THE RESPONSE OF EXPENDITURES TO ANTICIPATED INCOME CHANGES: PANEL DATA ESTIMATES*

Martin Browning and Dolores Collado

WP-AD 99-19

Correspondencia a: Dolores Collado, Universidad de Alicante., Facultad de Ciencias Económicas.
Dpto. Fundamentos de Análisis Económico, Ctra. San Vte. del Raspeig, s/n, 03071 ALICANTE,
E-mail: collado@merlin.fae.ua.es.

Editor: Instituto Valenciano de Investigaciones Económicas, S.A.
First Edition October 1999.
Depósito Legal: V-4232-1999

* We are grateful to participants at a conference in UPF (Barcelona) and at seminars at University College of London and CEMFI (Madrid) for comments.

** Martin Browning: University of Copenhagen; Dolores Collado: University of Alicante.

THE RESPONSE OF EXPENDITURES TO ANTICIPATED INCOME CHANGES: PANEL DATA ESTIMATES

Martin Browning and Dolores Collado

A B S T R A C T

Standard models of intertemporal allocation predict that the time path of expenditures should be independent of the time path of income. Recently two papers, Parker (1999) and Souleles (1999) have suggested that U.S. households have a high marginal propensity to spend within year anticipated income changes. We use an expenditure survey panel from Spain to re-examine this issue. We exploit two important features of the Spanish data. First, we have quarterly panel data that follows households for more than four quarters. Second, we use the fact that workers are exogenously sorted into one of two payment schemes: some receive the same amount each month of the year and others receive an extra payment in June and December. The extra payment is large and predictable. We examine the detailed pattern of expenditures over the year to see whether they differ between the two groups. We fail to find even weak differences. We complement this with a conventional Euler equation analysis of 'excess sensitivity'. Our predicting equation for (quarterly) earnings growth is much better than usual and is likely to give a powerful test of the hypothesis that predictable changes in income do not lead to changes in expenditure patterns. The results of this analysis confirm the graphical analysis: we find no evidence of excess sensitivity. We conclude that households in 'normal' times do 'smooth' consumption over the year. We suggest a reconciliation of our results with those of Parker and Souleles.

KEYWORDS: Consumption; Excess Sensitivity; Smoothing.

1.- INTRODUCTION

The fundamental prediction of standard models of intertemporal allocation is that the shape of the paths of anticipated income and expenditures are independent. This is true whatever the time period considered. Thus over the very short run, whether someone is paid daily, weekly or monthly should be irrelevant for the path of expenditures within the month. Equally over the period of, say, a year or over a span of a few years, the receipt of anticipated bonuses or anticipated changes in income should not have an effect on the pattern of expenditures over the period. Similarly, over the very long run, expenditures in the pre-retirement and post-retirement periods should be independent of the very different income level in the two periods (neglecting non-separabilities between consumption and labour supply). Of course, these predictions are attenuated if we have uncertainty and agents are prudent but still the issue of whether and how much agents smooth consumption is of prime importance for many policy debates[1]. The great power of the standard intertemporal optimising model is that it gives predictions for allocation over the very short run and over the long run, with the same set of preference parameters governing both. Thus evidence that agents fail to 'smooth' at any frequency would be disquieting evidence against the standard model. For example, if we observe agents who are paid monthly and are constantly 'running out' of money at the end of the month we would be suspicious of claims that they nevertheless manage to smooth over, say, the business cycle. Thus it is worthwhile looking at consumption smoothing over different frequencies.

In recent papers Parker (1999) and Souleles (1999) present analyses of the reaction to predictable within year changes in income. They present complementary evidence that expenditures and income within the year are synchronised even when the income changes are anticipated. Parker's analysis is based on the impact of changes in take home pay that result from the pattern of Social Security payments over the year. Souleles uses the receipt of income tax rebates. Using the quarterly U.S. Consumer Expenditure Survey they both find significant increases on some expenditures coincident with the income increases used in the analysis. Parker also finds that these changes are concentrated on semi-durables and goods that can be postponed

---

1 We use the terminology 'consumption smoothing' as a short hand for 'keeping the expected marginal utility of expenditure constant'. This is consistent with the fact that consumption itself is not 'smooth' - at a weekly or annual or life-cycle frequency it may be higher at the weekend or around the end of the year or when there are children in the household, respectively.

more than other goods. This suggests that the timing of buying such goods is partially synchronised to anticipated changes in income. Although these findings could be reconciled with a standard model with liquidity constraints there is also the puzzling aspect that even households with assets display high marginal propensities.

Here we present Spanish panel data evidence that provides an alternative investigation of the link between income and expenditure paths within the year. The Spanish data - the *Encuesta Continua de Presupuestos Familiares* (ECPF) - have two principal advantages over other data on expenditures. First, this is the only large panel data set that gives information on expenditures over more than four quarters. Specifically, we have information for between six and eight quarters for each household on a detailed set of expenditures as well as demographics, incomes and labour force status. As we shall show below, having a fifth quarter of information is essential for controlling for the seasonality and annual effects in our data. For example, in modelling the quarterly earnings process we find that we can predict quarterly differences much better if we have fourth lagged differences. This is critical in increasing the power of tests of excess sensitivity.

The second major advantage of the Spanish data is an institutional feature of the Spanish economy. This is that very many full time workers receive extra payments in Summer (usually at the end of June but at the end of July for some workers) and Winter (mid-December) of each year - effectively twelve unequal payments per year rather than twelve equal payments of the same annual value. The usual practice for workers who receive this 'bonus' is to receive one fourteenth of their annual pay in most months and one seventh in the bonus months. Thus for some workers the path of earnings over the year varies in a large and predictable way. Moreover which payment scheme a worker has is determined by the job and can reasonably be taken to be exogenous to demands. Since the extra Summer and Winter payments are completely anticipated, a standard smoothing model would predict that the expenditure paths over the year of the two types of households will be the same. Given that we can predict income changes almost as well as the agents themselves, this provides a simple yet powerful test of the smoothing hypothesis.

We consider a sample of 'married' households in which the husband is in full-time employment and the wife is not employed for the whole sample period. The restriction to the wife not being in the work force is so that we have only one paid worker in the household who may or may not receive the bonus. We consider these to be households that are in 'normal' times (the husband is always employed); as we discuss in the conclusion, we would not expect the same results for households that are experiencing unemployment.

Contrary to Parker (1999) and Souleles (1999) we do not find any effect of anticipated changes in income on expenditure patterns over the year. In particular, the paths of expenditure patterns over the year for those who receive the bonus payments are indistinguishable from the patterns of those who do not receive a bonus. This is true even for those goods such as holiday expenditures, clothing and durables that are, *a priori*, most likely to be affected. The largely graphical investigation is complemented by a conventional Euler equation analysis with an 'excess sensitivity' test; the latter test strongly suggests that expenditures do not react to large predictable changes. Thus our conclusion is that agents in 'normal' times *do* smooth over the year even if there are large and predictable income changes. In the conclusion we discuss one possible reconciliation of our results with those of Parker and Souleles that emphasises bounded rationality and the fact that the income fluctuations they consider are relatively small and variable from year to year whereas we consider large changes that are the same every year.

2.- THE EMPIRICAL SPECIFICATION

Our sample comes from a representative rolling quarterly panel drawn from the Spanish population, the ECPF; fuller details of this data set are given in the Appendix. The maximum length any household stays in the panel is eight quarters but not all households completed a full cycle so we select out households that did not give at least six contiguous quarters of information. The first wave of the data was collected in the first quarter of 1985 and the final wave we have available was collected in the fourth quarter of 1995. We consider only households headed by a married couple in which the husband is in full time employment[2] and the wife is out of the labour force; the Appendix presents the exact selections made and the effects on sample size. The household may contain children and other adults. We shall allow for variations in these in our analysis.

The timing of the income and expenditure values in our data is important for our tests and somewhat complex. In each quarter (January-March, April-June, July-September and October-December) there are eight one week survey periods, beginning in the first full week of the quarter

2 But note that the employment variable refers only to the interview week within the quarter; it is possible that some of our sample experience spells of unemployment outside the survey week. The fact that husbands have to be in full-time employment at all interviews, however, suggests that this will not be a common occurrence.

and spread out evenly across the quarter. A participating household is interviewed in the same week in successive quarters. Thus in each year we have information from 32 weeks spread more or less equally across the whole year. There are four contacts with the household around each survey period (week). In the first interview (which actually takes place the day before the survey week starts), the interviewer explains the questionnaires and the household is asked about current labour force status and demographics. The household is also given diaries for each adult member to keep a log of all expenditures in the coming week. In the second visit, information is gathered on expenditures on a range of small durables and clothing in the three weeks immediately before the first interview. In the third visit, information on the income and earnings of the adult members of the household and expenditures on a range of large durables and cars in the three full calendar months prior to the first interview is collected. At the fourth interview, which takes place at the end of the survey period, the completed diaries are collected and some information is checked. In the data we have, the diary expenditures on clothing, small durables and large durables are added to the values collected at the beginning of the survey week to give aggregated expenditures over one month or three months respectively. To give an example, suppose the first interview takes place on June 12. Then the expenditure data on non-durables and services relates to June 13-19; the clothing expenditures relate to the four weeks ending June 19 and the income information relates to the calendar months March, April and May. Given this survey design, we can relate the timing of income and expenditures to each other with reasonable precision.

The power of our test of the smoothing hypothesis relies on the existence of a particular feature of the Spanish pay system. During our sample period the great majority of workers were paid monthly. Some firms paid a regular worker the same amount in each month of the year. Other firms paid out more in a Summer month and December than was paid in the other months - we refer to this as a bonus scheme (but note that payment of the bonus is *not* performance related). The most common schedule for bonus schemes was to pay one fourteenth of the annual salary each month and then to pay double the usual monthly amount in December and June or July. Sometimes the extra gross pay in these months was less than double (with a corresponding increase in the other months). Finally, Social Security payments are withheld on a regular monthly basis with one twelfth of the expected annual payment being made each month. Consequently, the net of deductions payments in June and December may be more than double the net of taxes payments in other months.

Generally a worker has no discretion over which payment scheme he is in. Assuming that the choice of job is independent of the payment scheme chosen, we can take the sorting into the two groups to be exogenous to the seasonal demand pattern. However, some firms did offer workers a choice of the payment schedule they want. This latter introduces a potential correlation between idiosyncratic differences in seasonal patterns of expenditures and whether a worker participates in the bonus scheme. Assuming that workers who have a more seasonal pattern of expenditures would be more likely to participate in the bonus scheme, this introduces a possible correlation between monthly expenditures and anticipated monthly income changes. That is, this selection biases us toward finding that seasonal patterns are synchronised with earnings. Since we do not find any such effect, our conclusion is that this selection into the bonus scheme is not a problem.

In Figure 1 we present a histogram of the quarterly difference in the husband's log real net of tax earnings reported in the first quarter. Since earnings reports are for the three full months previous to the survey, these reports (made in January, February or March) should all include December. As can be seen, the distribution has two modes at about zero and 0.285 (= ln(4/3)), with a somewhat larger proportion in the higher mode. This reflects the payment structure we exploit and the fact that a majority of full-time workers in the economy participate in the bonus scheme (and receive four payments in the bonus quarter as against three in non-bonus quarters). For our analysis we also need to identify whether the husband in a particular household participates in the bonus scheme; this is not recorded in the original survey so we need to infer it from the earnings path. To do this we use information on the quarterly earnings change. Thus, a household that receives a December (respectively, June) bonus would report a large first quarter change in all three months of quarter I (respectively, III)[3]. For a given household, the exact number of such changes we could observe depends on when in the year the household joins the survey and whether the household stays in the survey for six, seven or eight quarters. If the household is a 'bonus household' the earnings changes across these quarters should all be of the order of 30%. We could use a strong criterion and classify households as bonus households only if they report large positive changes in all the first and third quarters in which we observe them.

[3] In practice our classification is complicated by the fact that some households receive their Summer bonus in July (the first month of quarter III) rather than June (the last month of quarter II). To simplify the exposition we ignore this here but we take account of it in constructing our 'bonus household' dummy variable. Indeed, we drop the 'July' bonus households to give us a cleaner sample (see the Data Appendix for details).

We prefer the weaker criterion of classifying households as 'bonus households' if they have at least a 15% earnings change in all or all but one of these transitions. To be sure, this mis-classifies some households (for example, workers who change jobs and move between the two schemes will usually be classified as non-bonus) but we believe that the effect of this is fairly small. To illustrate why we think this, in Figure 2 we present the mean quarterly change in log real earnings against the week of the survey for bonus and non-bonus households. It will be clear from this figure that the average bonus household displays a very strong seasonal pattern whilst the non-bonus households have a much smoother earnings path over the year (albeit with some residual bonus-like pattern due to 'non-bonus' households receiving an extra payment now and then - perhaps because of a change of job). Our basic test is to see whether expenditures patterns across the year also display significant differences between the two groups. We shall supplement this (largely graphical) analysis with a conventional 'excess sensitivity' test using an Euler equation analysis. We have tried a wide variety of other sample splits for bonus/non-bonus households and they all give the same qualitative results as the sample split described here.

To set up the Euler equation analysis, let expenditure on good i in month t by household h be denoted by x_{iht}. The quarterly change in the log of this demand is modelled using a conventional iso-elastic specification (see, for example, Browning and Lusardi (1996)):

$$\Delta \ln(x_{iht}) = \alpha_i + \sum_k \delta_{ik} \Delta z_{kht} + \sum_j \beta_{ij} \Delta \ln(p_{jt}) + \beta_{i0} r_t + \varepsilon_{iht}$$

where Δ is the first difference operator, p_{jt} is the absolute price of good j in quarter t (assumed common across households sampled in the same quarter), r_t is the (common) nominal interest rate between periods (t-1) and t and z_{kht} is the level of demographic k in quarter t. If we allow for white noise measurement error and taste shocks then the error term may be correlated with once lagged information so we assume only that the error term is uncorrelated with all information dated (t-2) and earlier.

The most conspicuous missing set of variables from the right hand side of the Euler equation above are any controls for seasonality. There are two basic reasons why our expenditure variables will display seasonal variation. The first is that there is (exogenous) variation in demand due to, for example, Christmas (which leads to a higher demand for food, toys and alcohol) or expenditures on holidays in August (the traditional holiday period in Spain). The other source of seasonal variation in expenditures comes from seasonal variations in prices which are only partially captured in our (quarterly) price indices. For example, January sales traditionally start on January 7 and last until the end of February. To capture seasonal variation we construct 32 dummies for the survey weeks in our data (remember, these 32 weeks are more or less equally spaced across the year with eight survey weeks in each quarter). In our analytical analysis we include these dummies in equation (1). However, we found a less formal graphical analysis more revealing so we turn first to this. In this analysis we first run the regression in the Euler equation for each of our goods[4]. We then take averages of the residuals for the bonus and non-bonus groups within each week. Finally we plot these two series against the interview week. Our graphical 'test' is then to see whether, for any good, there are significant differences between the plots for bonus and non-bonus households.

3.- RESULTS

The commodity groups we construct for use in our analysis are largely determined by prior guesses about which goods might be sensitive to anticipated income changes. The four main commodities (and frequencies) we consider are clothing (a monthly sample period), large durables (cars, white goods, electronic goods, large furniture etc. which have a quarterly sampling period), small durables (pillows, books, toys etc. which have a monthly sampling period) and holiday expenditures (quarterly). As well as these goods we shall also consider 'food' (food at home, food outside the home, alcohol and tobacco) and 'other non-durables' (other non-durables and services). Our prior was that these aggregates were less likely to be affected by the pattern of income over the year. Finally, we also consider the sum of all these expenditures, 'total expenditures' (all expenditures except for housing). We do not consider housing since mortgage payments are not recorded for homeowners.

In figure 3 we plot the path of (real) expenditures on food, alcohol and tobacco against the survey week for our two groups. The first thing to notice about these paths is that there is a distinct seasonal pattern with high expenditures for the final weeks of the year (reflected in high

[4] In doing this by OLS we are implicitly assuming that there are no price or demographic shocks. Instrumenting the variables on the right hand side made no discernible difference to the graphs we present so we prefer the simpler OLS procedure. In the more formal analysis presented later we do take account of possible endogenetic.

reports in the first weeks and large negative residuals one quarter later). There are not, however, any discernible differences between the seasonal patterns of the two groups. The same is true of 'other non-durables and services', see figure 4. This is as we expected: household demand patterns for non-durables are independent of the payment schedule. What of the goods for which we did expect some differences? In figure 5 we plot the seasonal patterns for clothing. The January sale effect is very prominent as is a Christmas and Summer buying peak but there are no differences between the two groups. This figure provides strong evidence that the seasonal patterns of purchases is independent of whether the household is a 'bonus' household or not. The same is true for 'small durables' (figure 6) and 'large durables' (figure 7). Of particular interest is holiday expenditure since the Summer bonus is ostensibly to help with these expenditures. In practice, holiday expenditures tend to be spread out across the year since payments for much of the cost of holidays is made in advance. Although there is a very distinct increase in August (see figure 8) once again there is no difference between 'bonus' and 'non-bonus' groups. Finally we present the seasonal pattern of expenditures on all items (except housing); see figure 9. Given the foregoing results it will be no surprise that the total expenditure patterns of the two groups are virtually identical.

To complement the graphical analysis of residuals we also present a conventional Euler equation test of excess sensitivity. To do this we add quarterly earnings growth and 31 week dummies (to control for seasonality - we exclude the dummy for week 8 which is at the end of the first quarter) to the Euler equation above and instrument for all right hand side variables except for the weekly dummies and the change in the number of children and adults (it is assumed that these are perfectly anticipated). As discussed we use only second or longer lagged variables as instruments (except for the anticipated variables). Since we use fourth lags of first differenced variables in the instrument set we can only use interview six and later information in the regression. The exact list of instruments can be seen by referring to Table 1 which presents the auxiliary equation for earnings growth. The OLS estimates here have two noteworthy features. First the fit is far better than we usually observe in an earnings change equation: an R^2 of 0.485 as against the usual value of 0.02 or thereabouts. This is because the major changes in earnings from quarter to quarter are due to the bonus system for those who have it. Thus we can predict quarter to quarter earnings changes very well. This is in contrast to the usual situation where we usually have annual data and most changes are lost in the noise due to measurement error. The second noteworthy feature of the parameter estimates is related to this: the 'most significant' predictors (apart from the week dummies) are the twice and fourth lags of earnings growth and these variables crossed with the bonus dummy. This shows the importance of having a fifth quarter for the panel; if we had only four quarters (as in the U.S. CEX) then we would not predict earnings growth so well. This is not only because of the bonus scheme but also because workers in steady jobs tend to receive pay rises once a year, almost always in the same month. The fact that we predict earnings growth well means that our test of excess sensitivity is more powerful than usual tests; this has been the principal objection to the results of those papers that do not find any excess sensitivity.

In Table 2 we present Euler equation estimates for our six commodity groupings and for total expenditure as whole. Since we have the total expenditure price index on the right hand side the latter can be thought as a conventional consumption Euler equation whereas the first equation - for food (and alcohol and tobacco) - is analogous to the Euler equation usually estimated on the PSID. We shall not discuss in detail the substantive implications of the parameter estimates. For example, we have made no attempt to impose any theoretical restrictions. We simply observe that in no equation does the expected earnings growth variable have a t-value of greater than 1 (in absolute value). Furthermore, the over-identification test does not reject for any commodity grouping[5]. If the argument concerning the power of our test is accepted then this points unequivocally to the conclusion that *for this sample* we do not observe any excess sensitivity to (large) predictable earnings changes. Unfortunately the data available do not allow us to split the sample on assets at the beginning of the period but tests on a low income sub-sample (the bottom one third of the sample by income averaged over the time spent in the panel) revealed very similar results.

4.- CONCLUSIONS

We have used a unique expenditure panel data set from Spain to examine whether the demands of households react to predictable and large changes in household income within the year. We find that for our sample of households in which the husband is in full-time employment

5 We have also conducted a similar analysis using just 'bonus' households. This provides a potentially more powerful test of excess sensitivity. The qualitative results were the same as for the sample discussed above: there is no evidence of excess sensitivity.

at all the interviews of the panel, there is no evidence of any synchronisation between the income flow in the year and expenditures in the year. We emphasise the sample selection. These are households who are least likely to be in temporarily straitened circumstances; our results may not hold for households in which one member is experiencing a spell of unemployment. Although we could investigate smoothing by households with a member experiencing unemployment, this would take us away from using the differences that arise from being 'permanently' in different pay schemes so we leave this for later work.

On the face of it, our empirical finding appears contrary to those of Parker (1999) and Souleles (1999). Note, however, that when Souleles replaces income changes with expected income changes - that is, the analogue to our conventional Euler equation approach above - he does not find any significant effect for any group of goods[6]. This suggests that it may be that households in the U.S. samples treat these income changes as unanticipated although, as Parker notes, to reconcile this conclusion with a conventional 'full adjustment' smoothing story, we must believe that households regard the changes as partly permanent. Nevertheless, it may be that one or the other set of results is inadvertently confounding the 'experimental' effect with some (as yet undetected) contamination.

If our results are different, there are many possible reasons why. First, our samples are from different countries but we are reluctant to advance this as an explanation of the differences. Second, we condition on being in full-time employment for the whole sample period (between eighteen and twenty four months) and Parker and Souleles have no such sample exclusion. Thus their samples contain households who we might expect to be sensitive to the timing of income. On the other hand, when Parker and Souleles split their samples along conventional high/low asset lines they do not find any evidence that low asset households are markedly more sensitive to earnings changes. One possible reconciliation builds on Parker's suggestion that his results may be due to households using bounded rational procedures so that they do not bother to adjust optimally to small income changes since the utility cost, particularly for durables and semi-durables, is small. That would be consistent with our results since for us the very fact that the income changes are large (a doubling from one month to the next) means that treating the changes as unanticipated would impose a large welfare cost. Additionally, the mechanics of the income

6 Parker does not present any results that can strictly be considered instrumental variables estimates. In our sample, when we do not instrument income changes (that is, follow Souleles and Parker) we find that food and total expenditure do respond to the income changes, albeit with 't-values' only slightly above 2.

changes we exploit are transparent and occur in the same form year after year whereas the changes that Parker and Souleles consider are relatively small and variable fluctuations that come at different times of the year. Thus the benefits of making the optimal expenditure calculations in our income scheme are large and the costs are small and for the Parker and Souleles income processes the converse is likely to be the case.

Whether the explanation given at the end of the previous paragraph is valid requires more theoretical and empirical investigation. If it is correct then it means that although households might not smooth over small within year income changes that are anticipated, they will take account of large changes, particularly if the latter are transparent. Thus they will take care to plan optimally for, for example, the fall in income consequent on retirement. In the end, though, our empirical analysis is presented more to highlight that the finding that households do ‘over react’ to anticipated changes in within year income is not yet well established.

Table1 Quarterly earnings growth (OLS)	
Δ number of children	-0,0555 (-1,6623)
Δ number of adults	-0,0136 (-0,7515)
Age of husband	-0,0005 (-2,0303)
Age*(University dummy)	0,0001 (0,3203)
Age*(High school dummy)	0,0000 (-0,1488)
Nominal interest rate (-4)	2,7512 (1,8754)
Inflation rate for food, alcohol and tobacco (-4)	2,7162 (1,0556)
Inflation rate for clothing (-4)	1,2156 (2,4591)
Inflation rate for small durables (-4)	-0,1470 (-0,3314)
Inflation rate for large durables (-4)	-0,4607 (-0,8556)
Inflation rate for holidays (-4)	-0,3734 (-1,5494)
Inflation rate for other non-durables and services (-4)	0,5289 (0,4235)
Inflation rate for total expenditure (-4) dlpall4	-5,8758 (-1,0690)
Δ ln(earnings) (-2)	-0,1457 (-3,4526)
Δ ln(earnings) (-3)	0,0160 (0,3660)
Δ ln(earnings) (-4)	-0,0225 (-0,8808)
(Δ ln(earnings)* (Bonus dummy)) (-2)	0,3087 (6,4027)
(Δ ln(earnings)* (Bonus dummy)) (-3)	-0,0205 (-0,3342)
(Δ ln(earnings)* (Bonus dummy)) (-4)	0,2324 (6,0966)
Week 1	-0,1039 (-4,1841)
Week 2	-0,0977 (-3,7556)
Week 3	-0,0186 (-1,0148)
Week 4	-0,0180 (-1,0630)
Week 5	-0,0321 (-1,5020)
Week 6	-0,0099 (-0,7094)

Table 1 (cont.) Income growth (OLS)	
Week 7	-0,0023 (-0,1616)
Week 9	-0,0996 (-3,2414)
Week 10	-0,1435 (-2,6539)
Week 11	-0,2082 (-7,2450)
Week 12	-0,2329 (-8,0203)
Week 13	-0,2606 (-8,1198)
Week 14	-0,2179 (-7,0750)
Week 15	-0,2456 (-8,1336)
Week 16	-0,2547 (-8,5775)
Week 17	-0,1908 (-6,6785)
Week 18	-0,1457 (-4,5924)
Week 19	-0,0821 (-2,7525)
Week 20	-0,1151 (-3,3247)
Week 21	0,0132 (0,4426)
Week 22	-0,0114 (-0,4338)
Week 23	-0,0095 (-0,3563)
Week 24	-0,0059 (-0,2339)
Week 25	-0,2287 (-6,7206)
Week 26	-0,1814 (-5,2195)
Week 27	-0,2609 (-10,0386)
Week 28	-0,2044 (-6,8544)
Week 29	-0,3044 (-11,5347)
Week 30	-0,2916 (-10,4507)
Week 31	-0,3173 (-11,8818)
Week 32	-0,3091 (-10,5268)
Constant	0,1552 (5,3077)
R^2	0.485

Table 2
Euler Equations

	Clothing	Small durables	Large durables	Holidays	Food	Non-durables	Total expenditures
dnch	0.100 (1.639)	0.079 (1.628)	-0.040 (-0.502)	-0.003 (-0.126)	0.073 (1.588)	0.002 (0.027)	0.035 (0.731)
dnad	0.113 (2.142)	0.061 (1.462)	-0.046 (-0.698)	-0.007 (-0.526)	0.018 (0.508)	0.038 (0.894)	0.036 (0.962)
it	-2.322 (-0.178)	-5.150 (-0.503)	-16.643 (-0.937)	-1.790 (-0.307)	4.763 (0.454)	-24.140 (-1.632)	-11.636 (-1.143)
dlpfat	-0.608 (-0.027)	0.934 (0.051)	7.902 (0.240)	-11.760 (-1.080)	9.558 (0.512)	22.511 (0.846)	13.264 (0.723)
dlpclo	-1.411 (-0.095)	-2.646 (-0.228)	5.834 (0.280)	-7.614 (-1.148)	0.866 (0.072)	11.333 (0.660)	6.549 (0.570)
dlpsdur	1.327 (0.586)	1.387 (0.802)	-4.280 (-1.316)	-0.940 (-0.675)	2.294 (1.226)	1.581 (0.610)	0.446 (0.241)
dlpdur	-5.093 (-0.402)	-0.671 (-0.069)	-18.122 (-0.995)	-10.202 (-1.654)	7.470 (0.718)	2.535 (0.165)	-3.695 (-0.362)
dlphol	-1.580 (-0.469)	-0.214 (-0.081)	-5.045 (-1.025)	-2.103 (-1.310)	2.391 (0.873)	-0.245 (-0.061)	-1.394 (-0.501)
dlpnds	-1.629 (-0.075)	-1.527 (-0.089)	10.549 (0.345)	-10.973 (-1.113)	-1.045 (-0.059)	21.425 (0.852)	9.069 (0.532)
dlpall	10.827 (0.148)	7.513 (0.130)	-21.626 (-0.207)	39.321 (1.166)	-10.567 (-0.176)	-56.718 (-0.666)	-25.777 (-0.445)
dly	-0.026 (-0.162)	-0.026 (-0.222)	0.202 (0.899)	0.039 (0.583)	0.052 (0.405)	-0.035 (-0.212)	0.068 (0.543)
Week 1	0.369 (3.986)	0.106 (1.405)	-0.162 (-1.062)	-0.063 (-2.364)	0.221 (2.516)	0.014 (0.127)	0.192 (2.102)
Week 2	0.385 (4.465)	0.336 (5.053)	-0.188 (-1.599)	-0.057 (-1.522)	0.201 (2.954)	-0.035 (-0.279)	0.274 (3.656)
Week 3	0.232 (3.210)	0.202 (3.280)	-0.084 (-0.792)	-0.043 (-1.961)	0.210 (3.954)	-0.115 (-1.315)	0.175 (3.044)
Week 4	0.181 (2.895)	0.202 (4.398)	-0.036 (-0.470)	-0.034 (-1.725)	0.115 (2.471)	-0.075 (-1.158)	0.143 (2.965)
Week 5	0.064 (1.013)	0.182 (3.961)	-0.038 (-0.460)	-0.028 (-1.718)	0.176 (3.230)	-0.017 (-0.253)	0.131 (2.605)
Week 6	0.052 (0.845)	0.150 (3.051)	0.083 (0.990)	-0.030 (-1.526)	0.113 (2.118)	-0.063 (-0.923)	0.127 (2.305)
Week 7	0.033 (0.538)	0.071 (1.463)	-0.060 (-0.810)	-0.025 (-1.436)	0.075 (1.545)	-0.062 (-0.967)	0.052 (1.098)
Week 9	0.183 (0.337)	0.067 (0.157)	0.429 (0.556)	0.347 (1.397)	-0.058 (-0.130)	0.057 (0.088)	0.203 (0.466)
Week 10	0.363 (0.653)	0.015 (0.034)	0.477 (0.616)	0.365 (1.436)	-0.027 (-0.059)	-0.019 (-0.028)	0.256 (0.582)
Week 11	0.355 (0.651)	0.081 (0.191)	0.492 (0.638)	0.386 (1.550)	-0.034 (-0.076)	0.048 (0.075)	0.294 (0.678)
Week 12	0.397 (0.744)	0.134 (0.323)	0.457 (0.605)	0.335 (1.368)	-0.029 (-0.066)	0.011 (0.017)	0.332 (0.778)
Week 13	0.492 (0.899)	0.229 (0.537)	0.546 (0.701)	0.365 (1.448)	-0.051 (-0.115)	-0.088 (-0.135)	0.360 (0.818)
Week 14	0.682 (1.222)	0.186 (0.424)	0.568 (0.718)	0.367 (1.432)	-0.001 (-0.003)	-0.003 (-0.005)	0.463 (1.038)

Table 2 (cont.) Euler Equations							
	clothing	Small durables	durables	Holidays	Food	Non-durables	Total expenditures
Week 15	0.609	0.158	0.451	0.358	-0.011	-0.019	0.368
	(1.120)	(0.375)	(0.588)	(1.432)	(-0.024)	(-0.029)	(0.846)
Week 16	0.629	0.224	0.515	0.340	0.019	-0.152	0.389
	(1.168)	(0.537)	(0.679)	(1.375)	(0.045)	(-0.238)	(0.908)
Week 17	0.503	0.177	0.379	0.164	-0.035	-0.022	0.347
	(2.419)	(1.121)	(1.258)	(1.720)	(-0.209)	(-0.086)	(1.961)
Week 18	0.450	0.132	0.427	0.112	-0.024	0.092	0.383
	(2.470)	(0.940)	(1.600)	(1.386)	(-0.162)	(0.414)	(2.420)
Week 19	0.354	0.123	0.451	0.088	-0.012	0.070	0.348
	(1.750)	(0.799)	(1.538)	(0.946)	(-0.072)	(0.283)	(2.003)
Week 20	0.400	0.102	0.356	0.160	-0.098	0.059	0.279
	(2.056)	(0.696)	(1.286)	(1.759)	(-0.637)	(0.249)	(1.680)
Week 21	0.293	0.040	0.399	0.132	0.085	0.127	0.376
	(1.622)	(0.292)	(1.529)	(1.608)	(0.601)	(0.576)	(2.406)
Week 22	0.253	0.176	0.491	0.205	0.019	0.223	0.413
	(1.279)	(1.193)	(1.696)	(2.157)	(0.119)	(0.937)	(2.421)
Week 23	0.262	0.122	0.466	0.150	-0.056	0.085	0.310
	(1.398)	(0.884)	(1.766)	(1.814)	(-0.366)	(0.373)	(1.954)
Week 24	0.287	0.097	0.264	0.143	-0.096	0.150	0.236
	(1.493)	(0.658)	(0.947)	(1.640)	(-0.620)	(0.631)	(1.424)
Week 25	0.190	0.222	-0.083	0.003	0.240	0.028	0.200
	(1.738)	(2.638)	(-0.601)	(0.047)	(2.561)	(0.221)	(2.250)
Week 26	0.056	0.064	-0.037	0.060	0.113	-0.003	0.116
	(0.510)	(0.672)	(-0.217)	(0.906)	(1.211)	(-0.019)	(1.145)
Week 27	0.212	0.120	-0.038	0.032	0.179	-0.024	0.124
	(2.071)	(1.493)	(-0.243)	(0.628)	(1.940)	(-0.207)	(1.384
Week 28	0.304	0.160	-0.083	-0.020	0.245	0.066	0.232
	(3.156)	(2.076)	(-0.639)	(-0.441)	(2.914)	(0.615)	(2.930)
Week 29	0.380	0.056	-0.227	-0.036	0.175	-0.079	0.085
	(3.393)	(0.669)	(-1.430)	(-0.743)	(1.922)	(-0.642)	(0.938)
Week 30	0.337	0.072	-0.320	-0.140	0.188	-0.157	0.021
	(3.188)	(0.877)	(-2.087)	(-2.324)	(1.972)	(-1.291)	(0.225)
Week 31	0.355	0.159	-0.097	-0.082	0.364	-0.025	0.257
	(3.207)	(1.794)	(-0.630)	(-1.649)	(3.755)	(-0.211)	(2.864)
Week 32	0.383	0.188	-0.204	-0.079	0.379	-0.174	0.231
	(3.464)	(2.231)	(-1.349)	(-1.744)	(4.021)	(-1.510)	(2.611)
const	-0.331	-0.128	0.322	-0.049	-0.262	0.346	-0.060
	(-0.910)	(-0.454)	(0.657)	(-0.326)	(-0.909)	(0.842)	(-0.214)
Sarg. test df = 8	9.701	4.760	3.701	5.312	8.660	9.721	7.899

Data Appendix

The *Encuesta Continua de Presupuestos Familiares* (ECPF) data set is a rotating panel that is conducted every quarter by the Spanish Statistics Office (INE). It covers forty four quarters, from first quarter 1985 to last quarter 1995. We observe households for at most eight consecutive quarters, but there is an important percentage of household not completing all the interviews. The number of observations in the original data set is 136,120 and the distribution of households according to the number of interviews is the following:

Table A1

Number of Interviews	Number of Households
1	4323
2	2974
3	2519
4	2853
5	2866
6	2423
7	2324
8	7718
Total	28000

For the purpose of this research, we have only considered households reporting full information for at least six consecutive quarters; this gives 12,465 households. We have selected couples with or without children, with this sample selection we lose 2735 households (20287 observations). We have only considered households with the husband in full-time employment (we lose 4271 households, 31758 observations) and the wife out of the labour force (we lose 2117 households, 15800 observations). We have also excluded from our sample agricultural and self-employed workers, with this selection we lose 1035 households (7666 observations). We have also deleted household reporting zero earnings (37 household, 269 observations) and those reporting zero expenditures on ‘other non-durables’ (2 households, 14 observations). In our sample all the households report positive expenditures on food in every quarter. Finally, we have also excluded people receiving a bonus in July (499 households, 3703 observations). Our final data set contains 1769 households (13053 observations); the distribution of households according to the number of interviews is the following:

Table A2	
Number of Interviews	Number of Households
6	375
7	349
8	1045
Total	1769

The data set provides detailed information on quarterly expenditures, income and household characteristics. Summary statistics for the variables that we have used in this study are provided in the table below. We use quarterly expenditures and income in 1995 pesetas.

Table A3
Descriptive Statistics (1995)

	mean	St. dev.	Min.	Max.
Number of adults	2.87	1.04	2	8
Number of children	1.23	1.04	0	5
Husband's age	44.11	9.45	21	66
Clothing	68,192	77,281	0	622,956
Small durables	34,869	76,500	0	1,462,086
Large durables	62,609	189,073	0	2,214,735
Holidays	5,777	28,604	0	324,900
Food	271,103	146,519	29,770	1,047462
Other non-durables	213,394	171,090	19,196	1,799,332
Total expenditures	825,199	454,136	188,806	3,704,017
Husband's earnings	550,377	218,900	76,350	1,950,000

	Education level
Univ. degree	8.26 %
High school degree	37.66 %

Figure 1: Fourth quarter differenced log earnings

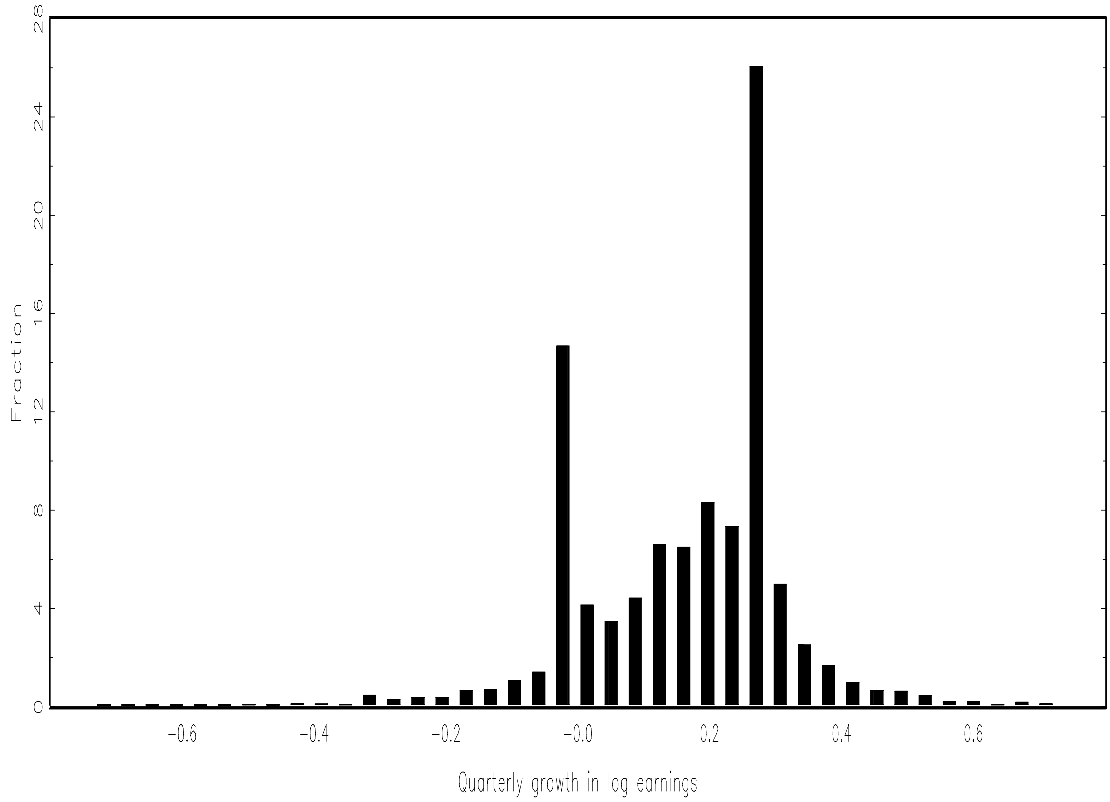


Figure 2: Quarterly earnings growth

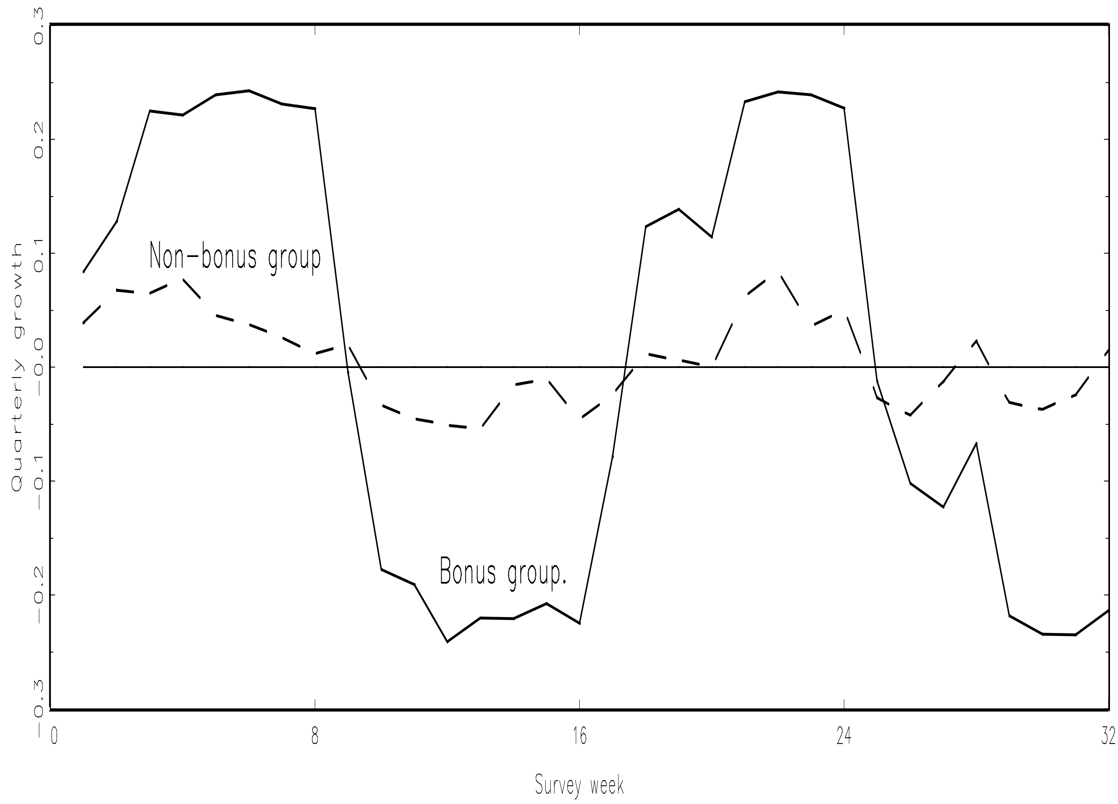


Figure 3: Food, alcohol and tobacco

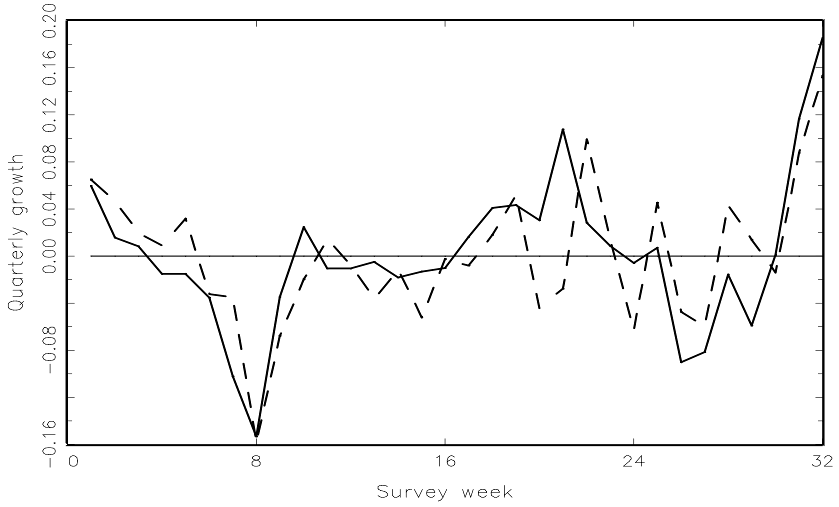


Figure 4: Non−durables and services

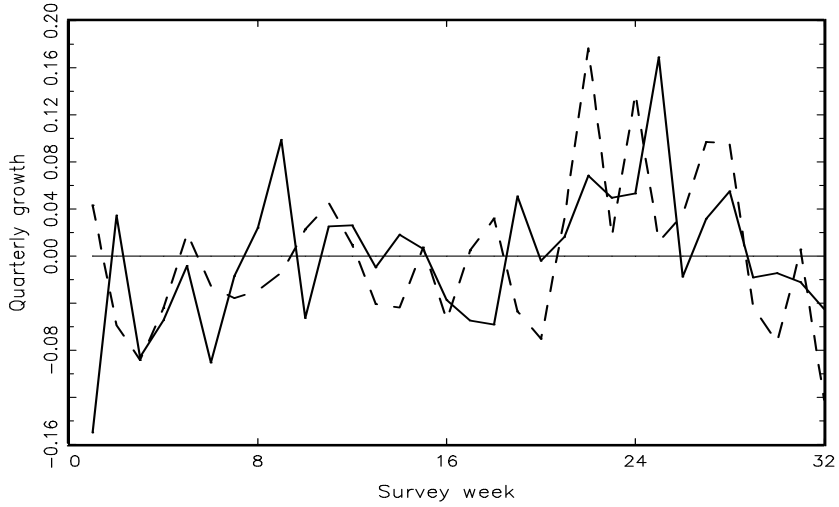


Figure 5: Clothing

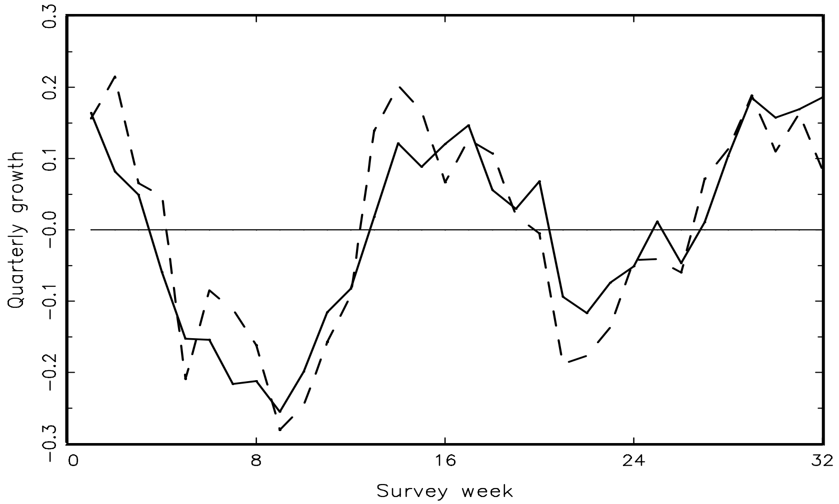


Figure 6: Small durables

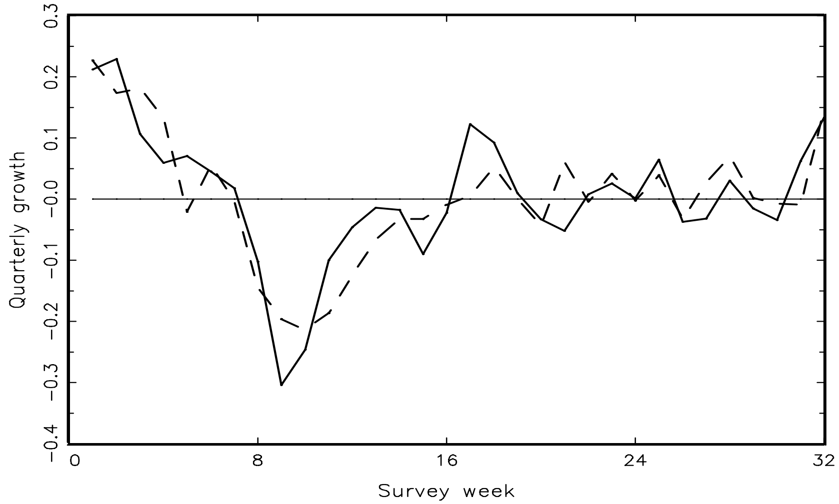


Figure 7: Large durables

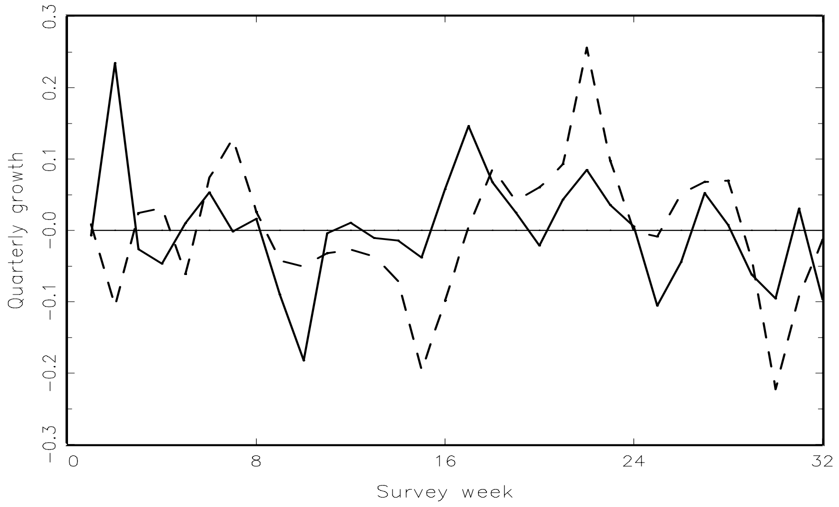


Figure 8: Holidays

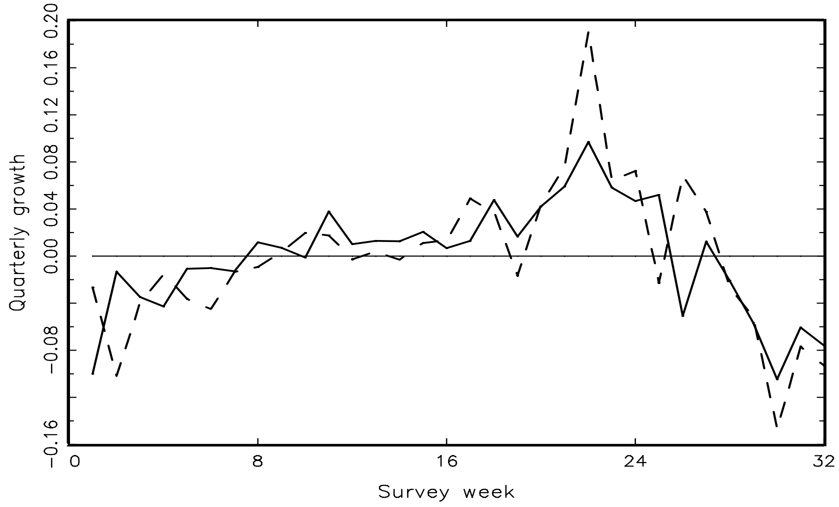
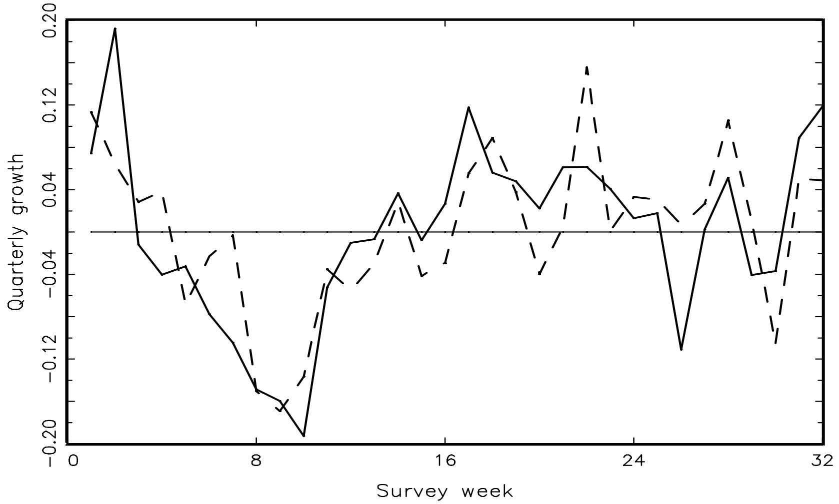


Figure 9: Total expenditure



R E F E R E N C E S

Browning, Martin and Annamaria Lusardi (1996), "Household saving: micro theories and micro facts", *Journal of Economic Literature*, 34, December 1996, 1797-1855.

Parker, Jonathan (1999), "The reaction of household consumption to predictable changes in payroll tax rates", *forthcoming, American Economic Review.*

Souleles, Nicholas S. (1999), "The response of household consumption to income tax refunds", *forthcoming, American Economic Review.*