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BALANCE SHEET EFFECTS ON HOUSEHOLD CONSUMPTION: EVIDENCE FROM MICRO DATA

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Abstract

Using micro data from the Consumer Expenditure Survey of U.S. households, this paper estimates wealth effect on nondurable and durable consumption with a semiparametric regression model. The wealth effect is estimated by a nonlinear smooth function that can detect asymmetric response of consumption at different configurations of household assets and liabilities. The major finding is that durable consumption is subject to particularly large balance sheet effects, especially from net additions to household liabilities, and from net reductions in household assets. Estimated debt-consumption profiles indicate that the ongoing slump in durable consumption and residential investments in the United States can be largely explained by the sharp reduction in debt accumulation (*i.e.*, deleveraging) among households since the recent burst of the housing bubble. Compared with the significant debt effects on consumption, I found little evidence of direct wealth effect from increased household assets.

1 Introduction

Wealth effects on consumer spending has attracted attention recently as a strategy to speed up the sluggish recovery from 2007-2009 recession in the United States. The positive wealth effect on consumption from rising asset prices was a reason for the U.S. Federal Reserve to start the second round of quantitative easing, with expectation that "higher stock prices will boost consumer wealth and help increase confidence, which can also spur spending" (Bernanke, 2010). Similarly, Greenspan (forthcoming) referred to the positive wealth effect on consumption as a substitute for activist fiscal policy, with increased stock prices carrying "a significant wealth effect that should enhance economic activity" (p. 17).

These claims are based on extensive research that have examined the link between wealth and consumption in both aggregate and household data. Due to better data availability, most studies focused on the consumption behavior of U.S. households, and a broad agreement has been reached that one dollar increase in household wealth rises consumption by 2 to 7 cents (Congressional Budget Office, 2007). This estimate is close to theoretical predictions from the life cycle theory of savings of Modigliani and Brumberg (1954). For example, Skinner (1996) examined the extent of wealth effect in several life-cycle models, and calculated that the marginal propensity to consume (*mpc*) from housing wealth is 2.5 cents on the dollar with no moving costs, while the addition of moving costs reduces the *mpc* to 1.4 cents on the dollar. Similarly, Poterba (2000) estimated that for life-cycle consumers with no bequest motive and the planning horizon of 30 years, the *mpc* out of wealth ranges between 3.8 to 7.5 cents for a dollar increase in wealth.

Early studies of the wealth effect typically examined aggregate data. For example, Case *et al.* (2005) studied the link between wealth and consumption with two datasets: a panel of 14 developed countries, and a panel dataset of U.S. states, and found that housing market wealth had a much larger effect on consumption than stock market wealth. However, this study estimated wealth effects from gross measures of wealth, without making adjustments for household liabilities. Subsequent macro studies paid more attention to net measures of wealth (such as net worth of households), with representative studies including Carroll *et al.* (forthcoming) for the United States, and Catte *et al.* (2004) for OECD economies.

With aggregate data, it is possible to estimate both short-term and long-term wealth effects on consumption, and it is possible to study how consumption adjusts to wealth shocks over time. But aggregate data also have serious drawbacks for studying wealth effects. First, such data contain only averages for consumption and wealth across households, and there is no way to verify that it is households with increased wealth that actually rise their consumption after a wealth shock. Second, with aggregate data, it is difficult to control for specific characteristics of households, with the most serious problem for common factors that can affect both wealth and consumption of households. For instance, households with better education are likely to have relatively high levels of lifetime wealth and consumption. In consequence, a positive relation will emerge in aggregate data, but will not reflect the causal wealth effect from wealth to consumption, but instead the common causality among households with higher human capital. This omitted-variable bias may create a serious bias in estimates of wealth effect. Finally, aggregate data does not allow to differentiate between alternative explanations of wealth effect. In addition to the direct wealth effect on spending, King (1990) and Pagano (1990) suggested that the correlation between wealth and consumption may reflect some common factors, such as improved expectations of future earnings. Similarly, Aoki *et al.* (2004) suggested another indirect mechanism for the link between wealth and consumption that draws attention to the the collateral role of housing assets for household borrowing. With aggregate data, it is very difficult to compare which of these alternative mechanisms of wealth effect is better supported by empirical evidence.

Studies of wealth effect with micro data are less affected by the limitations of aggregate data. However, micro data have their own problems, and the most difficult challenge has been the low quality of wealth data in household surveys. Two groups of micro studies can be identified depending on how they dealt with the problem.

The first group of studies approximates changes in household wealth by indexes of asset prices. For example, Attanasio *et al.* (2009) and Campbell and Cocco (2007) approximated changes in housing assets with regional house prices in the U.K., while Dynan and Maki (2001) approximated changes in stock market assets with a broad index of U.S. stock prices. However, as pointed by Paiella (2009), the indexes of asset prices may be a poor proxy to actual household wealth, and a particularly poor correspondence is likely for stock market wealth (p. 969). The use of stock market indexes implies that households have diversified stock portfolio, but there is ample evidence that actual stock holdings of households are concentrated in just several stocks, so that very few households have truly diversified portfolios (Goetzmann and Kumar, 2008). In addition, the use of asset price indexes deals with gross measures of household wealth, with no adjustment for household liabilities.

The second group of studies typically uses net measures of household wealth (such as net worth). Because it is rare for household surveys to contain both consumer expenditures and net worth, it has been common to create a combined dataset, in which a survey with good consumption data is matched with another survey with reliable net wealth data. The matching approach was most often applied to U.S. household data, and typical combinations included the Consumer Expenditure Survey (CES), with a good coverage of consumption expenditures, and various surveys with detailed wealth holdings. For example, Bostic *et al.* (2009) combined the consumption data in the CES with wealth data from the Survey of Consumer Finance (SCF), while Skinner (1996) similarly matched the CES and the Panel Study of Income Dynamics (PSID).

The matching of household surveys requires that households are initially classified by several characteristics, such as age of household head, education level, region of residence, and other characteristics that can be identified in both surveys. After grouping households by these characteristics, a combined dataset is created from the group averages (or medians) for consumption, wealth and other variables that can be aggregated across households. A limitation of this approach is that it is not known how a choice of particular classification scheme to create matched datasets is affecting estimation results (after all, a different classification scheme produces a new matched database). Such robustness checks across feasible classification schemes are likely to be a daunting task, and they have rarely been attempted in studies that used the matching approach.

So far, the vast majority of micro studies of wealth effect have used either of two approaches to measure household wealth. The only exception is the study by Paiella (2007), where consumption and net wealth data were taken from the same survey of Italian households. In particular, there seems to be no study of U.S. households that used data on net wealth and consumption from the same source.

This paper will deal with the gap in past studies by using consumption and balance sheet data from the CES. It is common to view balance sheet information in the CES as either limited or unreliable (see, for example, Dynan and Maki (2001) or Bostic *et al.* (2009)). However, comparisons with alternative surveys of household wealth indicate that the CES data may be not as bad as commonly believed. For example, Attanasio (1994) concluded that in the CES, "the main features of the financial asset data are similar to those found in other surveys" (p. 63). In particular, there is some evidence that the CES data for household debt are consistent with other household surveys. For example, Maki (2001) compared credit card and auto loan data in the CES and SCF, and found them broadly similar. More recently, Johnson and Li (2009) compared household liabilities in the CES and the SCF from 1992 and 2007. They found that that household debt balances in the CES were measured well, and the survey "may be used to examine household debt and its relation to household economic decisions" (p. 18). Finally, Sabelhaus (1993) used the CES to compare two measures of household saving, first derived as a residual measure (*i.e.*, disposable income less consumption), and second, derived as a change in household net worth. The study found that these alternative measures of household savings were similar, indicating that the net worth in the CES may have similar measurement errors, as compared with income and consumption data.

Another novel feature of this paper is the study of possible asymmetries in wealth effects, by estimating wealth effects with a nonparametric nonlinear function. The possibility of asymmetric wealth effects was discussed by Poterba (2000) for positive and negative changes in wealth, and empirical evidence for such asymmetric responses was reported by Skinner (1996), Engelhardt (1996), and Parker (2000). These studies used dummy variables to separate negative and positive wealth effects, while in this paper I estimate wealth-consumption profiles across a broad range of wealth changes.

To preview major findings, this paper begins with a conventional life-cycle model of consumption that includes age, cohort and year effects on consumption, and estimates separate models for nondurable and durable consumption. Then the benchmark model is extended with a net wealth effect from a change in net worth of households. The net wealth effect is specified by a smooth nonparametric function, allowing to identify possible nonlinearities at different levels of net worth. Estimates of these wealth-consumption profiles showed that increased net worth had almost no effect on both types of consumer expenditures. However, there was a substantial increase in consumption with *reduced* net worth, especially for expenditures on durables. To trace the source of this negative wealth effect, I split net worth into its constituent parts, and estimated balance sheet effects on consumption from household assets and liabilities. While changes in household assets continued to have limited effect on both types of consumption, there was a notable positive effect from increased liabilities, especially for durable consumption. In sum, changes in household assets have small effect on consumption, with much larger effects produced from changes in household liability, especially on durable consumption. Using estimated debt-consumption profiles, back-of-the-envelope calculations indicate that around two-third of the latest slowdown in durable consumption and residential investments in the U.S. can be attributed to the reversal in their debt accumulation (namely, deleveraging) after the burst of housing bubble in past several years.

2 Data.

As already discussed, this study used U.S. household data from the CES. This is an annual survey, conducted by the Bureau of Labor Statistics (BLS) mainly to collect expenditure weights for calculating consumer price indexes. This explains why the CES contains highly detailed information on expenditure categories. The survey also collects data on sources of household income, and on changes in household assets and liabilities over the preceding year.

The CES is a rotating panel, with households participating in five quarterly interviews. The first interview is used only to classify households, and no data is collected about consumption expenditures, incomes, or changes in balance sheets of households. In the remaining four interviews, households mainly report their expenditures on a large number of consumption categories. As for the data for current income and changes in household balance sheets, they are collected only in the second and fifth interviews. The survey gathers information from about 5,000 households, but in practice only one half of households complete all five interviews. However, the BLS provides special weights that take into account the high attrition rate, making even this reduced sample a representative snapshot of the U.S. population.

Household surveys often contain a large number of incomplete or unreliable household data, and the CES is not exception. When cleaning-up the dataset, I omitted households that met the following major criteria:

1. households with top-coded records;

2. households with incomplete income or expenditure data (*i.e.*, households that did not participate in all five interviews);

3. households that had a large absolute discrepancy between sources and uses of financial funds. Let SR denote sources of funds, with $SF = YD + T + \Delta L$, where YD is disposable income, T is net monetary transfers to households from other sectors, and ΔL is net borrowing from other sectors. On the other hand, let UF denote uses of funds, with $UF = C + I_h + \Delta A$, where C is total consumption expenditure of households, I_h is net capital formation of households (in practice, essentially residential investments), and ΔA is the acquisition of financial assets. A basic accounting identity requires that sources and uses of funds are identical, but in practice they rarely match. For each household, I calculated sources and uses of funds, and then compared them with a discrepancy index, calculated by $\frac{|SF-UF|}{0.5\times(SF+UF)} \times 100\%$. I dropped households with this measure exceeding 33.3 percent.[1]

Original CES data were downloaded from the homepage of National Bureau of Economic Research (NBER). The NBER provides the CES data from 1980 and 2004, but I did not use data for 1980-1983 because these early surveys are of relatively low quality, or included only urban households (Attanasio, 1998; Dynan and Maki, 2001). The CES provides expenditures in nominal terms, and real real consumption expenditures were calculated with consumer price indexes for major expenditure categories, downloaded from the BLS homepage.

[1] Sabelhaus (1993) used the same consistency check for the CES data.

The original sample included 127495 households. After applying to them the three selection criteria, the sample size decreased to 116254, 48451 and 30516 households, respectively.

In subsequent cleaning, I dropped households that met the following minor selection criteria:

1. households with implausible values of stock holding (such as 1 dollar);
2. student households;
3. households with negative values of income or total consumption.

Withe these minor criteria, the sample size decreased only slightly, to 30188 households.

In total consumption expenditures, I separated nondurable and durable consumption. Nondurable consumption included expenditures on food, tobacco, alcohol, clothing, personal care, utilities, services, personal transportation, readings, household supplies, and communication. Durable consumption contained expenditures on jewelry, rent (including imputed rent for home-owners), furniture, vehicles, recording equipment, health care and education.

Compared with consumption or income data, the CES contains much less data for household balance sheets. In particular, data on the stock of asset holdings has numerous nonresponses (Attanasio, 1994). But as previously discussed, the CES data on net changes in household net worth appears to be compatible with income and consumption data. Changes in net worth were calculated from changes in housing and financial assets, less changes in housing and non-housing liabilities.

Changes in housing assets equal to the difference between the value of properties purchased and sold, plus additions and alterations to the housing assets. On the other hand, changes in housing liabilities were calculated as the difference between mortgage loans originated and payments of mortgage principal.

Changes in financial assets had the most detailed data, and included changes in checking and saving accounts, stocks, bonds, and mutual funds, various private and public retirement contributions, and investments to own business. Corresponding changes in non-housing liabilities included changes in installment credit, vehicle loans, and other loans owned to households.

These changes in housing and non-housing new worth were summed up, and then normalized by disposable income of households. This measure of normalized net worth of households will be denoted by $\Delta NW/YD$.

This final measure of net worth was very noisy, and I followed much of micro-level studies by omitting households with extreme values of $\Delta NW/YD$. Specifically, households were omitted if they were below 5 percentile and above 95 percentile in the distribution of $\Delta NW/YD$. The final sample included 27168 households, with $\Delta NW/YD$ ranging between -0.42 and 0.36.

3 Life-cycle models of household consumption

First I introduce a baseline model of household consumption, in which consumption depends on the total lifetime wealth of households. The baseline model is based on life-cycle models from Attanasio *et al.* (2009) and Fernández-Villaverde and Krueger (2007). Households consume a fraction of their lifetime wealth, and the fraction depends on the age of household head:

$$Y_{i,t} = \delta\left(age_i\right) W_i \exp\left(\varepsilon_{i,t}\right) \tag{1}$$

where $Y_{i,t}$ is consumption expenditures of household i at time t, W_i is the total lifetime wealth of household, and $\varepsilon_{i,t}$ is the regression disturbance.

In this specification, $\delta\left(age_i\right)$ denotes the age profile of consumption that reflects the composition of households, varying needs of household members, and other factors that change with age. The total household wealth W_i consist of two parts: the human capital (given by the sum of discounted future earnings), and the current net worth of households (*i.e.*, net housing wealth, and net financial wealth). In the baseline model of household consumption, I do not differentiate between these two major parts of W_i.

After taking logs of (1), we obtain an additive specification with age and wealth effects on consumption. The specification is extended with a vector of observable variables $z_{i,t}$ that may have effect on the level of household consumption:

$$\log\left(Y_{i,t}\right) = \log\left(\delta\left(age_i\right)\right) + \beta' z_{i,t} + \log\left(W_i\right) + \varepsilon_{i,t} \tag{2}$$

The observable variables in $z_{i,t}$ include the number of adults and children in household, various characteristics of the household head, such as occupation, education, race, marital status, gender, and similar control variables.

The baseline model (2) is specified for individual households, but the CES has very short panel dimension of just 4 quarters. Due to the short panel dimension, the model (2) is expressed in terms of household cohorts, identified by the birth year of household heads. Let birth year be denoted by c (so that $c = t - age$, where t is the current year). After averaging (2) across birth cohorts c, we get

$$\log\left(Y_{c,t}\right) = \log\left(\delta\left(age_c\right)\right) + \beta' z_{c,t} + \alpha_c + \varepsilon_{c,t} \tag{3}$$

where index c identifies a particular birth cohort, and α_c is the average logarithm of lifetime wealth of households belonging to cohort c.

To account for the time variation in household consumption, specification (3) is further extended by a set of year dummies D_t for observation years t. In additional, the age effect $\log\left(\delta\left(age_c\right)\right)$ is approximated by a flexible function of age, specified by a set of dummy variables D_a. Similarly, cohort effect is estimated by a set of cohort dummies D_c:

$$\log\left(Y_{c,t}\right) = \alpha_a D_a + \alpha_c D_c + \alpha_t D_t + \beta' z_{c,t} + \varepsilon_c \tag{4}$$

However, this model has exact linear relationship among age a, birth cohort c, and current year t (i.e., current year minus age equals the birth year), and due to the exact collinearity it is not possible to estimate (4) by linear regression estimators. Fernández-Villaverde and Krueger (2007) proposed to solve the identification problem by replacing age dummies D_a with a smooth nonlinear function of age $f(a)$. With this substitution, model (4) becomes a partial additive model that can be estimated by various nonparametric regression estimators (Härdle *et al.*, 2004). For example, Fernández-Villaverde and Krueger (2007) choose a semiparametric estimator, suggested by Speckman (1988). However, a serious limitation of the Speckman estimator is that it can be used for models with only a single nonparametric term. With more than one nonparametric effects, alternative estimators of the partial linear model has to be used.

In this paper, I apply nonparametric effects not only to break the identification problem among age, cohort and year effects, but also to examine nonlinearities in the wealth effect on consumption. Initially, the nonparametric effect is applied to cohort effect on consumption[2] , by replacing the set of cohort dummies D_c with a single smooth function $f(c)$ of birth year c. Apart from assuming that $f(c)$ is a smooth function, its shape is left unspecified. After introducing the nonparametric cohort effect in (4), the baseline model of household consumption becomes

$$\log\left(Y_{c,t}\right) = \alpha_a D_a + f(c) + \alpha_t D_t + \beta' z_{c,t} + \varepsilon_c \tag{5}$$

Specification (5) can be estimated in two ways: either by calculating cohort averages, or by using raw data, as discussed in Attanasio *et al.* (2009). The second approach introduces a special term $u_{i\rightarrow c,t}$ for consumption deviations of household i from the corresponding cohort average. With this modification, we obtain the follow-

[2]Alternatively, one may follow Fernández-Villaverde and Krueger (2007) and apply the nonparametric specification to age effect. In practice, results turned out similar when nonparameric effects were specified in either cohort or age effects.

ing benchmark model of household consumption:

$$\log\left(Y_{i\to c,t}\right) = \alpha_a D_a + f(c) + \alpha_t D_t + \beta' z_{i\to c,t} + u_{i\to c,t} + \varepsilon_{c,t} \tag{6}$$

where subscript $h \to c$ denotes household i belonging to cohort c.

The model has two distinctive features. First, it contains two components: a nonparametric part with cohort effect $f(c)$, and parametric part with sets of age and year dummies, as well as other control variables. Second, the model does not include household income as an explanatory variable, because, as discussed in Attanasio *et al.* (2009), the *expected* levels of income are already accounted by the deterministic part of (6), while *unexpected* shifts in income are attributed to the regression disturbance $\varepsilon_{c,t}$.

The baseline model (6) uses cohort dummies to estimate the impact of lifetime wealth on consumption. To estimate the impact of current net wealth of households, I subdivide the total lifetime wealth of households into current net wealth, accumulated from from past income flows, and the sum of discounted future earnings. The impact of accumulated net wealth is measured by changes in net worth, normalized by disposable income $\Delta NW/YD$.

This model is augmented by a new wealth variable that measures a change in net worth of households, normalized by their disposable income, while cohort dummies evaluate the impact of discounted future earnings of households:

$$\begin{aligned}\log\left(Y_{i\to c,t}\right) &= \alpha_a D_a + s(c) + \alpha_t D_t + \beta' z_{i\to c,t} \\ &+ f\left(\Delta NW_{i,t}/YD_{i,t}\right) + u_{i\to c,t} + \varepsilon_{c,t}\end{aligned} \tag{7}$$

where $\Delta NW_{i,t}$ denotes net worth of ith household at time t, and YD denotes the corresponding disposable income. In particular, the model allows nonlinear wealth effects, due to the use of nonparametric term $f\left(\Delta NW_{i,t}/YD_{i,t}\right)$ for normalized changes in household net worth.

4 Estimation method

In this section I discuss details of semiparametric estimation of regression models (6) and (7). These partially linear models can be estimated in several ways (Liang, 2006). The most well-known estimator uses the backfitting algorithm of Hastie and Tibshirani (1990), but the algorithm requires that smoothness parameters for each nonparametric part are specified prior to estimation. These smoothness parameters specify the number of degrees of freedom that are used to approximate nonparametric terms. Denote these smoothness parameters by v. In the special case of $v = 1$, a single variable is used in estimation, which corresponds to a linear regression model. On the other hand, semiparametric effects are obtained with $v > 1$, with larger values of v indicating increasingly nonlinear effects.

In most applications, there is no prior information about likely linearity of nonparametric effects. So instead of essentially *ad hoc* selection of v in the backfitting algorithm, I used a data-driven estimator of Wood (2004) that selects v by minimizing the modified generalized cross validation (*mgcv*). Essentially, the *mgcv* algorithm searches for an optimal degree of smoothness by evaluating the generalized cross-validation criteria of Wahba (1990) for different choices of v. In practice, the algorithm can select any degree of smoothing, including the special case of linear age effect, when $v = 1$. Specifically, I used *mgcv* library (Wood, 2010), which is a part of *R* statistical package (R Development Core Team, 2010).

The *mgcv* library contains a large selection of smoothing functions to estimate nonparametric effects. All of them are based on some kind of spline approximation to the unknown smooth function. In this section I will introduce penalized cubic regression splines that were used in estimating models (6) and (7), as well as the data-based selection of the degree of smoothness.

Consider a reduced specification of the standard life-cycle model (6), which includes only the nonparametric part $f(c)$, with no parametric terms[3]. In the reduced specification, the dependent variable y_i is explained by a single explanatory variable for birth cohorts c_i with a nonlinear effect on y_i:

$$y_i = f(c_i) + \epsilon_i \tag{8}$$

where $f(\cdot)$ is an arbitrary smooth function and ϵ_i is the error term with zero mean and variance σ^2.

Let $\kappa_1 < \cdots < \kappa_M$ be a sequence of breakpoints ('knots') that are distinct numbers that span the range of c_i. In the *mgcv* algorithm, the smooth function $f(c_i)$ is approximated by a sequence of splines with cubic basis functions. These splines are a sequence of piecewise polynomials that are joined at the knots. Due to special restrictions, the cubic splines are continuous at the knots, and also have continuous first and second derivatives. Let M be the number of knots. Then a cubic spline can be represented by truncated cubic basis functions:

$$f(c_i) = \delta_0 + \delta_1 c_i + \delta_2 c_i^2 + \delta_3 c_i^3 + \sum_{m=1}^{M} \delta_{m+3}(c_i - \kappa_m)_+^3 \tag{9}$$

[3]After discussing the estimation of the nonparametric part $f(c)$, it will be trivial to extend the reduced form back to its full semiparametric specification (6).

where

$$(c_i - \kappa_m)_+ = \begin{cases} 0 & c_i \leq \kappa_m \\ c_i - \kappa_m & c_i > \kappa_m \end{cases}$$

In this representation, the cubic spline has a simple interpretation of a *global* cubic polynomial $\delta_0 + \delta_1 c_i + \delta_2 c_i^2 + \delta_3 c_i^3$ and M *local* polynomial deviations $\sum_{m=1}^{M} \delta_{m+3}(c_i - \kappa_m)_+^3$. In matrix form, the truncated cubic basis becomes $\boldsymbol{y} = \boldsymbol{C}\boldsymbol{\delta} + \boldsymbol{\epsilon}$, where $\boldsymbol{C}$ is design matrix with ith row vector $\boldsymbol{C}_i = \begin{bmatrix} 1 & c_i & c_i^2 & c_i^3 & (c_i - \kappa_1)_+^3 & \cdots & (c_i - \kappa_M)_+^3 \end{bmatrix}$, δ is the corresponding vector of regression parameters, and ϵ is the error term. The smooth function $f(\boldsymbol{C}, \boldsymbol{\delta})$ is linear in $M + 4$ regression parameters, and can be fitted by minimizing the sum of squared residuals $(\boldsymbol{y} - \boldsymbol{C}\boldsymbol{\delta})'(\boldsymbol{y} - \boldsymbol{C}\boldsymbol{\delta}) = \|\boldsymbol{y} - \boldsymbol{C}\boldsymbol{\delta}\|^2$, where $\| \cdots \|$ stands for the Euclidean norm.

By increasing the number of knots M, the model becomes more flexible in approximating y. But if M is too large, the estimates $\hat{f}(c)$ may follow y too closely. In the limit, when $M = n$, the cubic spline simply interpolates y. To prevent too much wiggliness in the estimated curve, the *mgcv* algorithm fixes the number of knots at some sufficiently large number[4], and introduces a special term that penalizes rapid changes in $\hat{f}(c)$. A common penalty is $\lambda \int [f_{cc}(c)]^2 \, dx$, which has a smoothing parameter λ and an integrated squared second derivative $f_{cc}(c)$ of $f(c)$. This results in the penalized least-squares criterion

$$Q(f, \lambda) = \|\boldsymbol{y} - \boldsymbol{C}\boldsymbol{\delta}\|^2 + \lambda \int [f_{cc}(c)]^2 \, dx$$

If $\hat{f}(c)$ is too rough, this will increase the penalty term $\int [f_{cc}(c)]^2 \, dx$. The smoothing parameter λ controls the trade-off between the model fit $\|\boldsymbol{y} - \boldsymbol{C}\boldsymbol{\delta}\|$ and *the roughness penalty* $R = \int [f_{cc}(c)]^2 \, dx$. When $\lambda = 0$, the roughness penalty R has no effect on the minimization criterion $Q(f, \lambda)$, producing unpenalized estimates $\hat{f}(x)$ that just interpolate data. In contrast, when $\lambda = +\infty$, this results in the perfectly smooth line, *i.e.*, in a linear regression line with a constant slope.

The minimization of the penalized criterion $Q(f, \lambda)$ is simplified by noting that derivatives and integrals of $f(c)$ are linear transformations of parameters $d^m(c)$ in the cubic spline basis, with $f_{cc}(c) = \sum_{m=1}^{M} \delta_m d_{cc}^m(c)$ and $\int f(c) dc = \sum_{m=1}^{M} \delta_m \int d^m(c) dc$, where $d^m(c)$ denotes a particular form of basis function (such as the truncated cubic basis function in (9)). Thus, $f_{cc}(c) = \boldsymbol{d}_{cc}(c)'\boldsymbol{\delta}$, from which it follows that $[f_{cc}(c)]^2 = \boldsymbol{\delta}'\boldsymbol{d}_{cc}(c)'\boldsymbol{d}_{cc}(c)\boldsymbol{\delta} = \boldsymbol{\delta}'F(c)\boldsymbol{\delta}$. In matrix form, the roughness penalty becomes

$$R = \int [f_{cc}(c)]^2 dc = \boldsymbol{\delta}' \left(\int F(c) dc \right) \boldsymbol{\delta} = \boldsymbol{\delta}'\boldsymbol{S}\boldsymbol{\delta}. \tag{10}$$

[4]The default value of M in the *mgcv* library is set to 10, but the default value can be changed.

In sum, the roughness penalty R can be represented as a quadratic form in the parameter vector δ and matrix $\boldsymbol{S}$ of known coefficients that are derived from the basis function $d^m(c)$.

Substituting the roughness penalty R with $\boldsymbol{\delta}'\boldsymbol{S}\boldsymbol{\delta}$, the penalized least-squares criterion becomes

$$Q(f, \lambda) = \|\boldsymbol{y} - \boldsymbol{C}\boldsymbol{\delta}\|^2 + \lambda\boldsymbol{\delta}'\boldsymbol{S}\boldsymbol{\delta} \tag{11}$$

Differentiating $Q(f, \lambda)$ with respect to $\boldsymbol{\delta}$ and setting the derivative to zero produces an estimate of $\boldsymbol{\delta}$:

$$\hat{\boldsymbol{\delta}} = \left(\boldsymbol{C}'\boldsymbol{C} + \lambda\boldsymbol{S}\right)^{-1}\boldsymbol{C}'\boldsymbol{y}. \tag{12}$$

The estimate of δ depends on the value of unknown smoothing parameter λ. The *mgcv* algorithm selects an appropriate value of λ by using the concept of hat matrix from the OLS estimator. In the linear model, the hat matrix $\boldsymbol{H}$ projects the vector of dependent variable $\boldsymbol{y}$ into the vector of predicted values $\hat{\boldsymbol{y}} = \boldsymbol{H}\boldsymbol{y}$, with $\boldsymbol{H} = \boldsymbol{C}\left(\boldsymbol{C}'\boldsymbol{C}\right)^{-1}\boldsymbol{C}'$. Using the estimate of $\hat{\delta}$ from (12), the hat matrix of the penalized spline model can be similarly defined as $\boldsymbol{H}_S = \boldsymbol{C}\left(\boldsymbol{C}'\boldsymbol{C} + \lambda\boldsymbol{S}\right)^{-1}\boldsymbol{C}'$. Since the matrix $\boldsymbol{H}_S$ transforms the vector of $\boldsymbol{y}$ into the vector of its smoothed values, the matrix $\boldsymbol{H}_S$ is commonly called a smoother matrix. In the *mgcv* algorithm, the optimal value of λ is found by minimizing the generalized cross-validation (*gcv*) criterion $V_g(\lambda)$ that depends on the sum of squared residuals $\|\boldsymbol{y} - \boldsymbol{C}\hat{\boldsymbol{\delta}}\|^2$ and the trace of smoother matrix $\boldsymbol{H}_S$:

$$V_g(\lambda) = \frac{n\|\boldsymbol{y} - \boldsymbol{C}\hat{\boldsymbol{\delta}}\|^2}{\left[n - \mathrm{tr}\left(\boldsymbol{H}_S\right)\right]^2} \tag{13}$$

where n is the number of observations, and $\mathrm{tr}\left(\boldsymbol{H}_S\right)$ is the trace of $\boldsymbol{H}_S$.

Though the *mgcv* algorithm selects an appropriate degree of smoothness with respect to parameter λ, this parameter is not very useful in evaluating the estimated degree of smoothness. It is much easier to interpret the trace of the smoother matrix $\mathrm{tr}\left(\boldsymbol{H}_S\right)$, since it is equal to the number of degrees of freedom, needed to approximate the smoothed function $f(c)$ (Ruppert *et al.*, 2003). Let $\nu = \mathrm{tr}\left(\boldsymbol{H}_S\right)$. Since the smoothing parameter λ is a part of $\boldsymbol{H}_S$, λ and ν are correlated. In particular, a small degree of smoothing is indicated by $\lambda \to 0$ and $\nu \to \infty$. Conversely, a high degree of smoothing corresponds to $\lambda \to \infty$ and $\nu \to 0$. An important special case is when $\nu = 1$. This range of ν indicates a parametric effect, when a single variable is sufficient to approximate the smoothed function $f(c)$, which is the original vector of cohort effects c.

There is, however, one problem in practical use of the *gcv* criterion $V_g(\lambda)$. Monte Carlo studies by Kim and Gu (2004) demonstrated that $V_g(\lambda)$ may choose too small values of λ, which results in under-smoothing. The problem can be solved by multiplying $\mathrm{tr}\,(\boldsymbol{H}_S)$ in (13) by a parameter η that increases the cost per trace of $\boldsymbol{H}_S$:

$$\bar{V}_g(\lambda) = \frac{n\|\boldsymbol{y} - \boldsymbol{C}\hat{\boldsymbol{\delta}}\|^2}{[n - \eta \cdot \mathrm{tr}\,(\boldsymbol{H}_S)]^2} \tag{14}$$

Based on recommendations from Kim and Gu (2004) and Wood (2006), η was set to 1.4.

Once the smooth function $f(c)$ is estimated by cubic spline basis, the reduced specification (8) can be easily extended back to the full semiparametric model (6). Define the parametric part of (6) by the matrix $\boldsymbol{W}$ that contains dummy variables for age and year effects D_a and D_t, and the vector of other control variables z. Let a new design matrix be defined as $\tilde{\boldsymbol{C}} = [\boldsymbol{C}, \boldsymbol{W}]$. With the expanded design matrix, the truncated cubic basis (9) still has the form $\boldsymbol{y} = \tilde{\boldsymbol{C}}\tilde{\boldsymbol{\delta}} + \epsilon$, but the basis $\tilde{\boldsymbol{C}}$ now includes the expanded design matrix with all parametric components. The estimate of $\tilde{\boldsymbol{\delta}}$ is obtained from (12), where the smoothing parameter λ is found by minimizing either $V_g(\lambda)$ or $\bar{V}_g(\lambda)$.

5 Estimation results

Table 1 reports parameter estimates of the baseline model (6) and its extended version with net wealth (7). Similar estimates for durable consumption are reported in Table 2.

The goodness-of-fit of the semiparametric model is measured by 'deviance explained', which is a similar measure to R^2 in linear regression models[5]. The ratio of explained deviance increased after the net wealth effect was added to the baseline model. The improvement in fit was particularly large for durable consumption, with the deviance explained rising from 0.583 to 0.619.

Estimates of linear effects in both regression models broadly agreed with prior expectations, with little differences between estimates for nondurable and durable consumption. For brevity, I will discuss estimates for nondurable consumption from Table 1.

Consumption expenditures were higher for households where household heads had more advanced education, with the largest increases in consumption among household heads with graduate degrees. When households were differentiated by the type of employment, the highest consumption was for the 'full time–full year'

[5]Deviance for models (6) and (7) is made up of the sum of squared residuals, because both models belong to the normal family of generalized linear models with identical link function. The proportion of explained deviance compares deviances of two models: the null model with just the intercept term, and the alternative model with all explanatory variables. Let these deviances by D_0 and D_1, respectively. Then the deviance explained is $(D_0 - D_1)/D_0$.

category of households. Differences in marital status also had significant impact on household consumption. Compared with the control category of married households, other categories of marital status were associated with about 20 percentage point less nondurable consumption. Finally, the number of adult members was increasing consumption expenditures, while more children reduced consumption.

Estimates for nonparametric effects are reported at the bottom of Tables 1 and 2. For the cohort effect in the baseline model (6), the number of estimated degrees of freedom v was 3.27 for nondurable consumption, and 3.68 for durable consumption, indicating a moderate nonlinearity in the shape of cohort effect. The cohort effect in the net wealth model (7) similarly was close to the linear effect, with $v = 3.42$ for both types of consumption expenditures. In contrast, the effect from the normalized change in net worth $\Delta NW/YD$ was highly nonlinear, with $v = 8.91$. Both nonparametric components were highly significant, with p-values less than 0.001.

Figure 1 plots parameter estimates for age, cohort, and year effects in the net worth model of household consumption (7)[6]. The life-cycle theory assumes that households smooth their consumption over their lifetime, and predicts that age-consumption profiles are flat. However, estimated age-consumption profiles in Panel (a) of Figure 1 shows little smoothing[7]. In particular, there is a notable increase in both types of consumption among households up to the early 30s. In the middle age, both consumption profiles follow similar declining trends, but then diverge among households with age in mid-60s. Nondurable consumption continues to trend back to its level in the early part of life cycle, while durable consumption stays at relatively elevated level.

Panel (b) plots the nonparametric estimate of the cohort effect for nondurable consumption[8]. The figure contains 95% confidence bands for estimated effects on consumption, while the y-axis reports the number of estimated degrees of freedom v. The estimate of v was 3.42, indicating only minor nonlinearity[9]. Compared with oldest cohorts of households that were born in the early 1910s, the most recent birth cohorts were consuming about 10 percentage points less. However, it is also important to note that the confidence band for cohort effect is also wider for the oldest and youngest cohorts due to relatively small number of households in these cohorts.

Panel (c) shows estimates for year dummies, with the effect of the first observation year (i.e., 1984) set to zero. The year effect for nondurable consumption remained unchanged up to the late 1990s, but increased by about 10 percentage points later on. In contrast, durable consumption expenditures showed a significant increase since the late 1980s, with accelerated pace since the mid-1990s.

[6]Estimates for the baseline model (6) were very similar, and are omitted for brevity

[7]Estimates of consumption-age profiles are normalized to zero at age 20

[8]The shape of cohort effect for durable consumption was similar, and is omitted for brevity.

[9]The same estimate of v is reported among nonparametric estimates at the bottom of Table 1.

Figure 2 reports nonparametric estimates of normalized net worth $\Delta NW/YD$ on consumption. Compared with estimated cohort-consumption profile in Figure 1, the effect from wealth is clearly nonlinear, particularly for durable expenditures. In addition, confidence bands are also relatively narrow in Figure 2, thus allowing to identify several patterns in the wealth effect on consumption.

First, the wealth-consumption profile for nondurable expenditures was generally flat. This indicates that nondurable consumption responded little to changes in the flow of household net wealth, except for the narrow interval for net worth in the range $-0.10 \lessapprox \Delta NW/YD \lessapprox 0.05$. Within this interval, household consumption was rising when $\Delta NW/YD$ was moving away from zero in both positive and negative directions.

For durable expenditures, the wealth-consumption profile was flat when the net change in wealth $\Delta NW/YD$ was positive. For negative values of $\Delta NW/YD$, durable consumption rose significantly. Compared with consumption at zero $\Delta NW/YD$, durable consumption grew by almost 70 percentage points when $\Delta NW/YD$ declined to -0.4[10].

The negative correlation between net worth and durable consumption can be due to the special role of debt in financing purchases of durable goods. While purchases of nondurable goods may be financed from the current disposable income or from reduced financial assets, running up new debts is often required to purchase durable goods. By increasing their liabilities to finance purchases of durables, households reduce their net worth, which leads to the negative correlation between durable consumption and net worth.

To examine whether debt had a special role in explaining the negative relation between net worth and consumption, I replaced the change in net worth $\Delta NW/YD$ in (7) with similar changes in assets and liabilities, normalized by disposable income:

$$\begin{aligned} \log\left(Y_{i\to c,t}\right) &= \alpha_a D_a + s(c) + \alpha_t D_t + \beta' z_{i\to c,t} \\ &+ f\left(\Delta A_{i,t}/YD_{i,t}\right) + f\left(\Delta L_{i,t}/YD_{i,t}\right) u_{i\to c,t} + \varepsilon_{c,t} \end{aligned} \tag{15}$$

where ΔA and ΔL denote net change in household assets and liabilities, respectively.

While the net worth model (7) assumes that assets and liabilities of households have identical, but opposite in sign, effects on consumption, model (15) relaxes this

[10]The possibility that reduced net worth of households may be associated with rising consumption expenditures has been mentioned in some studies of wealth effect (see, for example, Dynan and Maki (2001, p. 17) and Paiella (2007, p. 954), but was largely dismissed as a 'spurious correlation'.

restriction, and allows distinct effects from both sides of household balance sheets. The model will be referred as balance sheet model of consumption[11].

Tables 3 and 4 reports estimates for three alternative models of household consumption. Estimates for the benchmark model (6) and for the net-worth model (7) are very similar to estimates in Tables 1 and 2, respectively. This is hardly surprising, since estimates are obtained from samples of 27168 and 26463 households with substantial overlap. The crucial point whether the introduction of separate balance sheet effects on consumption has produced a better fit in the balance sheet model (15). As shown in the bottom of Tables 3 and 4, the explained deviance indeed increased in model (15) for both nondurable and durable consumption. Similarly, the balance sheet model of consumption was a preferable model according to the generalized cross validation (GCV) and Akaike information criteria (AIC).

Parameter estimates for the parametric part of the balance sheet model were very similar with the previously discussed estimates for the baseline and net worth models of consumption. Estimates of age, cohort and year effects on both types of consumption also turned out very close to corresponding estimates from the net worth model (as reported in Figure 2), and are omitted for brevity.

Asset-consumption and debt-consumption profiles are shown in Figures 3 and 4 for for nondurable and durable consumption, respectively. I begin with balance sheet effects on nondurable consumption. Positive values of $\Delta A/YD$ and $\Delta L/YD$ had largely flat profiles, indicating that increases in normalized household assets and liabilities had little effect on nondurable consumption. Nondurable consumption increased only when $\Delta A/YD$ was shifting from zero to -0.1, with consumption eventually rising by about 20 percentage points. This correlation may indicate that nondurable expenditures were financed by running down the stock of assets. On the other hand, negative values of $\Delta L/YD$ were associated with relatively little changes in nondurable consumption of households.

Figure 4 shows that changes in household debt had much larger effects on durable consumption. As reported in Panel (b), the increased borrowing of households from zero to 20 percent of disposable income (i.e., when $\Delta L/YD$ moved from 0 to 0.2) increased the logarithm of durable consumption from about -0.2 to 0.2, or by about 40 percentage points. Panel (a) of Figure 4 shows that the impact from the asset side on durable consumption turned out much smaller. There is again no increase in consumption for positive increases in $\Delta A/YD$. The largest impact on consumption was

[11] Before estimating the balance sheet model, the sample was cleaned of households with extreme values of $\Delta L/YD$, namely households below 5 percentile and above 95 percentile of the distribution of $\Delta L/YD$. In practice, this reduced the sample to 27168 households with $-0.23 \leq \Delta L/YD \leq 0.46$. To keep the effect from net assets comparable with the variation in net debts, I also omitted households that had $\Delta A/YD$ outside of the range for $\Delta L/YD$ (namely, between -0.23 and 0.46). This resulted in the final sample of 26463 households.

for minor decreases in household assets (in the range between 0 and -0.15) which may indicate that purchases of some durables were financed by running down household assets.

6 Discussion

Estimates of balance sheet effects on consumption provide new evidence on the direct wealth effect on consumption, when consumption is increased due to improved balance constraints of households. Estimated asset-consumption effects in Panel (a) of Figures 3 and 4 indicate little change in both nondurable and durable consumption for positive $\Delta A/YD$. The only significant effect on consumption occurred among households that were drawing down their assets, but the effect was limited to the small interval of $\Delta A/YD$, when the normalized change in assets was declining from zero and -0.1, indicating households that draw down their assets up to 10 percent of disposable income. While the increased consumption from reduced household assets is rarely mentioned among expected wealth effects, the paper found little evidence to much common expectation that positive changes in household wealth may boost consumption spending. Among different configurations of balance sheet effects, it is mainly increased debts, but not increased assets, that drive up household consumption, especially for durable categories.

Another implication of balance sheet effects in this paper is that they may explain why the 2007-2009 recession turned out so severe, and why its subsequent recovery continues to be weak. Figure 5 illustrates the relative harshness of the 2007-2009 recession by comparing it to the median pattern among post-war recession, as well as to the worst macroeconomic conditions. Panel (a) shows the accumulated changes in output over 10 quarters since the peak of business cycles. In the 2007-2009 recession, the output dropped by more that 4 percentage points, and this exceeded the previous worst record among post-war recessions. In addition, the current recovery still remains unusually subdued, with output remaining below its pre-recession level, once again in sharp contrast to other post-war recoveries. To identify possible sources of this output shortfall, I compared the accumulated contribution to growth from two categories of consumption that were examined in this paper. Namely, panel (b) reports the accumulated contribution to GDP growth from nondurable consumption (including services), while panel (c) does the same for durable consumption (including residential investments).

To put these changes in historical perspective, I compared these growth contributions from consumption with median and worst recoveries among previous post-war recessions. The accumulated contribution of nondurable consumption has already recovered over 10 quarters to its original pre-recession level at the peak of business cycle in the last quarter of 2007. This is much lower that the increase by 17 percentage points in median post-war recessions, but at least this component of GDP no longer pulls down output below its pre-recession level. In contrast, the contribution from durable consumption continues to drag output below its pre-recession level by about 6 percentage points.

How much the sharp decline in durable consumption can be explained by changes in household debt? Figure 6 displays changes in the net debt-to-income ratio $\Delta L/YD$ in historical perspective. During the early post-war period, the ratio did not deviate much from its long-term median of about 0.06. However, starting from the early 1970s, the ratio became increasingly volatile. In particular, $\Delta L/YD$ started to rise rapidly after the late 1990s, and eventually reached its postwar peak of around 0.13 in 2006, allowing households at that time to supplement 13 percent of disposable income with net borrowings. But when the credit bubble burst in the United States, households promptly switched to rebuilding their balance sheets, and avoided new debts altogether, so $\Delta L/YD$ slumped to minus 1 percent of disposable income in 2010.

Using the estimated debt-consumption profiles in panel (b) of Figure 4, it is possible to estimate the effect from the deleveraging process on durable consumption of households. Values of $\Delta L/YD$ at 0.13 and -0.01 correspond to the log of durable consumption at around 0.20 and -0.15, implying that the recent unprecedented slump in $\Delta L/YD$ reduced durable consumption by roughly 35 percentage points. To estimate the corresponding contribution to GDP growth, we need the share of durable consumption and residential investments in GDP, which varied from 12.1 percent at the end of 2007 to 9.8 percent in the second quarter of 2010. Using the average from during these endpoints, the deleveraging among U.S. households reduced economic growth by around $35\% \times 0.110 = 3.8\%$. As previously discussed, durable consumption and residential investments contributed to the 6 percent reduction in the U.S. output (panel (c) of Figure 5). Therefore, the reduced debt accumulation among households during 2007-2010 accounts for $3.8/6.0 \approx 0.64$, or 64 percent of the total negative cumulative contribution to output growth.

7 Conclusion.

Results of this paper suggest that changes in balance sheet of households may have an important role in macroeconomic fluctuations, and the major effect operates through variation in the household expenditures on durables. Simple back-of-the-envelope estimates indicate that the negative debt effect from sharply reduced household borrowing in recent years accounts for two-third of the current unprecedented slump in durable consumption and residential investments. Compared with the significant debt effects on consumption, changes in household assets had much smaller effects. In fact, the largest changes in household consumption were localized around small changes in household assets, while large changes in $\Delta A/YD$ showed essentially flat asset-consumption profiles.

By estimating wealth effects with nonparametric regression models, this paper showed that these effects may be more complex that has been considered in the literature on wealth effects on consumption. A promising direction for future research is to check whether wealth effects are similarly highly nonlinear among households in other countries.

Appendices

A Robustness of estimated balance sheet effects on consumption.

Estimates of nonparametric effects on consumption were obtained using the truncated cubic spline basis, defined by (9). Though cubic splines are often used because of their simple interpretation as local deviations from the global cubic trend, this basis can lead to ill-conditioned matrices and numerical instability in estimated parameters (Ruppert *et al.*, 2003, p. 70). To verify whether estimated nonparametric effect change with an alternative basis function, I estimated the balance sheet model of household consumption (15) with P-spline basis function of Eilers and Marx (1996). P-splines are constructed from the B-spline basis that have an important advantage of local support, which results in better numerical stability of P-splines compared with cubic splines. Another advantage of P-splines is that their penalty function is much simpler than the integrated squared second derivative in cubic splines, and is simply given by finite-order differences of the coefficients of adjacent B-splines. In the next subsection I will briefly describe the setup of the alternative basis function.

A.1 Basis function and penalty term of P-splines

Similarly to the truncated cubic basis, B-splines contain a sequence of polynomial pieces, joined at knots $\kappa_1 < \cdots < \kappa_M$. Let R be the degree of B-spline basis. B-spline basis is the simplest for $R = 0$. For $i = 1, \cdots, M$, B-spline of degree zero is

$$B_i^0(x) = \begin{cases} 1 & if \quad x \in [k_i, k_{i+1}) \\ 0 & otherwise \end{cases}$$

For B-splines of degree 1, basis functions are defined by a sequence of local 'hat' functions that are nonzero in the interval between k_i and k_{i+2}:

$$B_i^1(x) = \begin{cases} \frac{x-k_i}{k_{i+1}-k_i} & if \quad x \in [k_i, k_{i+1}) \\ \\ \frac{k_{i+2}-x}{k_{i+2}-k_{i+1}} & if \quad x \in [k_{i+1}, k_{i+2}) \\ \\ 0 & otherwise \end{cases}$$

Basis functions for higher degrees of B-splines are becoming more complicated, but can be obtained from a simple recursive formula from basis functions of lower degrees. For B-spline of order r, the basis function is given by

$$B_i^r(x) = \left(\frac{x - k_i}{k_{i+r} - k_i}\right) B_i^{r-1}(x) + \left(\frac{k_{i+r+1} - x}{k_{i+r+1} - k_{i+1}}\right) B_{i+1}^{r-1}(x)$$

A useful property of the B-splines is its strict locality, with basis function nonzero over the interval of $r+2$ adjacent knots (for example, in the interval of two neighboring knots for B-splines of zero order). This makes B-splines much less sensitive to the collinearity among basis functions.

Define matrix B denote basis functions for B-spline with M knots. With sample size n, B is $n \times M$ matrix, and the smooth function $f(c_i)$ from (8) is estimated similarly to (10, by minimizing the penalized least-squares function

$$Q(f, \lambda) = \|\boldsymbol{y} - \boldsymbol{B\alpha}\|^2 + \lambda \|D_d\alpha\|^2 \tag{16}$$

where D_d is a dth order differencing matrix, such as $D_d\alpha = \Delta^d\alpha$. P-splines use a second-order difference penalty D_2, and are defined for knots that are equally spaced, with $h = k_{j+1} - k_j$. Then the differencing penalty D_2 can be easily constructed, with (i, j) elements equal to

$$[D_2]_{i,j} = \frac{1}{h}\begin{cases} 1 & if \quad j = i,\ i = 1, ..., M+2 \\ -2 & if \quad j = i+1,\ i = 1, ..., M+2 \\ 1 & if \quad j = i+2,\ i = 1, ..., M+2 \\ 0 & otherwise \end{cases}$$

After replacing $D_2'D_2$ in (16) by S^*, we get the penalized least-squared criterion for P-splines

$$Q(f, \lambda) = \|\boldsymbol{y} - \boldsymbol{B\alpha}\|^2 + \lambda\boldsymbol{\alpha}'\boldsymbol{S}^*\boldsymbol{\alpha}$$

The minimization of this penalized criterion is essentially identical to the minimization problem with truncated cubic basis functions, given by equation (11). The estimate of α is derived similarly to equation (12), and the appropriate degree of smoothness parameter λ can be obtained by minimizing the GCV criterion of equations (13) or (14).

P-splines can be defined for different combinations of the degree of B-spline basis R and the order of differencing d in the differencing penalty D_d. Eilers and Marx (1996) demonstrated the conventional choice of truncated cubic basis function (9) and the roughness penalty with the integrated squared second derivative most closely corresponds to P-splines with a cubic B-spline basis function (with $R = 3$) and the second-order differencing penalty with $d = 2$).

A.2 Estimation results with P-spline basis

Parameter estimates with P-spline for parametric part of balance sheet model of consumption (15) were very close to results reported in Tables 3and 4for truncated cubic spline basis, and are omitted for brevity. Major differences were in estimated nonparametric effects. Figure A-1 reports estimates of age, cohort, and year effects. The most notable difference was in estimates of age effect (panel (a), which showed an increased effect on durable consumption among aged households. The estimate of cohort effect in panel (b) was no longer approximately linear, with a notable decline in consumption among cohorts that were born after the late 1970s. The increased nonlinearity of cohort effect is also demonstrated by a larger number of estimated degrees of freedom (8.38 versus 3.68 for truncated cubic splines in Figure 1. As for estimates for year effect in panel (c), they did not change much.

Similarly, estimated balance sheet effects on nondurable and durable consumption in Figures A-2 and A-3 were little changed. For instance, the effect on durable consumption from changing $\Delta L/YD$ ratio produced very similar debt-consumption profile. When $\Delta L/YD$ changed from its peak level of 0.13 in 2007 to -0.01 in 2010, these values of $\Delta L/YD$ corresponded to 0.21 and -0.10 of the log of durable consumption. This implied that the deleveraging of U.S. households reduced their durable consumption by about 31 percentage points, which is not much different from the difference of 35 percentage points, derived from debt-consumption profile in Table 4. In sum, the use of an alternative spline basis to estimate nonparametric effects did not change previously reported estimates.

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Table 1.
Estimates of net wealth effect on nondurable consumption.

The table reports estimates of the benchmark life-cycle model (6) and the net worth model (7) on the log of nondurable consumption. The table omits estimates of age and year effects that reported in panels (a) and (c) of Figure 1. The table also omits parameter estimates for survey month, and for household regions. Statistically significant estimates at the level of 10, 5, and 1 percent are shown with *, **, ***, respectively. *E.d.f.* abbreviates the estimated degrees of freedom for nonparametric terms.

Dependent variable: log of nondurable consumption expenditures				
	Benchmark model		*Net worth added*	
	Coef.	p-value	Coef.	p-value
Intercept	9.255	< 0.001 ***	9.265	< 0.001 ***
High school	-0.088	0.000 ***	-0.077	< 0.001 ***
College	0.152	< 0.001 ***	0.146	< 0.001 ***
Graduate	0.305	< 0.001 ***	0.309	< 0.001 ***
Full time/Full year	0.443	< 0.001 ***	0.408	< 0.001 ***
Part time/Full year	0.279	< 0.001 ***	0.246	< 0.001 ***
Full time/Part of year	0.303	< 0.001 ***	0.265	< 0.001 ***
Part time/Part of year	0.176	< 0.001 ***	0.149	< 0.001 ***
Empl. in agriculture	-0.001	0.967	0.003	0.916
Empl. in construction	0.069	0.004 ***	0.064	0.006 ***
Empl. in manufacturing	0.033	0.077 *	0.026	0.137
Empl. in transportation	0.085	< 0.001 ***	0.076	< 0.001 ***
Empl. in trade	0.017	0.392	0.008	0.648
Empl. in finance	0.142	< 0.001 ***	0.125	< 0.001 ***
Empl. in profess. services	0.043	0.023 **	0.034	0.060 *
Empl. in other services	0.047	0.037 **	0.050	0.019 **
Empl. in public administ.	0.068	0.007 ***	0.053	0.028 **
Empl. in other industries	0.235	0.006 ***	0.168	0.041 **
Widowed	-0.253	< 0.001 ***	-0.248	< 0.001 ***
Divorced	-0.262	< 0.001 ***	-0.255	< 0.001 ***
Separated	-0.290	< 0.001 ***	-0.277	< 0.001 ***
Never married	-0.336	< 0.001 ***	-0.314	< 0.001 ***
Black	-0.233	< 0.001 ***	-0.223	< 0.001 ***
American Indian	-0.147	< 0.001 ***	-0.133	< 0.001 ***
Asian	-0.029	0.175	-0.011	0.598
Race n.e.s.	-0.104	0.366	-0.094	0.392
Female	0.002	0.752	0.002	0.773
Homeowner w/o mortgage	-0.233	< 0.001 ***	-0.220	< 0.001 ***
Renter	-0.751	< 0.001 ***	-0.722	< 0.001 ***
Occupied w/o payment	-0.856	< 0.001 ***	-0.814	< 0.001 ***
Rural	-0.211	< 0.001 ***	-0.218	< 0.001 ***
Number of adults	0.133	< 0.001 ***	0.126	< 0.001 ***
Number of children	-0.040	< 0.001 ***	-0.035	< 0.001 ***
Estimated smooth functions				
	E.d.f.	p-value	E.d.f.	p-value
f(cohort)	3.68	< 0.001 ***	3.42	< 0.001 ***
f(net worth/disposable income)			8.91	< 0.001 ***
Deviance explained	0.583		0.619	
GCV score	31,902		29,189	
AIC score	43,932		41,510	
Number of households	27,168		27,168	

Table 2.

Estimates of net wealth effect on durable consumption.

The table reports estimates of the benchmark life-cycle model (6) and the net worth model (7) on the log of durable consumption. The table omits estimates of age and year effects that reported in panels (a) and (c) of Figure 1. The table also omits parameter estimates for survey month, and for household regions. Statistically significant estimates at the level of 10, 5, and 1 percent are shown with *, **, ***, respectively. E.d.f. abbreviates the estimated degrees of freedom for nonparametric terms.

Dependent variable: log of durable consumption expenditures						
	Benchmark model			*Net worth added*		
	Coef.	p-value		Coef.	p-value	
Intercept	8.947	< 0.001	***	8.954	< 0.001	***
High school	-0.082	< 0.001	***	-0.076	< 0.001	***
College	0.095	< 0.001	***	0.092	< 0.001	***
Graduate	0.256	< 0.001	***	0.253	< 0.001	***
Full time/Full year	0.288	< 0.001	***	0.263	< 0.001	***
Part time/Full year	0.160	< 0.001	***	0.139	< 0.001	***
Full time/Part of year	0.204	< 0.001	***	0.183	< 0.001	***
Part time/Part of year	0.129	< 0.001	***	0.114	< 0.001	***
Empl. in agriculture	-0.072	0.007	***	-0.074	0.005	***
Empl. in construction	0.013	0.498		0.012	0.523	
Empl. in manufacturing	-0.009	0.507		-0.012	0.394	
Empl. in transportation	0.066	< 0.001	***	0.063	< 0.001	***
Empl. in trade	0.006	0.711		0.001	0.944	
Empl. in finance	0.088	< 0.001	***	0.080	< 0.001	***
Empl. in profess. services	-0.008	0.606		-0.012	0.397	
Empl. in other services	-0.012	0.474		-0.012	0.473	
Empl. in public administ.	0.032	0.104		0.027	0.167	
Empl. in other industries	0.088	0.186		0.058	0.384	
Widowed	-0.234	< 0.001	***	-0.227	< 0.001	***
Divorced	-0.213	< 0.001	***	-0.208	< 0.001	***
Separated	-0.212	< 0.001	***	-0.204	< 0.001	***
Never married	-0.243	< 0.001	***	-0.234	< 0.001	***
Black	-0.072	< 0.001	***	-0.065	< 0.001	***
American Indian	-0.129	< 0.001	***	-0.124	< 0.001	***
Asian	-0.106	< 0.001	***	-0.101	< 0.001	***
Race n.e.s.	-0.071	0.424		-0.066	0.455	
Female	0.000	0.964		-0.002	0.700	
Homeowner w/o mortgage	-0.062	< 0.001	***	-0.049	< 0.001	***
Renter	-0.293	< 0.001	***	-0.266	< 0.001	***
Occupied w/o payment	-0.326	< 0.001	***	-0.293	< 0.001	***
Rural	-0.149	< 0.001	***	-0.150	< 0.001	***
Number of adults	0.155	< 0.001	***	0.152	< 0.001	***
Number of children	0.028	< 0.001	***	0.031	< 0.001	***
Estimated smooth functions						
	E.d.f.	p-value		E.d.f.	p-value	
f(cohort)	3.27	< 0.001	***	3.42	< 0.001	***
f(net worth/disposable income)				8.91	< 0.001	***
Deviance explained	0.506			0.515		
GCV score	19,137			18,818		
AIC score	30,048			29,584		
Number of households	27,168			27,168		

Table 3.
Regression estimates for balance sheet effects on nondurable consumption.

The table reports estimates of the benchmark life-cycle model (6), the net worth model (7) and the balance sheet model (15) on the log of nondurable consumption. The table omits estimates of age and year effects, as well as for survey month and for regions. Statistically significant estimates at the level of 10, 5, and 1 percent are shown with *, **, ***, respectively. E.d.f. abbreviates the estimated degrees of freedom for nonparametric terms.

Dependent variable: log of nondurable consumption expenditures						
	Benchmark model		Net worth added		Balanse sheet added	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
Intercept	9.259	< 0.001 ***	9.277	< 0.001 ***	9.278	< 0.001***
High school	-0.086	< 0.001 ***	-0.077	< 0.001 ***	-0.071	< 0.001***
College	0.150	< 0.001 ***	0.143	< 0.001 ***	0.134	< 0.001***
Graduate	0.302	< 0.001 ***	0.306	< 0.001 ***	0.292	< 0.001***
Full time/Full year	0.453	< 0.001 ***	0.416	< 0.001 ***	0.388	< 0.001***
Part time/Full year	0.278	< 0.001 ***	0.249	< 0.001 ***	0.237	< 0.001***
Full time/Part of year	0.309	< 0.001 ***	0.271	< 0.001 ***	0.252	< 0.001***
Part time/Part of year	0.180	< 0.001 ***	0.156	< 0.001 ***	0.142	< 0.001***
Empl. in agriculture	0.023	0.510	0.023	0.481	0.033	0.311
Empl. in construction	0.083	0.001 ***	0.068	0.004 ***	0.075	<0.001***
Empl. in manufacturing	0.037	0.052 *	0.023	0.189	0.019	0.288
Empl. in transportation	0.092	< 0.001 ***	0.074	< 0.001 ***	0.078	< 0.001***
Empl. in trade	0.026	0.198	0.011	0.543	0.021	0.269
Empl. in finance	0.149	< 0.001 ***	0.131	< 0.001 ***	0.120	< 0.001***
Empl. in profess. services	0.044	0.026 **	0.031	0.090 *	0.021	0.256
Empl. in other services	0.042	0.068 *	0.041	0.055 *	0.042	0.047**
Empl. in public administ.	0.084	0.001 ***	0.052	0.035 **	0.050	0.038**
Empl. in other industries	0.276	0.002 ***	0.212	0.012 **	0.205	0.014**
Widowed	-0.258	< 0.001 ***	-0.252	< 0.001 ***	-0.242	< 0.001***
Divorced	-0.267	< 0.001 ***	-0.262	< 0.001 ***	-0.251	< 0.001***
Separated	-0.290	< 0.001 ***	-0.277	< 0.001 ***	-0.261	< 0.001***
Never married	-0.342	< 0.001 ***	-0.318	< 0.001 ***	-0.307	< 0.001***
Black	-0.227	< 0.001 ***	-0.219	< 0.001 ***	-0.207	< 0.001***
American Indian	-0.149	< 0.001 ***	-0.126	< 0.001 ***	-0.119	< 0.001***
Asian	-0.033	0.123	-0.015	0.463	-0.006	0.748
Race n.e.s.	-0.101	0.393	-0.061	0.587	-0.059	0.593
Female	0.008	0.285	0.008	0.253	0.013	0.063*
Homeowner w/o mortgage	-0.236	< 0.001 ***	-0.224	< 0.001 ***	-0.204	< 0.001***
Renter	-0.751	< 0.001 ***	-0.724	< 0.001 ***	-0.683	< 0.001***
Occupied w/o payment	-0.844	< 0.001 ***	-0.807	< 0.001 ***	-0.762	< 0.001***
Rural	-0.210	< 0.001 ***	-0.217	< 0.001 ***	-0.212	< 0.001***
Number of adults	0.136	< 0.001 ***	0.129	< 0.001 ***	0.129	< 0.001***
Number of children	-0.042	< 0.001 ***	-0.037	< 0.001 ***	-0.032	< 0.001***
Estimated smooth functions						
	E.d.f.	p-value	E.d.f.	p-value	E.d.f.	p-value
f(cohort)	7.61	< 0.001 ***	3.64	< 0.001 ***	5.02	< 0.001***
f(net worth)			8.95	< 0.001 ***		
f(assets/disposable income)					8.91	< 0.001***
f(debt/disposable income)					8.99	< 0.001***
Deviance explained	0.583		0.622		0.635	
GCV score	32,177		29,182		28,215	
AIC score	40,395		40,395		39,496	
Number of households	26,463		26,463		26,463	

Table 4.

Regression estimates for balance sheet effects on durable consumption.

The table reports estimates of the benchmark life-cycle model (6), the net worth model (7) and the balance sheet model (15) on the log of durable consumption. The table omits estimates of age and year effects, as well as for survey month and for regions. Statistically significant estimates at the level of 10, 5, and 1 percent are shown with *, **, ***, respectively. E.d.f. abbreviates the estimated degrees of freedom for nonparametric terms.

Dependent variable: log of durable consumption expenditures						
	Benchmark model		Net worth added		Balanse sheet added	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
Intercept	8.968	< 0.001 ***	8.975	< 0.001 ***	8.975	< 0.001***
High school	-0.081	< 0.001 ***	-0.074	< 0.001 ***	-0.069	< 0.001***
College	0.095	< 0.001 ***	0.092	< 0.001 ***	0.083	< 0.001***
Graduate	0.254	< 0.001 ***	0.249	< 0.001 ***	0.233	< 0.001***
Full time/Full year	0.293	< 0.001 ***	0.265	< 0.001 ***	0.243	< 0.001***
Part time/Full year	0.163	< 0.001 ***	0.141	< 0.001 ***	0.128	< 0.001***
Full time/Part of year	0.203	< 0.001 ***	0.180	< 0.001 ***	0.165	< 0.001***
Part time/Part of year	0.135	< 0.001 ***	0.119	< 0.001 ***	0.107	< 0.001***
Empl. in agriculture	-0.067	0.011 **	-0.072	0.006 ***	-0.069	0.008***
Empl. in construction	0.020	0.291	0.020	0.280	0.025	0.174
Empl. in manufacturing	-0.008	0.573	-0.010	0.473	-0.018	0.212
Empl. in transportation	0.062	< 0.001 ***	0.058	< 0.001 ***	0.058	0.001***
Empl. in trade	0.009	0.549	0.005	0.722	0.010	0.517
Empl. in finance	0.086	< 0.001 ***	0.080	< 0.001 ***	0.073	< 0.001***
Empl. in profess. services	-0.003	0.818	-0.008	0.591	-0.015	0.289
Empl. in other services	-0.013	0.466	-0.012	0.477	-0.011	0.526
Empl. in public administ.	0.042	0.035 **	0.037	0.057 *	0.033	0.092*
Empl. in other industries	0.092	0.179	0.061	0.368	0.065	0.327
Widowed	-0.238	< 0.001 ***	-0.228	< 0.001 ***	-0.221	< 0.001***
Divorced	-0.215	< 0.001 ***	-0.209	< 0.001 ***	-0.200	< 0.001***
Separated	-0.209	< 0.001 ***	-0.200	< 0.001 ***	-0.188	< 0.001***
Never married	-0.244	< 0.001 ***	-0.234	< 0.001 ***	-0.227	< 0.001***
Black	-0.069	< 0.001 ***	-0.061	< 0.001 ***	-0.050	< 0.001***
American Indian	-0.112	< 0.001 ***	-0.106	< 0.001 ***	-0.101	< 0.001***
Asian	-0.107	< 0.001 ***	-0.103	< 0.001 ***	-0.096	< 0.001***
Race n.e.s.	-0.095	0.299	-0.085	0.349	-0.095	0.285
Female	-0.001	0.869	-0.004	0.538	0.000	0.954
Homeowner w/o mortgage	-0.067	< 0.001 ***	0.070	< 0.001 ***	-0.043	< 0.001***
Renter	-0.298	< 0.001 ***	-0.006	0.701	-0.240	< 0.001***
Occupied w/o payment	-0.326	< 0.001 ***	-0.031	0.038 **	-0.258	< 0.001***
Rural	-0.150	< 0.001 ***	-0.013	0.389	-0.142	< 0.001***
Number of adults	0.155	< 0.001 ***	-0.054	< 0.001 ***	0.155	< 0.001***
Number of children	0.027	< 0.001 ***	-0.268	< 0.001 ***	0.034	< 0.001***
Estimated smooth functions						
	E.d.f.	p-value	E.d.f.	p-value	E.d.f.	p-value
f(cohort)	3.43	< 0.001 ***	3.60	< 0.001 ***	3.68	< 0.001***
f(net worth)			8.95	< 0.001 ***		
f(assets/disposable income)					8.91	< 0.001***
f(debt/disposable income)					8.99	< 0.001***
Deviance explained	0.509		0.519		0.532	
GCV score	19,086		18,742		18,244	
AIC score	29,167		28,678		27,958	
Number of households	26,463		26,463		26,463	

Figure 1. Estimated life cycle effects on household consumption.

The figure reports estimates of standard life-cycle model of household consumption, specified by equation (7). Estimates of age and year effects are from corresponding dummy variables for the age of household head, and for the current year, respectively. Cohort effects are represented by a smooth nonlinear function with truncated cubic spline basis (9). The degree of smoothness is measured by the the estimated number of degrees of freedom, and is shown in the y-axes of panel (b).

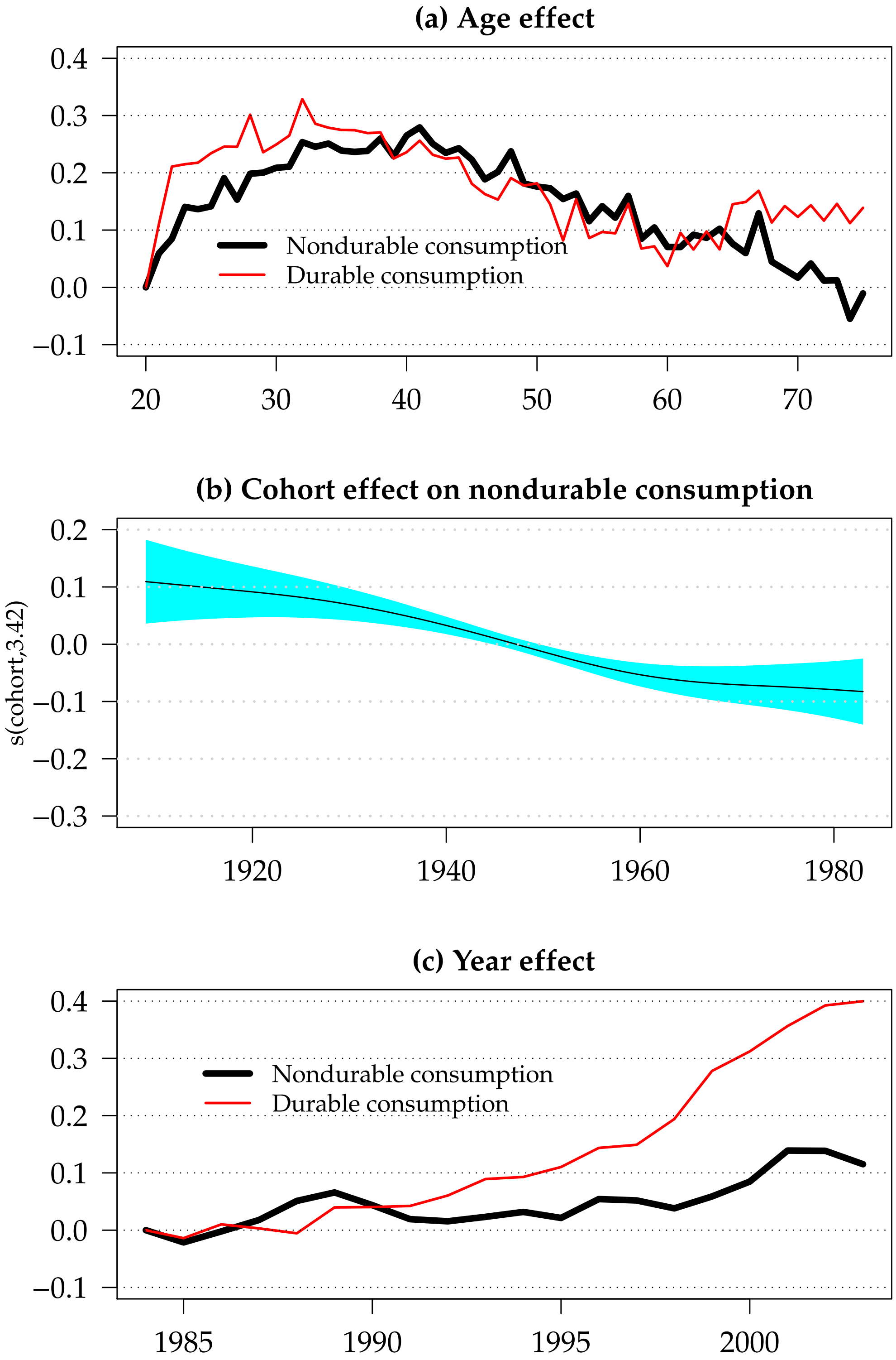
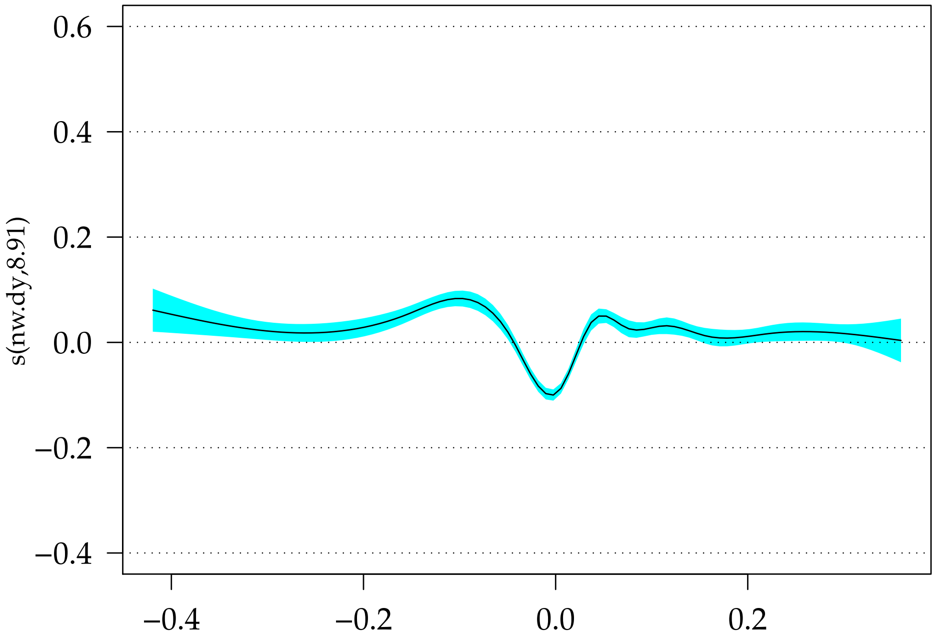


Figure 2. Net wealth effect on household consumption.

The figure reports nonparametric estimates of the net worth effect on nondurable and durable consumption, estimated by model (7). Net worth is represented by index $\Delta NW/YD$, in which net changes in net worth of households are normalized by their current disposable income. Net worth includes the sum of financial and housing assets, less total household liabilities. Nonparametric effects are estimated with truncated cubic spline basis (9). The degree of smoothness is measured by the the estimated number of degrees of freedom, and is reported in y-axes.

(a) Nondurable consumption



(b) Durable consumption

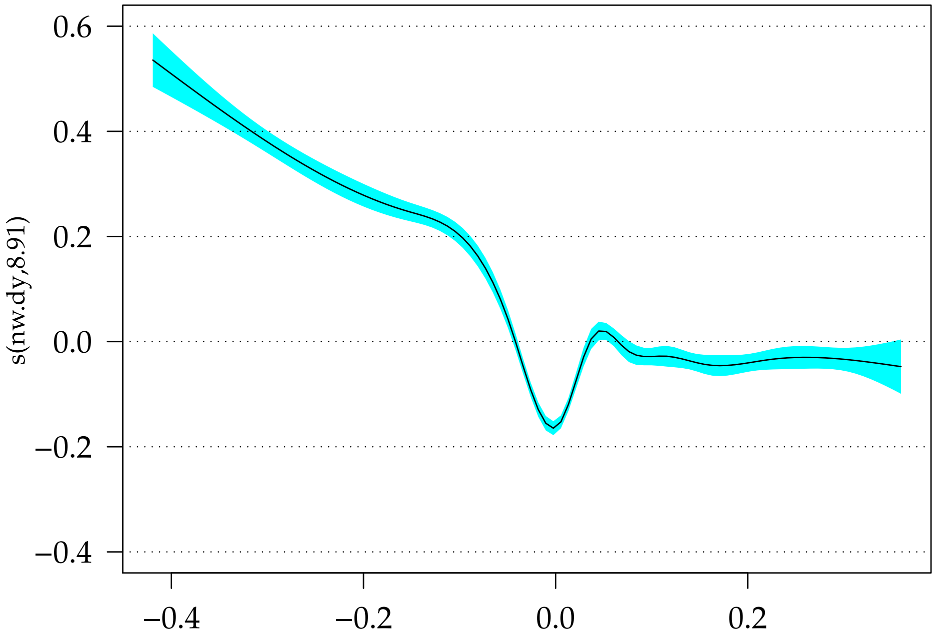


Figure 3. Balance sheet effects on nondurable consumption.

The figure reports nonparametric estimates of balance sheet effects on nondurable consumption, estimated by model (15). Balance sheet effects are measured by indices of net changes in assets and liabilities $\Delta A/YD$ and $\Delta L/YD$, respectively. The range of balance sheet effects omits households with extreme values of $\Delta A/YD$ ratio, defined by the lowest and highest 5 percentiles in the distribution of $\Delta A/YD$. Nonparametric effects are estimated with truncated cubic spline basis (9). The y-axes reports the number of degrees of freedom in approximating the asset and debt effects, with larger values indicating more nonlinear effects. Detailed results of estimating model (15) for nondurable consumption are reported in Table 3.

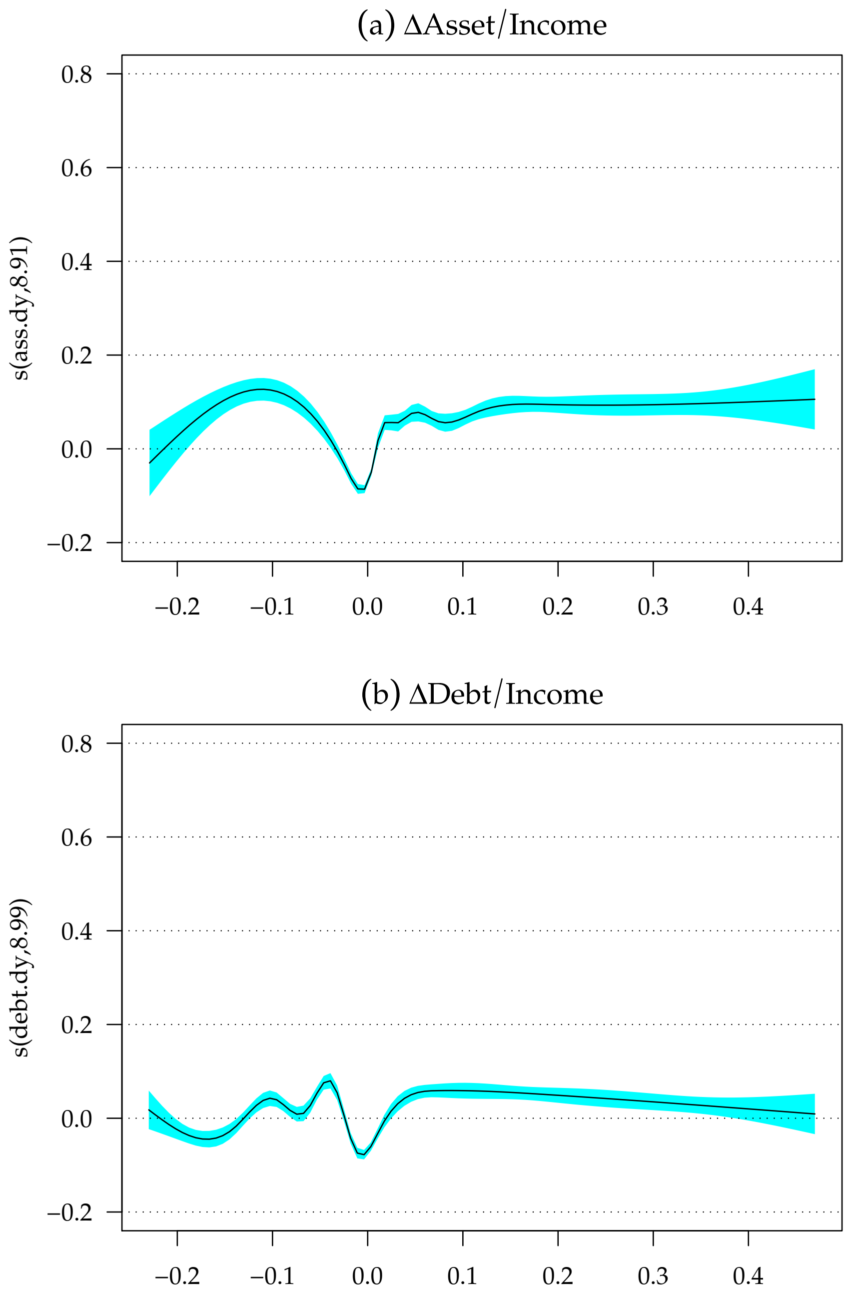
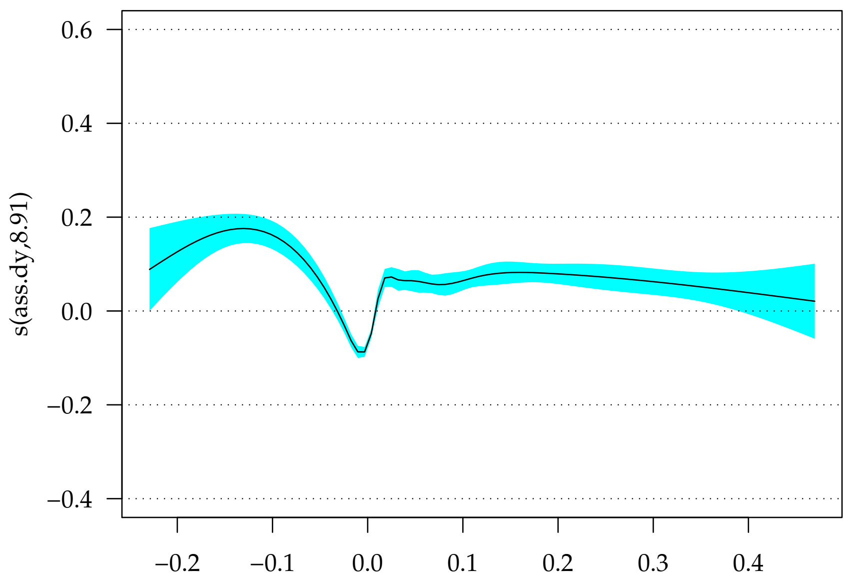


Figure 4. Balance sheet effects on durable consumption.

The figure reports nonparametric estimates of balance sheet effects on durable consumption, estimated by model (15). Balance sheet effects are measured by indices of net changes in assets and liabilities $\Delta A/YD$ and $\Delta L/YD$. The range of balance sheet effects omits households with extreme values of $\Delta L/YD$ ratio, defined by the lowest and highest 5 percentiles in the distribution of $\Delta L/YD$. Nonparametric effects are estimated with truncated cubic spline basis (9). The y-axes reports the number of degrees of freedom in approximating the asset and debt effects, with larger values indicating more nonlinear effects. Detailed results of estimating model (15) for nondurable consumption are reported in Table 4.

(a) ΔAsset/Income



(b) ΔDebt/Income

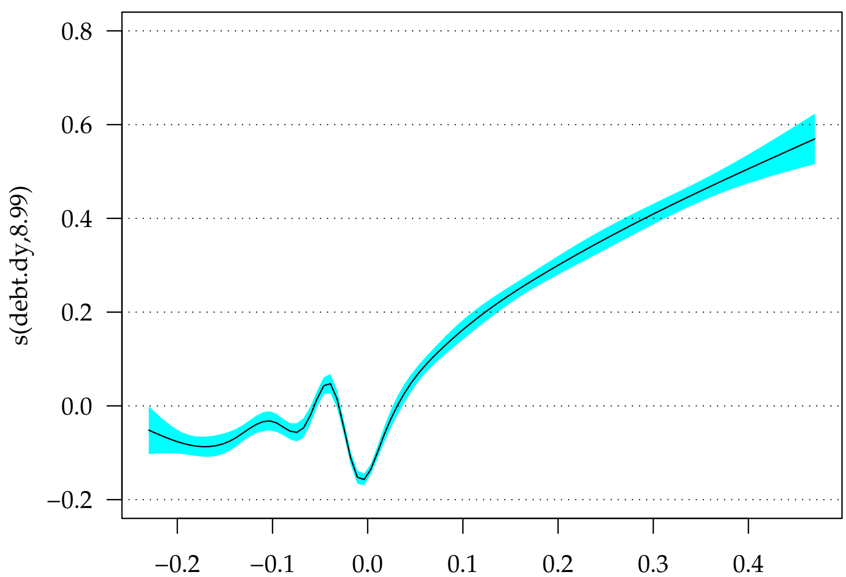
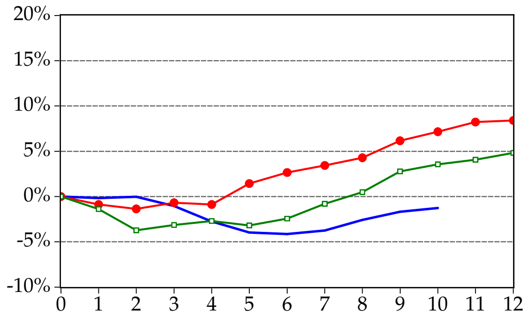


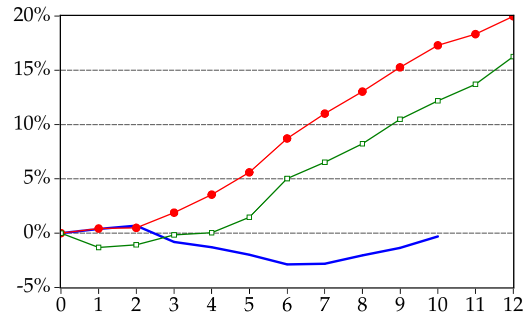
Figure 5. Subdued recovery from the 2007-2009 recession in the United States.

The figure shows the accumulated output growth after the peak of business cycle in the 2007-2009 recession, and compares it with median and worst recoveries among postwar recessions. The X-axis denotes peaks of business cycle with zero, and shows the number of quarters since the start of post-war recessions. GDP growth and output contributions from consumption are taken from the National Income and Product Accounts, compiled by the Bureau of Economic Analysis. Peaks of business cycles are defined according to the National Bureau of Economic Research. Post-war recessions do not include the short-lived recession in 1980.

(a) Accumulated GDP growth (%)



(b) Accumulated contribution to growth from non-durable consumption (%)



(c) Accumulated contribution to growth from durable consumption and residential investments (%)

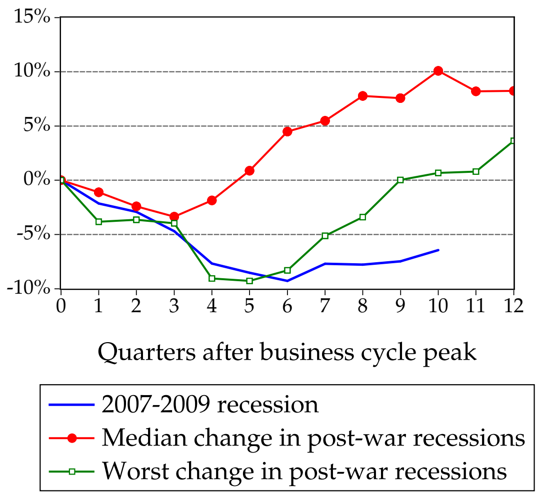


Figure 6. Net debt/disposable income ratio of U.S. households in 1946-2010.

The figure shows changes in $\Delta L/YD$ ratio. The stock of household debt L and personal disposable income YD were taken the Flow of Funds accounts of the Federal Reserve (table F.100, 'Balance Sheet of Households and Nonprofit Organizations').

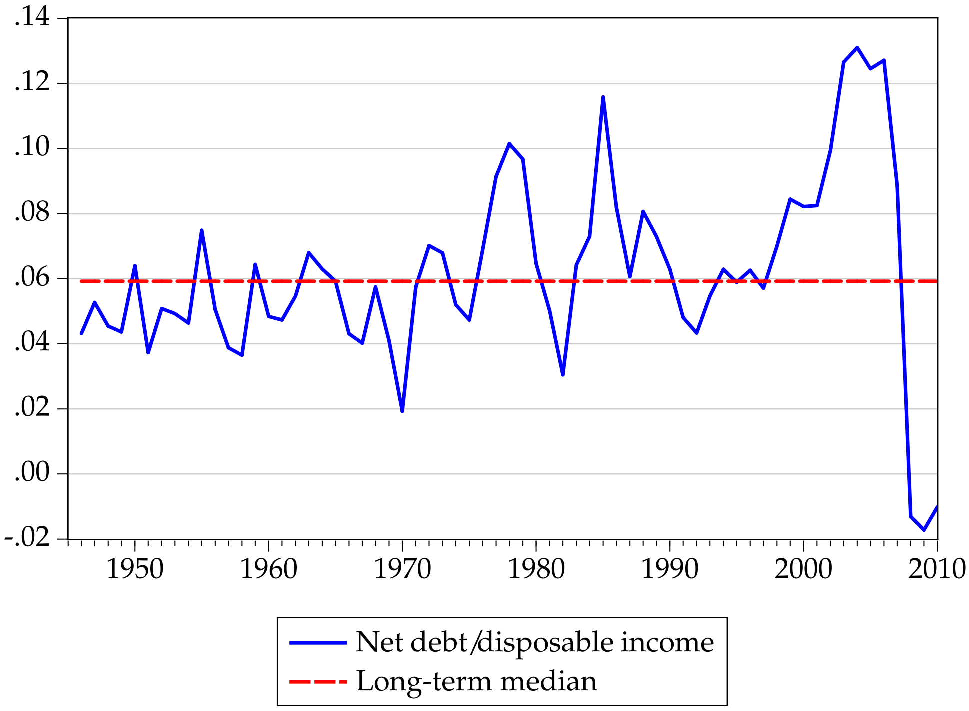


Figure A-1. Life cycle effects on household consumption with P-spline basis.

The figure reports estimates of standard life-cycle model of household consumption, specified by (7). Estimates of age and year effects are from corresponding dummy variables for the age of household head, and for the current year, respectively. Cohort effects are represented by a smooth nonlinear function with P-spline basis, discussed in subsection A.1. The degree of smoothness is measured by the estimated number of degrees of freedom, and shown in the y-axes of panel (b).

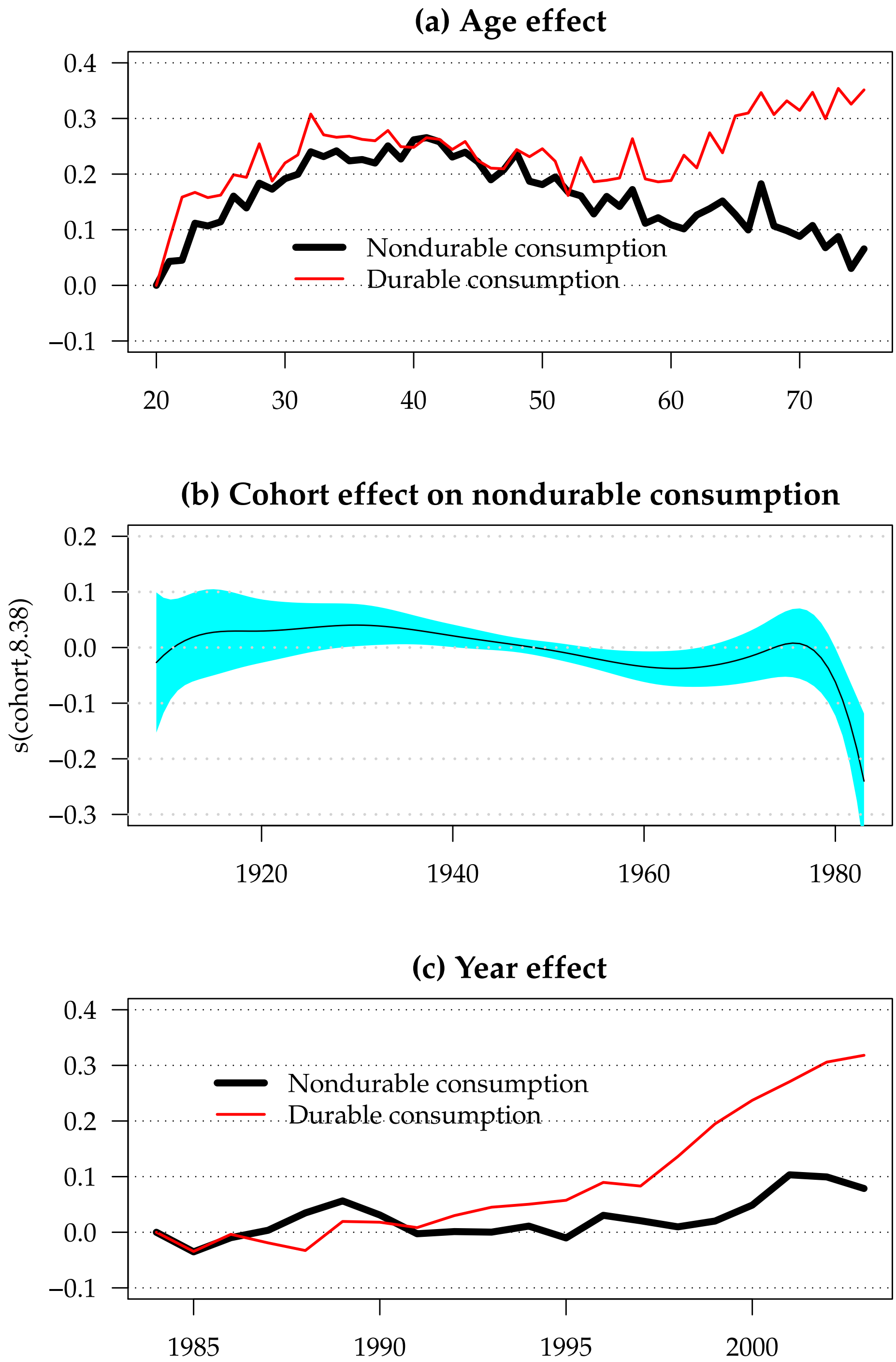
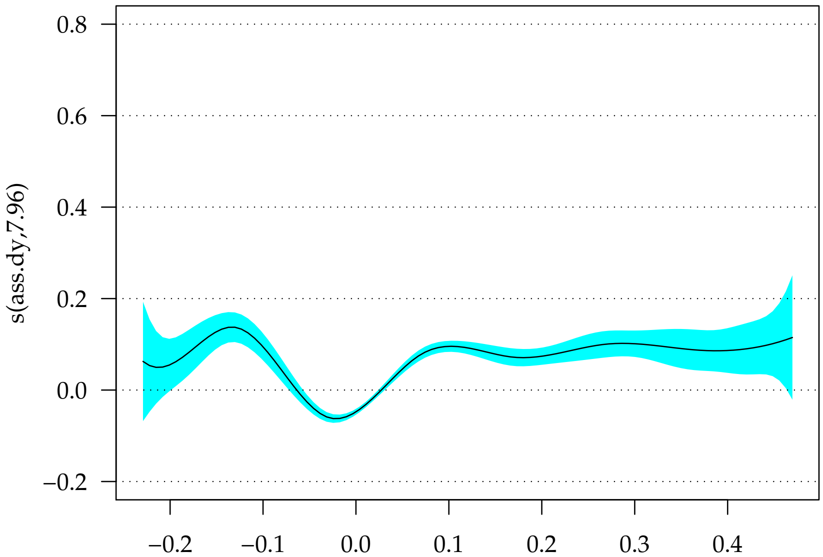


Figure A-2. Balance sheet effects on nondurable consumption with P-spline basis.

The figure reports nonparametric estimates of balance sheet effects on nondurable consumption, estimated by model (15). Balance sheet effects are measured by indices of net changes in assets and liabilities $\Delta A/YD$ and $\Delta L/YD$. The range of balance sheet effects omits households with extreme values of $\Delta A/YD$ ratio, defined by the lowest and highest 5 percentiles in the distribution of $\Delta A/YD$. Nonparametric effects are estimated with P-spline basis, discussed in subsection A.1. The y-axes reports the number of degrees of freedom in approximating the asset and debt effects, with larger values indicating more nonlinear effects.

(a) ΔAsset/Income



(b) ΔDebt/Income

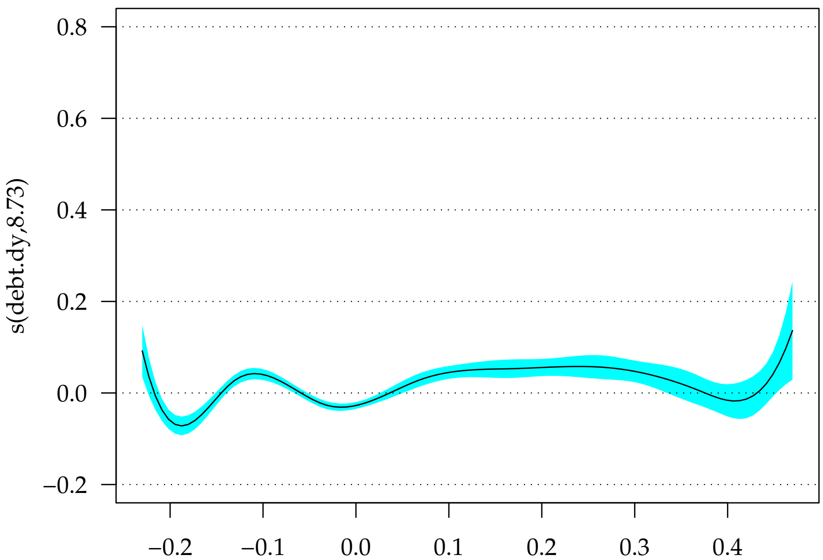
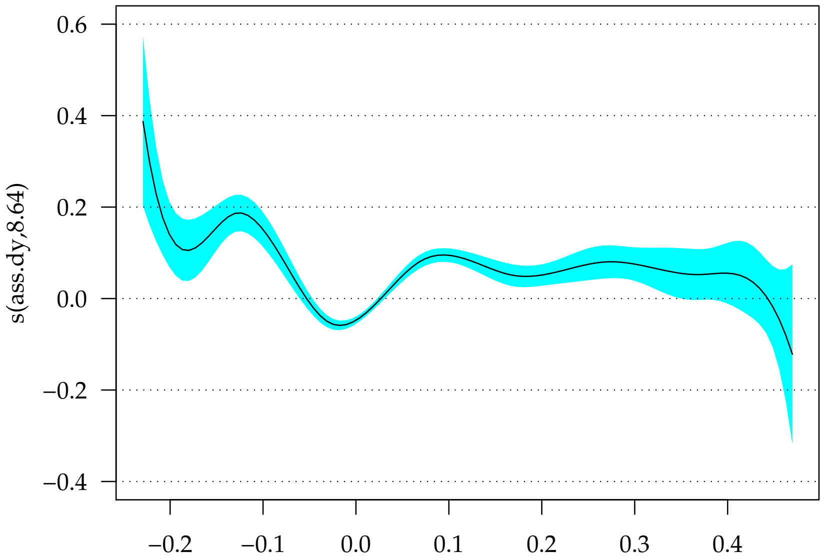


Figure A-3. Balance sheet effects on durable consumption with P-spline basis.

The figure reports nonparametric estimates of balance sheet effects on durable consumption, estimated by model (15). Balance sheet effects are measured by indices of net changes in assets and liabilities $\Delta A/YD$ and $\Delta L/YD$. The range of balance sheet effects omits households with extreme values of $\Delta A/YD$ ratio, defined by the lowest and highest 5 percentiles in the distribution of $\Delta A/YD$. Nonparametric effects are estimated with P-spline basis, discussed in subsection A.1. The y-axes reports the number of degrees of freedom in approximating the asset and debt effects, with larger values indicating more nonlinear effects.

(a) ΔAsset/Income



(b) ΔDebt/Income