1$, in Panel C we consider newborns in the last quarter.

The positive effect on sold quantities can be considered the simple effect of an increase in the number of consumers. The positive effect on price, however, contradicts the result that could be obtained with a standard model that assumes perfect information from consumers. Instead, it is consistent with our proposed model in which an increase in the number of uninformed consumers increase the 'rent extraction effect' and thus generates a raise in the equilibrium price.

The theoretical model suggests, in addition, that the number of competitors may affect the strength of the ‘rent extraction effect’. As a first assessment, we stratify model A by number of pharmacies in the City. Notably, we distinguish Cities where there is a single pharmacy with Cities where there are more than one pharmacy. Results, summarized in Table 4.5, show that the positive effect is solely reported among municipalities where there is a single pharmacy.

This stratification, however, cannot be used to infer any causal relationship between the number of competitors and the elasticity of price to newborns. Indeed, the number of pharmacies in a City is clearly endogenous, being likely to be correlated with several relevant confounding factors. It is, thus, necessary to identify a source of exogenous variation in this variable.

4.6 The Regression Discontinuity design

As previously discussed, entry and exit in the pharmacy market is regulated by a law (L.475/1968) enforced in 1968. The ‘demographic criterion’ in it establishes a set of thresholds for each City according to the number of residents. An additional pharmacy should be opened at 7,500, 12,500, 14,000, and from there on every 4,000 additional inhabitants. Unfortunately, our sample size allows us to focus solely on the first threshold (i.e., from one to two pharmacies). Thus, we focus on Cities in a neighborhood of 7,500 inhabitants and study whether there is a significant change in the number of pharmacies at the threshold.

The left panel of Figure 4.3 shows the local polynomial smoothing estimates of the number of pharmacies, together with the 95% confidence intervals. As it can be seen, we fail to identify a significant difference at the threshold. Our conjecture is that this may be due to the fact that the Law does not specifiy the criterion for choosing the pharmacies that should be closed if the population declines below 7,500. This, coupled with the likely resistance by incumbents to be forced to exit from the market, would imply that there is a substantial downward rigidity in compliance to the law. If, however, compliance is larger upwardly than downwardly, we are likely to have a stronger result by using the maximum population reached in the last decades to predict the actual number of pharmacies. The result of this exercise, plotted in the right panel of Figure 4.3, shows that the number of pharmacies display a positive and significant change at the threshold. Still, there is a significant non-compliance with respect to the 'demographic criterion', as the average number of pharmacies right before the threshold is significantly higher than 1.

Table 4.3 confronts the expected values of several possible confounding factors right before and after the threshold, and tests the null of equality between the means. There is no evidence of significant differences at the threshold for any of the control variables.[16] Nonetheless, in some empirical specifications we include these regressors to control for any possible effect driven by marginal differences in covariates.

4.7 Model B: estimating the effect of competition on the average price and quantity sold

We start exploiting the RD design integrating observations over time and obtaining City-level averages in variables, to study the effect of competition on the average price and quantity. Figure 4.4 plots the local polynomial estimates of log(quantity) against the population (measured at its maximum in the period 1961-2006). The polynomial has been estimated separately below and above the 7,500 inhabitants threshold. There are strong evidence that sold quantity is continuous at the threshold. A similar finding is obtained by looking at the average (log) price (Figure 4.5: the confidence intervals plotted show that there is no signficant jump in the variable around the threshold.)

We turn to regression analysis, and here we focus on the intention-to-treat effect.[17] Table 4.6 reports results using different windows around the threshold and different polynomial functions in the population. The first Panel shows results using a local linear regression in

[16] We even test for continuity of the density of control variables at the threshold with a local linear regression, as suggested by Imbens and Lemieux [37]: we fail to reject the null of continuity for all covariates. Results are available upon request.

[17] Results of the IV estimate are both qualitatively and quantitatively very similar.

a narrow window of ± 1,500 inhabitants around the 7,500 threshold. Subsequent panels use higher-order polynomials with larger windows. As previously noticed, the threshold has a positive effect on the number of pharmacies in the City, which raises significantly by around 0.5. The effect on the average price and quantity is, however, never statistically different from zero. This zero effect is robust to the inclusion of the afore-mentioned set of covariates.

4.8 Model C: can competition between sellers offset the effect of less informed buyers?

In our last empirical exercise, we study how the elasticity of price and quantity to an increase in newborns changes around the 7,500 inhabitants threshold. For this, we follow the empirical strategy explained in Section 4.3.

Figures 4.6 and 4.7 plot the local polynomial estimate of the elasticity of, respectively, the average quantity sold and price charged. The former displays an increase right after the threshold, though its statistical significance is poor, the latter displays a decrease after 7,500 inhabitants. In particular, consistently with the results of the naive stratification of model A, the elasticity is slightly positive and significant when the law imposes a single pharmacy in the City, and declines to zero when the law allows for an additional competitor.

Turning to regression results, Table 4.7 reports results for quantity and prices considering different time spans to measure newborns (as with model A) and different windows around the threshold and polynomials in population (as with model B). Again, here we focus on the ITT effect, leaving IV results to Section 4.9. We fail to identify a significant positive effect of the threshold on elasticity of sold quantities: although the point estimate is always positive, it is never statistically different from zero. For what regards price, instead, being right above the threshold induces a significant decline in its elasticity to an increase of newborns.

This finding is consistent with the theoretical model that predicts that an increase in the number of competitors reduces the positive effect of uninformed buyers on the average price.

4.9 Discussion of alternative interpretations and robustness checks

We now discuss and check the robustness of our results against several possible alternative explanations.

First, both the theoretical model and our empirical strategy crucially relies on the assumption of non-increasing marginal costs for the pharmacy. Although we cannot directly observe the price paid by pharmacists to wholesalers, we are confident that this assumption holds. Indeed, it is well-known that pharmacies do not experience shortages of products, as suppliers perform deliveries more than once per day, and that wholesalers usually use pricing schemes that are either constant or declining. Secondly, and perhaps more importantly, increasing marginal costs may represent a relevant confounding factor for model A, but does not explain why the elasticity of price to newborns changes discontinuously at the 7,500 threshold.

Results of model A may be biased if log-newborns displays autocorrelation, even after partialling out both City and aggregate time trends.[18] To rule out this hypothesis, we included lags of newborns in the specification. The results, summarized in Table 4.8, give us two important messages. First, even if we add lagged values, the coefficient on log-newborns at time t remains positive and significant and the point estimate is virtually unchanged (i.e., we are reassured that the possible positive autocorrelation does not explain the result obtained). Second, newborns have a positive and significant effect up to 10 months before the present. This implies that parents of newborns have a relatively slow learning curve, so that the 'rent extraction effect' persists over time.

In model A, we studied the effect of changes in newborns with respect to the City average. This empirical strategy sums up to assuming that there is no correlation between changes in uninformed consumers and changes in informed consumers at time t. We consider a stock

[18]Notice, however, that the direction of the bias would depend on whether the autocorrelation is positive or negative and whether the effect of lagged values of newborns on price is positive or negative.

of informed consumers, whose stability over time is supported by the evidence of Table 4.8. Given the time parents need to acquire information we can claim that when they become informed they exit to this market (children no more need this kind of products).

Despite that the difficulty to clearly identify the group of informed consumers remains. In Table 4.9, we study the effect of a change in the share between newborns and the overall population, under the assumption that total population is a good proxy for the set of informed consumers. Results are robust to this new specification of the independent variable of interest.

In Section 4.8 we have shown ITT results for the effect of an increase in competitors on the elasticity of quantity and price to newborns. Given that there is substantial non-compliance to the assignment rule, and in particular that municipalities are likely to have more than 1 pharmacy right below the threshold, we may expect the coefficients obtained to be a very conservative measure of the Local Average Treatment Effect (LATE). In Table 4.10, we exploited the fuzzy nature of the RD design and instrument the number of pharmacies with the threshold. As expected, the point estimates of the effect are nearly doubled (particularly for prices). The IV estimate, however, coupled with the small sample size reduces the significance, which is reached solely at the 10% level.

So far, we have estimated the average price charged and sold quantity at the City level using pharmacies sampled by Newline. The Newline sample, however, is far from being randomly chosen among the reference universe. Comparisons of socio-demographic characteristics measured between Newline and non-Newline pharmacies shows that the latter are usually placed in richer and more populated municipalities. Although we do not claim that our result is nationally representative, sample selection may represent a relevant bias for the RD results. Indeed, this may be the case if the Newline systematically selects its sample within municipalities: in this case, as the number of pharmacies within a municipality increase the bias between the expected value measured within Newline sample and the real mean value at the municipal level would increase.[19] To check the robustness of our finding to the sample selection, we focus on the subsample of Cities for which Newline has sampled 100% of pharmacies. Tables 4.11 and 4.12 estimate model A and C in this subsample. Results are very similar to those obtained with the total sample.

Results obtained from model A may be simply spurious correlations if the time-series of both log-price (or quantity) and log-newborns display serial correlation in the demeaned values. We performed several tests for identifying both serial correlation and unit-root in these series, and the results are reassuring. In particular, a Harris-Tzavalis test rejects the null of unit-root for all three variables. Similar results are obtained with the Levin-Lin-Chu test and the Im-Pesaran-Shin test. Wooldridge test fail to reject the null of no-serial correlation for the residuals of a regression of log-newborns on time and City fixed effects. Conversely, log-price and log-quantity do display serial correlation in the residuals, but we take care of it by using cluster-robust standard errors in all models.

Finally, so far we did not consider the role of other types of stores in which some of the products included in the basket can be purchased. Although it is not possible to control for the number of other shops in the municipality, because this variable is endogenous due to free entry and exit from the market, we can nonetheless test whether there are differences in the number of grocery stores at the threshold. At present, we have only information on mass retail channels, and for the convenience stores that are allowed to sell over-the-counter drugs (so-called 'parafarmacie'). Notice, however, that child hygiene products may be sold even by smaller groceries for which we do not have any information, so far. Figure 4.8 shows the local polynomial smoothed estimate of the number of mass retail stores (upper panel) and 'parafarmacie' (lower panel) in 2010. As it can be seen, there are no significant differences at the threshold.

[19]For example, assume that in each municipality Newline samples the top 10% pharmacies on the basis of the distribution of monthly sold volumes (price-per-quantity). Obviously, when there is one pharmacy in the City both the expected price and quantity is measured consistently. As the number of pharmacies in the City increases, however, the bias will increase according to the City-level distribution of sold volumes.

4.10 Conclusions

In this paper we have provided new evidence on the role of consumers' information in the retail sector, and its interplay with competition among sellers. Theory predicts that an inflow of uninformed consumers should have a positive effect on the average price charged by sellers. This effect, known in the literature as the 'rent extraction effect', is counterbalanced by the 'business stealing effect' (i.e., the incentive to reduce price in order to gain a bigger market share). The relative strength of the former should decline as the number of competitors increases.

We gather data for a large sample of Italian pharmacies, and estimate the effect of a positive shock in the number of newborns on the average price at the City level, for a basket of child hygiene products. Consistently with the model, an increase in newborns has a positive effect on price.

To study the effect of competition on the elasticity of price to newborns, we exploit a legislative feature of the Italian pharmacy market: the law imposes that Cities under 7,500 inhabitants should have a single pharmacy, while Cities right above this threshold should have two pharmacies. We exploit the fuzzy regression discontinuity design provided by this law and estimate how the effect of newborns on price changes around the threshold. As the model predicted, we find that the elasticity is positive when the average number of competitors is lower, and becomes zero at the right of the 7,500 threshold.

4.11 Tables and Figures

Table 4.1: Top products in the basket - by average monthly sold quantity and by average price

Name	Description	Price	Quantity
Top-5 by Sold Quantity			
Salviette Assorbello	Hygienic Towels	2.04	39.94
GP Baby Pasta all'Ossido di Zinco	Zinc-Oxyde Paste	4.91	23.3
Bluedermin Pasta BB 100ml	Diaper Change Ointment	5.83	17.21
Trudi Baby Care Salviettine	Hygienic Towels	2.07	16.53
GP Baby Detergente	Cleansing Cream	5.02	15.3
Top-5 by Price			
Soin de Fee 24-Hour Baby Cream 50ml	Barrier Cream	45	0.21
Vidermina 3 Soluzione 1000ml	Cleansing Cream	40.32	0.01
Buba Shampoo e Bagno	Shampoo and Bath Foam	37.61	0.04
Unilen Gel 15ml	Barrier Cream	36.06	0.11
Protezione Solare Bambini Vichy	Suntan Cream	30.9	0.02

Table 4.2: Descriptive statistics - 2007-2010.

	Mean	Standard deviation	Minimum	Maximum
Price Index	1	0.03	0.8	1.25
Quantity Index	0.8	0.48	0.004	7.3
Sold Quantity	68	55	0	808
Newborns	9	0.09	0	819
No. of Pharmacies	6	27.6	1	719
No. of Obs.	51326			

Table 4.3: Mean of control variables, by treatment group

	Population $\in$ [7000, 7500[	Population $\in$ [7500,8000[	p-value
Log-Newborns	1.80	1.81	0.88
	(0.31)	(0.21)	
Municipal Area	32.57	46.10	0.27
	(47.84)	(46.17)	
Northern Italy	0.63	0.77	0.21
	(0.49)	(0.43)	
Pop. Growth	-0.006	-0.009	0.87
(from peak to 2007)	(.08)	(.04)	
No. of Obs.	48	22	

Notes: standard errors in parentheses; the p-value is obtained from a two-tiers test on equality of means (assuming unequal variances).

Table 4.4: Fixed-effects estimates of Model A

	Log Quantity Index	Log Price Index
Panel A: newborns measured at time t		
Log Newborns	0.0177	0.0005
	(0.0029)***	(0.0001)***
Constant	-0.3473	-0.0185
	(0.0207)***	(0.0010)***
Time effects	Yes	Yes
No.Obs.	57289	57289
No.Munic	1671	1671
Panel B: newborns measured at time t and $t-1$		
Log Newborns	0.0297	0.0009
	(0.0048)***	(0.0003)***
Constant	-0.3260	-0.0165
	(0.0148)***	(0.0009)***
Time effects	Yes	Yes
No.Obs.	56821	56821
No.Munic	1671	1671
Panel C: newborns at time t, $t-1$ and $t-2$		
Log Newborns	0.0364	0.0012
	(0.0066)***	(0.0004)***
Constant	-0.4199	0.0069
	(0.0211)***	(0.0013)***
Time effects	Yes	Yes
No.Obs.	56353	56353
No.Munic	1671	1671

Notes: Heteroskedasticity robust standard error (clustered at municipality level) in parentheses.

Table 4.5: Fixed-effects estimates of Model A - Cities with one pharmacy VS Cities with more than one pharmacy.

	1 pharmacy		> 1 pharmacies	
	Log Quantity Index	Log Price Index	Log Quantity Index	Log Price Index
Panel A: newborns measured at time t				
Log newborn	0.0186	0.0006	0.0168	0.0001
	(0.0037)***	(0.0002)***	(0.0043)***	(0.0002)
Constant	-0.3376	0.0029	-0.1701	-0.0147
	(0.0262)***	(0.0011)***	(0.0331)***	(0.0020)***
Time effect	Yes	Yes	Yes	Yes
No.Obs.	22798	22798	34491	34491
No.Munic	723	723	978	978
Panel B: newborns measured at time t and $t-1$				
Log newborn	0.0300	0.0011	0.0311	-0.0001
	(0.0060)***	(0.0003)***	(0.0078)***	(0.0005)
Constant	-0.4843	-0.0027	-0.1512	-0.0127
	(0.0188)***	(0.0009)***	(0.0275)***	(0.0019)***
Time effect	Yes	Yes	Yes	Yes
No.Obs.	22567	22567	34254	34254
No.Munic	723	723	978	978
Panel C: newborns at time t, $t-1$ and $t-2$				
Log newborn	0.0385	0.0016	0.0351	-0.0004
	(0.0080)***	(0.0005)***	(0.0110)***	(0.0008)
Constant	-0.5824	0.0110	-0.3103	0.0092
	(0.0212)***	(0.0011)***	(0.0421)***	(0.0029)***
Time effect	Yes	Yes	Yes	Yes
No.Obs.	22336	22336	34017	34017
No.Munic	723	723	978	978

Notes: Heteroskedasticity robust standard error (clustered at municipality level) in parentheses.

Table 4.6: Regression discontinuity results of Model B

	No. of Pharmacies	Log-Quant. Index	Log-Quant. Index	Log-Price Index	Log-Price Index
Panel A: Local linear estimate - ± 1,500 inhabs.					
Thresh. Dummy	0.520	-0.125	-0.058	0.005	-0.001
	(0.168)***	(0.114)	(0.106)	(0.009)	(0.009)
Constant	0.708	-0.146	-0.600	0.002	-0.004
	(0.123)***	(0.076)*	(0.259)**	(0.005)	(0.017)
Controls	N	N	Y	N	Y
No. of Obs.	235	235	235	235	235
Panel B: Spline 2^{nd} - ± 2,000 inhabs.					
Thresh. Dummy	0.441	-0.038	0.019	0.008	0.000
	(0.223)**	(0.146)	(0.138)	(0.010)	(0.010)
Constant	0.754	-0.155	-0.604	0.001	-0.004
	(0.165)***	(0.101)	(0.215)***	(0.006)	(0.015)
Controls	N	N	Y	N	Y
No. of Obs.	296	296	296	296	296
Panel C: Spline 3^{rd} - ± 3,000 inhabs.					
Thresh. Dummy	0.557	-0.032	0.010	0.005	-0.001
	(0.246)**	(0.157)	(0.150)	(0.010)	(0.010)
Constant	0.727	-0.179	-0.607	0.001	-0.001
	(0.178)***	(0.107)*	(0.173)***	(0.006)	(0.010)
Controls	N	N	Y	N	Y
No. of Obs.	462	462	462	462	462
Panel D: Spline 4^{th} - ± 4,000 inhabs.					
Thresh. Dummy	0.568	0.012	0.039	0.004	-0.003
	(0.270)**	(0.170)	(0.164)	(0.011)	(0.010)
Constant	0.738	-0.179	-0.462	0.000	-0.009
	(0.192)***	(0.113)	(0.147)***	(0.007)	(0.010)
Controls	N	N	Y	N	Y
No. of Obs.	631	631	631	631	631

Notes: heteroskedasticity robust standard errors in parentheses. Controls include log-newborns, municipal area, northern Italy dummy, and population growth rate between the population peak and year 2007.

Table 4.7: Regression discontinuity results of Model C

	Elasticity to NBorns at time t		Elasticity to NBorns at time t, $t-1$		Elasticity to NBorns at time t, $t-1$, $t-2$	
	Log-Quant Index	Log-Price Index	Log-Quant Index	Log-Price Index	Log-Quant Index	Log-Price Index
Panel A: Local linear estimate - ± 1,500 inhabs.						
Thresh. Dummy	0.032	-0.005	0.037	-0.004	0.037	-0.004
	(0.036)	(0.002)**	(0.028)	(0.002)**	(0.028)	(0.002)**
Constant	-0.003	0.002	0.008	0.001	0.008	0.002
	(0.021)	(0.001)*	(0.019)	(0.001)	(0.019)	(0.001)
No. of Obs.	227	227	227	227	227	227
Panel B: Spline 2^{nd} - ± 2,000 inhabs.						
Thresh. Dummy	0.006	-0.006	0.039	-0.006	0.039	-0.006
	(0.047)	(0.003)**	(0.040)	(0.002)**	(0.040)	(0.003)**
Constant	-0.001	0.003	0.018	0.001	0.018	0.002
	(0.024)	(0.002)*	(0.025)	(0.001)	(0.025)	(0.001)*
No. of Obs.	288	288	288	288	288	288
Panel C: Spline 3^{rd} - ± 3,000 inhabs.						
Thresh. Dummy	0.017	-0.007	0.057	-0.006	0.057	-0.006
	(0.049)	(0.003)***	(0.040)	(0.002)**	(0.040)	(0.003)**
Constant	-0.003	0.003	0.012	0.002	0.012	0.003
	(0.024)	(0.002)*	(0.026)	(0.001)	(0.026)	(0.001)*
No. of Obs.	454	454	454	454	454	454
Panel D: Spline 4^{th} - ± 4,000 inhabs.						
Thresh. Dummy	0.017	-0.007	0.066	-0.006	0.066	-0.006
	(0.053)	(0.003)**	(0.044)	(0.003)**	(0.044)	(0.003)**
Constant	-0.006	0.003	0.015	0.002	0.015	0.003
	(0.025)	(0.002)*	(0.028)	(0.001)	(0.028)	(0.001)*
No. of Obs.	621	621	621	621	621	621

Notes: heteroskedasticity robust standard errors in parentheses. The municipality-specific elasticities are obtained by (i) regressing the dependent variables on municipality and time fixed effects, and (ii) regressing the residuals obtained on log-newborns for each municipality.

Table 4.8: Effects of changes in log-new born on log price

	Log priceindex	Log priceindex	Log priceindex	Log priceindex
Log Newborn	0.0006	0.0006	0.0005	0.0004
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)**
Log Newborn(t-1)	0.0005	0.0005	0.0005	0.0003
	(0.0002)***	(0.0002)***	(0.0002)**	(0.0002)*
Log Newborn(t-2)	0.0003	0.0003	0.0003	0.0002
	(0.0002)*	(0.0002)*	(0.0002)*	(0.0002)
Log Newborn(t-3)	0.0003	0.0004	0.0004	0.0003
	(0.0002)**	(0.0002)**	(0.0002)**	(0.0002)
Log Newborn(t-4)	0.0003	0.0004	0.0004	0.0004
	(0.0002)**	(0.0002)**	(0.0002)**	(0.0002)**
Log Newborn(t-5)	0.0005	0.0006	0.0006	0.0005
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)**
Log Newborn(t-6)	0.0007	0.0007	0.0008	0.0008
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***
Log Newborn(t-7)	0.0006	0.0007	0.0007	0.0007
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***
Log Newborn(t-8)	0.0005	0.0007	0.0006	0.0007
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***
Log Newborn(t-9)		0.0006	0.0007	0.0006
		(0.0002)***	(0.0002)***	(0.0002)***
Log Newborn(t-10)		0.0004	0.0005	0.0005
		(0.0002)**	(0.0002)***	(0.0002)**
Log Newborn(t-11)			0.0003	0.0003
			(0.0002)*	(0.0002)
Log Newborn(t-12)			0.0002	0.0002
			(0.0002)	(0.0002)
Log Newborn(t-13)				0.0000
				(0.0002)
Log Newborn(t-14)				0.0002
				(0.0002)
Log Newborn(t-15)				-0.0000
				(0.0002)
Time effect	Yes	Yes	yes	Yes
Constant	-0.0413	-0.0519	-0.0560	-0.0548
	(0.0084)***	(0.0108)***	(0.0132)***	(0.0172)***
No.Obs.	5.18e+04	5.03e+04	4.87e+04	4.63e+04
No.Munic	1634	1634	1634	1634

Notes: Fixed effect estimation. Heteroskedasticity robust standard error (clustered at municipality level) in parentheses.

Table 4.9: Effects of changes in log-newborns on log-quantity and log-price - newborns measured as ratio of total population

	Log Quantity Index	Log Price Index
Panel A: newborns measured at time t		
Log(Newborns/Pop)	0.01785	0.00046
	(0.00286)***	(0.00014)***
Constant	-0.10487	-0.01210
	(0.02228)***	(0.00114)***
Time effects	Yes	Yes
No.Obs.	5.73e+04	5.73e+04
No.Munic	1.67e+03	1.67e+03
Panel B: newborns measured at time t and $t-1$		
Log(Newborns/Pop)	0.03005	0.00081
	(0.00482)***	(0.00027)***
Constant	-0.05582	-0.00903
	(0.03336)*	(0.00191)***
Time effects	Yes	Yes
No.Obs.	5.68e+04	5.68e+04
No.Munic	1.67e+03	1.67e+03
Panel C: newborns at time t, $t-1$ and $t-2$		
Log(Newborns/Pop)	0.03690	0.00110
	(0.00658)***	(0.00040)***
Constant	-0.08784	0.01704
	(0.04096)**	(0.00249)***
Time effects	Yes	Yes
No.Obs.	5.64e+04	5.64e+04
No.Munic	1.67e+03	1.67e+03

Notes: Fixed effect estimates. Heteroskedasticity robust standard error (clustered at municipality level) in parentheses.

Table 4.10: Regression discontinuity results of Model 3 - 2SLS results

	Elasticity to NBorns at time t		Elasticity to NBorns at time t, $t-1$		Elasticity to NBorns at time t, $t-1$, $t-2$	
	Log-Quant Index	Log-Price Index	Log-Quant Index	Log-Price Index	Log-Quant Index	Log-Price Index
Panel A: Local linear estimate - ± 1,500 inhabs.						
No. of Pharm.	0.068	-0.010	0.078	-0.009	0.078	-0.009
	(0.084)	(0.005)*	(0.067)	(0.005)*	(0.067)	(0.005)*
Constant	-0.052	0.009	-0.048	0.007	-0.048	0.008
	(0.075)	(0.005)*	(0.063)	(0.005)	(0.063)	(0.005)*
No. of Obs.	227	227	227	227	227	227
Panel B: Spline 2^{nd} - ± 2,000 inhabs.						
No. of Pharm.	0.032	-0.013	0.086	-0.011	0.086	-0.013
	(0.105)	(0.008)	(0.098)	(0.008)	(0.098)	(0.009)
Constant	-0.026	0.013	-0.049	0.010	-0.049	0.013
	(0.095)	(0.008)	(0.096)	(0.007)	(0.096)	(0.008)
No. of Obs.	288	288	288	288	288	288
Panel C: Spline 3^{rd} - ± 3,000 inhabs.						
No. of Pharm.	0.034	-0.014	0.115	-0.011	0.115	-0.012
	(0.105)	(0.008)*	(0.098)	(0.007)	(0.098)	(0.007)*
Constant	-0.028	0.013	-0.073	0.010	-0.073	0.011
	(0.092)	(0.008)*	(0.098)	(0.007)	(0.098)	(0.007)
No. of Obs.	454	454	454	454	454	454
Panel D: Spline 4^{th} - ± 4,000 inhabs.						
No. of Pharm.	0.033	-0.014	0.131	-0.011	0.131	-0.012
	(0.111)	(0.008)*	(0.114)	(0.007)	(0.114)	(0.008)
Constant	-0.031	0.013	-0.083	0.010	-0.083	0.012
	(0.098)	(0.008)	(0.114)	(0.007)	(0.114)	(0.008)
No. of Obs.	621	621	621	621	621	621

Notes: heteroskedasticity robust standard errors in parentheses. The municipality-specific elasticities are obtained by (i) regressing the dependent variables on municipality and time fixed effects, and (ii) regressing the residuals obtained on log-newborns for each municipality.

Table 4.11: Fixed-effects estimates of Model A - municipalities in which Newline samples all pharmacies

	Log Quantity Index	Log Price Index
Panel A: newborns measured at time t		
Log newborn	0.0191	0.0006
	(0.0036)***	(0.0002)***
Constant	-0.3234	0.0026
	(0.0252)***	(0.0010)**
Time effect	Yes	Yes
No.Obs.	24743	24743
No.Munic	792	792
Panel B: newborns measured at time t and $t-1$		
Log newborn	0.0311	0.0011
	(0.0058)***	(0.0003)***
Constant	-0.4664	-0.0028
	(0.0181)***	(0.0008)***
Time effect	Yes	Yes
No.Obs.	24542	24542
No.Munic	792	792
Panel C: newborns at time t, $t-1$ and $t-2$		
Log newborn	0.0399	0.0016
	(0.0078)***	(0.0005)***
Constant	-0.6439	0.0123
	(0.0199)***	(0.0010)***
Time effect	Yes	Yes
No.Obs.	24261	24261
No.Munic	792	792

Notes: Heteroskedasticity robust standard error (clustered at municipality level) in parentheses.

Table 4.12: Regression discontinuity results of Model 3 - municipalities in which Newline samples all pharmacies

	No. of Pharmacies	Log-Price ITT	Log-Price IV	Log-Quant ITT	Log-Quant IV
Thresh. Dummy	1.012	-0.003		0.011	
	(0.154)***	(0.001)*		(0.031)	
No. of Pharm.			-0.003		0.011
			(0.001)*		(0.031)
Constant	0.143	0.003	0.003	-0.002	-0.003
	(0.051)***	(0.001)**	(0.001)***	(0.019)	(0.022)
No. of Obs.	202	201	201	201	201

Notes: heteroskedasticity robust standard errors in parentheses. The municipality-specific elasticities are obtained by (i) regressing the dependent variables on municipality and time fixed effects, and (ii) regressing the residuals obtained on log-newborns for each municipality.

Figure 4.1: Trends in average quantity and price indexes of hygiene products (left panels), and histograms of the residuals of a regression of quantity and price on City and time fixed effects (right panels)

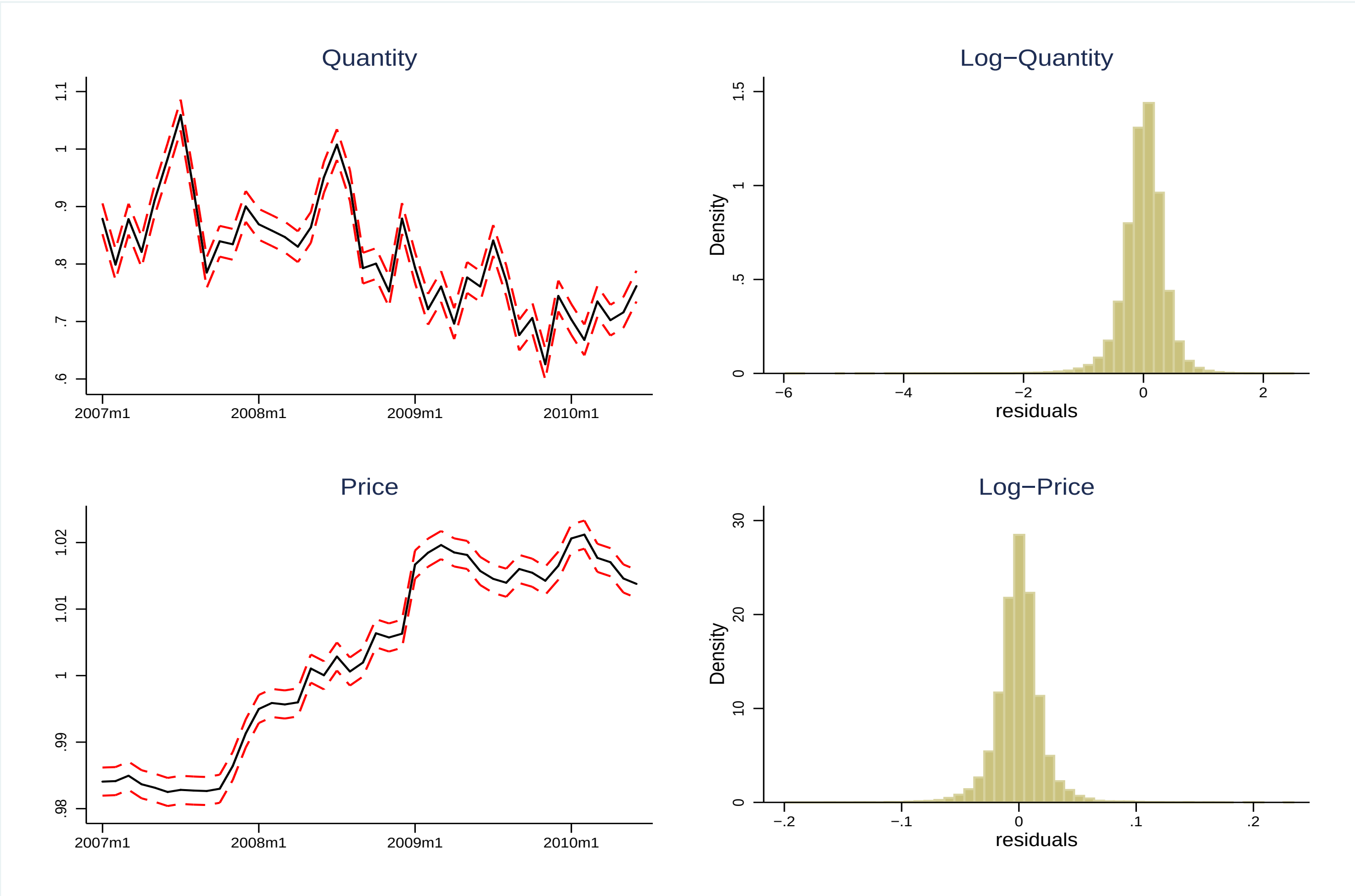


Figure 4.2: Trends in average newborns per City (left panel), and histograms of the residuals of a regression of log-newborns on City and time fixed effects (right panel)

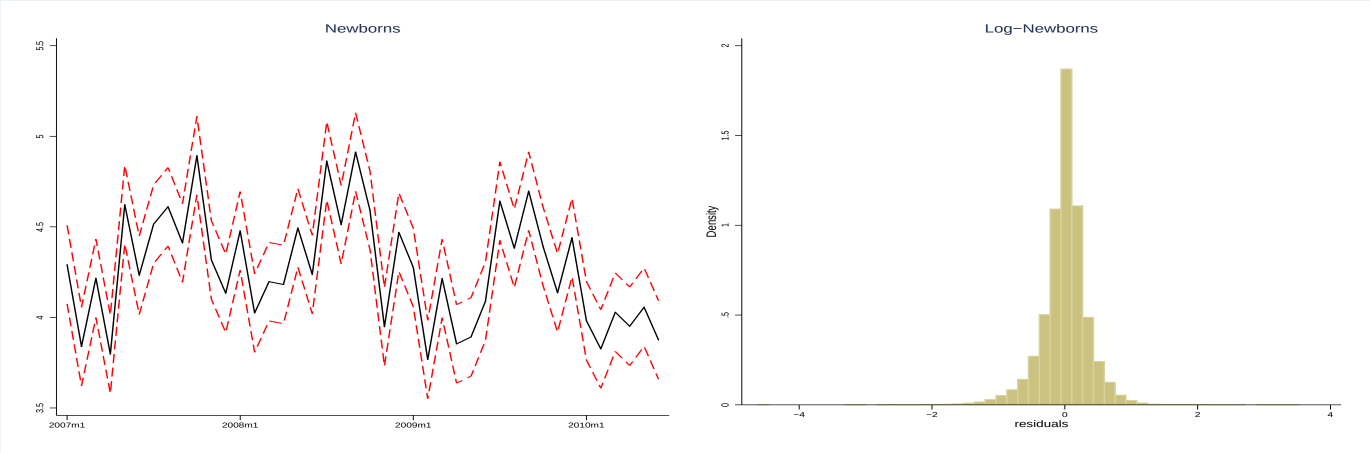


Figure 4.3: Scatter plot and local polynomial smoothing of the number of pharmacies - actual population in 2006 and maximum population over the period 1961-2006

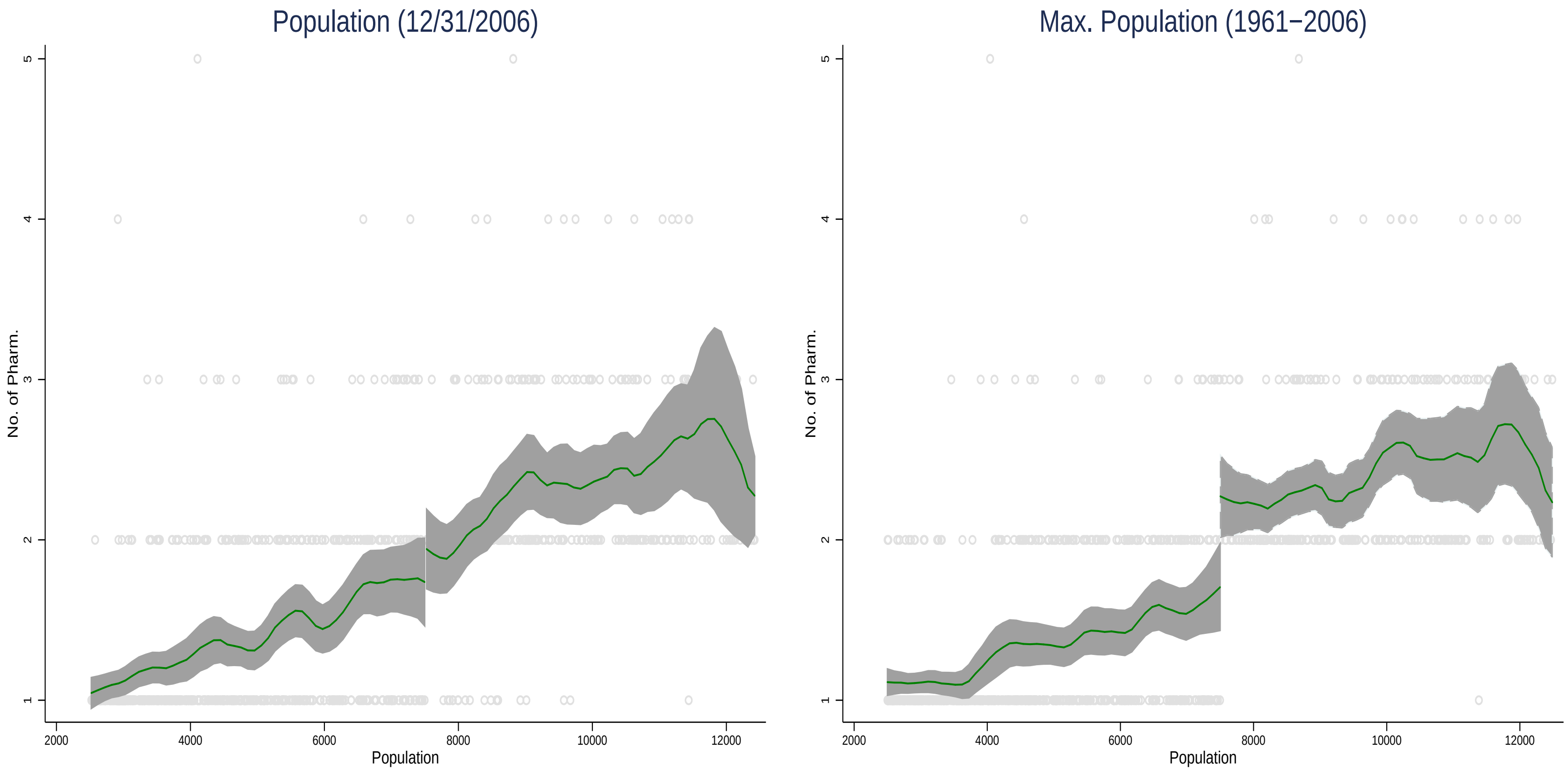


Figure 4.4: Scatter plot and local polynomial smoothing of the (log) quantity index around the threshold

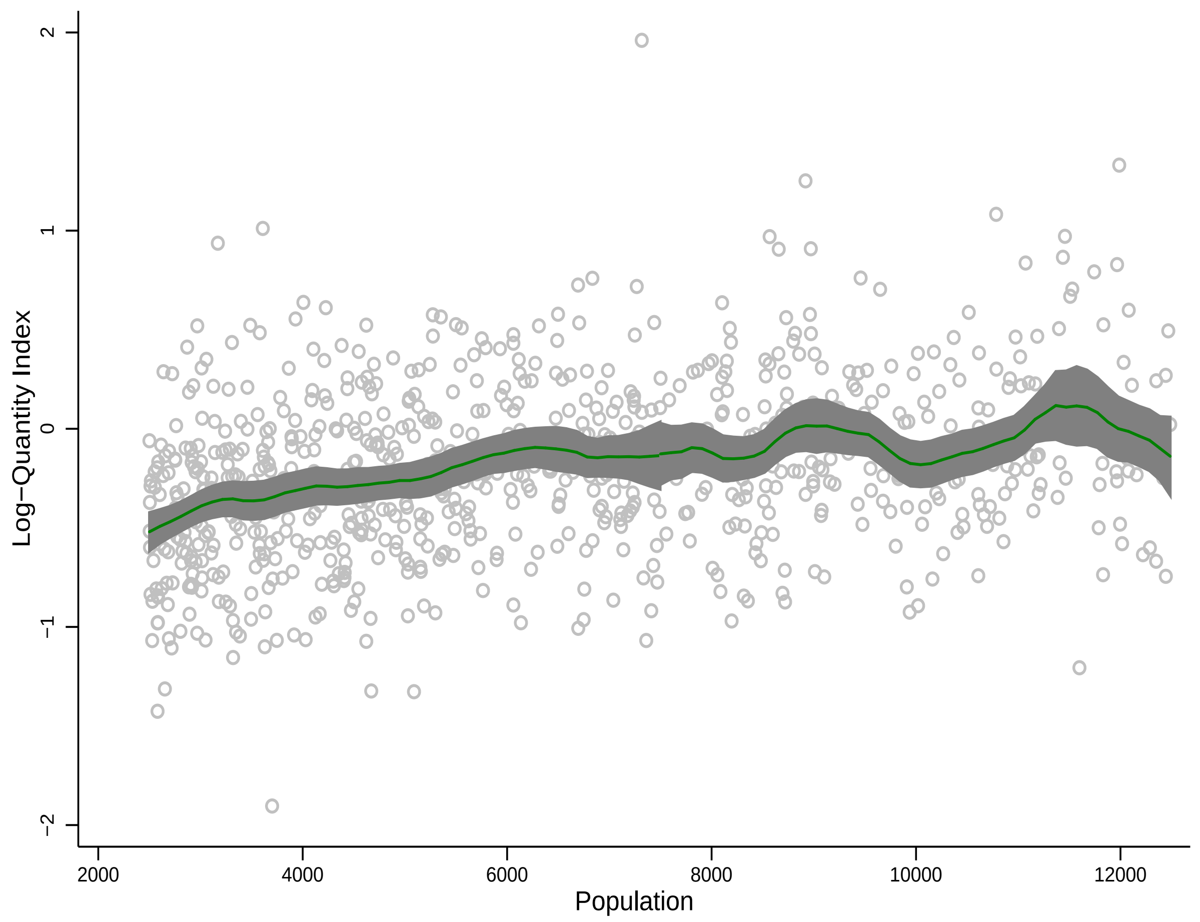


Figure 4.5: Scatter plot and local polynomial smoothing of the (log) price index around the threshold

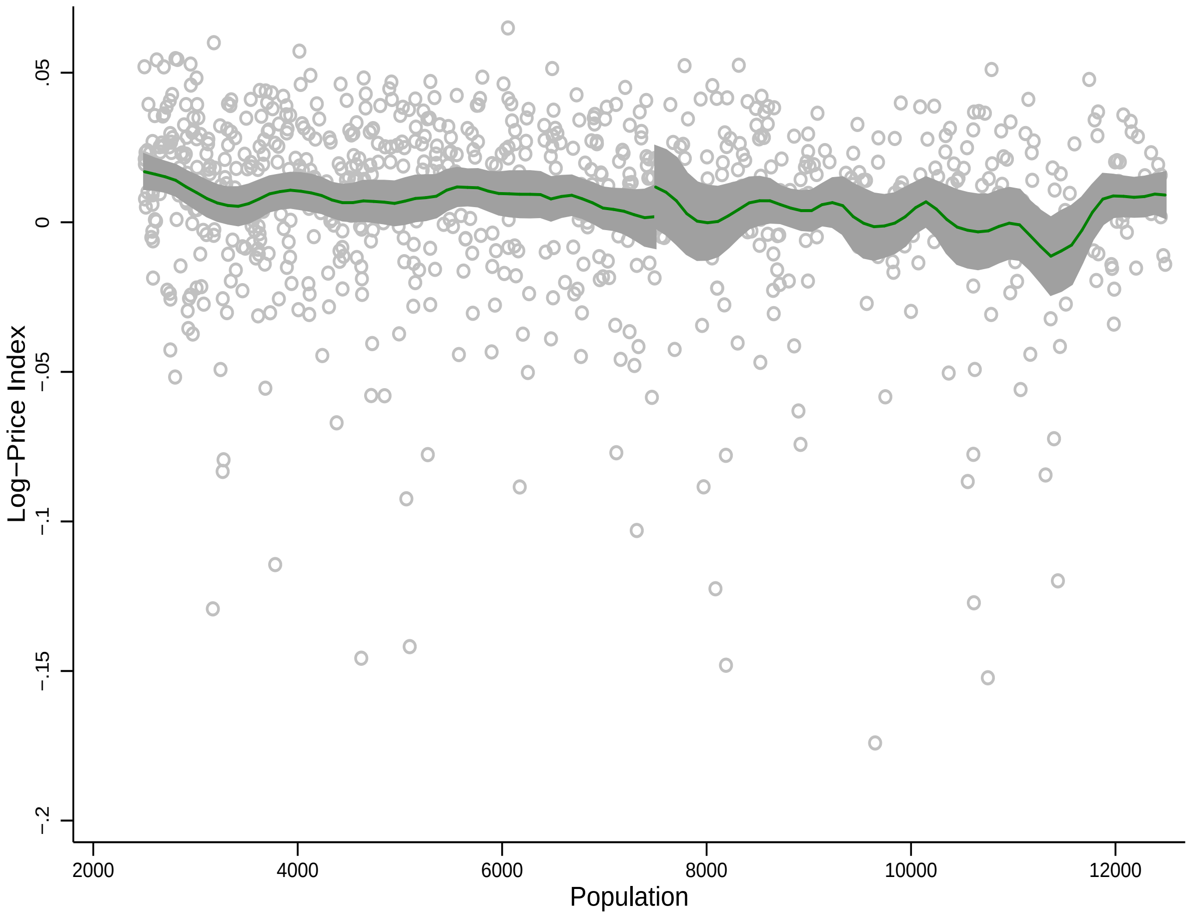


Figure 4.6: Scatter plot and local polynomial smoothing of the municipality-specific elasticity of quantities to newborns

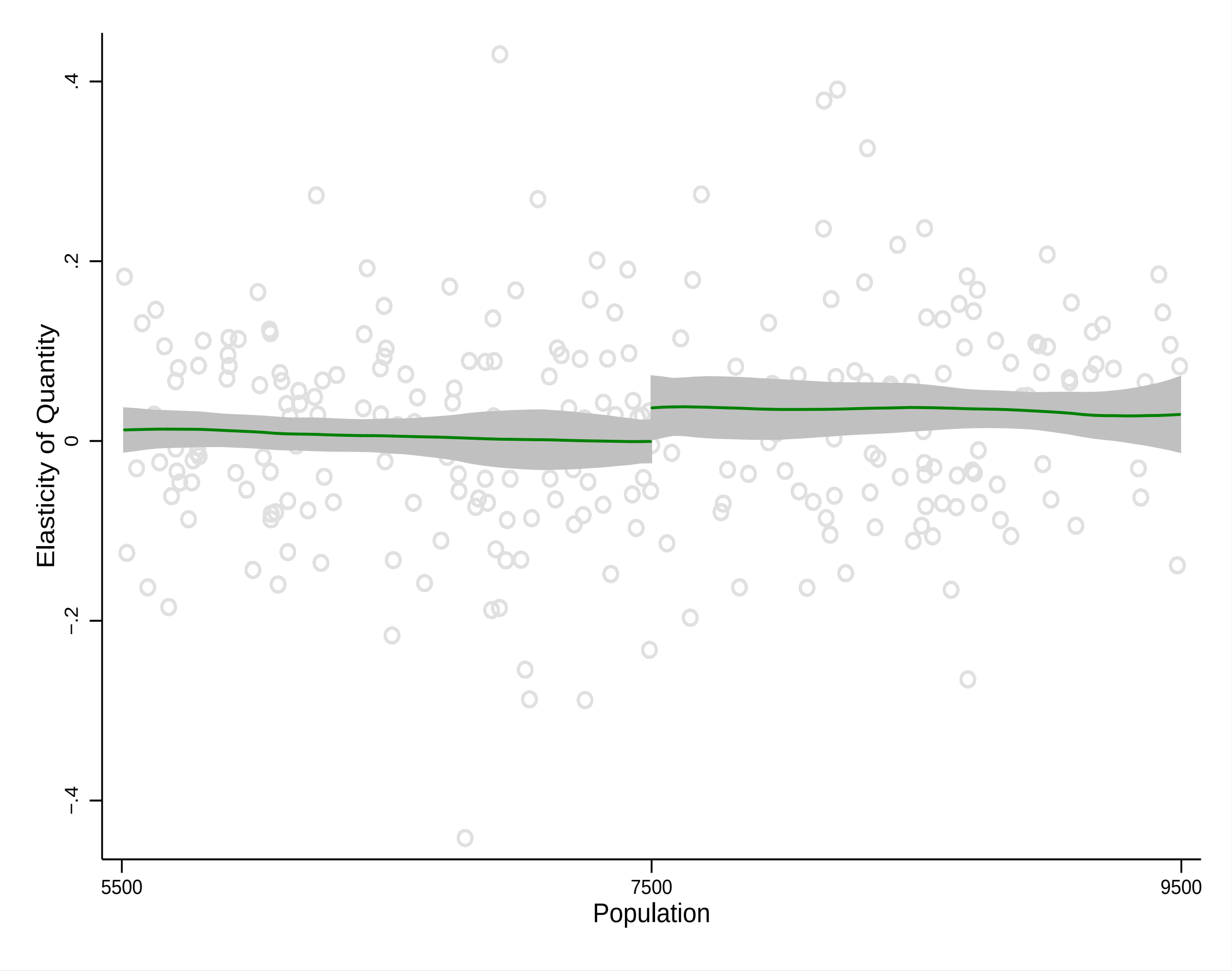


Figure 4.7: Scatter plot and local polynomial smoothing of the municipality-specific elasticity of prices to newborns

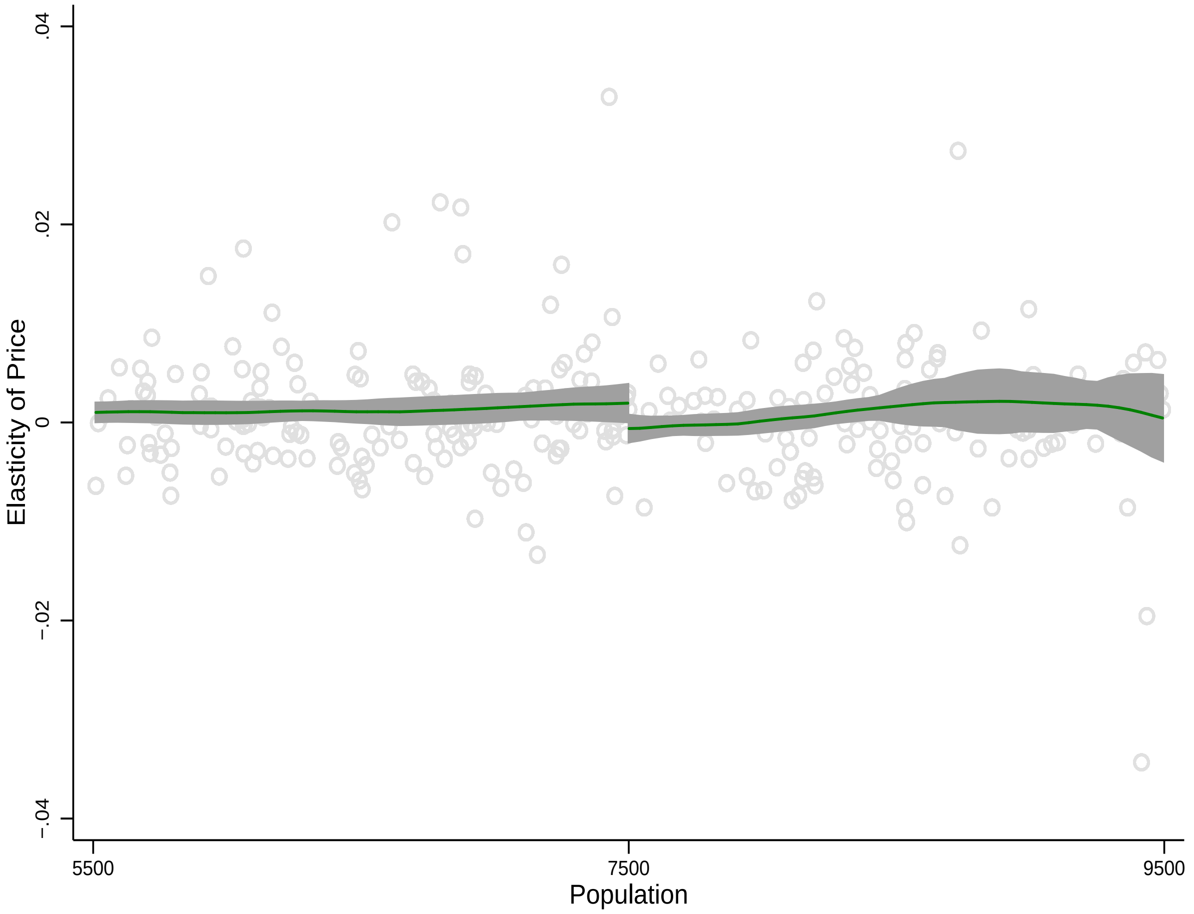
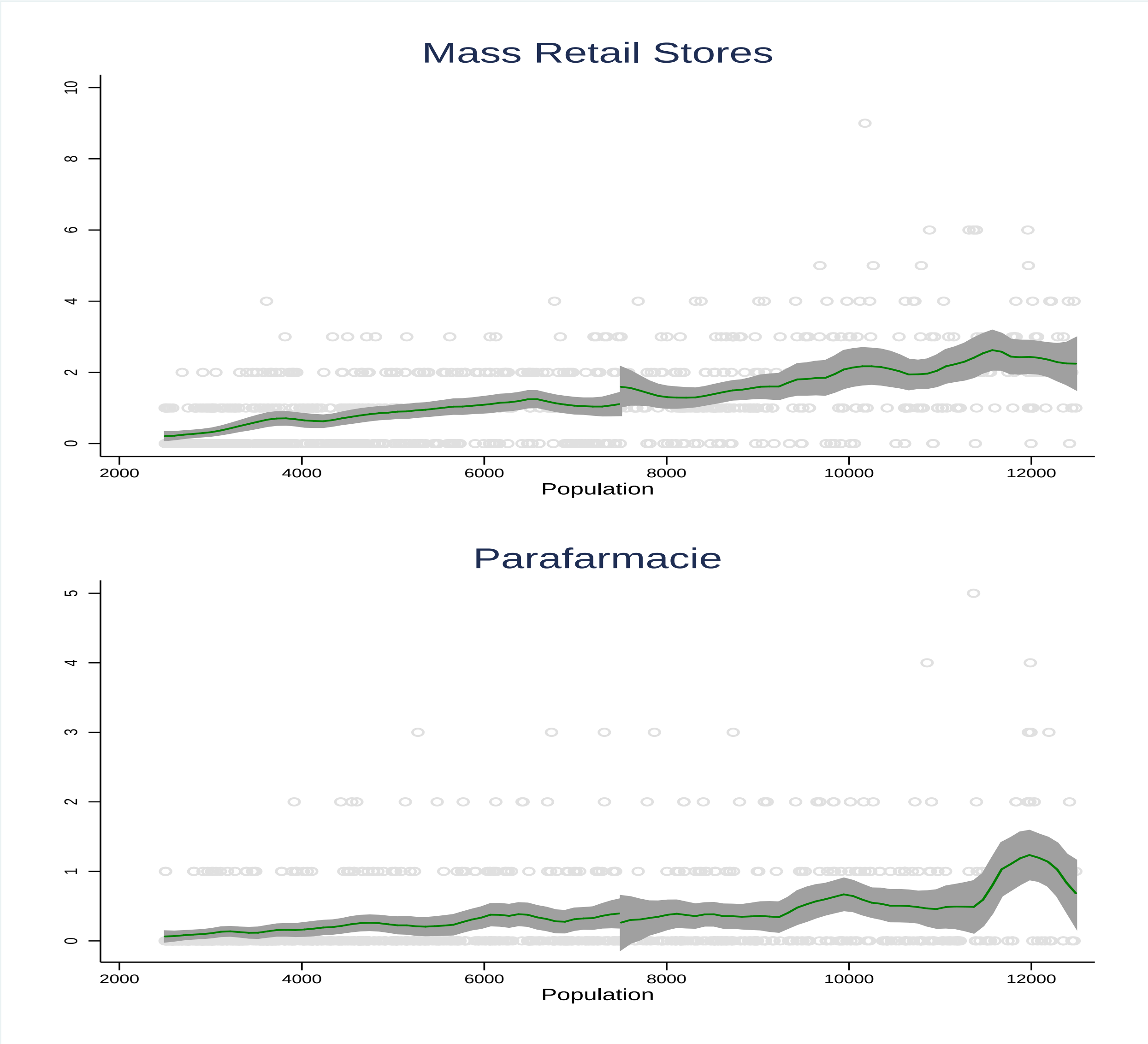


Figure 4.8: Scatter plot and local polynomial smoothing of the number of mass retail stores and parafarmacie around the threshold



Chapter 5

Immigration and house price distribution[1]

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[1]Elisa Ravazzoli has provided fundamental support in working with GIS data. We thank David Card, Fernando Ferreira, Gaetano Alfredo Minerva, and Robert Helsley for useful discussions and suggestions. The views expressed herein are our own and do not necessarily reflect those of Institutions with which we are affiliated.
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Abstract

We study the effect of an immigrant inflow at the neighborhood level on house prices within cities. We develop a spatial equilibrium model that shows how immigration shock to a part of the city propagates to the rest of the city through changes in local amenities and local prices. On the empirical side, we rely on two different empirical strategies. First, we collect data at the neighbourhood level for a sample of main Italian cities and we analyze the impact of immigration on natives' residential choice and house price dynamics. We find that there is a negative relationship between changes in native population and changes in immigrant population across neighbourhoods; we also find some evidence that price growth is lower than the average in those neighbourhoods where immigrants settle. Second, we extend the analysis to all Italian municipalities and we investigate the impact of immigration on indicators of city price distribution. We find that immigration causes an increase in the average price. This effect, however, is driven by the upper two deciles of the price distribution: the effect on immigration on lower prices is never statistically different from zero.

5.1 Introduction

Economists have recently begun studying the effect of immigration on house prices. Starting from the seminal work of Albert Saiz [58], empirical analyses have shown that an inflow of immigrants has a positive effect on rental and house prices at the municipal level. This can be considered a simple consequence of an increase in housing demand in the presence of a positively sloped supply curve. However, the average effect at the municipal level may hinder opposing forces *within* the city boundaries. Indeed, immigrant inflows may reduce the price in the neighborhood where they settle by inducing natives to move in other areas of the city. The resulting average price at the municipal level may still grow, but the effect on house price distribution may be different. Identifying this effect is particularly relevant for its positive and normative implications in terms of both urban segregation and social interactions between natives and foreigners, as well as for the study of real estate market dynamics.

In this paper, we provide both theoretical and empirical preliminary findings on the effect of an inflow of immigrants on native flight and house prices within the city.

To examine the effects of an immigration shock in a spatial equilibrium framework and to guide the empirical investigation, we develop a theoretical model à la Rosen-Roback.[2] The model clarifies how a localized immigrant shock to a neighborhood propagates to the rest of the city through changes in local amenities and local prices.

On the empirical side, we rely on two different empirical strategies. First, we investigate the causal impact of immigration on indicators of city price distribution. To address endogeneity, we adopt an IV strategy which uses historical enclaves of immigrants across municipalities to predict current settlements (Card [11]). We find that a 10 percent shock to the immigrant population increases the spread between maximum and minimum prices by 5.3 percentage point. A quantile analysis shows that the effect of immigration is significantly positive only

[2]The models by Rosen [57] and Roback [56] are the most frequently used general equilibrium models to analyze shocks to local economies.

for higher deciles of the price distribution. Thus, we provide evidence that immigrant inflows lead to a relatively slower house price appreciation in poorer neighborhoods. Using this strategy, however, we cannot identify where immigrants settle, and whether there are evidence of native flight from areas affected by migration towards other areas of the city.

In order to do so, we are going to pursue a second empirical strategy. In the future development of the paper, we will focus on a smaller sample of 19 main Italian municipalities for which we are gathering data on immigrant inflows and demographic dynamics at the administrative district level (so called "quartieri"). In this paper, we develop an empirical strategy which allows us to identify the effect of an immigrant inflow at the district level on native mobility and on house prices, taking into consideration the (likely) violation of the Stable Unit-Treatment Value Assumption (SUTVA). In addition, we provide preliminary OLS estimates showing that an inflow of immigrants in a district reduces the number of native population living in it, and reduces the growth rate of prices vis-à-vis other parts of the city.

This research contibutes to the literature on urban segregation and on the impact of immigration on house prices. For what regards the former, economists have mostly studied the determinants and consequences of the emergence of ghettos. See, among the others, Cutler et al. [17], Bayer et al. [6], Durlauf [23], Card et al. [12][3]

So far, the effect of immigration on house prices have been almost uniquely studied by looking at the average price at the municipal level as the variable of interest. Researches performed in several OECD countries have confirmed that there is a significant and positive effect on the expected price, though the magnitude of this effect may change.[4] As far as

[3]Cutler et al. [17] examine segregation in American cities. They argue that in the past segregation was a product of collective actions taken by whites to exclude blacks from their neighborhoods. By 1990, legal barriers were replaced by "decentralized racism": whites pay more than blacks to live in predominantly white areas. Card et al. [12] find that population flows exhibit tipping-like behavior: once the minoriy share in a neighborhood exceeds a "tipping point", all whites leave. Bayer et al. [6] analyze segregation patterns in the San Francisco Bay Area and conclude that racial differences in socio-demographic characteristics explain a considerable amount of the observed segregation.

[4]In the US, Saiz [59] founds that a raise in immigrant stock that equals 1% of the city population raises prices by 2%. A similar finding is obtained for New Zealand by Stillman and Mare [64]. Gonzales and Ortega [28] estimate a 3% effect for Spain, Degen and Fischer [21] find a effect 2.7% elasticity for Switzerland,

we know, Saiz and Wachter [60] is the only paper that examines the distributional impact of immigration on house prices. They focus on US metropolitan areas and use two census waves to document that housing values have grown relatively more slowly in neighborhoods characterized by immigrant settlements.

Most of the existing literature in both fields concerns the US, whereas evidence for Europe is much more limited. Moreover, almost all of the previous studies have used decennial census data, thus focusing on the long-term dynamics of segregation and house prices. We provide novel evidence of the displacement effect of immigration on natives in the Italian context, and study the effect of immigration on housing in a markedly different setting with respect to the US market. Indeed, Italy is characterized by stickier supply of housing and much less developed capital markets. The pure effect of a demand shock may then be more pronounced. In addition, we identify short/medium-term effects using yearly observations, rather than decennial data.

The rest of the paper is organized as follows. In Section 5.2, we develop a spatial equilibrium model to inform our empirical exercises. In Section 5.3, we describe the data and provide some descriptive analysis on urbanization patterns, house price dynamics and their relationship with immigrant settlements. In Section 5.4 we present evidence of the effect of an immigrant inflow on measures of city price dispersion. In Section 5.5 we introduce our second empirical exercise based on data at the neighborhood level for a subset of Italian metropolitan areas. Section 5.6 provides preliminary concluding remarks.

De Blasio and D'Ignazio [19] estimate 0.5% effect for Italy. Akbari and Aydede [2] study the Canadian real estate market, and they are the only paper that fails to identify any significant effect.

5.2 Theoretical model

5.2.1 Assumptions and equilibrium in the housing market

Consider a city composed of 2 neighborhoods, $s \in \{1, 2\}$. Each individual i located in a neighborhood s maximizes her utility function:

$$U_{is} = A_s \frac{C_i^{1-\alpha} L_i^{\alpha}}{(1-\alpha)^{1-\alpha} \alpha^{\alpha}} \tag{5.1}$$

where A_s are the amenities in neighborhood s, C_i and L_i are the amount of, respectively, tradable good and housing consumed by i.

Using the tradable good as the numeraire, and assuming that income does not depend on location within the city, budget constraint is $C_i + r_s L_i = Y_i$, where r_s and Y_i represent, respectively, rents prevailing in area s and individual income.

Standard utility maximization leads to the following marshallian demands:

$$L_i^* = \frac{\alpha Y_i}{r_s} \tag{5.2}$$

$$C_i^* = (1-\alpha) Y_i \tag{5.3}$$

There are two types of workers: natives and immigrants. The total number of natives in the city is N, a share ω of which locates in area 1. Natives are free to move across neighborhoods and their income is equal to Y. We assume that a mass m of immigrants locate in the city and concentrate in area 2. Immigrant income is equal to γY, with $\gamma \in (0, 1]$.

Aggregate housing demand for each area is therefore:

$$L_1^d = \omega N \frac{\alpha Y}{r_1} \tag{5.4}$$

$$L_2^d = [(1-\omega) N + \gamma m] \frac{\alpha Y}{r_2} \tag{5.5}$$

Neighborhood s housing supply is assumed to be equal to:

$$L_s^o = \beta_s r_s \tag{5.6}$$

where β_s is the price elasticity of housing services. β_s is allowed to be different across locations, since neighborhoods may be characterized by different space constraints. Indeed, housing supply in a historical city center (e.g., Rome or Venice) is much more constrained than the one in sprawled peripheries.

Equilibrium prices are determined by the equations (5.4), (5.5), and (5.6):

$$r_1^* = \left(\omega N \frac{\alpha Y}{\beta_1}\right)^{\frac{1}{2}} \tag{5.7}$$

$$r_2^* = \left\{\left[(1-\omega) N + \gamma m\right] \frac{\alpha Y}{\beta_2}\right\}^{\frac{1}{2}} \tag{5.8}$$

5.2.2 Where do natives locate?

Natives are free to move across locations. This implies that in equilibrium the utility levels equalize across locations.

Given Cobb-Douglas preferences, indirect utilities are determined by the product between real wages and amenities. We now assume that natives' appreciation of local amenities is influenced by migration. On one hand, natives might be concerned by a deterioration of local standards of living due to an increase in crime or a crowding effect of local indivisible public goods (e.g., parks, libraries, transports). On the other hand, natives perception of local amenities in response to migration can increase due to cultural diversity and a rise in the variety of local public goods (e.g., ethnic restaurants).

We assume that amenities in neighborhood 1, unaffected by migration, are fixed and equal to A, while amenities in area 2 are a function of migration, $A(m)$, whose derivative depends on the balance between the above described forces.

The equalization between indirect utilities leads to the following equilibrium condition:

$$\frac{A}{\left(\frac{\omega N}{\beta_1}\right)^{\frac{\alpha}{2}}} = \frac{A(m)}{\left[\frac{(1-\omega)N+\gamma m}{\beta_2}\right]^{\frac{\alpha}{2}}} \tag{5.9}$$

Equilibrium area 1 share of natives is therefore:

$$\omega^* = \frac{N+\gamma m}{N}\phi(m) \tag{5.10}$$

where $\phi(m) = \frac{\frac{A^{\frac{2}{\alpha}}}{\beta_2}}{\frac{A^{\frac{2}{\alpha}}}{\beta_2}+\frac{A(m)^{\frac{2}{\alpha}}}{\beta_1}} \in (0,1)$ represents the amenities effect of migration on population location.

The term $\frac{N+\gamma m}{N}$ can be interpreted, instead, as an income effect: the crowding out of natives due to he increased demand of housing services by immigrants.

The native flight phenomenon (i.e., the relocation of native population ot other neighborhoods due to immigration) can be computed as:

$$\frac{\partial \omega^*}{\partial m} = \frac{\gamma}{N}\phi(m) + \frac{N+\gamma m}{N}\phi'(m) \tag{5.11}$$

The first term on the right-hand side represents the change in the income effect, that is always positive. Note that the larger the immigrants' income the stronger this effect and, thus, the native flight. The second term is the amenities effect, which is positive whenever migration decreases perceived amenities in the area (i.e., if $\partial A(m)/\partial m < 0$). In other words, the price effect is emphasized (attenuated) by the amenities effect whenever immigrants decrease (increase) local amenities in area 2.

5.2.3 Migration and rents: local and average effects

It is now easy to assess the effect of migration on local rents. By deriving the log of (5.7) and (5.8) by m, we obtain:

$$\frac{\partial r_1^*}{\partial m} = \frac{1}{2}\left[\frac{\gamma}{N+\gamma m} + \frac{\phi'(m)}{\phi(m)}\right] \tag{5.12}$$

$$\frac{\partial r_2^*}{\partial m} = \frac{1}{2}\left[\frac{\gamma}{N+\gamma m} + \frac{\phi'(m)}{1-\phi(m)}\right] \tag{5.13}$$

Note that the income effect is the same in both areas, since the propagation of the migration shock from area 2 to area 1 is immediate due to the free mobility of natives. Income effect in area 1 is attenuated (emphasized) if migration increase (reduce) amenities in area 2. In other words, whenever migration generates a reduction in neighborhood 2 amenities, native workers decide to migrate and pay higher rents in area 1 to "escape" foreigners. The effect on area 2 is just the opposite. Whenever immigrants deteriorate local amenities housing costs in the area hit by migration grow less than the other areas of the city due to the native flight effect (i.e., larger residential migration from area 2 to area 1).

It is now possible to compute the city-level average rents and assess the effects of an inflow of immigrants. By using (5.6), (5.7), and (5.8), city-level rents are equal to:

$$r^* = 2\left[\frac{(N+\gamma m)\alpha Y}{\phi(m)\beta_1 + [1-\phi(m)]\,\beta_2}\right]^{\frac{1}{2}} \tag{5.14}$$

By taking logs and deriving by m, we obtain the average rent elasticity to migration (whose empirical counterpart has been estimated for the US by Saiz [59]):

$$\frac{\partial r^*}{\partial m} = \frac{1}{2}\left[\frac{\gamma}{N+\gamma m} + \frac{(\beta_2-\beta_1)\,\phi'(m)}{\phi(m)\beta_1 + [1-\phi(m)]\,\beta_2}\right] \tag{5.15}$$

As before, the first term in braces is the income effect on rents. However, at city level the spatial distribution of immigrants matters. In particular, the expression $(\beta_2 - \beta_1)\phi'$ signals that the effects on amenities and the elasticity of housing supply play an important role. First, note that whenever housing supply is the same across neighborhoods, the second term in braces cancels out. This implies that amenities have an effect on average prices only if neighborhoods are characterized by different supply elasticities.

We can then distinguish four cases:

i. $\beta_2 > \beta_1$ and $\phi'(m) > 0$. In this case immigrants reduce amenities and area 2 is characterized by a larger elasticity in the housing supply (i.e., immigrants settle in the periphery). In this case, natives leave area 2 and move to the area characacerized by a more rigid supply curve, thus increasing local and average prices.

ii. $\beta_2 < \beta_1$ and $\phi'(m) > 0$. In this case immigrants reduce amenities and area 2 is characterized by a smaller elasticity in the housing supply (i.e., immigrants settle in the historical city centers). In this case, natives leave area 2 and move to the area characterized by a less rigid supply curve, thus attenuating the income effect.

iii. $\beta_2 > \beta_1$ and $\phi'(m) < 0$. In this case immigrants increase amenities and area 2 is characterized by a larger elasticity of the housing supply (periphery). Natives leave area 1 and move to an area characterized by a less rigid supply curve, attenutating the income effect.

iv. $\beta_2 < \beta_1$ and $\phi'(m) < 0$. Immigrants increase amenities and area 2 has a smaller elasticity of housing supply (city center). Native-flight from area 1, then emphasizes the income effect.

5.3 Data and descriptive analysis

Data on house prices are obtained from the Italian Land Registry Office ("Agenzia del Territorio" - AdT). The AdT has divided each Italian municipality into microzones (neighborhoods that are homogeneous in socioeconomic terms). For each microzone, AdT collects information on house prices by type of house (villas and cottages, mansions, economic houses, typical houses), and the state of the building (poor, normal, excellent). We focus on economic houses (the most widespread housing typology) in a normal state (because of the very limited number of observations available for poor or excellent houses). Because most municipalities are composed of very few microzones, in order to obtain stronger measures of variability we aggregate observations at the local labor system level. There are 640 local labor systems for which we have information on house prices from 2003 to 2009.[5]

Figure 5.1 reports trends in several price indicators, averaged at the local labor system level, over the period 2003-2009. The left figure shows that the average house price has increased sharply in the last seven years, with the notable exception of 2009: in that year the crisis has lowered the average house price back to its 2007 level. At the same time, the ratio between the maximum and the minimum price within the city (middle figure) has lowered markedly. Finally, the coefficient of variation of prices (measured at the municipal level) reported a similar downward trend, which somehow reverts in 2009.

Data on immigrants and natives at the local labor system level is provided by the Italian National Statistical Office. Note that here we consider solely official immigrants.[6]

We now provide some descriptive results for the phenomena we are studying. Figure 5.2 shows the correlation between the change in immigrant population at the municipal level and the corresponding change in native population. The linear fit shows that there is a slightly positive correlation between the two variables. The regression coefficient, however, is rather small (0.004) and not significant at any conventional level.

A simple descriptive analysis confirms that immigration dynamics are strongly correlated with house prices. Indeed, Figure 5.3 shows immigration has grown more in municipalities

[5]The average municipal population in Italy is 7,690 inhabitants. Aggregating observations at the local labor system level yields an average size of 84,305 inhabitants per zone: a dimension more similar to standard U.S. metropolitan areas.

[6]Note, however, that the presence of unofficial immigrants would not bias our empirical estimate if they are proportional to official immigrants and the constant of proportionality is the result of a municipality-per-year fixed effect (for which we are able to control) and a stochastic term. See Bianchi et al. [9] for a discussion and some empirical evidence on this issue.

where beginning-of-the-period price was lower. On the other side, however, the municipalities in which immigration has grown more have been characterized by a stronger increase in house prices over the 2003-2009 period (Figure 5.4). Finally, immigration is only weakly correlated with a decrease in the coefficient of variation of prices within the local labor system (Figure 5.5).

All these correlations, however, are likely to be largely spurious, due to the presence of omitted variables (e.g., the business cycle) affecting both immigration and house prices, as well as because of reverse causality (immigrants may be pulled by housing opportunities). To deal with both issues, in the next Section we develop an instrumental variable approach.

5.4 The effect of immigration on house price distribution

We start estimating the following model for the price indicator PI_{it} measured in local labor system i and year t:

$$PI_{it} = \alpha + \beta M_{it} + \lambda_t + a_i + \varepsilon_{it} \tag{5.16}$$

where M_{it} is the log of the number of immigrants, λ_t is a year fixed-effect, and a_i is a local labor system fixed effect.

Table 5.1 reports results from the OLS estimate of 5.16. The first column shows that an increase in 1% in the stock of immigrants raises the mean price by around 0.13%. This positive mean effect has been identified by the preceding literature in most OECD countries, including Italy (De Blasio and D'Ignazio [19]). As the subsequent columns show, however, this effect is not uniform over the price distribution. The effect is somehow more pronounced for the maximum price (which increases by 0.137% for a 1% raise in immigrant stock) than for the minimum price (which increases by 0.12%). The difference between the maximum and minimum prices, then, increases significantly. The increase in the coefficient of variance related to an increase in the immigrant stock, however, fails to be significantly different from zero at any conventional level.

The OLS results, however, may suffer from the afore-mentioned endogeneity and reverse causality issues. To address these problems, we use an IV strategy that exploits historical enclaves and current total aggregate stocks in Italy to predict current stocks of immigrants at the municipal level. Following Card [11], for each municipality i the expected value of M_t is given by:

$$\hat{M}_{it} = \beta_0 + \beta_1 \sum_n Sh^n_{i,1991} \times M^n_t + \lambda_t + LLM_i \tag{5.17}$$

where $Sh^n_{i,1991}$ is the share of immigrants of nationality n that was in municipality i in 1991, and M^n_t is the total stock of immigrants from origin country n present in Italy in year t.[7]

Results, reported in Table 5.2, are somehow in line with the OLS estimates: an inflow of immigrants increases both the maximum and the average prices. The point estimate for the minimum price, however, is smaller and fails to be statisticaly different from zero. To assess the impact on the overall price distribution, we calculate the effect for each quartile of the price distribution. The estimated coefficients, together with those of minimum and maximum prices, are plotted in Figure 5.6. As it can be seen the effect is significantly different from zero only for the upper deciles (from the eight onward) of the price distribution.

Assume rank-invariance (Chernozhukov and Hansen [15])[8], then these findings show that immigrant inflows lead to a relatively slower housing price appreciation in poorer neighborhoods, thus widening the price distribution of wealth within the city.

Based on these results, however, it is not possible to discriminate between the four different cases highlighted by the theoretical model in Section 5.2.3. Indeed, a stronger increase in the right part of the price distribution may be obtained if:

- migrants settle in poor neighborhoods, but natives fly to richer ones;

[7]Due to data availability, we have to aggregate nationalities by geographical areas of origin: Western Europe, Eastern Europe, North Africa, other countries from Africa, Asia, North America, South America, and Oceania.

[8]That is, that the inflow of immigrants does not changes the ranking between quantiles of the price distribution.

- migrants settle in rich neighborhoods, and natives do not fly away;
- migrants settle uniformly over the municipality, but price elasticity of richer areas is lower.

To obtain clearer results, we need to directly identify an immigrant inflow localized within the city boundaries, and study its effect on both the neighborhood affected by it and the nearby areas.

5.5 Immigration and price dynamics at the neighborhood level

We are collecting data from 19 of the main Italian metropolitan areas.[9] For each administrative district of each metropolitan area, we obtain yearly data on immigrant residents by nationality in the period 2002-2009. We use AdT data for house prices, and georeference them in order to impute a yearly average house price for each administrative district. Figure 5.7 shows, as an example, the resulting map of Rome. In each different district (identified in the figure by a specific color) we compute the house price as the simple average between prices measured in each AdT microzone.[10]

5.5.1 Empirical strategy

For each district $d \in [1, \ldots, D]$, belonging to municipality $c \in [1, \ldots, C]$ in year $t \in [1, \ldots, T]$, we postulate the existence of a set of potential house prices $P_{dct}(M)$, each of them characterised by a different value of the treatment $M \in [M_0, \ldots, M_1]$. The treatment we are interested in is the stock of immigrants in the district: thus, $M_0 = 0$ and $M_1 \to \infty$.

[9] The cities included in the sample are Bergamo, Bologna, Brescia, Cagliari, Genoa, Florence, Lecce, Modena, Milan, Naples, Padua, Perugia, Prato, Reggio Emilia, Rome, Turin, Udine, Venice, Verona.

[10] As a robustness check, we may compute the weighted average, with weights proportional to the area of each microzone. Notice, however, that the eventual measurement error obtained by using a simple average would ultimately bias our result toward zero.

We want to estimate the effect of a percentage change in the number of immigrants on house prices *relative to the city average.* We allow for both a district-level unobserved heterogeneity and a city-year fixed effects. The resulting model is the following:

$$\log P_{dct} = FE_{dct} + \delta \log M_{dct} + \epsilon_{dct} \tag{5.18}$$

where $FE_{dct} = NEIGHBOURHOOD_{dc} + (CITY_c \times YEAR_t)$ is the district and the city-year fixed effects. The parameter $\delta = E[E(\log P_{dct} - FE_{dct}|M)]$ is the average treatment effect.[11] Both identification and inference using this simple model face several important challenges. They include:

i. endogeneity: identification relies on the assumption that $M_{dct} \perp \epsilon_{dct} | FE_{dct}$. This is unlikely to hold, because there may be time-varying unobserved factors that affect both immigrant inflows and house price;

ii. reverse causality: immigrants can be pulled or pushed by house price dynamics;

iii. externalities: identification requires that the stable unit treatment value assumption (SUTVA) holds.[12] This may be violated if inflows in a certain district affect the outcome in other districts. Although violation of the SUTVA represents a specific type of endogeneity, it is worthwhile to consider it separately. In addition, it has obvious implications for robust inference because it results in intra-municipal correlation in the error terms;

iv. other inference issues: they include possible heteroskedasticity of the error term and its potential serial correlation within district, cities, and time periods.

[11]Notice that in principle, if we have enough observations, we can even estimate the average dose-response function (Hirano and Imbens (2004)) $\mu(M) = E(\log P_{dct} - FE_{dct}|M)$.

[12]SUTVA can be stated as follows: '*The potential outcomes for any unit do not vary with the treatments assigned to any other units, and there are no different forms or versions of each treatment*' (Imbens and Rubin [38]). Here we deal with the first part of it, and we simply assume that the treatment has only one form. In general, however, migrant flows can vary in their composition..

Instruments

An instrumental variable approach can deal with issues of endogeneity and reverse causality. Consider the intra-municipal application of (5.17):

$$\hat{M}_{dct} = FE_{dct} + \beta Z_{dct} \tag{5.19}$$

where $Z_{dct} = \sum_n Sh^n_{dc,1991} \times M^n_t$ is the instrument, generated by the sum of the interactions between the share of immigrants of nationality n that settled in district d in 1991 and the inflow of immigrants from country n to Italy in year t.[13]

The exclusion restriction is based on two assumptions:

IV1: the exogeneity of stocks in 1991 with respect to present trends in house prices;

IV2: there exist no unobserved effect affecting both total immigrant inflows in Italy and changes in the intra-municipal distribution of prices.

Assumption [IV2] can be discussed more thoroughly. In principle, macroeconomic factors (such as the business cycle) may affect immigrant inflows and house price distribution. This is particularly so if trade and remittances from Italy represent a significant part of the national GDP. To partially control for this possibility, we may use flows directed to Western European countries other than Italy (Bianchi et al. [9]), or consider an indicator of origin country instability instead of migrant flows (Nellas and Olivieri [54]).

If we are willing to accept both [IV1] and [IV2], then, estimating (5.18) using $E(M_{dct}|Z_{dct})$ instead of M_{dct} would result in a consistent estimate of δ.

However, the externality problem is still present. Let us consider it in detail. First, the value of the instrument in district i may affect the treatment level in district j: being historically *near* to an immigrant enclave may be as much important for attracting new immigrants as being the enclave itself. Second, the treatment level in district i may affect the outcome

[13] Data on immigrant stocks in 1991 by areas of origin in each district have been computed from the 1991 census-tract data.

variable in district j: being *near* to a district in which there is a large inflow may indeed affect house prices.

Dealing with rejection of the SUTVA is possible, to the extent that we identify and model the mechanism that generates interdependences between observations (Imbens and Rubin 2006). In our case, the driving force seems to be their geographical distance. Then, a straightforward way to obtain consistent estimate of δ is to control for the (exogenous) treatment level of nearby areas. There are several ways in which this is possible. Here we advocate the following model that puts a very light structure to the data and is similar to the approach of Miguel and Kremer (2004):

$$\log P_{dct} = NEIGHBORHOOD_{d,c} + (CITY_c \times YEAR_t) + \delta M_{dct} + \sum_{d=1}^{D} \gamma_d \tilde{M}_{ndct} + \epsilon_{nct} \quad (5.20)$$

where M_{ndct} is the (log) of immigrants in the area d kilometers away from the district i's border. In order to instrument for both M_{ndct} and the vector of $\tilde{M}_{ndct}$'s, we consider two possibilities:

SUTVA1: estimate $Z_{nct} = M_{nc,1991} * I_t$ for each district n, and then compute $\hat{\tilde{M}}_{ndct}$ by manually averaging the predicted immigrant stocks among areas that are d kilometers away from the district i's border. This is the suggestion made by Card;

SUTVA2: instrument $\tilde{M}_{ndct}$ with $\tilde{Z}_{ndc,1991} = M_{ndc,1991} * I_t$, that is with the average migrant stock in an area d kilometers away from district i's border.

Notice that strategy SUTVA1 relies on the assumption that rejection of the SUTVA is present only at time t. SUTVA2, instead, makes our identification robust even to the possibility that 1991 stock in district i affects flows today in district j.

Inference

To perform inference on the results we should rely on heteroskedasticity-robust and cluster-robust standard errors. The cluster dimensions should in principle be two: city and time.[14] Notice, however, that two-way cluster-robust standard errors can be computed only if the number of clusters get to infinity (Thompson 2009). This represents a case in favor of the enlargement of the dataset, given that non-clustered standard errors may be biased downwardly in the presence of positive serial correlation over time or space (Bertrand et al. 2004), thus potentially inducing a type I error.

5.5.2 Preliminary OLS results

In this section, we provide some preliminary results for a set of 8 municipalities (Bologna, Florence, Genoa, Milan, Naples, Rome, Trieste, and Turin).
We start estimating the relationship between native and immigrant population growth at the neighborhood level. Formally, we run the following regression:

$$N_{dct} = \alpha + \beta M_{dct} + YEAR_t + NEIGHBORHOOD_{dc} + \nu_{dct} \tag{5.21}$$

The key explanatory variable is M, that is the log of immigrants in neighborhood d of city c in year t. We also include year dummies to take out the effects of economy wide conditions on population dynamics, and neighbourhood fixed effects to control for any time-invariant omitted variable at that level of analysis. In Table 5.3, we show that there is a negative relationship between immigration and native population growth. The coefficient is significant at the conventional levels. According to our estimates, the doubling of immigrant population in one neighbourhood leads to a 5 percent decrease in native population.
As far as house price dynamics are concerned, we perform the OLS estimate of (5.20). Results reported in Table 5.4 show that a 10% increase in immigrant stock relative to the

[14]The district cluster is nested into the city one.

city average is correlated with a house price growth that is 0.8% lower with respect to the city average. This effect is however not statistically different from zero.

5.6 Conclusions

In this paper we have summarized some preliminary findings obtained so far in the study of the impact of immigration on house price distribution within Italian metropolitan areas.
First, we have estimated the effect of an exogenous increase in the immigrant population on several indicators of house price distribution. We found a positive effect of immigration on the mean price, which can be mostly ascribed to the raise in the upper two deciles of the price distribution. Second, vary preliminary results from a unique dataset on residential population at the neighborhood level show that an inflow of immigrants is correlated with a within-city reallocation of natives towards areas less affected by immigrant inflows.
All these findings can be (at least in part) explained by the movement of natives from the neighbourhoods affected by the immigrant inflow toward other areas of the same city. This phenomenon is consistent with the huge evidence of residential segregation of immigrants in poorer and less wealthy areas. Although highly preliminary, our results point to a direct causal effect of immigration on segregation, net of any reverse causality or endogeneity issue.
What remains unclear is what drives this effect. We can consider three different causes for it through which immigrants negatively impact on what we name local amenities in our model. First, native outflow may be driven by preference for "ethnic segregation": natives display a ceteris paribus preference for living in an ethnically similar neighbourhood. Second, natives may have preferences for "socio-economic segregation": they prefer to live near individuals of same (or higher) status. Third, immigration may have a detrimental effect on the quality of real estate. This may happen for two reasons: on the one hand, immigrants may have less incentive to invest on the house they live in, maybe because they are likely to remain there for shorter periods with respect to natives; on the other hand, there

may be a lower incentive for the municipal administration to invest in areas where the share of immigrants increase, since in Italy (as in several other countries), non-EU immigrants are deprived of political rights and, thus, have less voice in the local political agenda. We may call this possible channel “political segregation”. Although a precise identification of each channel may be very difficult, it would be extremely important for policy implications. While the presence of socio-economic discrimination may be reduced by policies aimed at improving the economic integration of immigrants, ethnic discrimination may be harder to counter. Political discrimination, in turn, may be reduced by improving the political rights of immigrant residents. Future research to disentangle these different channels is needed.

5.7 Tables and Figures

Table 5.1: OLS estimate of the effect of an immigrant inflow on house prices

	Log Mean Price	Log Max Price	Log Min Price	Log (Max-Min) Price	Coeff. of Var.
Log-Immigrants	0.129	0.130	0.124	0.175	0.071
	(0.025)***	(0.028)***	(0.026)***	(0.063)***	(0.050)
Year Effects	Y	Y	Y	Y	Y
Unobs. Heterogeneity	Y	Y	Y	Y	Y
Overall R-sq.	0.310	0.410	0.155	0.129	0.067
No. of Obs.	4358	4358	4358	4358	4358
No. of FE	672	672	672	672	672

Notes: heteroskedasticity-robust standard errors clustered at the LLM level in parentheses.

Table 5.2: IV estimate of the effect of an immigrant inflow on house prices

	Log Mean Price	Log Max Price	Log Min Price	Log (Max-Min) Price	Coeff. of Var.
Log-Immigrants	0.272	0.303	0.218	0.531	-0.036
	(0.124)**	(0.128)**	(0.159)	(0.315)*	(0.054)
Year Effects	Y	Y	Y	Y	Y
Unobs. Heterogeneity	Y	Y	Y	Y	Y
Adj. R-sq.	0.475	0.483	0.283	-0.322	-0.181
No. of Obs.	4457	4457	4454	4457	4362
No. of FE	670	670	670	670	670
F-test of excl.instr.	53.08	53.08	53.08	53.08	53.08

Notes: heteroskedasticity-robust standard errors clustered at the LLM level in parentheses.

Table 5.3: OLS estimate of the effect of an immigrant inflow on native population at the neighborhood level

Log-Immigrants	-0.025	-0.024	-0.020	-0.020
	(0.004)***	(0.004)***	(0.004)***	(0.004)***
Year Effects	N	Y	Y	Y
City Effects	N	N	Y	Y
Neighborhood Effects	N	N	N	Y
R-sq.	0.04	0.06	0.18	0.34
No. of Obs.	833	833	833	833

Notes: heteroskedasticity-robust standard errors clustered in parentheses.

Table 5.4: OLS estimate of the effect of an immigrant inflow on house prices at the neighborhood level

Log-Immigrants	-0.077
	(0.051)
City x Year Effects	Y
Neighborhood Effects	Y
R-sq.	0.92
No. of Obs.	553

Notes: heteroskedasticity-robust standard errors clustered in parentheses.

Figure 5.1: Trends in Various House Price Indicators - 2003-2009

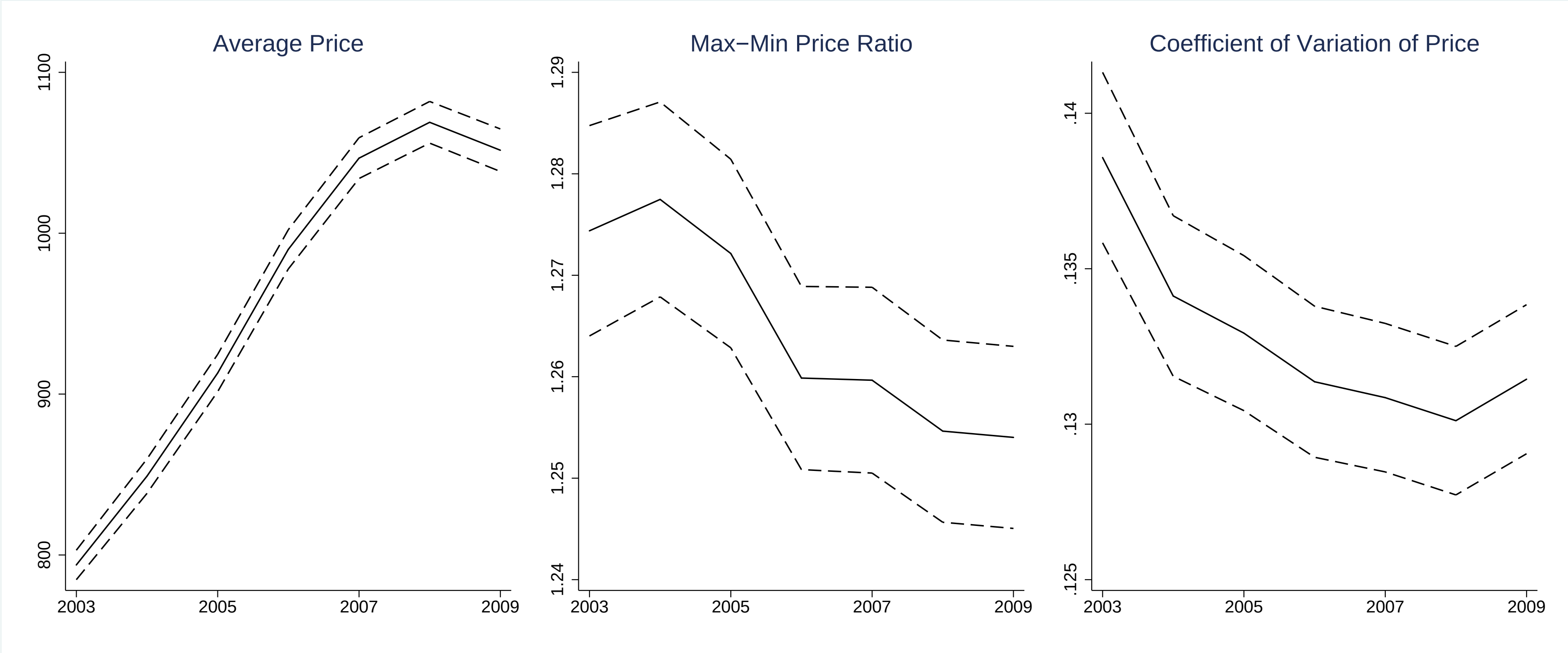


Figure 5.2: Correlation between changes in immigrant and native population - 2003-2009

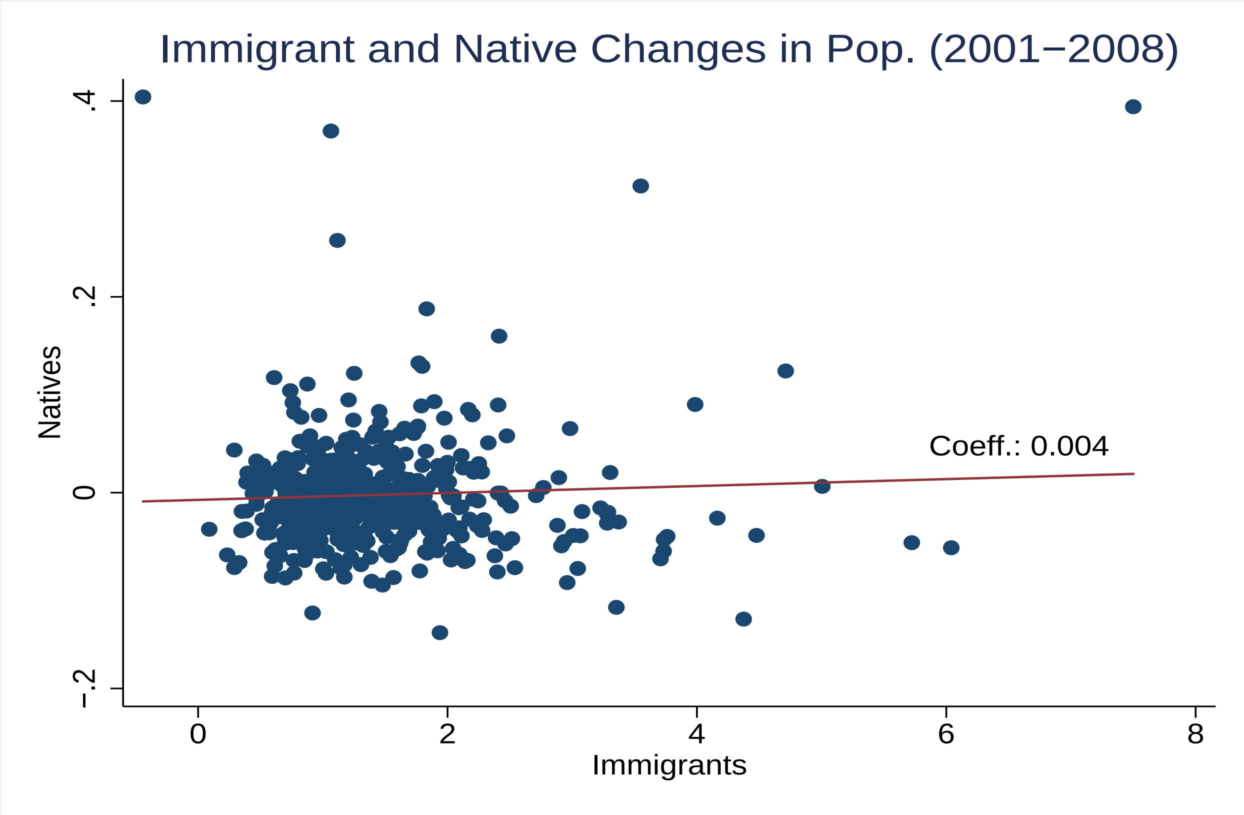


Figure 5.3: Correlation between changes in immigrant population (2003-2009) and house prices in 2003

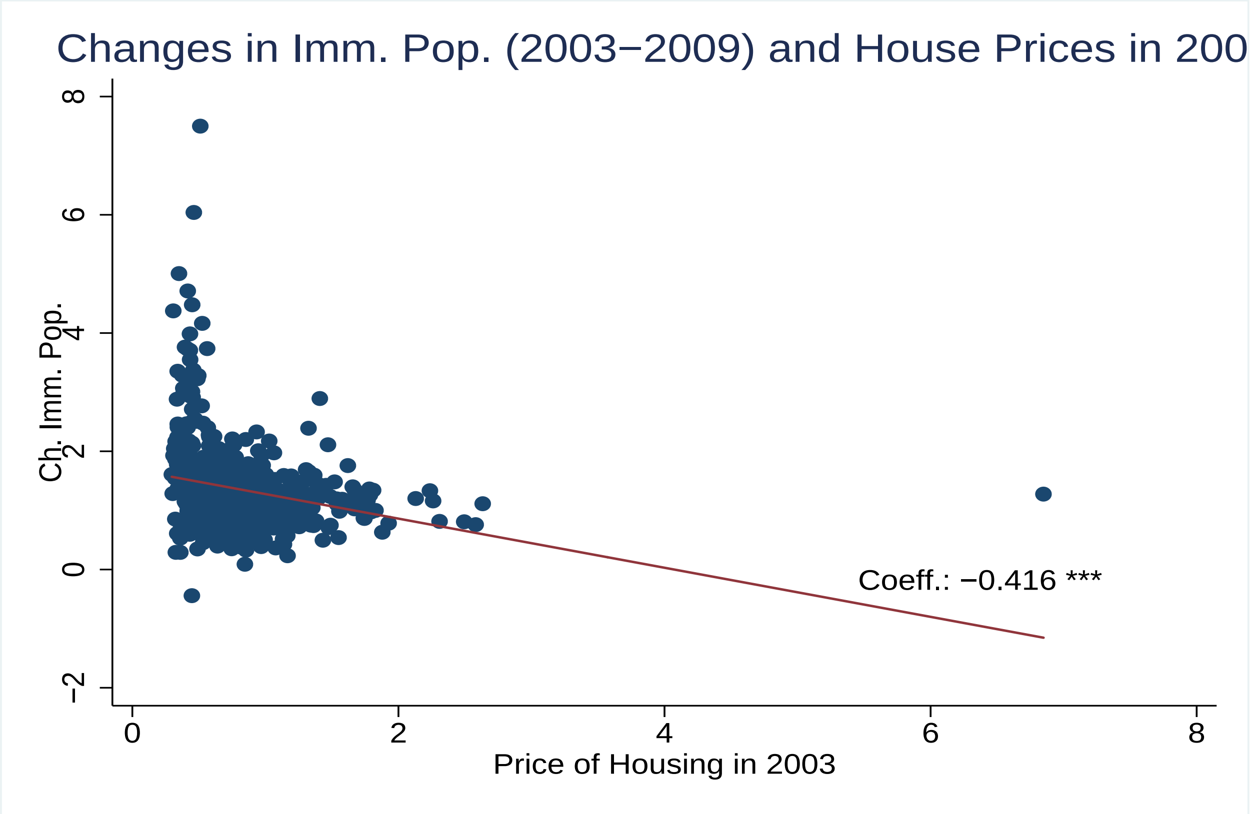


Figure 5.4: Correlation between changes in immigrant population and changes in house prices (2003-2009)

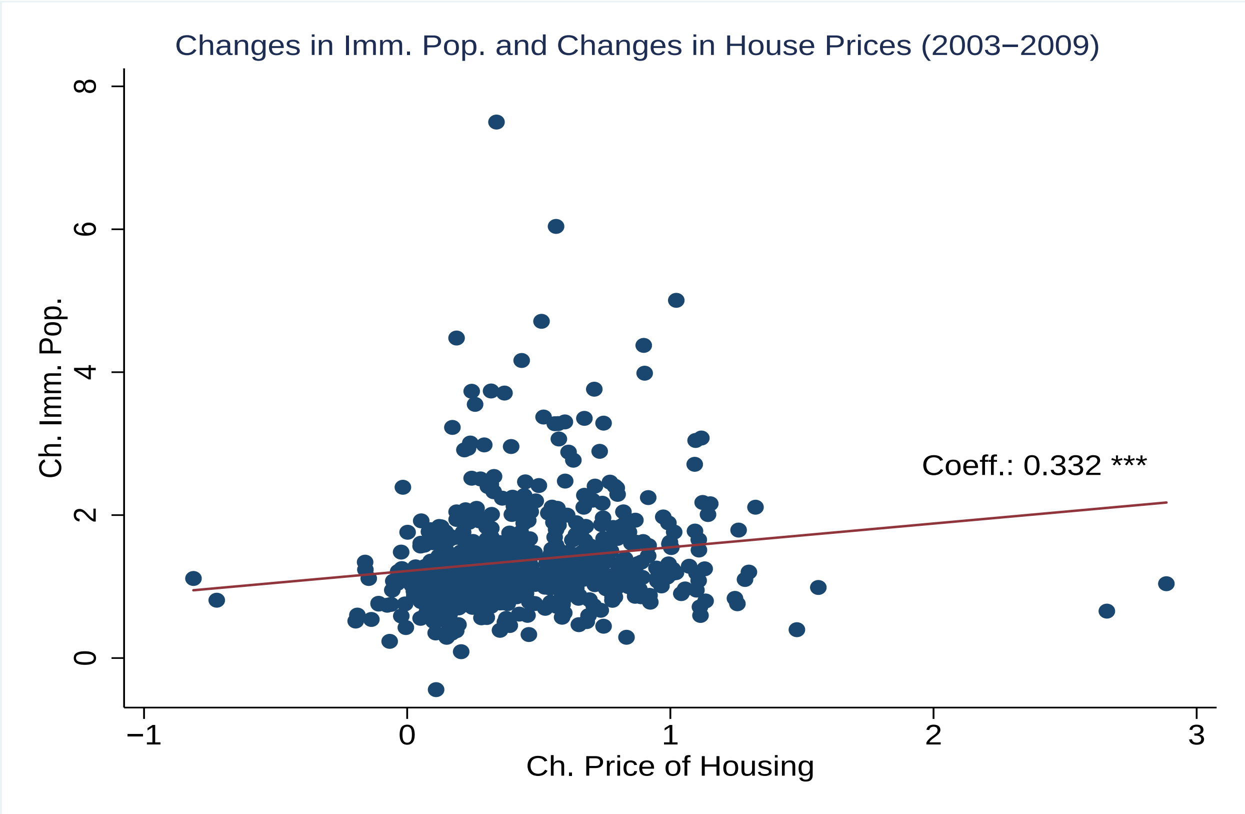


Figure 5.5: Correlation between changes in immigrant population and changes in the coefficient of variation of house prices (2003-2009)

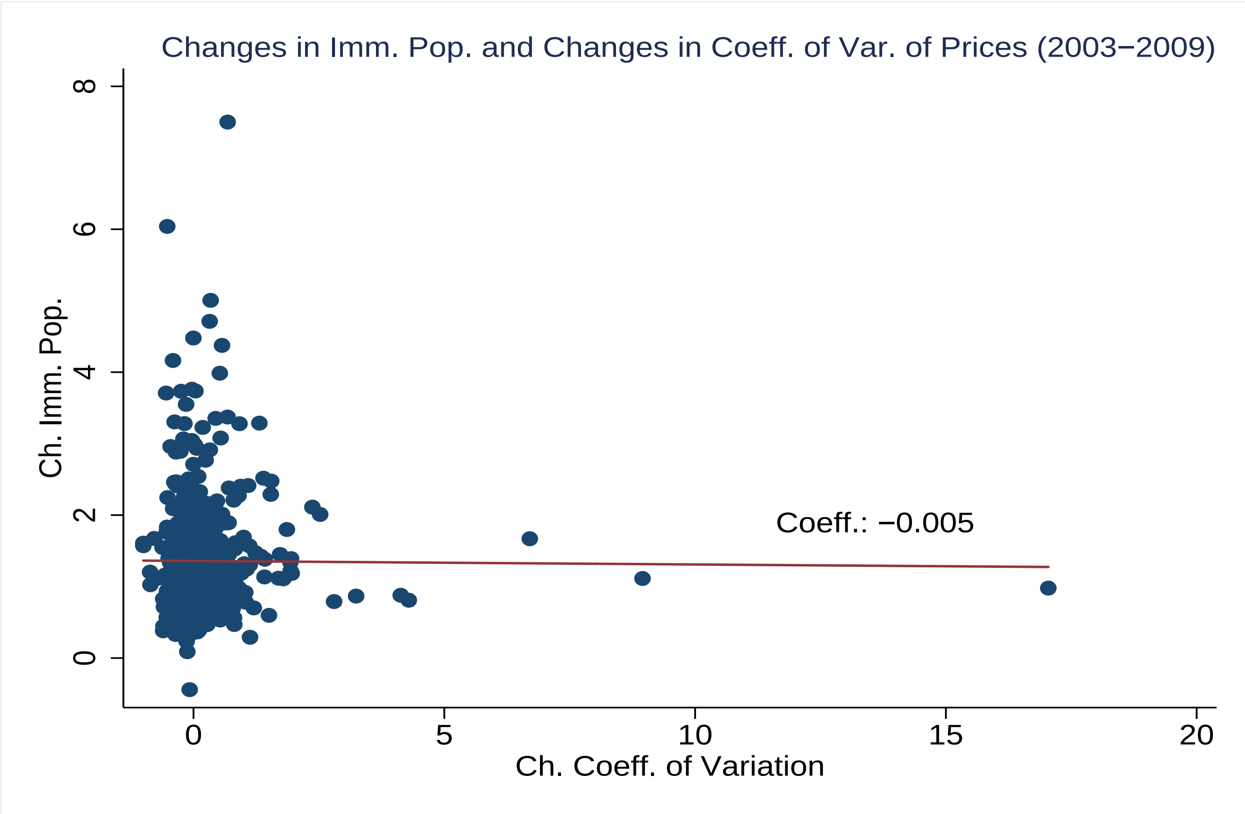


Figure 5.6: Estimates of the quantile treatment effect - IV estimates

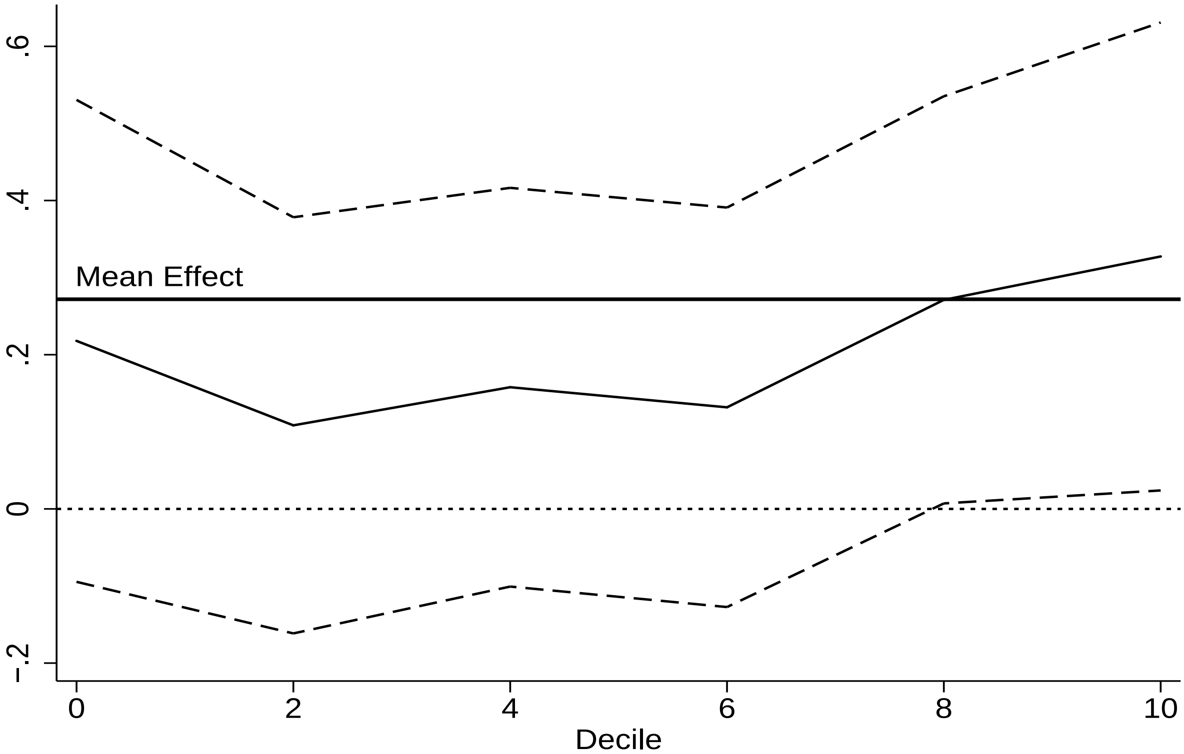
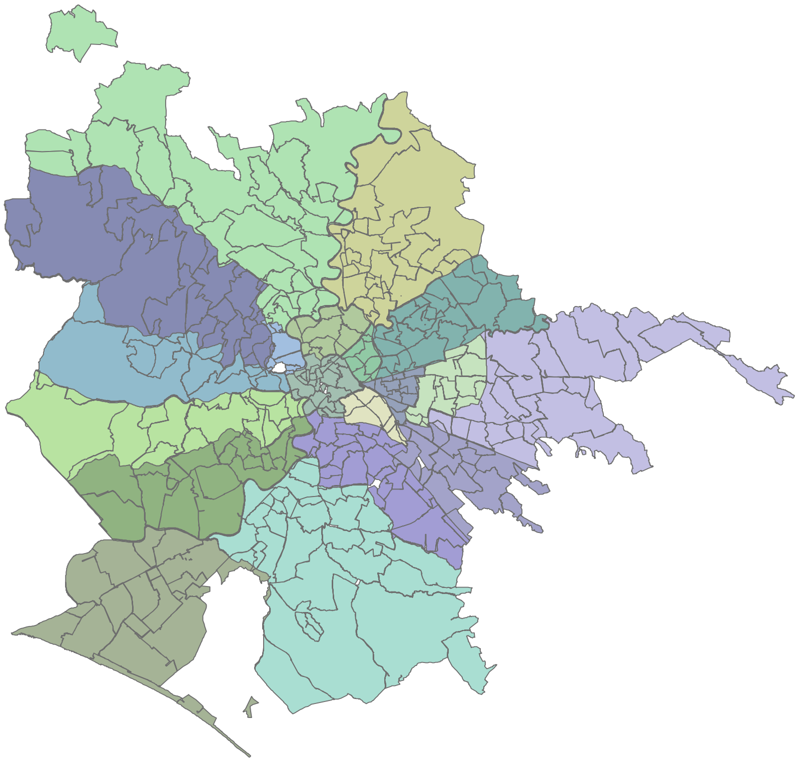


Figure 5.7: Map of Rome - administrative districts (colors) and AdT microzones (lines)



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