Consumption Heterogeneity over the Business Cycle

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CONSUMPTION HETEROGENEITY OVER THE BUSINESS CYCLE*

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Abstract

We study consumption heterogeneity over the business cycle. Using household panel data from 1984 to 2010 in the US we find that the welfare cost of the business cycle is non-negligible, once agents heterogeneity is taken into account, and sums to about 1% of yearly consumption. This is due to the structure of comovements between the different parts of the consumption distribution, in particular the tails are highly volatile and negatively related to each other. We also find that business cycle fluctuations originating from exogenous financial shocks only hit the top end of the consumption distribution and therefore reduce consumption inequality.

JEL classification: E21, E63, D12, C3

Keywords: Consumption, Heterogeneity, Aggregate Shocks, Structural Factor Model, FAVAR.

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1. Introduction

What is the cost of the business cycle? And who pays it? In a seminal paper, Lucas (1987) shows, using a representative agent model, that the cost of the business cycle is negligible. In recent years, however, several papers have stressed the importance of going beyond the representative agent framework by allowing some type of heterogeneity across consumers for meaningful welfare analysis (for a review, see Heathcote et al. (2009), Guvenen (2011)). Heterogeneity is also key to understand the patterns of inequality in income and consumption observed over the past decades (Cutler and Katz (1991), and Cutler and Katz (1992), Autor et al. (2008), Blundell et al. (2008).)

In this paper we provide an empirical investigation on the heterogeneity of consumption fluctuations over the business cycle. We use household panel data for the last 25 years in the US and conclude that the aggregate welfare cost of the business cycle is substantially larger than that previously computed by Lucas (1987) once agents heterogeneity is taken into account. Krusell and Smith (1999) introduce agents heterogeneity but their findings point to a similar direction as Lucas (1987) in a calibrated version of a heterogeneous agents model. Our analysis suggests that the overall welfare cost of the business cycle is about 1% of yearly household consumption. Further to that, the welfare costs appears larger for those households in the tails of the consumption distribution.

We combine micro (at the household level) and "macro" (for different deciles) analysis to detail the behavior of the different portions of the consumption distribution (Mankiw and Zeldes (1991), and Attanasio et al. (2002)). In order to develop our analysis, we construct household non-durable consumption (expenditures) from CEX data between the first quarter of 1984 and the fourth quarter of 2010. We then proceed with a descriptive analysis of the dynamics of household consumption in terms of levels, inequality, and volatility in the past 25 years. Then, we use a structural factor model (Bernanke and Eliasz (2005), and Forni et al. (2009)), as well as a household panel data approach, to study the dynamics of the consumption distribution in terms of comovements and volatilities, and to study the responses of the consumption distribution to exogenous macro shocks able to generate substantial fluctuations to the business cycle. The structural factor model provides a unified framework to model a large amount of macroeconomic data together with the consumption deciles. This framework allows us to analyze the underlying common dynamics of these variables driven by a number of common latent factors. In particular, each series is modelled as the sum of two orthogonal components: the common and the idiosyncratic component. The former is driven by the macroeconomy (e.g. monetary policies, TFP shocks, financial crisis and so on) transmitted to every variable through the impulse response functions, while the latter by series specific events unrelated to macro shocks (e.g. taste differences or measurement error in the consumption deciles). On the other hand, the micro-approach allows a more detailed treatment of household heterogeneity at the expenses of a more restrictive treatment of the macro-economic dynamics. It is reassuring that both approaches provide very similar results. The exogenous shocks that generate the macroeconomic fluctuations in the analysis are those financial shocks identified in Bloom (2009) plus the recent credit crunch. The advantage of using such shocks is that they are plausibly exogenous facts that substantially affect financial markets returns and volatility and have a large impact on the business cycle.

A number of facts stand out from the simple descriptive analysis of the data. First, real consumption increases overtime with a noticeable 10% drop at the onset of the latest financial crisis when consumption inequality also declines by about 5%. Second, consumption is more volatile (cross-sectionally and longitudinally) in the tails of the distribution than in the middle, and in particular at the top end. Third, the middle of the distribution of consumption moves together while the top and bottom seem to be unrelated to the rest and negatively related to each other. Business cycle and financial variables (e.g. employment, GDP and dividends) are positively correlated with the top end of the consumption distribution, while negatively with the bottom decile. The reverse is true for social benefits.

A deeper investigation through the lenses of our empirical models reveals to following results. First, common economic factors explain a large part of the variation in consumption in the middle of the distribution while quite little in the tails, in particular the top one. At the same time the idiosyncratic (component) variation is as large as the common one and particularly large in the top tail. Second, it is very important to notice that our modeling strategy allows to reconcile the business cycle fluctuations in consumption from the National Account to those derived from the same aggregate constructed using the CEX. This is rather crucial as there has recently been an ever growing disconnect between aggregate consumption measured by the national account statistics and that recovered by aggregation of the CEX (see for example Garner et al. (2006), Goldenberg and Ryan (2009), Battistin and Padula (2010), and Aguiar and Bils (2011)), we will come back to this point later in the text. Third, the pass through parameter from (log) income fluctuations to (log) consumption is about .06 for those households in the bottom 9 deciles, while it triples to .17 for those households in the highest decile of consumption. This means that limited stock ownership is not the only reason for the failure of full risk sharing in the aggregate (consistently with Guvenen (2007), and Parker and Vissing-Jorgensen (2009)). Fifth, financial shocks only affect the very top end of the distribution of consumption on impact, and therefore reduce consumption inequality. Sixth, the overall welfare cost of the business cycle is about 1% of yearly consumption, using the same computation as in Lucas (1987). Further, the welfare costs are greater in the tails of the distribution (with respect to the middle) by 50 to 100%.

A recent paper by Parker and Vissing-Jorgensen (2009) is the most closely related to ours, both papers investigate the relation between the consumption distribution and the macroeconomy distinguishing between a common and an idiosyncratic component. However, there are a number of substantive and methodological differences between the two papers. First, we study the heterogeneity in the responses of the consumption distribution to business cycle fluctuations that follows financial *shocks* rather than aggregate *variables*. This has a number of advantages as different aggregate shocks are likely to have different effects on consumption; these effects are obviously hidden when consumption units are simply regressed on aggregate variables or business cycles indicators. Second, the we can construct the whole dynamic profile of the responses of disaggregate consumption. This can provide information about the determinants of agents decisions at different points of the distribution, e.g. the presence of liquidity constraints. Third, allowing for a rich structure of the (macro) model permits to embed a wealth of information both in terms of business cycle indicators (as we do not need to take a stand on a particular one) and dynamic structure of the problem. Fourth, we can analyze the effects of specific episodes or shocks such as the recent credit crunch on the consumption of the poor, the middle class and the wealthy. Fifth, we can isolate business cycle fluctuations from those at other frequencies. We will come back to this in the conclusions. At the same time we also develop a household level analysis, micro approach, that is better able to capture household heterogeneity. We use a standard panel data approach were household unobserved heterogeneity is treated as a fixed effect.

The policy relevance of our results is quite striking since we show that any policy or shock might have very different implications for the tails and the middle of the distribution of consumption. This suggests that consumption fluctuations are way more disaggregate and heterogeneous than those hypothesized in the representative agent framework. A policy maker would then need to design policies able to address this heterogeneity. Further, this suggests that although the average costs of the business cycle might not be that large, this is because of the substantial heterogeneity in the consumption responses to shocks and the cycle. For example, the impact effect of the latest financial shock on consumption is small on average (-1.5%), while it reduced nondurable consumption expenditure for the top 10% of the consumption distribution by about 12%, an enormous effect.

The rest of the paper is organized as follows: Section 2 describes the data used and present some initial stylized facts; Section 3 introduces the econometric model. Section 4 presents the results. Section 5 provides a series of robustness checks for the main results; and finally, Section 6 concludes.

2. Data

2.1 Description

We construct household (non-durable) consumption from CEX data, first quarter of 1984 to the fourth quarter of 2010: these are all the available data at the time of writing. As is well known the CEX records consumption and expenditure for a large set of goods together with demographics and other households characteristics such as income, assets and so on. We focus on non durable consumption expenditure per adult equivalent as in Attanasio and Weber (1995), Krueger and Perri (2006), Attanasio et al. (2009), Parker and Vissing-Jorgensen (2009).

The focus on consumption arises naturally, as individuals and households typically derive utility from consumption and not income *per se*, as such consumption is the relevant measure of well being. Furthermore, we know that consumption is less volatile than income as it should respond very little to temporary income fluctuations and anticipated shocks. It is, however, true that good consumption data are rare to come across. In particular in developed economies where consumption and expenditure do not coincide as the consumption of durables is a relevant share of total consumption. In the presence of durables, expenditure and consumption are two quite different concepts as the former might be infrequent given the lumpiness of durables, e.g. car purchases, while consumption is more continuous as one enjoys the services of that car while driving. For these reasons we focus exclusively on household non durable consumption expenditure which we transform into per adult equivalent, to capture household size and economies of scale effects, as well as transforming our expenditure measure in real terms as to account for nominal variation.[1] For the construction of consumption deciles we also use the population weights provided in the CEX.

[1] We use an equivalence scale suggested by the World Bank, i.e. we divide our relevant variables by the squared root of the number of household members.

CEX data have been praised and criticized by several authors, e.g. Slesnick (2001), Goldenberg and Ryan (2009) and Battistin and Padula (2010). In particular, Attanasio and Weber (1995) detail the main advantages of using the CEX and focusing on non durable consumption rather than food expenditure or total expenditure including durables. However, in recent years, there appears to be a noticeable discrepancy between the aggregate consumption measures defined using the CEX and the National Accounts data or NIPA tables (Aguiar and Bils, 2011). It is our understanding that the literature is not conclusive on this particular aspect. In particular, in terms of the distribution, it would be very hard, if not impossible, to know when and where those discrepancies arise. Our strategy, using the factor loading model, is able to handle time-varying classical measurement in each decile of consumption. So that, as long as the measurement error in consumption is classical in each decile in a given time period, we are immune from bias. Importantly, we will later provide evidence that our empirical macro-model is able to produce a series of aggregate consumption from the CEX, that purged from the idiosyncratic component, captures extremely well the business cycle fluctuations of the aggregate consumption series from the National Account. It is worth stressing here that the estimation isn't in any way constructed to match the moments from the NIPA tables consumption.

In our paper we strictly follow the consumption expenditure definition used in Attanasio and Weber (1995), transformed in per adult equivalent and deflated by the CPI.[2]

We use this measure both at the household level, in the micro evidence, and at the more aggregate level, the mean value within each decile. As we observe households more than once, we need to decide how to define our deciles as households can move in and out of those deciles: in fact, we have evidence that those movements are neither negligible nor confined to the marginal households. We assign households to a given decile once and for all by ordering households mean nondurable consumption expenditure overtime. As a typical household is observed for 3 quarters, this in practice means that we average household consumption over that time period and we order that average to locate each household in the appropriate decile. This is quite important as we avoid confounding true variation with compositional changes in the various deciles. At the same time the averaging over the available waves, for each household, also reduces the extent of measurement error in the ranking of

[2] In particular we refer to the following definition extracted by Attanasio and Weber (1995), *"...In what follows we consider various components of nondurable expenditure. In particular, for reasons to be discussed below, we look at food (defined as the sum of food at home, food away from home, alcohol, and tobacco) and expenditure on other nondurable goods and services, such as services, heating fuel, public and private transport (including gasoline), and personal care, and semidurables, defined as clothing and footwear..."*

the consumption measure. As the sample sizes for the CEX cohorts have changed overtime, larger in more recent years, by using deciles rather than smaller aggregations we make sure that there are at least about 100 households per decile (Table C1), with a maximum of over 300 per decile. At the same time we still preserve a substantial amount of heterogeneity as our analysis shows.[3]

It has to be noticed that our non durable consumption measure corresponds to about 44% of the after tax income for a typical (average) household. That share increases with income and consumption deciles. So that it is a smaller share for the very bottom decile at about 40% with the share being about 62% in the highest decile. Another observation is that the food share over our consumption measure decreases across consumption deciles, from a high 50% at the bottom to about 25% for the top decile of the distribution.

An alternative partition of the consumption distribution could be based on income (averaged across waves) or a measure of permanent income such as education. The results of the analysis performed with income after tax per adult equivalent, as the partitioning variable, are similar to the ones presented in the current paper. This is not surprising given the correspondence between the two orderings, as shown in the first column of Table 1. However, as income is more volatile than consumption (closer to permanent income) and is top coded in the CEX, we prefer the partitioning in deciles based on consumption expenditures (there is no top-coding for such variable).

2.2 Stylized Facts

The consumption data show a series of remarkable facts summarized in Figures 1, 2 and 4. First, the mean of real consumption increases slowly overtime with a substantial dip in 2008, at the onset of the latest credit crunch. It is easy to detect some seasonal fluctuations with generally the fourth quarter being the highest quarter for non durable consumption. Second, inequality in consumption appears to be rather flat overtime and falling after 2008 (see the bottom panel of Figure 1 where we plot the cross-sectional std.dev. of log consumption (y-axis) over the past 25 years). This stylized fact is in stark contrast with the literature on income inequality over the past decade. Such difference has been highlighted by Krueger and Perri (2006), Blundell et al. (2008), and for wages in Moretti (2008). However, the aggregate series masks some important heterogeneity which is the core of the current paper. Third, see Figure 2, the consumption distribution has a very long right tail, with log-normality of the distribution formally rejected, however the (log) distribution appears quite symmetric as pointed

[3] Partitioning the data in twentiles has little qualitative effect on the results presented in the current paper.

out in Battistin et al. (2009). Fourth, see Figure 4, the longitudinal variability of consumption is much higher at the top decile, about two times larger than that of the other deciles. At the same time, the two tails have low correlation with the other deciles, see the right column of Figure 4. For instance the average correlation of the 1^{st} and 10^{th} deciles are 0.20 and 0.29 respectively. On the other hand, there is a big portion of the consumption distribution, corresponding to the middle class, which share a similar behavior in terms of consumption. In fact, the average correlation between deciles from the third to the seventh is much higher, about 0.8.[4] This tells us that the bottom and top decile of consumption do not comove much with the other deciles nor together. Fifth, as suggested by fact three, the within decile inequality is rather large in the top decile of the distribution, followed by the bottom decile, while the middle deciles show a smaller inequality (see the bottom panel of Figure 2). This collection of facts points towards the importance of analyzing the consumption distribution rather than its mean alone. What could be true in the middle of the distribution is certainly not accurate at the extremes.

In Table 1, we detail the composition of the different consumption deciles in terms of age, race and education. Older households, in terms of age of the head, tend to be in higher deciles of the distribution; the limited differences in the mean age mask however the larger variation in age at the bottom, i.e. the young and the old coexist in the left tail. The average age across the distribution is 45-46 years; however, in the bottom decile we have an average age of 45.5, while at the top head of households are one year older (this difference is statistically significant). More marked differences emerge in race: it is striking that the bottom 3 deciles contain more than 50% of the African American in the sample, with almost a quarter of blacks in the bottom decile. Whites are fairly evenly spread, being the large majority, however there is a mild over-representation in the top deciles. In terms of education, as one would expect, the lower educated cluster in the bottom deciles. In particular, more than half of the (up to) high-school drop outs are in the bottom 3 deciles, while one in two college graduates or higher is found in the top 3 deciles of consumption. As one would expect education is a close proxy for permanent income and therefore is positively related to consumption. The above characteristics are in most cases statistically different by consumption decile (see Tables in appendix A).

It is also interesting to look into the composition of non durable consumption in the different

[4] Actual numerical values of the correlations are given in Appendix B.

deciles, as we do in Table 2. As one would expect, food expenditure, both at home and out, is a substantial part of the consumption bundle, but it is less so at the higher end of the distribution. The food share is a large part of non durable consumption, from 50% in the bottom decile to 25% in the very top one. The high volatility of consumption in the top tail of the distribution might depend, at least partially, upon the income composition and volatility at different deciles (Piketty and Saez (2003); Parker and Vissing-Jorgensen (2009)). We show, again in Table 2, that the share of households holding any financial wealth, not including housing wealth, is about 25% on average (across deciles), but it goes from 6% in the bottom decile to 38% in the very top decile.

This last observation is consistent with the higher volatility (longitudinal and cross-sectional) of consumption found in the tails. Such findings are in line with the observation that capital and labor income are highly volatile for the right tail and the presence of binding liquidity constraints for the left tail (the liquidity constraint explanation is credible if the idiosyncratic component is big as we will show in the next section). Further, the time series volatility is higher in the right tail. Once again, as there are more stockholders in the right tail, we would expect that the higher volatility of stocks *vis à vis* average labor earnings could translate into a higher volatility in consumption. Such an explanation has been put forth by Attanasio et al. (2002); Mankiw and Zeldes (1991) show this point theoretically.

3. An Empirical "Macro"-Model

3.1 Representation

We here present an empirical model of the economy where we model the consumption distribution together with a large number of macroeconomic series.[5] Let c_{it} be the consumption of the i-th unit for $i = 1, ..., n_c$.[6] We assume that c_{it} is the sum of two orthogonal components, the common component χ_{it}^c and the idiosyncratic component ξ_{it}^c:

$$c_{it} = \chi_{it}^c + \xi_{it}^c \tag{1}$$

The common component is the part of consumption which is driven by common aggregate macroeconomic shocks, while the idiosyncratic component contains unit-specific characteristics unrelated

[5]The micro-approach estimating equations will be presented and discussed where appropriate.

[6]A unit in this context is meant to be a given percentile of the consumption distribution, e.g. a decile, it could however be an individual, a household, etc.

to aggregate shocks. If the units refer to individuals, the idiosyncratic component can, for example, be interpreted as health, luck, taste shocks or simply measurement error. If the units are deciles or percentiles of a distribution of individuals, the idiosyncratic component should tend to be smaller, although not necessarily zero (as we will in the results). The common components are common in that they are linear combinations of a relatively small number r of possibly unobserved factors in f_t,

$$\chi_{it}^c = a_i^c f_t \tag{2}$$

where the factor loading a_i^c are unit-specific. The factors f_t do not have a structural interpretation. Rather they simply represent a statistical tool which bears all the relevant information about macroeconomic dynamics. The dynamic relations between consumption units and macroeconomic shocks arise from the fact that the vector f_t follows the relation

$$f_t = N(L)u_t, \tag{3}$$

where u_t is a q-dimensional vector of orthonormal white noise structural macroeconomic shocks, i.e. productivity shocks, policy shocks etc., with $q \leq r$ and $N(L)$ a full-rank $r \times q$ matrix of polynomials in the lag operator L.

Using (1)-(3) we have

$$c_{it} = b_i^c(L)u_t + \xi_{it}^c \tag{4}$$

where $b_i^c(L) = a_i^c N(L)$. The first term on the right-hand side of equation (4), $b_i^c(L)u_t$, describes the relation between consumption units and the macroeconomy. Macroeconomic shocks are dynamically transmitted onto the consumption units through the impulse response functions $b_i^c(L)$. When the units refer to individual $b_i^c(L)$ represents the individual response. When the units refer to some aggregate like percentiles or deciles of the consumption distribution the responses are the average response of the individuals belonging to such aggregate.

Note that the modelling strategy adopted here is different from the one typically used in the literature where consumption is simply assumed to depend on aggregate variables. Here, on the contrary, the focus is on the effects of the shocks of interest on the consumption units. This has two advantages. First, different aggregate shocks are likely to have different effects on consumption; these effects are obviously hidden when consumption units are simply regressed on aggregate variables or business cycles indicators. Second, the whole dynamic profile of the response of disaggregate consumption is available. This can provide information on the determinants of agents decisions at different points of the distribution, e.g. the presence of liquidity constraints.

The goal of this paper is to investigate $b_i^c(L)$, that is, how the different parts of the consumption distribution respond to different macroeconomic shocks. To this end, the factors f_t and their dynamics $N(L)$ must be estimated being unobserved. The strategy we adopt here is to use a structural factor model (see Bernanke and Eliasz (2005); Stock and Watson (2005); Forni et al. (2009)). There are two main advantages in using this model. First, macroeconomic dynamics are typically well estimated since a rich information set is used. Second, both disaggregate and aggregate variables are easily modeled in a single framework with the same factor structure.

Every macroeconomic variable z_{it}, for $i = 1, ..., n_z$ is the sum of two mutually orthogonal components, the common component χ_{it}^z and the idiosyncratic component ξ_{it}^z

$$z_{it} = \chi_{it}^z + \xi_{it}^z \tag{5}$$

where the common component is again driven by common aggregate macroeconomic shocks

$$\chi_{it}^z = a_i^z f_t = b_i^z(L) u_t \tag{6}$$

where $b_i^z(L) = a_i^z N(L)$. The idiosyncratic component in this case should be interpreted as measurement errors for variables like GDP, or sectoral shocks in the case of sectoral variables.

The full model for the $n \times 1$ vector ($n = n_c + n_z$) $x_t = [c_t' \ z_t']'$ of all available variables, where $c_t = [c_{1t}, ...c_{n_c t}]'$ and $z_t = [z_{1t}, ...z_{n_z t}]'$, is therefore

$$\begin{aligned} x_t &= \chi_t + \xi_t \\ &= A f_t + \xi_t \\ &= B(L) u_t + \xi_t \end{aligned} \tag{7}$$

where $A = [a_1^{c\prime}, ..., a_{n_c}^{c\prime}, a_1^{z\prime}, ..., a_{n_z}^{z\prime}]'$, $B(L) = [b_1^c(L)', ..., b_{n_c}^c(L)', b_1^z(L)', ..., b_{n_z}^z(L)']'$ and $\xi_t = [\xi_t^{c\prime} \ \xi_t^{z\prime}]'$ where $\xi_t^c = [\xi_{1t}^c, ...\xi_{n_c t}^c]'$ and $\xi_t^z = [\xi_{1t}^z, ...\xi_{n_z t}^z]'$.

3.2 Identification

Representation (7) is not unique, since the impulse response functions and the related primitive shocks are not identified. In particular, if H is any orthogonal $q \times q$ matrix, then

$$\chi_t = C(L)v_t$$

where $C(L) = B(L)H'$ and $v_t = Hu_t$. However, assuming mutually orthogonal structural shocks, post-multiplication by H' is the only admissible transformation, i.e. the impulse response functions are unique up to orthogonal transformations. This means that, like in structural VAR models, economic shocks have to be identified. Specifically $q(q-1)/2$ restrictions have to be imposed on the matrix of impulse response functions $B_n(L)$ to pin down all the elements of H, just a case of triangularization. In the next section we will carefully explain the restrictions used to identify the shocks of interest.

3.3 Estimation

Estimation proceeds through the following steps.

1a *All the factors f_t are unobserved*. Starting with an estimate $\hat{r}$, the static factors are estimated by means of the first $\hat{r}$ principal components of the variables in the dataset, and the factor loadings by means of the associated eigenvectors. Precisely, let $\hat{\Gamma}^x$ be the sample variance-covariance matrix of the data: the estimated loading matrix $\hat{A}$ is the $n \times r$ matrix having on the columns the normalized eigenvectors corresponding to the first largest $\hat{r}$ eigenvalues of $\hat{\Gamma}^x$, and the estimated factors are $\hat{f}_t = \hat{A}'x_t$. The intuition behind this estimation method is that by taking appropriate linear combinations of a large number of variables (the principal components), the idiosyncratic components vanish, given their poor cross-sectional correlation. What is left are r independent linear combinations of the χ's, which are a basis of the linear space spanned by the factors.

1b *Some of the factors f_t are observed*. Suppose $f_t = [\bar{f}_t' \ \tilde{f}_t']$ where $\bar{f}_t$ is the vector of observed factors while $\tilde{f}_t$ is the vector of unobserved factors. $\tilde{f}_t'$ is estimated as in 1a.

2 $\hat{N}(L) = \hat{D}(L)^{-1}$ where $\hat{D}(L)$ is the matrix of VAR coefficients of a VAR($\hat{p}$) for $\hat{f}_t$ where the number of lags $\hat{p}$ is chosen according to some criterion.

3 Let $\hat{\Gamma}^\varepsilon$ be the sample variance-covariance matrix of the VAR residuals $\hat{\varepsilon}_t$ obtained in the previ-

ous step. Let $\hat{S}$ be the Cholesky factor of $\hat{\Gamma}^{\varepsilon}$. Therefore

$$\hat{C}(L) = \hat{A}\hat{N}(L)\hat{S}. \tag{8}$$

4 Let $\hat{H}$ be the matrix that satisfies the restrictions needed to identify the economic shocks. The resulting structural impulse response functions are

$$\hat{B}(L) = \hat{C}(L)\hat{H}. \tag{9}$$

In sum, unobserved factors are consistently estimated using the principal components and the loading with the projection of the variables included in the panel on the factors. Identification is implemented as in VARs using the reduced form residuals of a VAR in the factors. To account for estimation uncertainty, a non-overlapping block bootstrap technique is adopted. For details, see Forni and Gambetti (2010).

3.4 Empirical specification

The consumption unit, in this study, is the decile of the consumption distribution obtained as described in Section 2. The macroeconomic dataset contains 108 quarterly macroeconomic series from 1984:I to 2010:IV, the sample period for which we have the CEX data. The macroeconomic series are transformed to achieve stationarity. The full list of variables along with the corresponding transformations is reported in Appendix F. All series are taken from FRED Database of the Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2/).

We then add one additional variable, the series of financial shocks constructed from Bloom (2009) modified to take into account the recent credit crunch episode. The original variable contains all the exogenous episodes raising the variance of stock prices over a certain threshold. We "clean" the variable of all the non-financial episodes so that the variable is interpretable as a series of exogenous financial shocks (see Section 4.3 for details).

To determine $\hat{r}$, the number of common factors, we use the IC_{p2} criterion of Bai and Ng (2002) applied to our dataset which includes all the macro series and the ten consumption deciles. We obtain $\hat{r} = 9$. We set the lag structure to $\hat{p} = 1$ as suggested by the BIC criterion. We notice that the results are robust to the choice of $\hat{r}$, and $\hat{p}$ in a reasonable range.

4. Results

4.1 CEX vs National Account

Overtime the correspondence between the CEX and the National Account statistics on aggregate consumption has been fading. Campos et al. (2011) show that, at business cycle frequencies, on the one hand, the correlation between the two variable is low, around 0.5 for non-durable consumption, and, on the other hand, the variance of the CEX aggregate is substantially higher than the NIPA counterpart. A few papers have tried, with mixed results, to reconcile the two series or analyze the differences between the two measures of aggregate consumption (see for example Garner et al. (2006), Goldenberg and Ryan (2009), Battistin and Padula (2010), and Aguiar and Bils (2011)).

As a first step in our analysis, we compare fluctuations at business cycle frequencies of the aggregate NIPA and CEX consumption. As explained earlier, the model decomposes each series into a idiosyncratic and a common component, the latter representing the part of the series driven by common aggregate shocks. We focus on the common component of CEX aggregate which should be free of the measurement error and other noise captured by the idiosyncratic component. We estimate the cyclical part of the common component by applying a band pass filter which retains fluctuations between 2 and 8 years. The same filter is applied to the log of the NIPA per capita consumption. Figure 3 shows the two series. Interestingly, fluctuations in the common component track remarkably well fluctuations of the NIPA aggregate, with a correlation coefficient of 0.8. Nonetheless, the variance of the CEX aggregate is still slightly larger than that NIPA aggregate. When, on the contrary, we consider the cyclical component of the raw CEX aggregate, which includes both the common and the idiosyncratic component, the fit reduces remarkably, the correlation falling to 0.5, see bottom panel of Figure 3. The key feature here is to allow for an idiosyncratic component of a general form which cleans the data from measurement error or other idiosyncratic shocks that are not been averaged out from the aggregate and delivers a common component exclusively driven by aggregate shocks. Once the idiosyncratic component is removed from the data, the remaining common component displays fluctuations which are very similar to those observed in the NIPA aggregate. This is a very important result as such transformation can be then widely used for the study of consumption fluctuations, further this is an important validation of our modeling strategy. It is important to notice that this test should be interpreted as an out of sample test as we never use the NIPA consumption in our estimation. In other words, within the context of our macro-model there is no attempt to explicitly match the moments of the NIPA consumption aggregate.

The same exercise is repeated in the robustness section, see Figure 11, where we exclude the CEX consumption deciles from the dataset used to estimate the factors by means of the principal components; the results obtained are almost identical.

4.2 The Dynamics of the Consumption Deciles

We start off by examining the dynamics of the consumption deciles in terms of volatilities and correlations. Figure 4 shows the standard deviations and the correlations of the common component (second row), the idiosyncratic component (third row) and the common component at the business cycle frequencies (fourth row).

As for the raw data (first row), both the common and the idiosyncratic component are substantially more volatile at the top end of the distribution. Both the idiosyncratic and the common components of the 10^{th} decile are about twice more volatile than that of the other deciles. At business cycle frequencies the first and the tenth decile are the most volatile with standard deviations which are about 50% larger than those of the remaining deciles.

The second column of Figure 4 shows the correlations between consumption deciles.[7] Each rectangular cell displays the correlation between the consumption decile specified in the x-axis and the y-axis; the higher the correlation the lighter the color of the corresponding cell. It is quite evident, irrespective of whether one looks at the raw data or the common component, that consumption at the two tails of the distribution is less correlated with all the other deciles. The average correlation of the first and tenth deciles are 0.29 and 0.42. The numbers are higher than those obtained for raw data but still small. On the contrary, the consumption deciles from the second to the seventh present very high correlations, higher than those in the raw data. For instance the average correlation between the 2^{nd} and 7^{th} decile is about 0.93.

Figure 5 shows the percentage of variance of the consumption deciles accounted for by the common component. Given the orthogonality between the common and the idiosyncratic components, such a percentage reads as the variance of the common component over the total variance. An inverse U-shape pattern emerges. The common component is way more important in the middle of the distribution than in the tails. For instance, for the 3^{rd} to the 7^{th} deciles the common component accounts for about 70-80% of the variance of the series. On the contrary, only 55% and 30% of variance is

[7] Actual numerical values for those correlations are presented in appendix B.

accounted for in the 1^{st} and 10^{th} deciles respectively. This means that heterogeneity is rather important both between and within deciles of consumption and, in particular, for the very top end of the distribution.

Qualitatively very similar results are obtained using a micro-approach. We run, on disaggregated household data, a series of simple decile-by-decile regressions of the following form:

$$\ln c_{ht} = \alpha_0 + \sum_t \alpha_t Q_t + \sum_k \gamma_k x_{ht}^k + \eta_{ht} \tag{10}$$

where c_{ht} indicates consumption (at the household level h), Q is a dummy variable for each quarter (macro-shock) and $x's$ are a series of household controls such as race, education with η an error term potentially containing fixed unobserved heterogeneity. The R^2 of the above regressions (with and without $x's$) gives us a sense of how much of the consumption variance in each decile is explained by "macro-shocks" $Q's$. Not surprisingly the picture that emerges (omitted from brevity) is very similar to Figure 5, i.e. inverse U-shaped with very little of the variance of $\ln c_{ht}$ explained in the bottom and in particular in the top decile. The same inverse U-shape is maintained if one conditions upon relevant socioeconomic characteristics such as age, race and education.

We also run a series of insurance regression, as in Cochrane (1991) and Mace (1991), to understand whether households in the different parts of the distribution are insured against idiosyncratic fluctuations to income. Once again for each decile of consumption, we estimate the following equation:

$$\Delta \ln c_{ht} = \tau_0 + \sum_t \tau_t Q_t + \phi \Delta y_{ht} + \Delta \varepsilon_{ht}. \tag{11}$$

Where the rate of growth of household consumption $\Delta \ln c_{ht}$ is regressed on a series of quarterly dummies, $\sum_t \alpha_t Q_t$, i.e. the macro shocks, and on the rate of growth of income Δy_{ht}.[8] The test is meant to capture qualitatively the degree of insurance present in the different deciles as only macro factors should matter in a Pareto efficient equilibrium, i.e. $\phi = 0$. We find that households' consumption, for those households in the top 10% of the distribution, responds significantly more to own income shocks

[8]The estimation is in practice performed as a pooled fully interacted model for efficiency reasons.

than for those households in the bottom 9 deciles. The coefficient on own income shock is about 6% for the bottom 9 deciles, while it almost triple to 17% for the top decile. This fact suggests that asset ownership (significantly larger and more diffused at the top) is not the sole explanation for the failure of full insurance (consistently with Guvenen (2007), and Parker and Vissing-Jorgensen (2009)). For this exercise one has to bear in mind the fact that income is top coded, so that measurement error would be non-classical and bound to bias upwards those estimates for the very wealthy; it is, however, true that top-coding should affect the very top of the distribution and not the entire top decile. As deciles have no natural interpretation in terms of insurance groups, we repeat the exercise for those households where the head is older than 50 years, in that capturing the permanent nature of the position in the consumption distribution as income and wages typically peak, and stabilize, around that age mark. The results on this restricted set of households are very much in line with the previous ones. One would want in principle to impose some spatial proximity or familial ties (Hayashi et al. (1996); Angelucci et al. (2011)), as insurance groups are likely to form with proximate agents and possibly within deciles of the consumption distribution, unfortunately such exercise is not possible with the current data as the number of households per spatial unit would be very small and we have no information on family ties.

Next, we investigate the comovements between consumption deciles and real GDP at business cycle frequencies. The fourth column of Table 3 reports the correlation coefficient between the cyclical component of consumption deciles and real GDP. There is a clear tendency for correlations to increase with the decile: for instance, the correlations for the first, fifth and tenth decile are 0.24, 0.63 and 0.79 respectively. Consumption appears pro-cyclical at the top end of the distribution while it is a-cyclical at the bottom end. For the correlation between non-durable consumption from the CEX and the NIPA tables (see the second column of Table 3) the results are very similar, i.e. the cyclical component of the NIPA per capita consumption comoves fairly closely with the top deciles of the CEX distribution of consumption while it has low correlation with the bottom deciles.

Finally, we study the correlations between the common component of consumption deciles and some other macroeconomic variable of interest (all in their stationary transformation). Results are displayed in Table 4. Several interesting facts emerge. First, the correlation with real GDP growth is higher the higher the decile. This result largely confirms the above finding and suggests a strong pro-cyclical behavior in the middle and mostly at the top of the distribution. A similar conclusion is reached by looking at the unemployment. Second, dividends are strongly positively correlated with the tenth decile and to a lesser extent with the ninth decile and are negatively correlated with the first three deciles. For the middle part of the distribution correlations are essentially zero. Third, for government social benefits the pattern is the opposite: the correlation is declining across deciles, around 0.4 for the 1^{st} and -0.4 for the 10^{th} decile respectively. We will come back to this result later in the discussion of the effects of business cycle shocks. Fourth, the correlation with the federal funds rate displays a inverse U-shape. Such a correlation is low for the first decile, around 0.10 then increases starting from the second decile, reaches a maximal level at the 7-8 decile, around 0.91 and decreases again for the last two top deciles. Fifth, consumer loans are positively correlated with all the consumption deciles except the first one.

In sum, three main facts stand out. First, the top end decile of the consumption distribution is much more volatile than the other deciles. Second, the two tails of the distribution display little correlation with the rest of the distribution. Third, pro-cyclicality of consumption increases with the deciles, the bottom end is a-cyclical or counter-cyclical, while the top end is pro-cyclical.

Following Lucas (1987), we compute the aggregate welfare cost of the business cycle taking into account the heterogeneity. We find the total (across deciles) welfare costs of business cycle fluctuations to be .6 to 1.6% of yearly consumption, depending on the coefficient of risk aversion we choose, from (a low) 1.5 to (a quite high) 4. The computation is performed as is standard in the literature: we sum over the deciles welfare cost, i.e. $W_d = .5\rho\sigma_d^2$ where ρ is the curvature of a CRRA utility function and σ_d^2 is the variance of (log)consumption at the business cycle frequency.

Such a cost is about one order of magnitude larger that the one computed by Lucas (1987) and Krusell and Smith (1999). It is also interesting to notice, in line with the spirit of the paper, that the cost of the business cycle is rather heterogeneous across the distribution of consumption: the bottom and top deciles paying 36% and 80% more than the fifth decile respectively (a U-shaped curve).

4.3 The Effects of a Business Cycle Shock

In this section we move beyond simple correlations and we investigate the response of the consumption distribution to a shock that generates economic fluctuations to which we refer to as ”business cycle” shock. This type of ”conditional” analysis is important to understand potential differences in the transmission of economic shocks across the consumption distribution. At the same time, we use a plausibly exogenous source of variation in the business cycle.

The "business cycle" shock is defined as a sequence of exogenous events that produce significant recessionary and expansionary effects on real GDP and produce positive comovements in business cycle variables like employment, GDP, consumption, investment. In the macro model, we estimate the shock using a slightly modified version of the dummy variable constructed in Bloom (2009). The reason is twofold. First, it is clearly a collection of exogenous events. Second, it has substantial effects on output fluctuations. Whether the shock is also able to generate the typical business cycle comovement is addressed below. We choose to work with a shock of this type since our main interest is to investigate consumption heterogeneity over the business cycle.

The shock takes the value of one in coincidence of the following, arguably exogenous, episodes:

1. Black Monday: 1987:IV.
2. Gulf War I: 1990:III.
3. Asian Crisis: 1997:IV.
4. Russian, LTCM default: 1998:III.
5. 9/11 terrorist attack: 2001:III.
6. Worldcom and Enron: 2002:III.
7. Gulf War II: 2003:I.
8. Credit crunch I: 2007:III.
9. Credit crunch II: 2008:IV.

These episodes raise the HP-detrended volatility of stock prices over 1.65 standard deviations above the mean and have also a substantial effect on returns with an average drop of 11% on quarter on quarter growth rate. The shock can be therefore interpreted as a shock arising from financial markets or, at least, generating a significant turmoil in financial markets. Moreover, these episodes produce significant recessionary effects.

In practice, to estimate the effects of the shock in the macro empirical model, we follow Ramey (2009). Specifically, the dummy variable is treated as an observed factor and the financial shock is identified as the only shock having a contemporaneous effect on the dummy variable, which corresponds to the first shock in a recursive ordering of the factors where the dummy variable is ordered first.[9] A similar analysis in the micro approach relies upon the exogeneity of the episodes.

We start by analyzing the effects on a set of macroeconomic variables of interest to validate whether the shock under consideration has the features of a business cycle shock in terms of correlations between macro aggregate. Figure 6 shows the results. Solid lines are point estimates, while dotted lines are 68% confidence bands. The shock is scaled in such a way that it reduces real GDP growth by 1% on impact.

Real GDP investment and consumption significantly fall. The effects are sizable; after one year GDP falls by about 2.8%, investment by 12%, consumption, both CEX and NIPA, by about 2-3%. Consistently, unemployment significantly increases. All the effects are very persistent. It is also worth noticing how monetary policy responds by significantly lowering the federal funds rate. In summary, the shock not only produces sizable fluctuations in real and financial variables, but also generates the kind of comovement between main macro aggregate which are expected over the cycle.

Figure 7 and 8 show the impulse response functions of the consumption deciles. Solid lines are point estimates, while dotted lines are 68% confidence bands. Figure 7 focuses on the consumption decile (x-axis) at some selected horizon (k) to evaluate differences across deciles, while Figure 8 shows the entire time profile of the impulse response functions. The response of aggregate consumption masks important differences across deciles. On impact only the top 10% of consumption significantly falls by about 12%. On the contrary, the consumption of the first decile significantly increases, while for the remaining deciles the effects are insignificant. After one year for all the deciles but the first two, the responses are negative and significant with larger magnitudes for higher deciles, around 2-3% in the middle of the distribution and around 5% at the top end. After two years the responses become negative for all the deciles.

The behavior of the two tails of the consumption distribution reduces the dispersion of the consumption distribution during recessions and increases it in booms making consumption inequality, conditional on the identified shock, pro-cyclical. One can rationalize the responses of the bottom and top decile by looking at the effects of the shock on dividends and government social benefits in Figure 6. On the one hand, dividends fall significantly, with effects of the order of 10-15%. This

[9] Note in this case the dimension of f_t is ten and we use $\hat{q} = 10$ shocks. In this case, the model corresponds to a FAVAR model with the dummy variable as additional observed factor.

can explain the large fall in consumption at the top decile where stockholders are concentrated (as noticed in Table 2). On the other hand, the increase in consumption for the bottom decile is likely to anticipate the observed significant increase in social benefits following the shock.

The welfare computation performed previously for any business cycle fluctuation can here be replicated focusing on business cycle fluctuations generated by the financial shock. The variance of consumption conditional to the financial shock is generally smaller than the overall business cycle variance for all deciles but for the very top one, where it actually coincides with the former. This suggests that the large part of the business cycle fluctuations at the top of the distribution are due to financial shocks. Overall, the welfare cost of such shocks is .5% of yearly consumption; this, however, masks a tremendous amount of heterogeneity: in fact, the welfare cost of business cycle fluctuations due to the financial shocks are borne almost exclusively by the top 10%, with a ratio between welfare costs for the top 10 to the fifth decile of 13.

We can also focus on the recent credit crunch (third quarter of 2007), on impact at the top of the distribution of consumption drops by 0.6%. The welfare effect of this drop can be computed, to the first order approximation as before for a standard CRRA utility function as $.5\rho\frac{\Delta c_{ht}}{c_t}$, where ρ is the coefficient of relative risk aversion and c_{ht} is consumption. Assuming $\rho = 1.5$ would mean that the first order welfare losses of such a shock for the top decile households would be in the order of 2% on impact on a yearly basis. It is, however, true that the consumption of the top decile would then slowly return to its pre-shock level.

In Table 5 we perform a similar exercise relying upon the (micro) household data using standard panel data techniques, our micro-approach. In particular we look at the effects of the same shock for household in the different deciles of the distribution of consumption. In practice we run the following pooled (across all households) regression:

$$\ln c_{ht} = \omega_0 + \omega_1 Shock_t + \omega_2 D_h + \omega_3 D_h * Shock_t + \omega_4 \ln y_{ht} + \nu_h + \varepsilon_{ht}. \tag{12}$$

Where c_{ht} represent real household consumption (per adult equivalent), $Shock_t$ is the shock dummy, D_h indicates the decile of consumption, and we control for after-tax income y_{ht} and allow for fixed household unobserved heterogeneity ν_h; ε_{ht} is a standard error term that may arise from a multiplicative measurement error in consumption, i.e. $c_{ht} = c^*_{ht}e^{\varepsilon_{ht}}$. It is clear that the aggregate effects of such fluctuations originating in the financial markets have a negligible effect on the average household. On the other hand, the effects are large and significant at the top end of the distribution: on average, there is a reduction of 4.5% in the consumption of the very top end of consumers. Such results are robust to controlling for household income and unobserved heterogeneity. It is also noticeable that, if one where to run a similar regression on a partition of the household by education of the head, the fall in consumption would exclusively be concentrated on those with at least a college education.

5. Robustness

In this section we present a series of robustness checks for the results presented so far. The first check is to estimate the principal components of the macro-model excluding the consumption deciles for such step. We do so because it is possible that the some of the nine principal components, estimated in the analysis, may capture variations which are common to the deciles of consumption but unrelated to fluctuations arising from true aggregate shocks. The results, displayed in Figures 9-13 and Table 6, are very similar to those obtained in the benchmark model. The only difference is in the relative variance of the common component to the total variance. Indeed, in Figure 10, we observe that the portion of variance explained by the common component is slightly smaller for all the deciles, although the inverse U-shaped relation is preserved. Despite this difference, all the remaining results are virtually identical to those in the main analysis.

As a second robustness check, we use a different definition of the shock variable. Specifically we keep only the financial episodes. That is we use as an alternative variable that takes value one in the following periods:

1. Black Monday: 1987:IV.
2. Asian Crisis: 1997:IV.
3. Russian, LTCM default: 1998:III.
4. Worldcom and Enron: 2002:III.
5. Credit crunch I: 2007:III.
6. Credit crunch II: 2008:IV.

Figure 13 shows the results, which are indeed very similar to those discussed in our benchmark specification. The only minor differences is that for the deciles in the middle of the distribution the impact effect tend to become larger.

We also perform a placebo test where we move the original exogenous episodes randomly in the time interval considered, we do so because we want to make sure we are capturing some true effects of a shock rather than noise in the data. We perform 100 replications of such random allocation both in the micro and macro approaches: we find no effect of the placebo shocks on any of the deciles of consumption both in terms of magnitude and statistical significance.

6. Conclusions

In this paper we analyze the heterogeneous impacts of the business cycle on the different parts of the distribution of consumption. In particular, we focus on who pays the cost of business cycle fluctuations and shocks originating in the financial sector. Such investigation is crucial for policy design as well as welfare analysis. It is rather immediate how agents heterogeneity cannot be neglected for those purposes, unless one is willing to make heroic assumptions on market completeness and preferences. Our findings indeed show that households' consumption in different part of the distribution move quite heterogeneously: in particular, the tails move independently from the middle and are negatively related to each other. Further, once agents heterogeneity is taken into account the welfare costs of the business cycle are non-negligible and at least one order of magnitude larger that those found in Lucas (1987) and substantially larger than in Krusell and Smith (1999). We find that the benefit of eliminating the business cycle sums up, across the distribution of consumption, to at least 1% of yearly consumption, with larger benefits for the poor (bottom decile) and the wealthy (top decile). We also find that the effects of exogenous financial shocks are quite heterogeneous as we find that financial shocks only hit the top end of the distribution of consumption on impact. In this exercise we also learn that different races and educational groups have heterogeneous responses to shocks as it is noticeable to high clustering of race and education in different consumption deciles (see Table 1): for example, the latest credit crunch has had a substantial (negative) impact on college graduates consumption. Parker and Vissing-Jorgensen (2009) in a recent paper perform a related exercise to ours, in particular they find that consumption of the well off is more exposed to aggregate fluctuations than that of the rest of the households. They propose as a possible channel the high volatility of wage income for the very rich, analyzing the data from Piketty and Saez (2003). Our focus is quite different as we concentrate on the welfare costs of the business cycle and are able to distinguish between aggregate and idiosyncratic variation in the consumption distribution. Also, on the methodological side, we couple two approaches: i. a macro factor loading model, and ii. a micro household level analysis of aggregate versus idiosyncratic fluctuations as well as an analysis of risk sharing and insurance. We also notice that crucially our macro-approach is able to reconcile the measurement of consumption aggregates, at the business cycle frequency, between the CEX and the NIPA tables.

We do not, however, pin point any precise transmission mechanism, we leave this for future research. We, however, suggest that a combination of imperfect capital and insurance market, and the differential asset allocation between the rich and the poor are all ingredients one would need to account for in a formal modeling of the findings. We conclude by claiming that the recent crisis generated by the credit crunch is likely to reduce consumption inequality.

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Figures and Tables

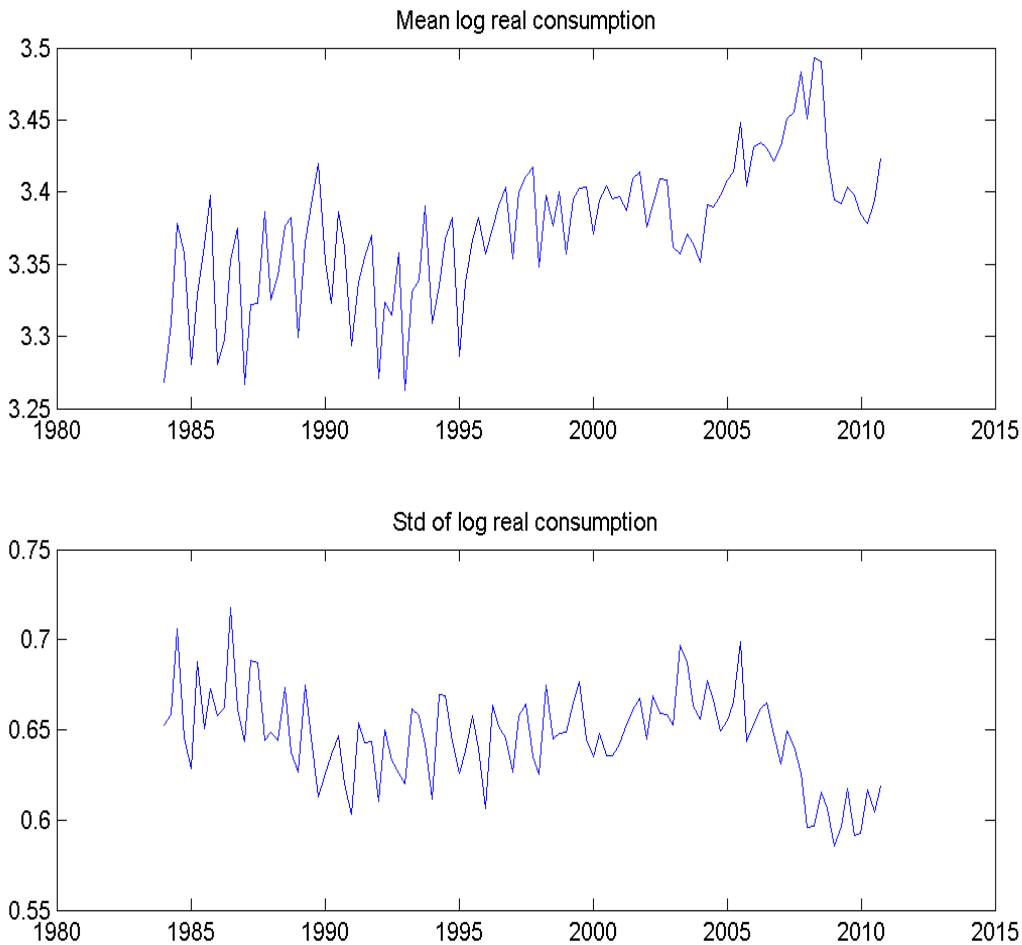

Figure 1: Mean and standard deviation of real log-consumption between 1984Q1 and 2010Q4.

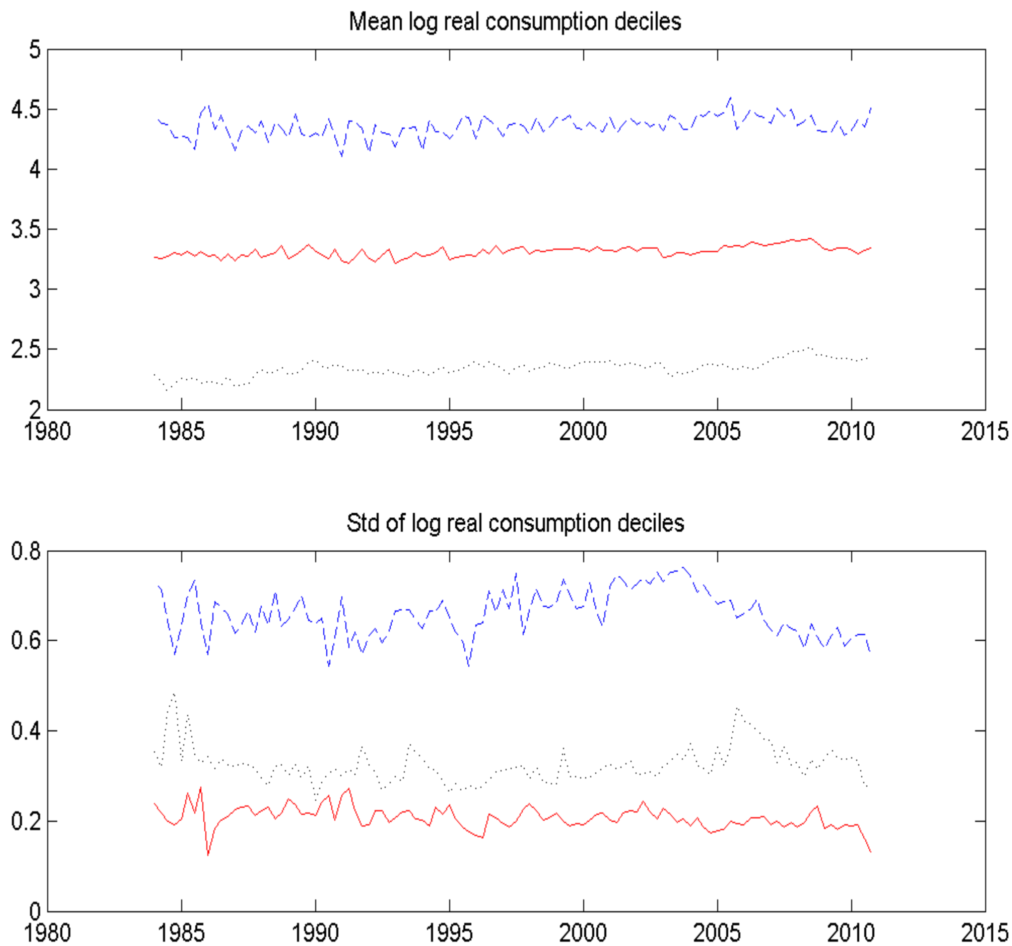

Figure 2: Mean and standard deviation of real log-consumption by decile between 1984Q1 and 2010Q4. Note: solid, dotted and dashed lines are first, fifth and tenth decile respectively.

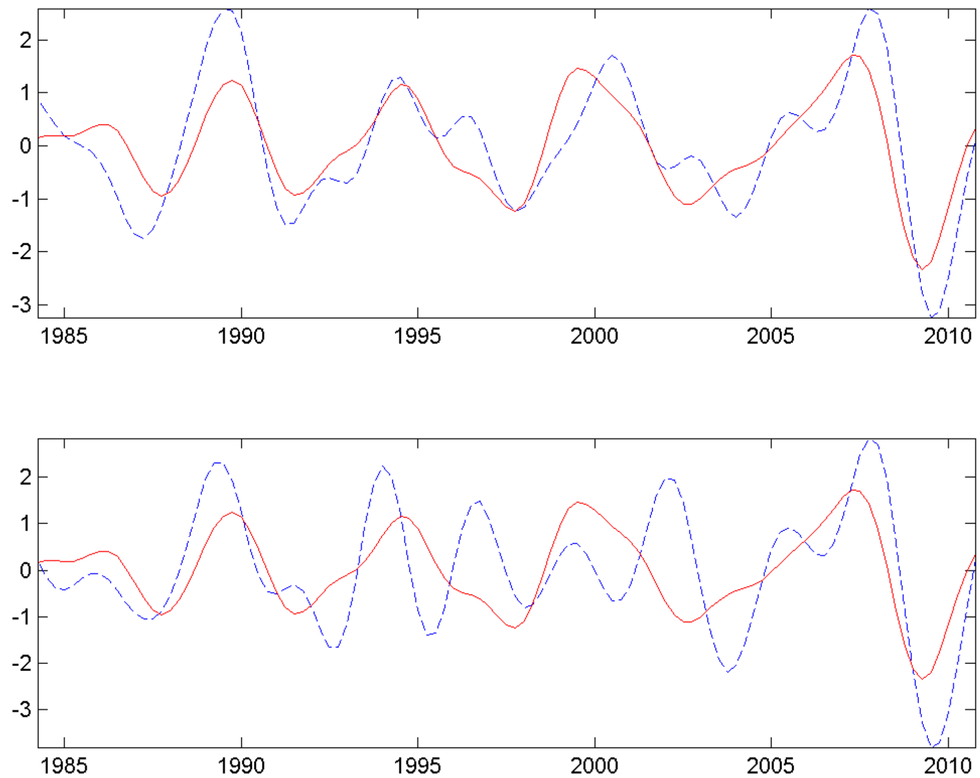

Figure 3: Top Panel: business cycle component of log PCE consumption (solid line) and business cycle component of the common component of the log CEX consumption (dashed) between 1984Q1 and 2010Q4. Bottom Panel: business cycle component of log PCE consumption (solid line) and business cycle component of the log CEX consumption (dashed) between 1984Q1 and 2010Q4.

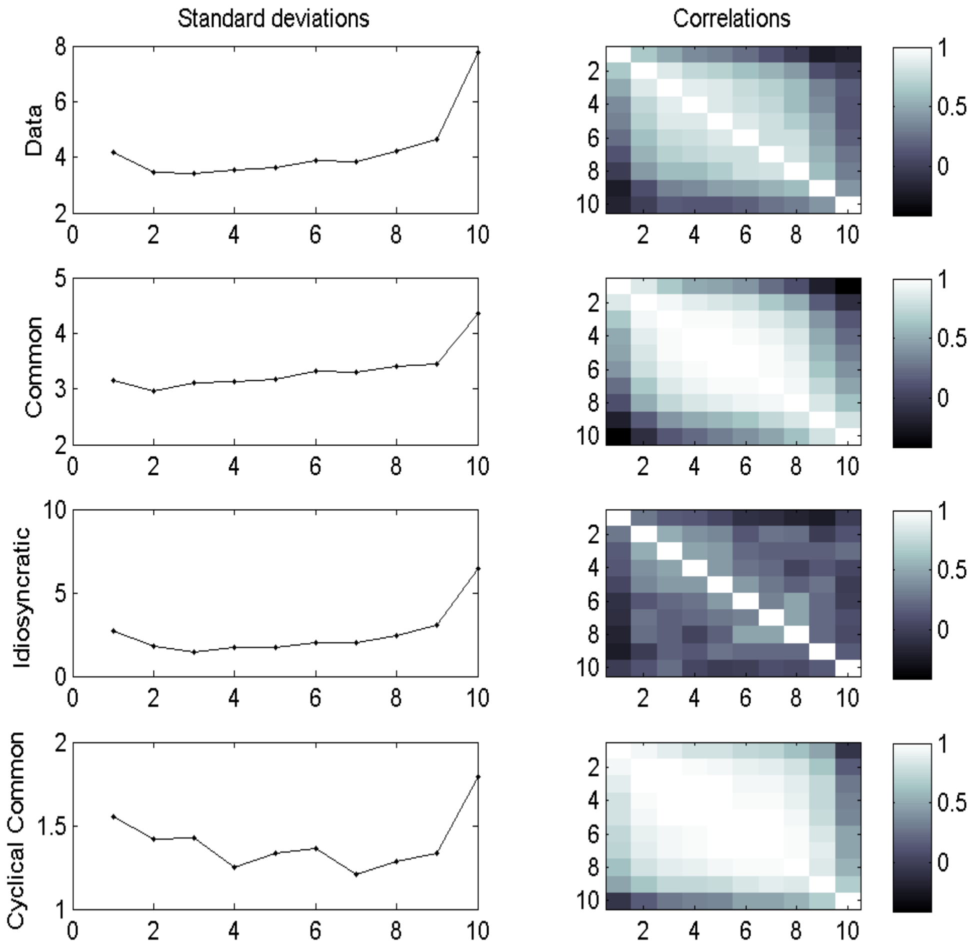

Figure 4: Standard deviations and correlations of consumption deciles. First row: raw data; second row: common component; third row: idiosyncratic component; fourth row: common component at the business cycle frequencies computed using a band bass filter which retains fluctuations between 2 and 8 years.

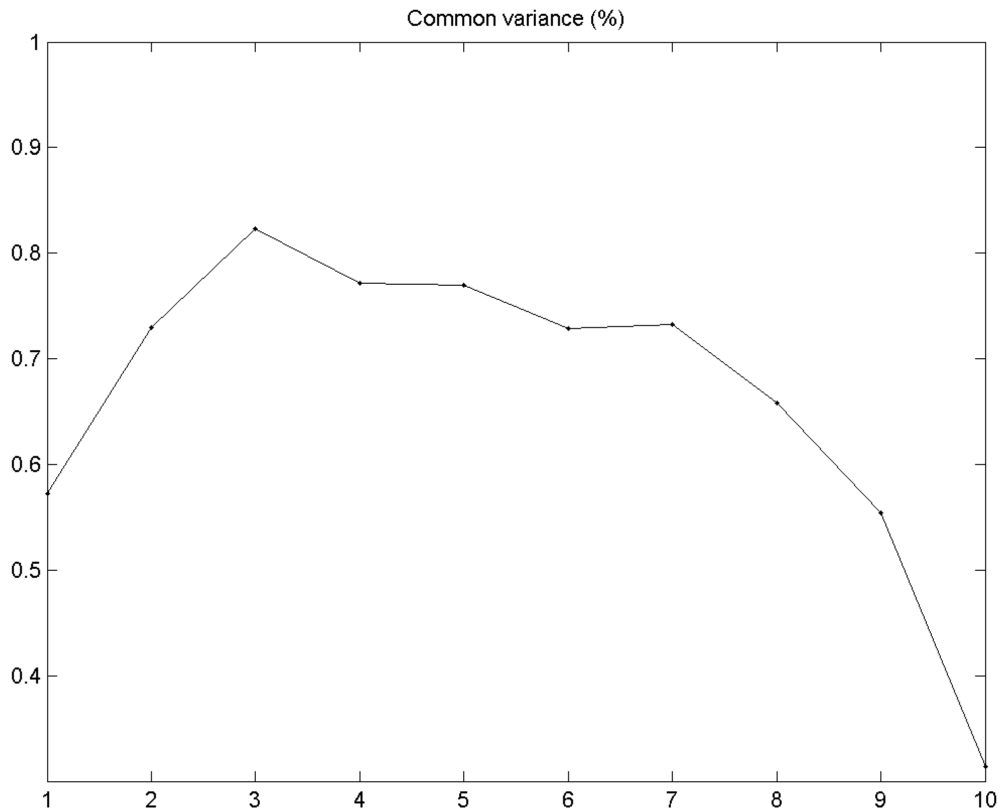

Figure 5: Share of the variance of consumption explained by the common component in the different deciles (x-axis).

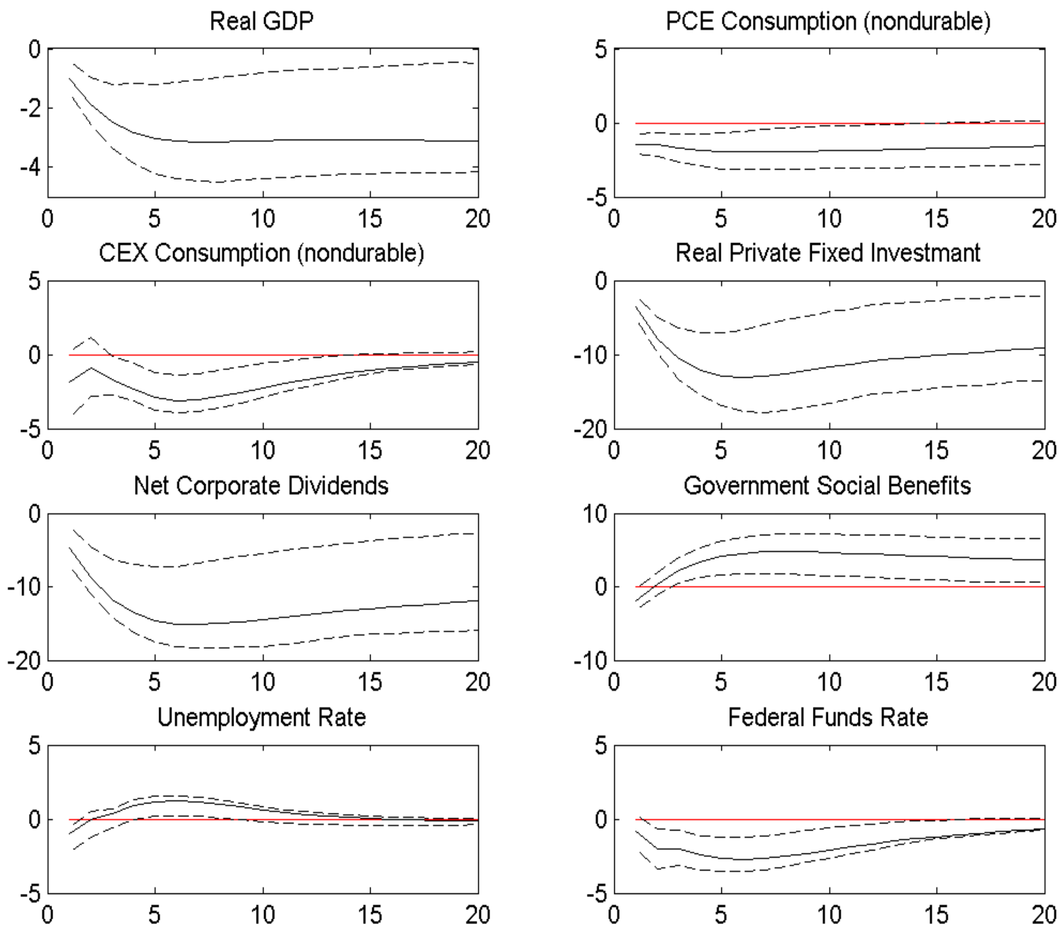

Figure 6: Impulse response functions of the consumption deciles for selected quarters. Number of quarters on the x-axis. Solid lines - estimates line; dotted lines - 68% confidence bands.

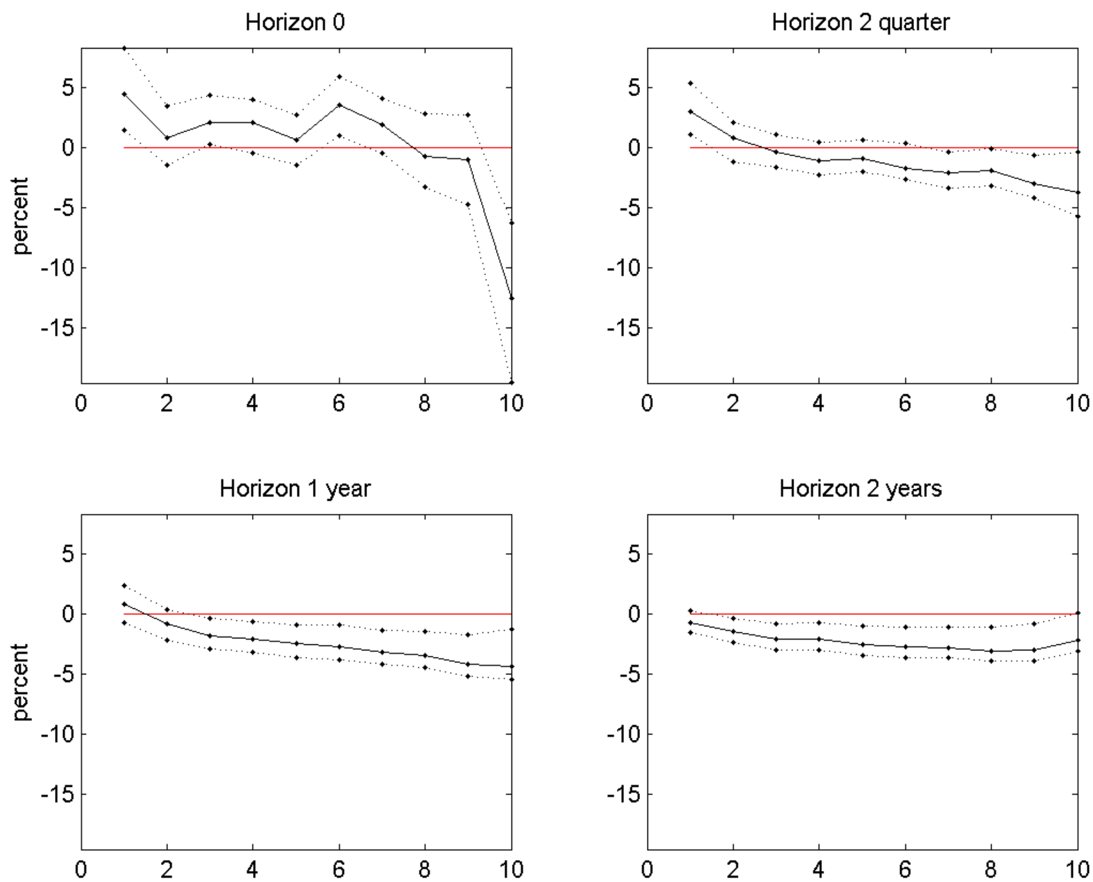

Figure 7: Impulse response functions of the consumption deciles for selected quarters. Solid lines - estimates line; dotted lines - 68% confidence bands.

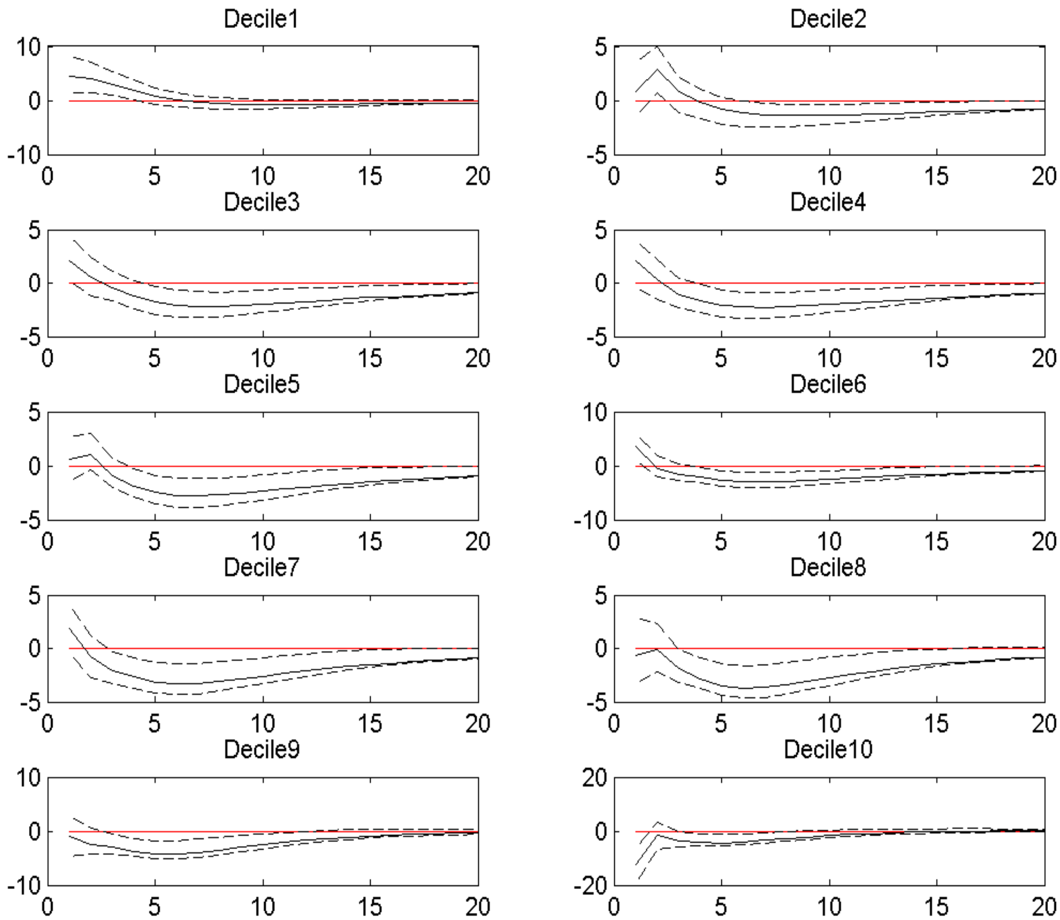

Figure 8: Impulse response functions of the consumption deciles for selected quarters. Number of quarters on the x-axis. Solid lines - estimates line; dotted lines - 68% confidence bands.

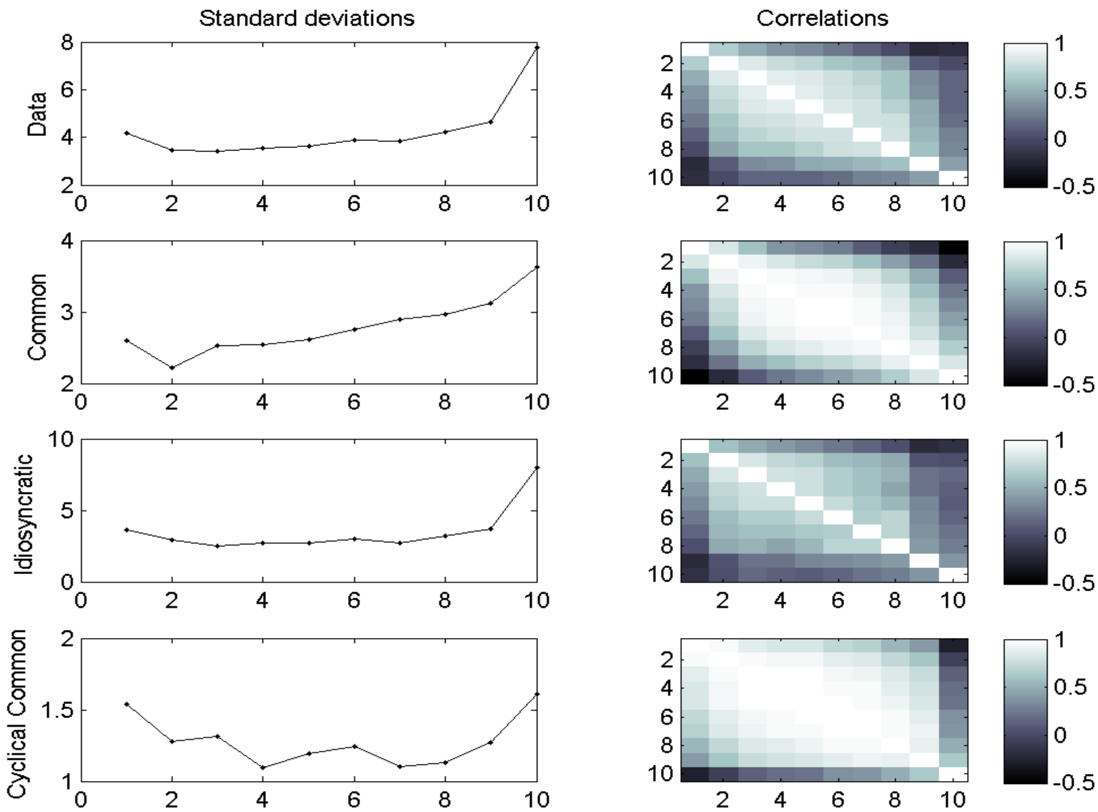

Figure 9: Robustness. Standard deviations and correlations of consumption deciles. First row: raw data; second row: common component; third row: idiosyncratic component; fourth row: common component at the business cycle frequencies computed using a band bass filter which retains fluctuations between 2 and 8 years.

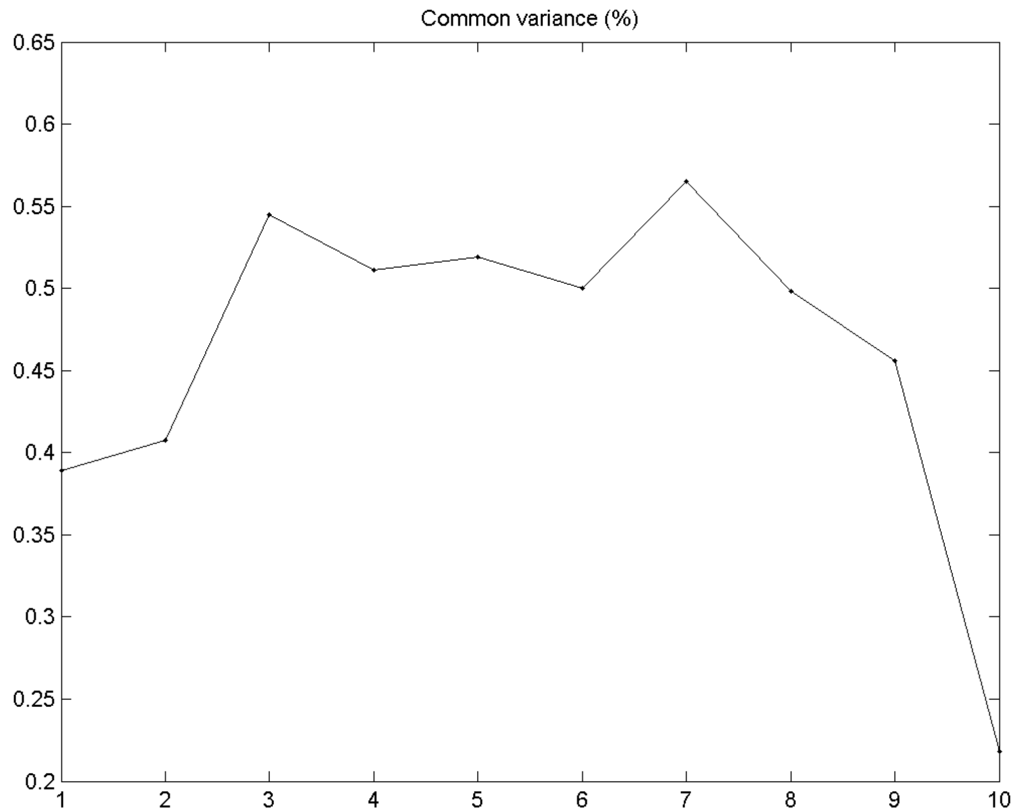

Figure 10: Robustness. Percentage of variance of consumption explained by the common component in the different deciles. The principal components here are computed excluding consumption deciles from the dataset.

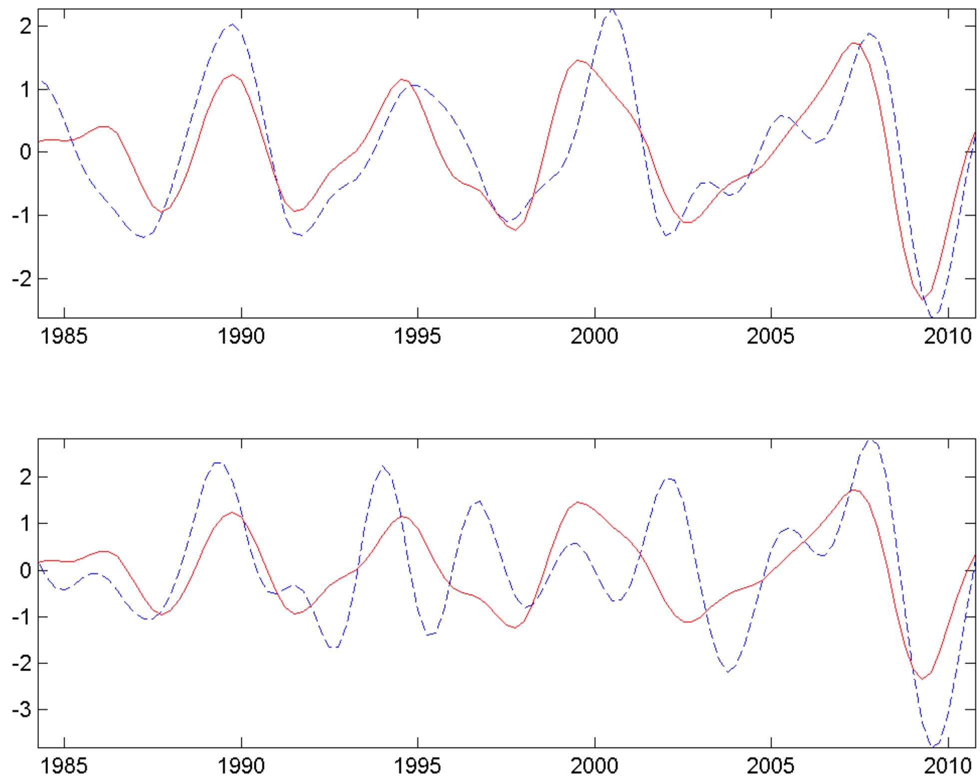

Figure 11: Robustness. Top Panel: business cycle component of log PCE consumption (solid line) and business cycle component of the common component of the log CEX consumption (dashed). Bottom Panel: business cycle component of log PCE consumption (solid line) and business cycle component of the log CEX consumption (dashed). The principal components here are computed excluding consumption deciles from the dataset.

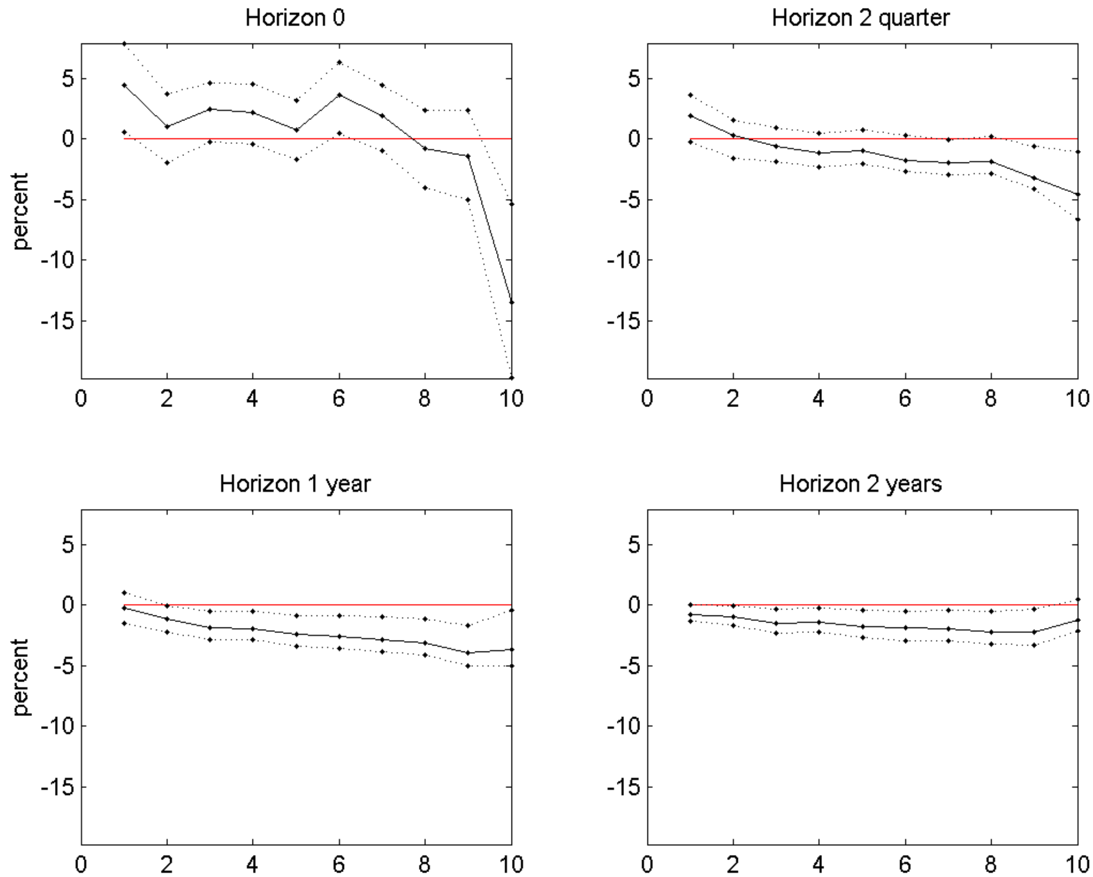

Figure 12: Robustness. Impulse response functions of the consumption deciles for selected quarters. Solid lines - estimates line; dotted lines - 68% confidence bands. The principal components here are computed excluding consumption deciles from the dataset.

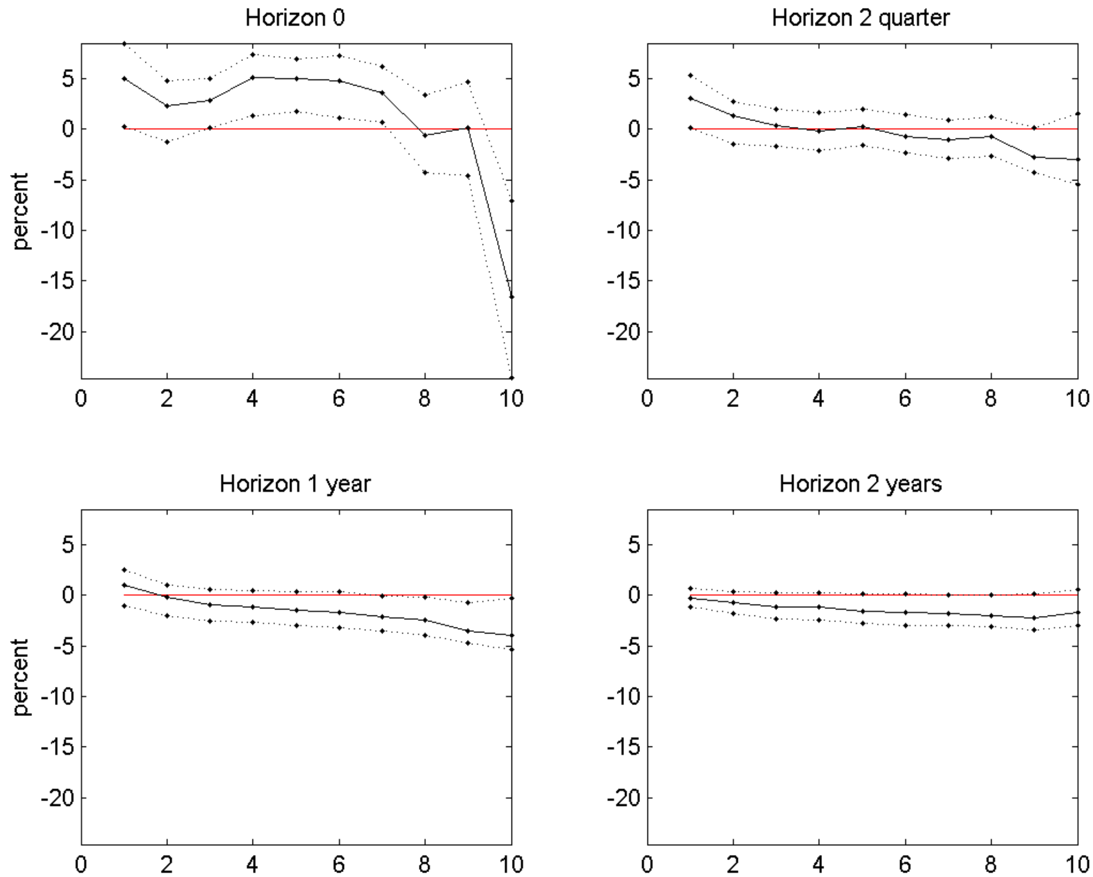

Figure 13: Robustness. Impulse response functions of the consumption deciles for selected quarters. Solid lines - estimates line; dotted lines - 68 confidence bands. Episodes 1990:III, 2001:III and 2003:II are excluded from the shock (dummy) variable.

Decile	(Real) Log Income		Age		Race (% by Column)				Education (% by Column)						
	Mean	Std.	Mean	Std.	White	Black	Asian	Natives	None	Elementary	HS drop	HS	College drop	College	Graduate
1	4.47	0.72	45.59	17.10	7.86	22.70	15.02	13.30	45.47	31.32	24.42	9.91	7.81	2.72	1.69
2	4.94	0.67	45.30	16.15	8.75	16.26	11.46	10.72	17.60	19.93	17.44	11.01	9.08	5.04	3.31
3	5.20	0.64	45.19	15.53	9.33	13.29	9.59	9.75	9.60	13.79	13.14	11.52	10.21	6.55	4.68
4	5.38	0.61	45.34	15.09	9.76	10.37	12.02	10.28	8.93	9.33	10.45	11.35	10.76	8.32	6.22
5	5.55	0.60	45.43	14.48	10.10	8.82	10.29	10.23	2.40	7.10	8.42	11.04	10.80	9.72	8.47
6	5.68	0.60	45.85	13.97	10.38	7.43	10.50	9.20	4.27	5.30	7.35	10.53	10.69	10.99	10.24
7	5.80	0.59	45.65	13.42	10.61	6.66	8.81	9.92	4.40	4.62	5.36	9.71	10.53	12.77	12.79
8	5.94	0.60	46.19	13.15	10.91	5.18	8.46	9.59	3.73	3.34	5.19	8.94	10.43	14.19	14.43
9	6.07	0.61	46.34	12.79	11.09	5.15	7.86	8.67	1.07	2.77	4.56	8.41	9.92	14.70	17.77
10	6.26	0.61	46.75	12.55	11.22	4.15	5.99	8.34	2.53	2.50	3.67	7.58	9.77	15.00	20.42

Table 1: Households (head) characteristics by decile.

Decile	Food share of non durables		Share of capital holders	
	Mean	Std. Dev.	Mean	Std. Dev.
1	0.48	0.17	0.06	0.25
2	0.41	0.14	0.12	0.33
3	0.38	0.13	0.17	0.37
4	0.37	0.12	0.21	0.41
5	0.35	0.12	0.25	0.43
6	0.34	0.12	0.27	0.45
7	0.33	0.11	0.31	0.46
8	0.32	0.12	0.33	0.47
9	0.30	0.13	0.35	0.48
10	0.25	0.15	0.38	0.49
Total	0.35	0.14	0.25	0.43

Table 2: Distribution of food shares and capital holders across deciles of consumption

x:	$\frac{\text{Std. Dev.}(x)}{\text{Std. Dev.(PCE)}}$	Corr(x,PCE)	$\frac{\text{Std. Dev.}(x)}{\text{Std. Dev.(RGDP)}}$	Corr(x,RGDP)
		Data		
CEX aggregate	1.51	0.56	1.36	0.61
		Common Components		
CEX aggregate	1.37	0.79	1.23	0.84
Decile 1	1.75	0.22	1.57	0.24
Decile 2	1.60	0.36	1.44	0.42
Decile 3	1.61	0.47	1.45	0.53
Decile 4	1.41	0.47	1.27	0.57
Decile 5	1.50	0.56	1.35	0.63
Decile 6	1.54	0.66	1.38	0.73
Decile 7	1.36	0.65	1.22	0.74
Decile 8	1.45	0.73	1.30	0.77
Decile 9	1.51	0.77	1.35	0.82
Decile 10	2.02	0.73	1.81	0.79

Table 3: Relative standard deviations and correlations of business cycle components. x refers to the cyclical component of the variables listed below. PCE refers to per capita NIPA non-durables consumption. RGDP refers to per capita real RGDP.

Variables	Decile									
	1	2	3	4	5	6	7	8	9	10
Real GDP	-0.53	-0.23	-0.07	0.06	0.07	0.15	0.17	0.35	0.24	0.54
Consumption: Nondurable	-0.64	-0.45	-0.33	-0.21	-0.17	-0.09	-0.06	0.19	0.14	0.41
Real Net Corporate Dividends	-0.68	-0.50	-0.31	-0.24	-0.21	-0.10	-0.02	0.09	0.39	0.54
Unemployed	0.60	0.31	0.11	0.00	-0.02	-0.11	-0.16	-0.27	-0.34	-0.55
Effective Federal Funds Rate	0.11	0.51	0.74	0.78	0.86	0.88	0.91	0.91	0.76	0.45
Consumer Loans	-0.17	0.23	0.42	0.54	0.53	0.56	0.67	0.69	0.77	0.63
Consumer Credit	-0.41	0.01	0.28	0.41	0.49	0.55	0.66	0.79	0.88	0.82
SP 500	-0.29	-0.25	-0.18	-0.17	-0.10	-0.03	-0.05	0.07	-0.01	0.06
Government social benefits	0.54	0.30	0.13	0.03	0.00	-0.11	-0.18	-0.22	-0.46	-0.59
Business Conditions: next 12 months	-0.63	-0.34	-0.08	0.03	0.15	0.24	0.34	0.52	0.63	0.71
Business Conditions: next 5 years	-0.56	-0.33	-0.09	-0.01	0.11	0.21	0.29	0.47	0.68	0.76

Table 4: Correlations with aggregate variables

	OLS	OLS	OLS	FE	FE	FE
shock	0.0044	0.0295	0.0286	0.0002	0.0035	0.0037
	[0.0033]	[0.0065]***	[0.0064]***	[0.0032]	[0.0065]	[0.0064]
(decile==2)*shock		-0.0177	-0.0186		-0.008	-0.0088
		[0.0077]**	[0.0076]**		[0.0089]	[0.0088]
(decile==3)*shock		-0.0124	-0.0143		0.0028	0.0034
		[0.0078]	[0.0077]*		[0.0092]	[0.0092]
(decile==4)*shock		-0.007	-0.009		0.0099	0.0095
		[0.0077]	[0.0076]		[0.0091]	[0.0091]
(decile==5)*shock		-0.0157	-0.0166		-0.0002	-0.0001
		[0.0080]*	[0.0079]**		[0.0096]	[0.0096]
(decile==6)*shock		-0.0075	-0.0086		0.0066	0.0064
		[0.0080]	[0.0080]		[0.0097]	[0.0097]
(decile==7)*shock		-0.0097	-0.0105		0.006	0.0062
		[0.0083]	[0.0082]		[0.0101]	[0.0101]
(decile==8)*shock		-0.0144	-0.0158		-0.0011	-0.0018
		[0.0092]	[0.0090]*		[0.0113]	[0.0113]
(decile==9)*shock		-0.0165	-0.0178		-0.0043	-0.0046
		[0.0110]	[0.0108]*		[0.0145]	[0.0145]
(decile==10)*shock		-0.0475	-0.0475		-0.0419	-0.0418
		[0.0151]***	[0.0150]***		[0.0203]**	[0.0203]**
lny	0.4699		0.0644	0.1948		0.1948
	[0.0017]***		[0.0009]***	[0.0100]***		[0.0100]***
Constant	0.7889	2.3467	2.0588	2.3119	3.3905	2.3119
	[0.0098]***	[0.0029]***	[0.0054]***	[0.0553]***	[0.0003]***	[0.0553]***
Observations	263711	263711	263711	263711	263711	263711
R-squared	0.35	0.74	0.74			
F-test on 10th decile effect=0		0.1843	0.1633		0.0463	0.0474
Households				112197	112197	112197

Standard errors in brackets, clustered at the household level
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: The Effects of Financial Shocks on Consumption

x:	$\frac{\text{Std. Dev.}(x)}{\text{Std. Dev.(PCE)}}$	Corr(x,PCE)	$\frac{\text{Std. Dev.}(x)}{\text{Std. Dev.(RGDP)}}$	Corr(x,RGDP)
		Data		
CEX aggregate	1.51	0.56	1.36	0.61
		Common Components		
CEX aggregate	1.21	0.80	1.09	0.82
Decile 1	1.73	0.20	1.56	0.18
Decile 2	1.44	0.35	1.29	0.35
Decile 3	1.48	0.49	1.33	0.49
Decile 4	1.23	0.52	1.11	0.56
Decile 5	1.34	0.59	1.21	0.61
Decile 6	1.40	0.69	1.26	0.69
Decile 7	1.24	0.68	1.11	0.72
Decile 8	1.27	0.78	1.14	0.77
Decile 9	1.44	0.76	1.29	0.80
Decile 10	1.82	0.68	1.63	0.73

Table 6: Robustness. Relative standard deviations and correlations of business cycle components. x refers to the cyclical component of the variables listed below. PCE refers to per capita NIPA non-durables consumption. RGDP refers to per capita real RGDP.

A. Individual characteristics

Decile	1	2	3	4	5	6	7	8	9	10
1	.	0.048	0.003	0.131	0.343	0.120	0.721	0.001	0.000	0.000
2	.	.	0.462	0.778	0.429	0.000	0.028	0.000	0.000	0.000
3	.	.	.	0.290	0.105	0.000	0.002	0.000	0.000	0.000
4	.	.	.	.	0.604	0.000	0.031	0.000	0.000	0.000
5	.	.	.	.	.	0.001	0.116	0.000	0.000	0.000
6	.	.	.	.	.	.	0.138	0.005	0.000	0.000
7	.	.	.	.	.	.	.	0.000	0.000	0.000
8	.	.	.	.	.	.	.	.	0.154	0.000
9	.	.	.	.	.	.	.	.	.	0.000

Table A1: Tests of the differences in mean age by cell, p-values reported

Decile	1	2	3	4	5	6	7	8	9	10
1	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	.	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	.	.	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	.	.	.	.	0.000	0.000	0.000	0.000	0.000	0.000
5	.	.	.	.	.	0.000	0.000	0.000	0.000	0.000
6	.	.	.	.	.	.	0.232	0.000	0.000	0.000
7	.	.	.	.	.	.	.	0.001	0.000	0.000
8	.	.	.	.	.	.	.	.	0.848	0.000
9	.	.	.	.	.	.	.	.	.	0.018

Table A2: K-Smirnov tests of the differences in the race distribution by decile, p-values reported

Decile	1	2	3	4	5	6	7	8	9	10
1	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	.	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	.	.	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	.	.	.	.	0.000	0.000	0.000	0.000	0.000	0.000
5	.	.	.	.	.	0.000	0.000	0.000	0.000	0.000
6	.	.	.	.	.	.	0.000	0.000	0.000	0.000
7	.	.	.	.	.	.	.	0.000	0.000	0.000
8	.	.	.	.	.	.	.	.	0.000	0.000
9	.	.	.	.	.	.	.	.	.	0.000

Table A3: K-Smirnov tests of the differences in the education distribution by decile, p-values reported

B. Correlations in Figure 4

	Decile									
	1	2	3	4	5	6	7	8	9	10
1	1	0.65	0.50	0.38	0.33	0.23	0.17	-0.01	-0.21	-0.18
2		1	0.85	0.75	0.71	0.62	0.55	0.45	0.09	0.00
3			1	0.87	0.85	0.77	0.71	0.60	0.34	0.15
4				1	0.86	0.79	0.75	0.60	0.36	0.13
5					1	0.85	0.79	0.68	0.46	0.14
6						1	0.80	0.79	0.48	0.19
7							1	0.81	0.55	0.27
8								1	0.59	0.31
9									1	0.43
10										1

Correlations of the consumption deciles (raw data).

	Decile									
	1	2	3	4	5	6	7	8	9	10
1	1	0.86	0.67	0.51	0.48	0.41	0.23	0.09	-0.20	-0.40
2		1	0.94	0.88	0.84	0.79	0.66	0.54	0.15	-0.11
3			1	0.97	0.96	0.93	0.86	0.76	0.42	0.12
4				1	0.98	0.97	0.93	0.83	0.49	0.22
5					1	0.99	0.96	0.89	0.58	0.30
6						1	0.97	0.92	0.63	0.39
7							1	0.95	0.74	0.48
8								1	0.82	0.62
9									1	0.82
10										1

Correlations of the common components of the consumption deciles.

	Decile									
	1	2	3	4	5	6	7	8	9	10
1	1	0.29	0.15	0.14	0.05	-0.08	-0.10	-0.18	-0.22	-0.01
2		1	0.53	0.39	0.35	0.14	0.28	0.24	-0.02	0.11
3			1	0.48	0.44	0.22	0.18	0.18	0.18	0.23
4				1	0.45	0.26	0.21	0.03	0.13	0.05
5					1	0.44	0.28	0.17	0.26	-0.01
6						1	0.32	0.49	0.22	0.00
7							1	0.48	0.33	0.10
8								1	0.22	0.07
9									1	0.15
10										1

Correlations of the idiosyncratic component of the consumption deciles.

	1	2	3	4	5	6	7	8	9	10
1	1	0.9428	0.8790	0.8092	0.8233	0.7491	0.7199	0.6181	0.4875	-0.0589
2	0.9428	1.0000	0.9837	0.9569	0.9511	0.9010	0.8823	0.8040	0.6416	0.1466
3	0.8790	0.9837	1.0000	0.9854	0.9839	0.9549	0.9430	0.8797	0.7414	0.2822
4	0.8092	0.9569	0.9854	1.0000	0.9839	0.9609	0.9589	0.9011	0.7405	0.3374
5	0.8233	0.9511	0.9839	0.9839	1.0000	0.9866	0.9789	0.9361	0.7775	0.3523
6	0.7491	0.9010	0.9549	0.9609	0.9866	1.0000	0.9866	0.9716	0.8274	0.4764
7	0.7199	0.8823	0.9430	0.9589	0.9789	0.9866	1.0000	0.9617	0.8694	0.4740
8	0.6181	0.8040	0.8797	0.9011	0.9361	0.9716	0.9617	1.0000	0.8470	0.5442
9	0.4875	0.6416	0.7414	0.7405	0.7775	0.8274	0.8694	0.8470	1.0000	0.6718
10	-0.0589	0.1466	0.2822	0.3374	0.3523	0.4764	0.4740	0.5442	0.6718	1.0000

Correlations of the common of the consumption deciles component at the business cycle frequency.

C. Correlations of Figure 9

	1	2	3	4	5	6	7	8	9	10
1	1	0.65	0.50	0.38	0.33	0.23	0.11	-0.01	-0.21	-0.18
2	0.65	1.00	0.84	0.75	0.71	0.61	0.55	0.44	0.09	-0.00
3	0.50	0.84	1.00	0.87	0.85	0.77	0.70	0.60	0.33	0.14
4	0.38	0.75	0.87	1.00	0.86	0.78	0.74	0.60	0.36	0.13
5	0.33	0.71	0.85	0.86	1.00	0.85	0.79	0.67	0.46	0.14
6	0.23	0.61	0.77	0.78	0.85	1.00	0.79	0.78	0.48	0.18
7	0.11	0.55	0.70	0.74	0.79	0.79	1.00	0.80	0.55	0.27
8	-0.01	0.44	0.60	0.60	0.67	0.78	0.80	1.00	0.58	0.31
9	-0.21	0.09	0.33	0.36	0.46	0.48	0.55	0.58	1.00	0.42
10	-0.18	-0.00	0.14	0.13	0.14	0.18	0.27	0.31	0.42	1.00

Correlations of the raw data of the consumption deciles.

	1	2	3	4	5	6	7	8	9	10
1	1.0000	0.8296	0.5771	0.3659	0.3252	0.2526	0.0930	-0.0759	-0.1849	-0.5045
2	0.8296	1.0000	0.9249	0.8137	0.7638	0.7098	0.5863	0.4146	0.2054	-0.2086
3	0.5771	0.9249	1.0000	0.9602	0.9436	0.9100	0.8381	0.7047	0.5043	0.0997
4	0.3659	0.8137	0.9602	1.0000	0.9763	0.9588	0.9270	0.8127	0.5938	0.2449
5	0.3252	0.7638	0.9436	0.9763	1.0000	0.9878	0.9656	0.8764	0.6905	0.3377
6	0.2526	0.7098	0.9100	0.9588	0.9878	1.0000	0.9754	0.9092	0.7336	0.4249
7	0.0930	0.5863	0.8381	0.9270	0.9656	0.9754	1.0000	0.9428	0.8119	0.5115
8	-0.0759	0.4146	0.7047	0.8127	0.8764	0.9092	0.9428	1.0000	0.8901	0.6664
9	-0.1849	0.2054	0.5043	0.5938	0.6905	0.7336	0.8119	0.8901	1.0000	0.8193
10	-0.5045	-0.2086	0.0997	0.2449	0.3377	0.4249	0.5115	0.6664	0.8193	1.0000

Correlations of the common component of the consumption deciles.

	1	2	3	4	5	6	7	8	9	10
1	1.0000	0.5886	0.4639	0.3989	0.3413	0.2276	0.1342	0.0222	-0.2218	-0.1519
2	0.5886	1.0000	0.8144	0.7255	0.6917	0.5691	0.5435	0.4647	0.0396	0.0186
3	0.4639	0.8144	1.0000	0.8020	0.7769	0.6613	0.5799	0.5200	0.2236	0.1691
4	0.3989	0.7255	0.8020	1.0000	0.7718	0.6662	0.5960	0.4521	0.2176	0.1130
5	0.3413	0.6917	0.7769	0.7718	1.0000	0.7490	0.6362	0.5303	0.3151	0.0995
6	0.2276	0.5691	0.6613	0.6662	0.7490	1.0000	0.6531	0.6990	0.3299	0.1415
7	0.1342	0.5435	0.5799	0.5960	0.6362	0.6531	1.0000	0.6965	0.3632	0.2236
8	0.0222	0.4647	0.5200	0.4521	0.5303	0.6990	0.6965	1.0000	0.3965	0.2524
9	-0.2218	0.0396	0.2236	0.2176	0.3151	0.3299	0.3632	0.3965	1.0000	0.3723
10	-0.1519	0.0186	0.1691	0.1130	0.0995	0.1415	0.2236	0.2524	0.3723	1.0000

Correlations of the idiosyncratic component of the consumption deciles.

	1	2	3	4	5	6	7	8	9	10
1	1.0000	0.9579	0.8766	0.8211	0.8138	0.7228	0.6808	0.5457	0.4054	-0.2819
2	0.9579	1.0000	0.9750	0.9471	0.9316	0.8662	0.8394	0.7284	0.6052	-0.0761
3	0.8766	0.9750	1.0000	0.9883	0.9821	0.9462	0.9282	0.8472	0.7458	0.1175
4	0.8211	0.9471	0.9883	1.0000	0.9830	0.9547	0.9530	0.8735	0.7921	0.1980
5	0.8138	0.9316	0.9821	0.9830	1.0000	0.9833	0.9740	0.9162	0.8131	0.2196
6	0.7228	0.8662	0.9462	0.9547	0.9833	1.0000	0.9828	0.9599	0.8636	0.3637
7	0.6808	0.8394	0.9282	0.9530	0.9740	0.9828	1.0000	0.9549	0.9131	0.3836
8	0.5457	0.7284	0.8472	0.8735	0.9162	0.9599	0.9549	1.0000	0.9054	0.4859
9	0.4054	0.6052	0.7458	0.7921	0.8131	0.8636	0.9131	0.9054	1.0000	0.6430
10	-0.2819	-0.0761	0.1175	0.1980	0.2196	0.3637	0.3836	0.4859	0.6430	1.0000

Correlations of the common of the consumption deciles component at the business cycle frequency.

Not For Publication

D. Data

quarter	Decile 1	2	3	4	5	6	7	8	9	10	Total
1984q1	132	130	170	120	126	113	131	111	100	90	1,223
1984q2	113	100	131	119	117	107	106	112	100	87	1,092
1984q3	99	92	90	112	106	110	107	109	104	108	1,037
1984q4	108	99	103	126	93	130	115	103	109	104	1,090
1985q1	107	120	110	117	93	111	112	96	107	98	1,071
1985q2	105	109	102	100	100	87	95	109	103	97	1,007
1985q3	92	96	111	102	122	112	103	120	122	114	1,094
1985q4	103	106	126	125	160	139	114	142	130	117	1,262
1986q1	196	195	173	187	190	178	158	152	128	138	1,695
1986q2	264	273	252	267	259	247	242	225	232	238	2,499
1986q3	258	264	228	252	246	259	260	256	284	286	2,593
1986q4	245	251	235	264	277	247	274	259	269	299	2,620
1987q1	270	253	263	268	268	258	266	245	251	284	2,626
1987q2	255	244	245	233	244	245	268	218	248	279	2,479
1987q3	254	230	234	242	243	237	259	265	274	264	2,502
1987q4	218	221	206	209	231	219	235	251	245	259	2,294
1988q1	232	219	197	210	224	221	208	241	226	219	2,197
1988q2	225	220	209	206	202	214	215	223	227	231	2,172
1988q3	225	227	210	220	220	218	237	237	246	243	2,283
1988q4	226	228	241	226	226	206	238	244	234	247	2,316
1989q1	187	201	218	206	209	192	211	206	210	202	2,042
1989q2	141	151	150	163	159	158	165	155	162	151	1,555
1989q3	103	115	110	122	125	142	126	127	136	131	1,237
1989q4	98	108	109	121	119	111	141	129	122	121	1,179
1990q1	112	114	113	118	109	111	125	125	108	113	1,148
1990q2	105	104	97	114	105	96	105	112	97	104	1,039
1990q3	103	78	96	98	103	109	111	111	111	103	1,023
1990q4	100	84	91	91	106	128	102	95	115	95	1,007
1991q1	97	95	111	111	97	121	103	109	127	99	1,070
1991q2	91	110	112	113	116	127	101	116	128	117	1,131
1991q3	140	128	152	142	151	155	146	141	149	142	1,446
1991q4	177	183	184	175	180	203	189	173	184	186	1,834
1992q1	220	222	209	213	212	239	225	203	232	235	2,210
1992q2	211	222	234	215	212	235	238	243	242	242	2,294
1992q3	223	212	238	225	234	248	249	249	250	237	2,365
1992q4	211	224	246	248	233	223	247	238	242	222	2,334

Table D1: Cells Frequencies

	Decile										
quarter	1	2	3	4	5	6	7	8	9	10	Total
1993q1	229	230	233	230	244	232	239	239	261	216	2,353
1993q2	208	222	218	211	237	222	229	234	242	239	2,262
1993q3	206	217	224	228	219	247	241	258	243	247	2,330
1993q4	200	220	213	245	247	243	239	246	251	249	2,353
1994q1	221	206	228	249	228	223	235	240	235	238	2,303
1994q2	213	224	208	226	234	206	215	239	237	222	2,224
1994q3	206	232	207	197	209	213	229	239	241	237	2,210
1994q4	192	196	213	197	215	237	232	242	230	212	2,166
1995q1	219	208	213	201	212	227	228	233	221	203	2,165
1995q2	202	214	217	197	197	223	220	232	216	206	2,124
1995q3	184	192	187	177	179	199	193	209	203	201	1,924
1995q4	179	181	178	191	189	174	205	191	216	194	1,898
1996q1	176	156	167	173	202	174	157	162	159	180	1,706
1996q2	210	217	195	194	198	209	200	187	193	186	1,989
1996q3	194	214	212	189	191	207	221	207	214	213	2,062
1996q4	223	227	226	230	220	216	225	211	229	212	2,219
1997q1	210	220	224	215	226	236	207	205	225	216	2,184
1997q2	209	209	208	213	227	216	236	206	236	217	2,177
1997q3	225	210	216	218	205	217	239	223	226	223	2,202
1997q4	226	223	248	215	215	216	233	234	219	249	2,278
1998q1	214	229	229	226	217	216	208	237	213	228	2,217
1998q2	207	213	197	225	224	204	209	234	217	223	2,153
1998q3	221	191	195	229	211	213	225	224	209	208	2,126
1998q4	226	192	209	206	208	189	227	239	208	203	2,107
1999q1	283	257	267	263	268	259	285	247	271	242	2,642
1999q2	270	278	286	280	303	284	295	297	303	297	2,893
1999q3	287	260	287	289	289	306	289	297	308	310	2,922
1999q4	292	265	286	301	286	279	283	291	296	330	2,909
2000q1	275	289	331	296	284	290	299	281	284	320	2,949
2000q2	264	289	294	288	296	300	311	313	308	314	2,977
2000q3	280	280	289	291	290	299	305	319	308	293	2,954
2000q4	306	273	266	287	305	288	284	292	305	281	2,887
2001q1	278	259	259	275	303	283	270	298	284	276	2,785
2001q2	284	277	276	307	291	282	278	315	317	281	2,908
2001q3	280	299	303	293	308	308	334	320	324	329	3,098
2001q4	318	305	341	325	312	337	337	315	326	343	3,259

Table cont'd: Cells Frequencies

	Decile										
quarter	1	2	3	4	5	6	7	8	9	10	Total
2002q1	301	306	332	301	333	335	344	320	310	329	3,211
2002q2	333	297	324	321	327	331	328	343	355	333	3,292
2002q3	316	316	313	341	317	326	338	343	349	345	3,304
2002q4	334	322	324	369	344	318	341	339	344	343	3,378
2003q1	329	339	315	363	350	340	360	336	336	352	3,420
2003q2	339	348	342	353	316	346	348	366	339	351	3,448
2003q3	347	353	350	336	339	372	361	355	332	360	3,505
2003q4	357	336	361	343	352	347	349	363	338	328	3,474
2004q1	356	336	319	328	349	334	319	317	351	333	3,342
2004q2	317	315	308	318	328	333	310	317	351	344	3,241
2004q3	303	324	318	311	317	332	334	333	336	366	3,274
2004q4	329	328	316	328	325	352	356	327	329	343	3,333
2005q1	294	277	282	268	288	298	305	275	288	306	2,881
2005q2	346	334	344	351	326	330	299	325	326	332	3,313
2005q3	319	338	328	342	308	334	335	349	335	345	3,333
2005q4	353	355	348	358	352	355	349	359	354	332	3,515
2006q1	319	305	308	267	326	331	322	311	321	300	3,110
2006q2	316	298	309	320	312	326	316	306	321	298	3,122
2006q3	324	323	307	316	324	317	326	330	322	323	3,212
2006q4	308	344	326	325	305	319	301	321	299	317	3,165
2007q1	329	319	325	308	319	294	315	310	299	327	3,145
2007q2	304	298	296	267	290	284	302	289	288	321	2,939
2007q3	305	290	293	292	293	295	286	328	313	314	3,009
2007q4	298	304	275	283	295	289	290	337	350	300	3,021
2008q1	311	282	301	304	309	304	279	323	333	310	3,056
2008q2	265	282	272	286	305	291	290	300	330	319	2,940
2008q3	282	289	294	284	284	309	301	292	303	319	2,957
2008q4	336	307	311	295	287	312	282	280	296	295	3,001
2009q1	305	284	314	302	289	288	298	313	307	304	3,004
2009q2	318	290	290	299	321	289	304	314	327	335	3,087
2009q3	328	317	296	306	315	305	315	295	319	347	3,143
2009q4	333	333	298	299	318	305	303	313	334	348	3,184
2010q1	327	324	313	290	299	312	329	329	313	315	3,151
2010q2	310	318	309	311	298	305	298	319	315	313	3,096
2010q3	323	291	283	314	308	309	307	309	318	315	3,077
2010q4	321	276	310	304	318	308	289	277	304	340	3,047
Total	26,003	25,695	25,915	26,064	26,286	26,391	26,601	26,796	27,041	26,919	263,711

Table cont'd: Cells frequencies

E. Micro Data

Total income before taxes, denoted by *tot_fam_inc_btax*, is the sum of:

- FSALARYX - Amount of wage and salary income before deductions received by all CU members in past 12 months (sum SALARYX from MEMB file for all CU members)
- FNONFRMX - Amount of income or loss from nonfarm business, partnership or professional practice received by all CU members in past 12 months (sum NONFARMX from MEMB file for all CU members)
- FFRMINCX - Amount of income or loss from own farm received by all CU members in past 12 months (sum FARMINCX from MEMB file for all CU members)
- FRRETIRX - Amount of Social Security and Railroad Retirement income prior to deductions for medical insurance and Medicare received by all CU members in past 12 months (sum SOCRRX from MEMB file for all CU members)
- FSSIX - Amount of Supplemental Security Income from all sources received by all CU members in past 12 months (sum SSIX from MEMB file for all members)
- UNEMPLX - Amount of unemployment compensation received by CU in past 12 months
- COMPENSX - Amount of workers' compensation and veterans' payments, including education benefits but excluding military retirement, received by CU in past 12 months
- WELFAREX - Amount of public assistance or welfare including job training grants such as Job Corps received by CU in past 12 months
- INTEARNX - Amount of interest on savings accounts or bonds received by CU in past 12 months
- FININCX - Amount of regular income from dividends, royalties, estates, or trusts, received by CU in past 12 months
- PENSIONX - Amount of income from pensions or annuities from private companies, military or government, IRA, or Keogh received by CU in past 12 months
- INCLOSSA - Amount of net income or loss from roomers or boarders received by CU in past 12 months
- INCLOSSB - Amount of net income or loss from other rental units received by CU in past 12 months
- ALIOTHX - Total amount received from alimony (regular receipts) and other regular contributions by CU in the past 12 months
- CHDOTHX - Total amount received for child support (non-lump sum) by CU in the past 12 months
- OTHRINCX - Amount of other money income including money from care of foster children, cash scholarships and fellowships, or stipends not based on working received by CU in past 12 months
- JFDSTMPA - Annual value of Food Stamps received

Total family income after tax is computed as total family income before tax minus total taxes, according to:
tot_fam_inc_atax=*tot_fam_inc_btax*- *tottax*
where *tottax* is the sum of:

- FAMTFEDX - Amount of Federal income tax deducted from last pay annualized for all CU members
- FSLTAXX - Amount of state and local income taxes deducted from last pay annualized for all CU members
- FEDTAXX - Amount of Federal income tax paid by CU, in addition to that withheld from earnings, in past 12 months
- SLOCTAXX - Amount of state and local income taxes paid by CU, in addition to that withheld from earnings, in past 12 months
- TAXPROPX - Amount of personal property taxes paid but not reported elsewhere by CU in past 12 months
- MISCTAXX - Amount of other taxes paid but not reported elsewhere by CU in past 12 months

minus

- FEDRFNDX - Amount of refund from Federal income tax received by CU in past 12 months
- SLRFUNDX - Amount of refund from state and local income taxes received by CU in past 12 months
- OTHRFNDX - Amount of refunds from other sources, including any other taxes, received by CU in past 12 months

F. Macro Data

Transformations: 1=levels, 2= first differences of the original series, 5= first differences of logs of the original series.

no.series	Transf.	Mnemonic	Long Label
1	5	GDPC1	Real Gross Domestic Product, 1 Decimal
2	5	GNPC96	Real Gross National Product
3	5	NICUR/GDPDEF	National Income/GDPDEF
4	5	DPIC96	Real Disposable Personal Income
5	5	OUTNFB	Nonfarm Business Sector: Output
6	5	FINSLC1	Real Final Sales of Domestic Product, 1 Decimal
7	5	FPIC1	Real Private Fixed Investment, 1 Decimal
8	5	PRFIC1	Real Private Residential Fixed Investment, 1 Decimal
9	5	PNFIC1	Real Private Nonresidential Fixed Investment, 1 Decimal
10	5	GPDIC1	Real Gross Private Domestic Investment, 1 Decimal
11	5	PCECC96	Real Personal Consumption Expenditures
12	5	PCNDGC96	Real Personal Consumption Expenditures: Nondurable Goods
13	5	PCDGCC96	Real Personal Consumption Expenditures: Durable Goods
14	5	PCESVC96	Real Personal Consumption Expenditures: Services
15	5	GPSAVE/GDPDEF	Gross Private Saving/GDP Deflator
16	5	FGCEC1	Real Federal Consumption Expenditures & Gross Investment, 1 Decimal
17	5	FGEXPND/GDPDEF	Federal Government: Current Expenditures/ GDP deflator
18	5	FGRECPT/GDPDEF	Federal Government Current Receipts/ GDP deflator
19	2	FGDEF	Federal Real Expend-Real Receipts
20	1	CBIC1	Real Change in Private Inventories, 1 Decimal
21	5	EXPGSC1	Real Exports of Goods & Services, 1 Decimal
22	5	IMPGSC1	Real Imports of Goods & Services, 1 Decimal
23	5	CP/GDPDEF	Corporate Profits After Tax/GDP deflator
24	5	NFCPATAX/GDPDEF	Nonfinancial Corporate Business: Profits After Tax/GDP deflator
25	5	CNCF/GDPDEF	Corporate Net Cash Flow/GDP deflator
26	5	DIVIDEND/GDPDEF	Net Corporate Dividends/GDP deflator
27	5	HOANBS	Nonfarm Business Sector: Hours of All Persons
28	5	OPHNFB	Nonfarm Business Sector: Output Per Hour of All Persons
29	5	UNLPNBS	Nonfarm Business Sector: Unit Nonlabor Payments
30	5	ULCNFB	Nonfarm Business Sector: Unit Labor Cost
31	5	WASCUR/CPI	Compensation of Employees: Wages & Salary Accruals/CPI
32	5	COMPNFB	Nonfarm Business Sector: Compensation Per Hour
33	5	COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour
34	5	GDPCTPI	Gross Domestic Product: Chain-type Price Index
35	5	GNPCTPI	Gross National Product: Chain-type Price Index
36	5	GDPDEF	Gross Domestic Product: Implicit Price Deflator
37	5	GNPDEF	Gross National Product: Implicit Price Deflator
38	5	INDPRO	Industrial Production Index
39	5	IPBUSEQ	Industrial Production: Business Equipment
40	5	IPCONGD	Industrial Production: Consumer Goods
41	5	IPDCONGD	Industrial Production: Durable Consumer Goods
42	5	IPFINAL	Industrial Production: Final Products (Market Group)
43	5	IPMAT	Industrial Production: Materials
44	5	IPNCONGD	Industrial Production: Nondurable Consumer Goods
45	2	AWHMAN	Average Weekly Hours: Manufacturing
46	2	AWOTMAN	Average Weekly Hours: Overtime: Manufacturing

no.series	Transf.	Mnemonic	Long Label
47	2	CIVPART	Civilian Participation Rate
48	5	CLF16OV	Civilian Labor Force
49	5	CE16OV	Civilian Employment
50	5	USPRIV	All Employees: Total Private Industries
51	5	USGOOD	All Employees: Goods-Producing Industries
52	5	SRVPRD	All Employees: Service-Providing Industries
53	5	UNEMPLOY	Unemployed
54	5	UEMPMEAN	Average (Mean) Duration of Unemployment
55	2	UNRATE	Civilian Unemployment Rate
56	5	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started
57	2	FEDFUNDS	Effective Federal Funds Rate
58	2	TB3MS	3-Month Treasury Bill: Secondary Market Rate
59	2	GS1	1-Year Treasury Constant Maturity Rate
60	2	GS10	10-Year Treasury Constant Maturity Rate
61	2	AAA	Moody's Seasoned Aaa Corporate Bond Yield
62	2	BAA	Moody's Seasoned Baa Corporate Bond Yield
63	2	MPRIME	Bank Prime Loan Rate
64	5	BOGNONBR	Non-Borrowed Reserves of Depository Institutions
65	5	TRARR	Board of Governors Total Reserves, Adjusted for Changes in Reserve
66	5	BOGAMBSL	Board of Governors Monetary Base, Adjusted for Changes in Reserve
67	5	M1SL	M1 Money Stock
68	5	M2MSL	M2 Minus
69	5	M2SL	M2 Money Stock
70	5	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks
71	5	CONSUMER	Consumer (Individual) Loans at All Commercial Banks
72	5	LOANINV	Total Loans and Investments at All Commercial Banks
73	5	REALLN	Real Estate Loans at All Commercial Banks
74	5	TOTALSL	Total Consumer Credit Outstanding
75	5	CPIAUCSL	Consumer Price Index For All Urban Consumers: All Items
76	5	CPIULFSL	Consumer Price Index for All Urban Consumers: All Items Less Food
77	5	CPILEGSL	Consumer Price Index for All Urban Consumers: All Items Less Energy
78	5	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy
79	5	CPIENGSL	Consumer Price Index for All Urban Consumers: Energy
80	5	CPIUFDSL	Consumer Price Index for All Urban Consumers: Food
81	5	PPICPE	Producer Price Index Finished Goods: Capital Equipment
82	5	PPICRM	Producer Price Index: Crude Materials for Further Processing
83	5	PPIFCG	Producer Price Index: Finished Consumer Goods
84	5	PPIFGS	Producer Price Index: Finished Goods
85	5	OILPRICE	Spot Oil Price: West Texas Intermediate
86	5	USSHRPRCF	US Dow Jones Industrials Share Price Index (EP) NADJ
87	5	US500STK	US Standard & poor's Index if 500 Common Stocks
88	5	USI62...F	US Share Price Index NADJ
89	5	USNOIDN.D	US Manufacturers New Orders for Non Defense Capital Goods (BCI 27)
90	5	USCNORCGD	US New Orders of Consumer Goods & Materials (BCI 8) CONA
91	1	USNAPMNO	US ISM Manufacturers Survey: New Orders Index SADJ
92	5	USVACTOTO	US Index of Help Wanted Advertising VOLA
93	5	USCYLEAD	US The Conference Board Leading Economic Indicators Index SADJ
94	5	USECRIWLH	US Economic Cycle Research Institute Weekly Leading Index
95	2	GS10-FEDFUNDS	
96	2	GS1-FEDFUNDS	
97	2	BAA-FEDFUNDS	
98	5	GEXPND/GDPDEF	Government Current Expenditures/ GDP deflator
99	5	GRECPT/GDPDEF	Government Current Receipts/ GDP deflator
100	2	GDEF	Governnent Real Expend-Real Receipts
101	5	GCEC1	Real Government Cons. Expenditures & Gross Investment, 1 Decimal
102	5		Real Federal Cons. Expenditures & Gross Investment National Defense
103	2		Federal primary deficit
104	5		Real Federal Current Tax Revenues
105	5		Real Government Current Tax Revenues
106	2		Government primary deficit
107	5		Real (/GDPDEF) Gov. Social Benefit
108	1		Gov. social benefits/ Gov. Curr Exp