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Income and the use of prescription drugs for near retirement individuals

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Abstract:

In this paper we estimate how demand for prescription drugs varies with income for a sample of near retirement individuals. The analysis is based on a novel panel data set with information about the purchase of prescription drugs for a large number of Danish individuals over the period 1995-2003. Our preferred model performs better in an external validation test than models that can be estimated on cross section data. Results indicate that demand does respond to variations in income and that reforms affecting income will therefore affect the use of prescription drugs.

JEL classification: I11, I18

Keywords: Prescription drugs demand; income; near retirement.

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1. Introduction

There is great interest in knowing if the demand for prescription drugs responds to changes in people's income. This information is important for assessing welfare effects of (tax) reforms affecting disposable income. However, at the more basic level it is important for understanding the link between income and health. The literature has shown a positive relationship between health and socioeconomic status; see Goldman (2001) for a review, but this finding is not unequivocal. Adams et al. (2003) run causality tests to identify these underlying mechanisms. Using data on elderly Americans they find that there is no causal link from socioeconomic status to mortality and sudden-onset diseases. In another study, also focusing on elderly Americans, Snyder & Evans (2006) use exogenous variation in income and show that higher income is associated with *higher* mortality rates. Other studies have shown that income is positively correlated with self reported health, Deaton & Paxson (1998), and that wealth is positively correlated with longevity, Attanasio & Emmerson (2003). This relationship is known as the income-health gradient. Recent theoretical work by Scholz & Seshadri (2010), and Dalgaard & Strulik (2011) extending the life cycle framework to include investments in health capital can reproduce the income-health gradient, but point out that the factors driving the income-health gradient remain unclear. One mechanism could be going through differential drug use to the extent that drug use is driven by income. Prescription drug usage is presumably correlated with health status and following Grossmann (1972), it could be viewed as a factor demand in the production of (good) health. If this is the case, then reforms affecting income may also affect health through drug use.

The objective of the paper is to estimate how the demand for prescription drugs varies with income for a sample of near retirement individuals. The focus is on near retirement individuals because the demand for prescription drugs increases dramatically from around age 55 and because this group experiences considerable income variations around the point of retirement. In contrast, younger people also experience considerable income variations but have low drug demand.

Few have previously worked on this topic. Moran and Simon (2006) estimate how the demand for different types of prescription medications varies with income. On a cross section of retirees they compare people that have different social security payments solely because they were born in different years. They find that a rise in Social Security income by US$ 1,000 increases the number of prescription medications used by 0.55 per month. Alan et al. (2002 and 2005) analyze senior and non-senior prescription drug demand and investigate the redistributive effects of a large scale prescription drug program. They do this (among other things) by estimating Engle curves on the Canadian Family Expenditure Survey consisting of repeated cross sections and investigating how Engel curve relationships differ between periods where the subsidy program is in operation and other periods where it is not.

Estimating how prescription drug demand responds to income variations is complicated by the fact that the demand for drugs is likely to be related to the health capital which is generally unobserved and can often, at best, be proxied only by including measures of self-reported health when analyzing cross section data. Controlling for health capital is important because the level of health capital tends to be related to marginal productivity so that individuals with a higher level of health capital also have a higher level of human capital. Therefore, comparing the demand of individuals with high income with that of individuals with low income in order to estimate Engle curves is likely to (also) reflect selection effects. Moreover, the use of prescription drugs is likely to be endogenous to the extent that consuming drugs improves health and thereby earnings capacity and income. Another issue relates to the dynamic aspects of drug demand. Some drugs are habitual and the consumption may be the consequence of treatments that extend beyond the period for which the data is collected, typically one year. At best, the above mentioned papers take into account one of these issues. We argue that it is crucial to control for all of them when modeling the dependence of demand for prescription drugs on income. In fact leaving out one of these elements from the analysis can lead to seriously biased Engle curve estimates.

The analysis presented in this paper is based on a panel data set with information about 20% of the Danish population under the age of 70. This data set has some unique features that are crucial in this context. Most importantly, and unlike any other data set that we know of, it holds person level panel information about the demand for prescription drugs for the period 1995-2003. This enables us to model the dynamic structure of demand and to take account of person-level fixed unobserved factors as well as correlation between income and the idiosyncratic error term. Moreover, covering 20% of the Danish population the data set is very large compared to expenditure surveys or other data sets with information about the demand for prescription drugs. This enables us to consider the prescription drug demand for subsets of the population without relying on small samples. We use this feature to illustrate that the effect of income on the demand for prescription drugs can vary significantly across different levels of income.

In the main analysis we focus on persons aged 55-65[1], i.e. persons near retirement. The results show a strong relationship between income and the demand for prescription drugs when estimated on a cross section. However, taking into account the dynamic structure of demand as well as fixed factors controlling for individual specific levels of health capital is very important

[1] Observations for age groups 66-69 are reserved for an external validation exercise where the estimated model's ability to capture the adjustment in demand following the change in income from age 66 to 68 is investigated.

in this context. Applying an appropriate panel data model weakens this relationship considerably. This suggests that Engle curve relationships estimated on cross section data may lead to biased estimates of the Engle curve relationship and that caution is warranted when giving such estimates a behavioral interpretation, i.e. as an estimate of the demand response to a change in income. This knowledge is essential for policy makers trying to design policies that affect the level of disposable income. If policies are based on relationships estimated on cross section data, then the effects on demand from welfare reforms can appear substantial when, in fact, they are small. Results from this study, however, still suggest that reforms affecting income, for example reforms of the public pension provision, will affect the demand for prescription drugs but in smaller magnitudes than previous studies suggest.

The remainder of the paper is organized as follows. In the next section we sketch the empirical problem and suggest a solution to it. Section 3 presents the data and shows how demand differs between young and old persons by estimating nonparametric Engle curves on cross sections from our gross data set. Section 4 presents a multivariate analysis in which we try to take into account potentially confounding factors. In this section we also show how the results differ between young and old persons. In section 5 we attempt to validate our model for the near-retirement sample by checking its ability to predict the adjustment in demand following the first receipt from a universal government public pension scheme that is awarded irrespectively of whether the individual has labor income. The idea is that this leads to an exogenous change in income that is arguably unrelated to the development in health status. Section 6 sums up and concludes.

2. Method

There are several complications associated with estimating Engle curves for prescription drug demand. First, demand is potentially driven by unobserved factors that we refer to as health capital, cf. Grossman (1972). More health capital leaves the individual more resistant to adverse health events and individuals equipped with more health capital are assumed to have a lower level of consumption of prescription drugs. The stock of health capital is likely heterogeneous across the population where some individuals are generally equipped with a high level of health capital and others with a low level of health capital. In general, health capital will be non-separable from human capital so that an adverse shock to the health capital also produces an adverse shock to earnings. The effects of such adverse shocks can be mitigated by consuming drugs that restore the health capital and stimulate productivity again. Another complication relates to the potential dynamic aspects of drug demand. Drug demand potentially follows a dynamic process because demand is habitual, but it can also reflect that the data are collected over a time frame that does not match the time frame of the treatment. This occurs, for example, when data are collected from January to December but the treatment program runs from November to March. In this section we formulate a demand model that can handle these concerns.

Consider the following demand function:

$$s_{it} = \beta_0 + \beta_1 s_{it-1} + \beta_2 y_{it} + \beta_3 y_{it}^2 + \beta_4 x_{it} + \mu_i + u_{it} \qquad (1)$$

where $i = 1, \dots, N$ is the person identifier and t identifies the period of observation. s_{it} is the share of income allocated to prescription drugs for individual i in year t, and s_{it-1} is the expenditure share for person i measured in the previous period. y_{it} is the natural log of disposable income. Following the standard in the demand literature we include a quadratic term in log-income, Banks, Blundell and Lewbel (1997), to allow the Engle curve to be nonlinear. x_i is a vector of control variables including age, sex, marital status, number of children, immigrant/native, education, occupation and geographical location. $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ are parameters to be estimated, but the focus in this paper is on the estimation of the income response, and β_2, β_3 are therefore the parameters of interest in this study. Prices are subsidized according to a complicated scheme that is generally independent of the level of income, and we therefore ignore price effects[2], see Simonsen et al. (2010). μ_i is an unobserved effect that is specific to person i, and u_{it} is an error term that may vary across time periods and individuals.

We think of μ_i as capturing innate unobserved health or the part of the health capital that is approximately fixed over the time span where we observe a person in our data set. Because health capital is potentially nonseparable from human capital, μ_i is potentially correlated with y_{it} and our estimation method should address this. u_{it} includes unanticipated adverse health shocks. An adverse health shock can generate a drop in income. The consumption of drugs on the other hand can help restore the income level. u_{it} is therefore potentially correlated with y_{it}. Estimating (1) by methods assuming orthogonality of the regressors is therefore not likely to produce consistent estimates of $\beta_1, \beta_2, \beta_3$. Moreover, the fact that $s_{it-1} = \beta_0 + \beta_1 s_{it-2} + \beta_2 y_{it-1} + \beta_3 y_{it-1}^2 + \beta_4 x_{it-1} + \mu_i + u_{it-1}$ implies that $cov(s_{it-1}, \mu_i) > 0$ in (1). Estimating the parameters of (1) by OLS will therefore produce biased estimates not only of β_2, β_3 but also of β_1 if μ_i is an important factor in explaining s_{it}.

[2] Income-tested subsidies are granted by municipalities. The empirical analysis is insensitive to the exclusion of individuals receiving these subsidies. Additionally, in 2000, the subsidy scheme was reformed so as to increase co-payment. This affected people with low levels of prescription drug use most. In section 4 we shall perform a sensitivity check so as to make sure that this reform does not bias the results.

To address these problems, we exploit the panel structure of the data and invoke the assumption that $cov(u_{it}, u_{it-1}) = 0, l = 1, \ldots, T-1$. This assumption is testable and it allows us to define a set of instrumental variables that enable us to solve the problems associated with estimating (1).

Consider first the solution to the problem associated with estimating β_1. Note that $cov(s_{it-1}, \mu_i) > 0$ but $cov(\Delta s_{it-1}, \mu_i) = 0, l \geq 1$. This suggests that $\Delta s_{it-l}, l \geq 1$ can be used as instrumental variables for s_{it-l} in equation (1). Moreover note that $cov(y_{it}, u_{it}) \neq 0$ and $cov(y_{it}, \mu_i) \neq 0$ but that $cov(\Delta y_{it-l}, u_{it}) = cov(\Delta y_{it-l}, \mu_i) = 0, l \geq 1$. This suggest that $\Delta y_{it-l}, l \geq 1$ can be used as instrumental variables for y_{it}.[3]

An alternative approach to addressing the problems associated with estimating the parameters of (1) starts out with solving the endogeneity problems arising because of the unobserved individual specific effect μ_i. To do this, consider a first differenced version of (1)

$$\Delta s_{it} = \beta_0 + \beta_1 \Delta s_{it-1} + \beta_2 \Delta y_{it} + \beta_3 \Delta y_{it}^2 + \beta_4 \Delta x_{it} + \Delta u_{it} \qquad (2)$$

In equation (2) still $cov(\Delta u_{it}, \Delta s_{it-1}) = cov(\Delta u_{it}, \Delta u_{it-1}) = -cov(u_{it-1}^2) < 0$, and OLS on (2) will still produce biased instruments. β_1 can be consistently estimated by applying GMM/IV using $s_{it-l}, l = 2, \ldots, T-2$ as an instrument for Δs_{it-1}. This follows the insights of Andersen and Hsiao (1981) and Arellano and Bond (1991). We still need to accommodate the potential endogeneity of Δy_{it} (and Δy_{it}^2). This arises because:

$cov(u_{it}, y_{it}) \neq 0 \Rightarrow cov(\Delta u_{it}, \Delta y_{it}) = cov(y_{it}, u_{it}) + cov(y_{it-1}, u_{it-1}) \neq 0$

[3] A static demand relation with a linear Engle curve is nested in (1). In the result section we shall estimate such a version of the model and compare its performance with the performance of (1) taking into account the endogeneity of s_{it-1}, y_{it}, and y_{it}^2.

(and correspondingly for Δy_{it}^2). We note that $cov(u_{it}, y_{it-l}) = cov(u_{it-1}, y_{it-l}) = 0, l = 2, \dots, T-2$, and that income lagged twice or more can therefore be used as instruments for Δy_{it}.

Arellano and Bover (1995) and Blundell and Bond (1998) suggest combining equations in levels, (1), and equations in first differences, (2), in order to obtain a more efficient estimator. When the autoregressive parameter is close to unity, i.e., the series is highly persistent, the lagged levels become weak instruments in the differenced equations and yield biased estimates. Further, if the variance of the individual fixed effect is large relative to that of the idiosyncratic error-term, using only equations in first differences will yield biased estimates. Even for low values of the autoregressive parameter, Monte Carlo simulations have shown that combining equations in differences and levels implies significant efficiency gains; see Blundell and Bond (1998). Our preferred estimator does exactly that[4].

3. Data

We use administrative data provided by Statistics Denmark. The data set contains information about a random sample of 20% of all Danish individuals in the period from 1995-2003. We construct a balanced panel of individuals aged 18 to 69 including 681,837 individuals. In the estimation part of the paper we focus on individuals between 55 and 65 years. 203,911 people in the data set are aged 55-65 at some point in the panel. For each individual in the sample we know the complete history of prescription drug purchases including date, prices etc. These data are augmented with socio-economic information on age, sex, marital status, number of children,

[4] One additional complication is that the dependent variable is censored at zero since some persons do not consume drugs. Not taking censoring into account can be associated with inconsistent estimates. No estimator exists that simultaneously handles the endogeneity problems presented above while addressing the censoring issue. In section 5 we show evidence that the censoring problem is likely to be less important than the endogeneity problems, and we therefore proceed ignoring the censoring problem.

immigrant/native, education, occupation and geographical location. The data set has one shortcoming: it does not hold information on diagnosis or other types of in- or out-patient care.

Descriptive Statistics

In table 1, descriptive statistics on a subset of the variables in the data set is presented. There are marginally more women than men in the 55-65 age brackets as well as for the full sample. The mean income for the full sample is DKK 255,058 and DKK 246,532 for the 55-65 year olds.

[Insert table 1 here]

In figure 1, a local polynomial regression of the drug expenditure share on age is depicted. As can be seen, there is a strong, positive relationship between the two. This may be explained by a deteriorating health status at old age, but as figure 2 shows, the average income is also falling from age 60 and onwards. That is, this does not necessarily imply that the elderly consume more drugs, only that they allocate a larger fraction of their income to drug consumption. Inspection of the actual levels (not reported) reveals that demand is quantitatively increasing markedly from around age 50.

[Insert figure 1 here]

[Insert figure 2 here]

The non-parametric Engel curve for total prescription drug consumption is graphed in figure 3. As can be seen, there is a negative, monotonic relationship between the expenditure share and income.

[Insert figure 3 here]

Note that a quadratic form seems to be able to capture the nonlinearities in drug demand. Given that the elderly have a higher average expenditure share, the Engel curve relationship might differ over age groups. In figure 4, two separate Engel curves are depicted: one for individuals below 55 ('young') and one for individuals aged 55 or above ('old'). The shapes of the two relations are very similar, but the levels are different (note the different scales). This suggests that the older part of the age distribution reacts more to income changes.[5]

[Insert figure 4 here]

4. Results

The estimation results for the sample of the 55 to 65 year-olds are reported in table 2. Columns (1) and (2) are OLS estimations of the Engel curves. A linear income term is included in (1), and income squared is included in (2). Both show a negative relationship between income and the expenditure share just as we found in the non-parametric Engel curve in figure 3. Columns (3) and (4) are the same as (1) and (2) but with income being treated as endogenous. Lagged differences of the endogenous explanatory variable are used as instruments; see section 2. In the linear case, treating income as endogenous does not affect the parameter estimates. When we include income squared, however, treating income as endogenous reduces the point estimates to both income terms. Note that the test of the overidentifying restrictions is rejected neither in (3) nor (4) at the usual levels of significance, suggesting that instruments are valid.

[Insert table 2 here]

[5] Deaton and Paxson (1998) also find that the income-health correlation becomes stronger as age progresses.

Column (5) holds the OLS results for the estimation with income, income squared and a lagged dependent variable as key explanatory variables. When compared to (2), including the lagged dependent variable reduces the numerical size of the point estimates of the income terms to about the half. The AR parameter is 0.62 indicating a high degree of state dependence. The OLS estimate of the AR parameter is known to be upward biased, Bond (2002). The within groups estimate of the AR parameter in column (6) is 0.12. This estimate is downwards biased, and so the true degree of persistence in demand is bounded by the estimates presented in columns (5) and (6). In any case, estimating the relation by OLS or within groups produces biased estimates of the AR parameter as well as the coefficients to the income terms.

The results for the GMM-SYS estimator that takes into account the endogeneity of the lagged dependent variable but still treats income as exogenous are presented in column (7) where $s_{i,t-2}, s_{i,t-3}, s_{i,t-4}$ are used as instrumental variables for the lagged dependent variable in the difference equations and $\Delta s_{i,t-1}$ is used as instrument for the lagged dependent variable in the level equations. In this model, the autoregressive parameter is more than halved (0.256) compared to the OLS counterpart in (5). The GMM estimate of the AR parameter lies between the OLS and within groups estimates in columns (5) and (6). Also, this is an informal test that the GMM-estimator of the AR parameter is not misspecified. The coefficients to the income terms are comparable to those of the static model in (2). The Arellano-Bond test for no autocorrelation in the first differenced error-term is also reported. We report the tests of the 1st, 2nd, and 3rd order autocorrelation. The identifying assumption of serially uncorrelated errors would lead to negative first-order serial correlation in the differenced errors, but no significant second or higher order serial correlation should be present. Test statistics show significant 1st order autocorrelation, but no significant 2nd or 3rd order autocorrelation suggesting that the model is not misspecified. The

Sargan test of overidentifying restrictions is rejected though. This latter test has, however, been shown to perform poorly; see Arellano & Bond (1991).

We also wish to control for the possible endogeneity of income in the GMM-SYS setup by using lagged levels and differences as instruments; see column (8). Specifically, we instrument the income terms with $y_{i,t-2}, y_{i,t-3}, y_{i,t-4}$ in the difference equations[6], and $\Delta y_{i,t-1}$is used as instrument in the levels equations (same procedure is used for the squared income term). The AR parameter is very close to that of (7), and we are not able to distinguish between the two statistically. However, there is a significant reduction in the numerical size of the point estimates to both income terms. They are now both individually statistically insignificant, yet jointly significant. The Sargan test still rejects the overidentifying restrictions, but the Arellano-Bond test of no second-order auto-correlation in the first differenced error-term is not rejected at the 5% level. The estimates presented in column (8) take into account all the complications that we listed in section 2, and this is our preferred set of estimates. We note that the Engle-curve relationship is considerably weaker than what is found when estimating it off cross section data whether taking into account the endogeneity of income or not.

The results from this study are comparable to the results obtained by Alan et al. (2005). They estimate static Engle curves for non-senior households on Canadian expenditure survey data and report[7] mean budget share elasticities with respect to income in the range [-0.0057;0] with more significant responses for lower income households. In this study the model with quadratic and instrumented income terms, column 4 in table 2, produces mean budget share elasticities with respect to income in the range [-0.019;-0,012] and in the range [-0.0057;-0.0036] for the

[6] Including further lags do not affect results.

[7] In table 4, page 141.

preferred model, column 8 table 2. Also in our case the response is stronger for lower incomes. The Engle curve estimates from this study are in general not far from the estimates obtained in their study, and the estimates from our dynamic model are closer to their estimates. However, our study suggests that estimates obtained from a dynamic model estimated on panel data tend to suggest smaller responses than what is indicated from the estimates obtained from a static model. The dynamic aspect may be important for describing the adjustment in demand to changing incomes. We shall return to this in section 5.

Before closing this section, we note that while we prefer the estimates presented in column (8), the IV estimates based on cross section data presented in column (4) pass the Sargan test. This suggests that researchers who are equipped only with cross section data while trying to estimate Engle curves for prescription drug demand will take such models to be well specified. Our results suggest that this may not be the case. In section 5 we shall compare the performance of the models in an external validation test in order to provide additional evidence of what model is to be preferred. Before doing this, we present some robustness checks.

Sensitivity Analysis

Full sample estimation

Figure 4 pointed towards the possibility that the Engel curve relation is not stable over different age groups. We therefore estimate our set of models on the entire group of people below the age of 65. The results are displayed in table 3.

[Insert table 3 here]

If we compare each specification to the counterpart in table 1, the income terms generally have the same sign, but the absolute value has decreased by around 50%. For our preferred specification, GMM-SYS with endogenous income, the estimates are still very small, and the individual coefficients are not statistically significantly different from zero. That is, based on a simple comparison of the individual coefficients, we are not able to distinguish the results generated from the large sample from the results generated from the small sample for the GMM-SYS model with endogenous income. However, the signs of the individual coefficients have changed. Note that the estimates of the autoregressive parameter reported in table 3 are comparable to those in table 2. Further, all the specification tests regarding validity of the instruments are rejected at trivial levels of significance. This is also the case for the Arellano-Bond test of no second-order autocorrelation in the first differenced residuals for both GMM-SYS models. The general pattern showing that the correlation between income and drug expenditure gets stronger as age progresses is consistent with the findings of Deaton & Paxson (1998) which show that the correlation between self reported health and income becomes stronger with age when persons younger than 70 are considered.

Censoring

Not all people have expenditures on prescription drugs. This means that some of the observations are censored at zero. In the 55-65 sample 23% of the observations are censored[8], and this may introduce bias in the estimates presented earlier. Unfortunately no estimator exists that can simultaneously handle all the complications listed in section 2 while also addressing the

[8] In the sample including all persons aged 65 or younger the degree of censoring is 26%.

censoring issue, see Arellano and Honoré (2003). However, to obtain a feel for the importance of censoring we estimate the two static Engel curve relations (corresponding to the results presented in columns (1) and (2) in table 2) using a Tobit-model and compare these estimates to the OLS counterparts. The results are shown in table 4.

[Insert table 4 here]

The OLS and Tobit estimates are very similar; the point estimates are only marginally different. The coefficients in the linear specifications are, however, statistically significantly different, but this is not the case when the squared term is included. It is questionable whether the differences in the estimates offer any economic significance. We take this as suggestive evidence that the endogeneity issues outlined in section 2 are of greater importance than the censoring.

Individual versus household income

So far, the analysis has been based on individual income. It is likely that couples will insure each other mutually. To shed light on this, we estimate the model using the income of the household instead of the individual income; see table 5. The results show that the estimated coefficients for the preferred model are very similar to the results using only individual income. We are not able to distinguish between the coefficients statistically, and the point estimates are so small that the difference is of no economic significance. We note, however, that the income terms are jointly insignificant when using household income. Further, the Arellano-Bond test for no second order autocorrelation in the first-differenced errors is rejected.

[Insert table 5 here]

Gender differences

Another dimension along which results can potentially vary is gender. On average women have lower income and a higher absolute level of drug use. Results for subsamples of men and women are presented in tables 6 and 7. The income response estimates are individually insignificant for both women and men. The income parameters are jointly significant for women, but not for men. However, plotting the estimated Engle curve relationship (not reported) suggests that the differences are of no economic importance.

[Insert table 6 here]

[Insert table 7 here]

Reimbursement reform in 2000

In 2000 the general population subsidy scheme for prescription drugs in Denmark was changed. Before 2000, all drugs that were qualified received a fixed percentage subsidy. After the reform the drug subsidies became a function of individual level consumption, offering no subsidies for low level of expenditures but with an increasing subsidy rate in yearly total expenditures; see Simonsen et al. (2010). Specifically, drug expenditure less than DKK 500 was not subsidized but for expenditures above DKK 500, a 50% subsidy is granted, increasing to 75% at DKK 1200 and so forth. This implied a higher copayment for people with relatively small expenditure levels. To shed light on the effects of this reform for the estimation of the income response of demand, we estimate the preferred model with an indicator on pre-post reform status and interact it with the income parameters. These effects turn out to be very small and statistically insignificant (results not reported). Further, as individuals with lower consumption pay relatively more for their drugs under the new regime, we estimate the model with an indicator that is equal to one if an individual is in the post-reform period and had an expenditure level less than DKK 1,000 in 1999 and zero otherwise. This indicator is then interacted with the income terms. These interaction terms are statistically significant, but the estimated coefficients are very small and they do not provide any meaningful economic significance.

Private insurance

As in most countries, there exists a private health insurance market as well. There is one player in the market for prescription drugs in Denmark, the company ”danmark”. None of the policies of “danmark” change around the reform date, and none of “danmark’s” policies change with yearly consumption of prescription drugs. It is not possible to enroll if aged 60+ or if prescription drugs have been purchased during the last 12 months[9]. Relevant for this study, the company offers two types of policies: Type I covers all remaining out-of-pocket expenditures related to products granted one of the government subsidies. Type II covers half of the remaining out-of-pocket expenditures for products that receive a government subsidy. A Type I membership costs around DKK 2,700 (in 2007) per year while Type II membership costs about DKK 1,000. When members of “denmark” purchase drugs they receive the refund directly from “denmark” after having purchased the drug at the pharmacy. Therefore, payments received by “danmark” are not accounted for in the above analysis. We are unable to directly observe and merge membership status of “danmark” with the random sample. However, we do have access to a smaller representative survey of the Danish adult population (Health and Sickness Survey, SUSY 2000)

[9] Individuals aged 61 or above cannot enroll either.

with roughly 4,200 respondents. This survey holds information on health care utilization including membership status of "danmark".[10] In SUSY, 11 % of the respondents hold a Type I insurance in "danmark" and 18 % hold a Type II insurance. 33 % report that they are members of 'danmark' but a few (2 %) do not remember their membership type and a few (another 2 %) are sleeping members with the option to enroll in either Type I or II at a later point in time.

To get a sense of which background variables are correlated with membership status, we run a probit model of the propensity to take up insurance. In the survey we have access to covariates that are similar or at least very good proxies to covariates that are present in the register data. Covariates included in the probit model are: gender, employment status, income (above/below median income), education (above/below 12 years of schooling) and prescription drug consumption (individual has taken prescription drugs within last 3 months). To investigate the interplay between income and drug consumption, we also include the cross-product of drug consumption and income. The results are presented in table 8.

[Insert table 8 here]

As can be seen, income is positively correlated with insurance membership, but uncorrelated with drug consumption. The interaction term between income and drug use is insignificant, indicating that insurance take-up is independent of drug use across income levels.

The analysis of insurance membership is based on cross section data and cannot tell us if membership is determined by the level of income or by temporal variations in income, and this is important for understanding the direction of a potential bias in our estimated income response parameters. At the cost of assuming that the relationship between membership and income is

[10] SUSY is collected by the National Institute of Public Health. The data set is available from the Danish Data Archive.

separable in temporal and fixed income components, it is possible to derive implications of unobserved membership for our choice of moment conditions and the consistency of our estimate of the income response. The fixed income component (which is likely to be a reasonable approximation to the permanent level of income for people close to retirement) will not affect the consistency of our estimated income parameter as the estimator controls for unobserved individual specific fixed effects. Temporal variations in income over the sample period will, however, lead to inconsistent estimates of the income response parameter if income is not instrumented appropriately. To be specific, if temporal variations in income are *iid*, then our IV estimation strategy should be able to deliver a consistent estimate of the income effect.[11] We therefore cautiously conclude that endogeneity of income due to insurance membership take-up is not likely to be an important issue in our application. We believe that this makes good sense since it is not possible to take up membership for ages 60+ or if a negative health shock has generated drug demand within the last 12 months.

5. External Validation

Several of the models that we presented parameter estimates for in table 2 of section 4 for age groups 55-65 pass standard specification tests. Specifically, we found that the static model with a quadratic Engle curve that was instrumented, column (4), passed the Sargan test for overidentifying restrictions, while our preferred model, column (8), did not.[12] As mentioned, the

[11] We have developed these arguments more formally in the appendix. Applying the instruments suggested in the appendix does not affect our results for the preferred model.

[12] This model did pass the more focused test for no autocorrelation in errors.

Sargan test is known to have low power, but is often used anyway as a standard specification test in cross section studies with endogenous regressors and overidentifying restrictions. Short of having access to data as rich as ours this could (justly) lead researchers to assume that such a model is well specified. Yet, we have found that static models can produce results that differ substantially from those of dynamic models.

In order to investigate further the benefits of modeling drug demand using our proposed dynamic specification, we conduct an external validation test in the spirit of Todd and Wolpin (2006). The idea of the test is to use the estimated models to make out-of-sample predictions of the demand response to an exogenous change in income. An estimated demand model ideally provides information about how demand responds to a change in income and not about how income responds to a change in demand. In our context demand could cause income if, for example, an adverse health shock leads to increased drug expenditures and retirement thereby lowering income. An external validation experiment should therefore examine the effect of a change in income that is not used for estimating the model and is not the consequence of a health shock. We argue that a feature of the Danish public pension system provides exactly this type of variation for a subsample of the persons entering the sample used in the estimations.

The income of retirees typically consists of one or more of three income sources: (1) Public pension (2) private pension and (3) labor market pensions. While private and labor market pensions are potentially related to historic health and earnings capacity, public pension is granted to *all* Danish citizens from the day they turn 67 irrespective of their previous, current and future labor market participation and health status[13]. In 2000, the yearly amount paid out was DKK

[13] In what follows, we describe the rules in effect at the time covered by the data.

72,096 (ca. US$ 12,000) per person if cohabiting or married and DKK 98,700 (approximately US$ 16,500) for singles.

The public pension scheme is supplemented by an early retirement scheme making it possible to retire at some point in the age interval 60-66. The yearly amount paid out in this program is DKK 148,200 (approximately US$ 24,700) in 2000. Between the ages 60-66, this amount is to be paid out for the first 2½ years in the program, and hereafter reduced to DKK 121,420 (approximately US$ 20,200), to provide an incentive to postpone retirement. The early retirement scheme was introduced in 1979, and the introduction was motivated as a scheme giving the opportunity for physically worn down individuals to retire earlier. Using US data, Rust & Phelan (1997) find that low health status is associated with the decision to opt for early retirement. Hence, we cannot be sure that early retirement and the accompanying change in income is not related to an adverse change in health.

The external validation experiment investigates whether the estimated models are able to explain how demand develops from age 66 to age 68 where the public pension is granted to all citizens irrespective of their health. We consider the change in income from 66 to 68 rather than from 66 to 67 for two reasons. First, the income data covers the calendar year but the public pension is supplied from each person's birthday and therefore does not follow the calendar year for most individuals. The full effect of the public pension is therefore not recorded in the data until age 68. Second, private capital pensions are also paid out at age 67 and this may give a transitory income that does not reflect the effect of the public pension.

[Insert figure 5 here]

We predict the expenditure share at age 66 and 68 respectively and calculate the difference[14]. In figure 5, the model predictions are plotted together with the associated income changes. The average income drop from age 66 to 68 is about 6.3%. However, the spread is large, and the graph has therefore been trimmed such that the top and bottom 10% of the income changes have been left out. The graph shows the actual expenditure share changes together with those predicted by the linear static model where income is treated as endogenous (specification (3)) and our preferred GMM-SYS estimator where income is treated as endogenous. As can be seen, the predictions from the GMM-SYS estimator are much closer to the actual changes compared to the linear specification. To assess the statistical significance we bootstrapped the procedure to provide a confidence band for the predictions. As can be seen, the actual changes lie within the confidence band of the preferred model. The confidence bands of the linear static model (not reported) are so wide that it is not possible to distinguish between the two models. The static model with a quadratic income term yields predictions similar to those of the linear static model, both with income treated as exogenous and endogenous (not reported). The same holds for the within groups model.

Individuals who have retired before age 67 in many cases experience relatively small changes in income when the public pension system kicks in. To investigate whether the model can handle significant income changes, we also perform the exercise for the subsample of persons who are recorded with labor income at age 66 and therefore have not opted for the early retirement scheme, and who are still present in the sample when 68. This amounts to 9,083 individuals[15].

[14] When we predict the expenditure share at age 68, we need to know the expenditure share at age 67 when we have a lagged dependent variable in the model. As this variable would not be observed in a real experiment, we use the expenditure share at age 66 instead.

[15] We also estimate the preferred model using only this subsample. The income response is comparable to that of the 55-65 years sample; however the coefficient to the lagged dependent variable is smaller.

Many of these people will retire at age 67 and this may be a consequence of the public pension. However, for this group the decision to retire and the accompanying change in income is not likely to be related to a discretionary change in health. Their average drop in income is 5.3% from 66-67, 15.3 % from 66-68 and 18.0% from 66-69. This suggests that the income change from age 66-68 is significant and that it reflects the permanent income drop associated with retirement. Density plots of the income changes (not reported) confirm that this is not driven by extreme observations. Again, we predict the expenditure share at ages 66 and 68, respectively, and calculate the difference. In figure 6, the model predictions are plotted together with the associated income changes. Also, this graph has been trimmed such that the top and bottom 10% of the income changes have been left out, and it shows the actual expenditure share changes together with those predicted by the linear static model where income is treated as endogenous (specification (3)) and our preferred GMM-SYS estimator where income is treated as endogenous. The graph clearly shows that the predictions from the GMM-SYS estimator are much closer to the actual changes than the prediction from the linear specification.

[Insert figure 6 here]

We take the evidence from the external validation as suggestive that our preferred model of prescription drug use captures the behavioral adjustment in drug demand following income changes better than a standard cross section model.

6. Summary and Conclusion

In this paper we present an analysis of how the demand for prescription drugs is affected by variations in income. Estimation of Engle curve relationships for the demand for prescription drugs is complicated because a central explanatory variable, the health capital, is unobserved and because demand has dynamic aspects, for example because some drugs are habitual.

The analysis is based on a novel panel data set with information about the purchase of prescription drugs for a very large number of Danish individuals over the period 1995-2003. Our analysis focuses on a pre-retirement group aged 55-65 where both average demand for prescription drugs and income vary markedly. Our preferred model, which takes into account the aforementioned complications, performs better in an external validation test than models that can be estimated on cross section data. Results indicate that demand does respond to variations in income but less so than what is suggested by cross section estimates. This suggests that reforms affecting incomes, for example reforms of public pension provision, will affect the demand for prescription drugs and therefore potentially affect health.

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Appendix: Consistency of our estimator in the presence of income shocks generating insurance take-up

Consider a simplified version of equation (1), augmented with a drug price, p and a subsidy $\phi(y_{it})$ that depends on income to mimic that insurance membership is a function of income.

$$s_{it} = \beta_0 + \beta_1 y_{it} + \left[\beta_2 p\left(1 - \phi(y_{it})\right) + \mu_i + u_{it}\right]$$

Now assume that the subsidy is unobserved, so that all components in the square bracket are unobserved. This implies that $cov\left(y_{it}, \beta_2 p\left(1 - \phi(y_{it})\right)\right) \neq 0$ and that OLS will yield a biased estimate of β_1. Further, assume that income follows $y_{it} = \omega_i + \varepsilon_{it}$, where ε_{it} is an *iid* component.

The challenge is to find a moment condition that can be exploited for estimation. To do this assume that $\phi(y_{it}) = \phi_1(\omega_i) + \phi_2(\varepsilon_{it})$ and take the difference of the above equation

$\Delta s_{it} = \beta_1 \Delta y_{it} + \left[\beta_2 p\left(1 - \Delta\phi(y_{it})\right) + \Delta u_{it}\right]$ and insert the expression for the income process.

$\Delta s_{it} = \beta_1 \Delta y_{it} + \left[\beta_2 p\left(1 - \Delta\phi_2(\varepsilon_{it})\right) + \Delta u_{it}\right]$ .Then valid instruments for Δy_{it} will be $y_{it-l}, l \geq 2$, since $cov\left(y_{it-l}, \beta_2 p\left(1 - \Delta\phi_2(\varepsilon_{it})\right)\right) = 0$, $l \geq 2$. Often it is assumed that income processes include an MA component. The arguments presented can be extended to this case. Assume for example that ε_{it} follows an MA(1) process, i.e. $\varepsilon_{it} = \nu_{it} - \theta\nu_{it-1}$. In this case valid instruments for Δy_{it} will be $y_{it-l}, l \geq 3$.

Tables to be inserted in the text

TABLE 1

DESCRIPTIVE STATISTICS

	age < 70 years			55 ≤ age ≤ 65 years		
	Mean	St.dev.	Median	Mean	St.dev.	Median
Age	43.91	13.22	43	59.47	3.14	59
Gender	0.4997	0.50	0	0.4962	0.50	0
Income	255,057.60	187,138.40	232,021.90	246,532.40	221,648.00	204,373.50
Log income	12.28	0.63	12.35	12.21	0.68	12.23
Household income	441,473.70	618,201.80	420,721.00	422,129.60	315,622.90	368,957.00
Log household income	12.80	0.68	12.95	12.77	0.62	12.82
Expenditure share	0.0037	0.0135	0.0008	0.0059	0.0183	0.0017
Obs.		5,518,532			1,043,423	

Selected descriptive statistics by age category. Household income is own plus spouse income when cohabiting/married.

TABLE 2

ESTIMATION RESULTS: 55-65 YEARS

	OLS	**OLS**	**IV 2SLS**	**IV 2SLS**	**OLS**	**WITHIN GROUPS**	**GMM-SYS EXOG.**	**GMM-SYS ENDOG.**
s	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***	***(8)***
INCOME	**-0.011**	**-0.053**	**-0.011**	**-0.042**	**-0.032**	**-0.051**	**-0.055**	-0.013
	(.0002)	(.0036)	(.0006)	(.0070)	(.0029)	(.0064)	(.0069)	(.0072)
INCOME SQ.	-	**0.002**	-	**0.001**	**0.001**	**0.002**	**0.002**	0.0004
	-	(.0001)	-	(.0003)	(.0001)	(.0003)	(.0003)	(.0003)
s_{t-1}	-	-	-	-	**0.618**	**0.118**	**0.256**	**0.296**
	-	-	-	-	(.0162)	(.0215)	(.0236)	(.0265)
Wald/F test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
Arellano-Bond test								
1	-	-	-	-	-	-	-14.29	-14.58
2	-	-	-	-	-	-	1.22	1.92
3	-	-	-	-	-	-	-0.35	-0.10
Sargan/OIR	-	-	2.80	0.79	-	-	100.05	407.89
			(1)	(2)			(23)	(61)
Obs.	852,714	852,714	852,714	852,714	852,714	852,714	852,714	852,714

Estimation on sample of 55 to 65 year olds. Controls include: Sex, age, education, occupation, geographic location, immigrant/native and marital status. Robust standard errors in parentheses. Bold indicates significance at 5% level. Wald/F test: p-value from test of joint significance of income and income sq. Arellano-Bond tests for first-, second- and third-order serial correlation in the first-differenced residuals. These are asymptotically distributed N(0,1) under the null of no serial correlation. Sargan test of the over-identifying restrictions is asymptotically chi sq. distributed under the null of instrument validity. Degrees of freedom are reported in parentheses.

TABLE 3

ESTIMATION RESULTS: ≤65 YEARS

s	OLS (1)	OLS (2)	IV 2SLS (3)	IV 2SLS (4)	OLS (5)	WITHIN GROUPS (6)	GMM-SYS EXOG. (7)	GMM-SYS ENDOG. (8)
INCOME	**-0.007**	**-0.029**	**-0.006**	**-0.026**	**-0.023**	**-0.024**	**-0.026**	0.003
	(.0001)	(.0014)	(.0002)	(.0028)	(.0012)	(.0017)	(.0020)	(.0031)
INCOME SQ.	-	**0.001**	-	**0.001**	**0.001**	**0.001**	**0.001**	-0.0002
	-	(.0001)	-	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
s_{t-1}	-	-	-	-	**0.531**	**0.124**	**0.221**	**0.244**
	-	-	-	-	(.0100)	(.0102)	(.0109)	(.0115)
Wald/F test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond test								
1	-	-	-	-	-	-	-25.99	-26.09
2	-	-	-	-	-	-	4.75	5.59
3	-	-	-	-	-	-	-1.54	-1.08
Sargan/OIR	-	-	13.00	7.41	-	-	282.46	1217.51
			(1)	(2)			(23)	(61)
Obs.	3,987,166	3,987,166	3,987,166	3,987,166	3,987,166	3,987,166	3,987,166	3,987,166

Estimation on sample of individuals aged 65 and below Controls include: Sex, age, education, occupation, geographic location, immigrant/native and marital status. Robust standard errors in parentheses. Bold indicates significance at 5% level. Wald/F test: p-value from test of joint significance of income and income sq. Arellano-Bond tests for first-, second- and third-order serial correlation in the first-differenced residuals. These are asymptotically distributed N(0,1) under the null of no serial correlation. Sargan test of the over-identifying restrictions is asymptotically chi sq. distributed under the null of instrument validity. Degrees of freedom are reported in parentheses.

TABLE 4

OLS VS. TOBIT ESTIMATION

s	OLS (1)	TOBIT (2)	OLS (3)	TOBIT (4)
INCOME	**-0.0113**	**-0.0121**	**-0.0535**	**-0.0527**
	(.0002)	(.0003)	(.0036)	(.0008)
INCOME SQ.	-	-	**0.0018**	**0.0018**
	-	-	(.0001)	(.00003)
Censored obs.	193,716	193,716	193,716	193,716
Uncensored obs.	658,998	658,998	658,998	658,998
Total obs.	852,714	852,714	852,714	852,714

Estimation on sample of 55 to 65 year olds. Controls include: Sex, age, education, occupation, geographic location, immigrant/native and marital status. Robust standard errors in parentheses. Bold indicates significance at 5% level.

TABLE 5

ESTIMATION RESULTS: 55-65 YEARS HOUSEHOLD INCOME

	OLS	OLS	IV 2SLS	IV 2SLS	OLS	WITHIN GROUPS	GMM-SYS EXOG.	GMM-SYS ENDOG.
s	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
INCOME	**-0.004**	**-0.033**	**-0.003**	**-0.034**	**-0.026**	**-0.040**	**-0.043**	-0.007
	(.0001)	(.0056)	(.0003)	(.0111)	(.0052)	(.0100)	(.0104)	(.0097)
INCOME SQ.	**-**	**0.001**	**-**	**0.001**	**0.001**	**0.001**	**0.001**	0.0003
	-	(.0002)	-	(.0004)	(.0002)	(.0004)	(.0004)	(.0004)
s_{t-1}	**-**	**-**	**-**	**-**	**0.638**	**0.110**	**0.256**	**0.278**
	-	-	-	-	(.0343)	(.0431)	(.0482)	(.0504)
Wald/F test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.757
Arellano-Bond test								
1	-	-	-	-	-	-	-7.68	-7.52
2	-	-	-	-	-	-	2.67	3.32
3	-	-	-	-	-	-	0.51	0.06
Sargan/OIR	-	-	4.05	3.73	-	-	381.46	1100.37
			(1)	(2)			(23)	(61)
Obs.	852,714	852,714	852,714	852,714	852,714	852,714	852,714	852,714

Estimation on sample of 55 to 65 year olds using household income. Controls include: Sex, age, education, occupation, geographic location, immigrant/native and marital status. Robust standard errors in parentheses. Bold indicates significance at 5% level. Wald/F test: p-value from test of joint significance of income and income sq. Arellano-Bond tests for first-, second- and third-order serial correlation in the first-differenced residuals. These are asymptotically distributed N(0,1) under the null of no serial correlation. Sargan test of the over-identifying restrictions is asymptotically chi sq. distributed under the null of instrument validity. Degrees of freedom are reported in parentheses.

TABLE 6

ESTIMATION RESULTS: 55-65 YEARS - WOMEN

	OLS	OLS	IV 2SLS	IV 2SLS	OLS	WITHIN GROUPS	GMM-SYS EXOG.	GMM-SYS ENDOG.
s	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
INCOME	**-0.016**	**-0.046**	**-0.015**	**-0.033**	**-0.028**	**-0.045**	**-0.051**	-0.015
	(.0004)	(.0046)	(.0010)	(.0092)	(.0036)	(.0079)	(.0084)	(.0093)
INCOME SQ.	**-**	**0.001**	**-**	**0.001**	**0.001**	**0.001**	**0.001**	0.0003
	-	(.0002)	-	(.0004)	(.0002)	(.0003)	(.0003)	(.0004)
s_{t-1}	**-**	**-**	**-**	**-**	**0.620**	**0.124**	**0.256**	**0.301**
	-	-	-	-	(.0181)	(.0242)	(.0275)	(.0311)
Wald/F test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond test								
1	-	-	-	-	-	-	-12.59	-12.80
2	-	-	-	-	-	-	0.49	1.05
3	-	-	-	-	-	-	0.14	0.42
Sargan/OIR	-	-	4.94	3.47	-	-	80.32	250.49
			(1)	(2)			(24)	(62)
Obs.	427,814	427,814	427,814	427,814	427,814	427,814	427,814	427,814

Estimation on sample of women, 55 to 65 year olds. Controls include: Age, education, occupation, geographic location, immigrant/native and marital status. Robust standard errors in parentheses. Bold indicates significance at 5% level. Wald/F test: p-value from test of joint significance of income and income sq. Arellano-Bond tests for first-, second- and third-order serial correlation in the first-differenced residuals. These are asymptotically distributed N(0,1) under the null of no serial correlation. Sargan test of the over-identifying restrictions is asymptotically chi sq. distributed under the null of instrument validity. Degrees of freedom are reported in parentheses.

TABLE 7

ESTIMATION RESULTS: 55-65 YEARS - MEN

	OLS	OLS	IV 2SLS	IV 2SLS	OLS	WITHIN GROUPS	GMM-SYS EXOG.	GMM-SYS ENDOG.
s	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***	***(8)***
INCOME	**-0.006**	**-0.039**	**-0.005**	**-0.029**	**-0.032**	**-0.045**	**-0.050**	-0.003
	(.0002)	(.0066)	(.0005)	(.0105)	(.0060)	(.0112)	(.0121)	(.0102)
INCOME SQ.	**-**	**0.001**	-	**0.001**	**0.001**	**0.002**	**0.002**	0.0001
	-	(.0003)	-	(.0004)	(.0002)	(.0004)	(.0005)	(.0004)
s_{t-1}	-	-	-	-	**0.589**	0.074	**0.225**	**0.256**
	-	-	-	-	(.0356)	(.0432)	(.0393)	(.0426)
Wald/F test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.455
Arellano-Bond test								
1	-	-	-	-	-	-	-7.22	-7.04
2	-	-	-	-	-	-	2.26	2.65
3	-	-	-	-	-	-	-1.04	-1.00
Sargan/OIR	-	-	0.78	0.01	-	-	179.97	650.50
			(1)	(2)			(24)	(62)
Obs.	424,900	424,900	424,900	424,900	424,900	424,900	424,900	424,900

Estimation on sample of men, 55 to 65 year olds. Controls include: Age, education, occupation, geographic location, immigrant/native and marital status. Robust standard errors in parentheses. Bold indicates significance at 5% level. Wald/F test: p-value from test of joint significance of income and income sq. Arellano-Bond tests for first-, second- and third-order serial correlation in the first-differenced residuals. These are asymptotically distributed N(0,1) under the null of no serial correlation. Sargan test of the over-identifying restrictions is asymptotically chi sq. distributed under the null of instrument validity. Degrees of freedom are reported in parentheses.

TABLE 8

PROBIT MARGINAL EFFECTS: PROBABILITY OF PRIVATE INSURANCE TAKE UP

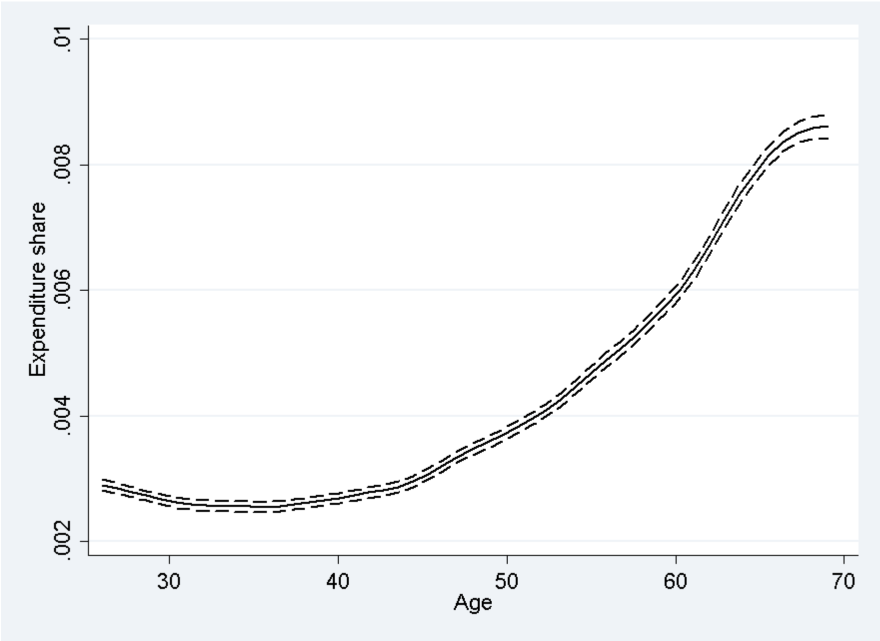
	Full sample		55-65 years	
	M.E.	S.E.	M.E.	S.E.
INCOME	**0.079**	(0.018)	**0.147**	(0.046)
DRUGS	-0.026	(0.017)	-0.049	(0.040)
INCOMEXDRUGS	0.001	(0.001)	0.001	(0.002)
CHILDREN	-0.018	(0.017)	-0.137	(0.121)
EDUC.	**0.130**	(0.015)	**0.193**	(0.039)
MALE	**-0.120**	(0.015)	**-0.150**	(0.041)
AGE	**0.002**	(0.001)	0.003	(0.007)
EMP.	**0.149**	(0.024)	0.148	(0.090)
UNEMP.	**0.104**	(0.034)	0.088	(0.114)
# Obs.	4,260		713	
R sq.	0.05		0.06	

Marginal effects evaluated at the mean. The excluded socioeconomic group is retirement. Bold estimates are significant at the 5 % level. ( ) standard errors. Response rate in SUSY is 75 %.

Figures to be inserted in the text

FIGURE 1

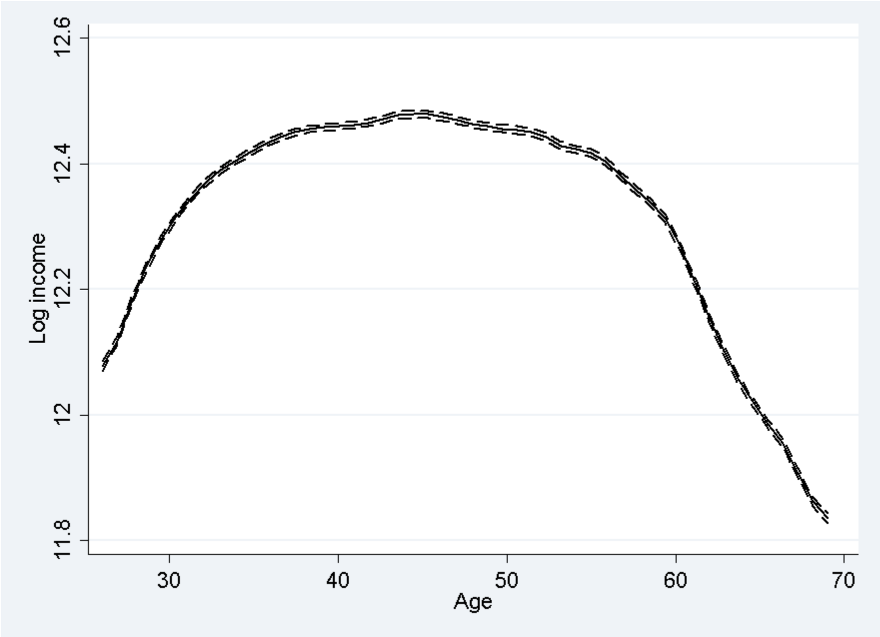
KERNEL REGRESSION OF EXPENDITURE SHARE ON AGE



Local polynomial regression of age on the expenditure share. Cross-section, year 2003. Dashed lines are 95% confidence interval.

FIGURE 2

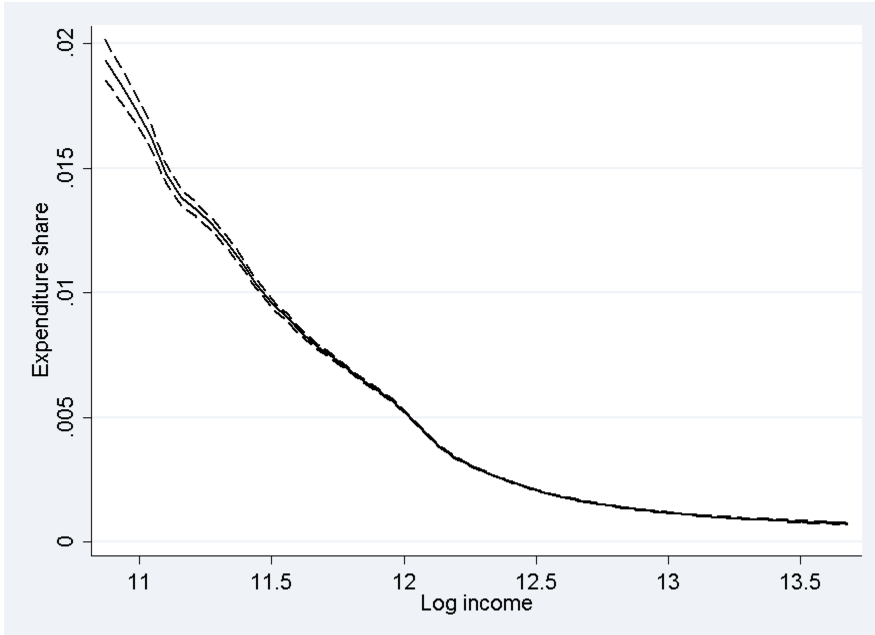
KERNEL REGRESSION OF LOG INCOME ON AGE



Local polynomial regression of age on the log income. Cross-section, year 2003. Dashed lines are 95% confidence interval.

FIGURE 3

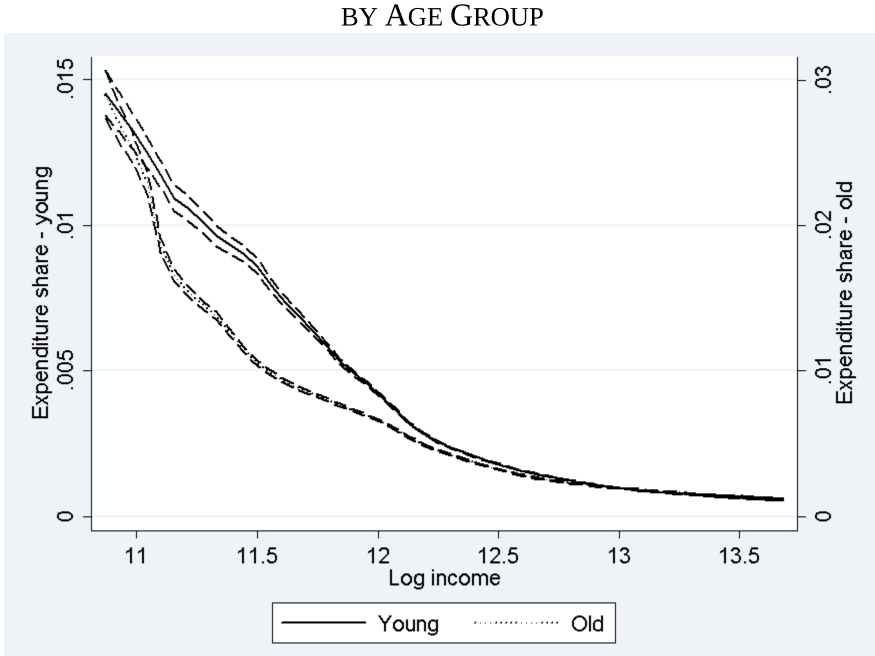
KERNEL REGRESSION OF EXPENDITURE SHARE ON LOG INCOME



Local polynomial regression of log income on the prescription drug expenditure share. Cross-section, year 2003. Dashed lines are 95% confidence interval.

FIGURE 4

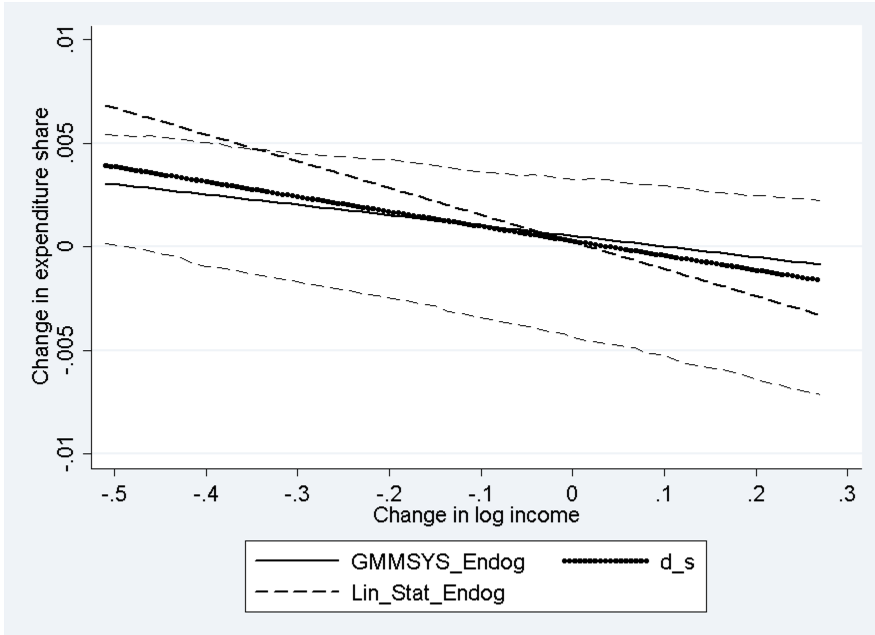
KERNEL REGRESSION OF EXPENDITURE SHARE ON LOG INCOME BY AGE GROUP



Local polynomial regression of log income on the prescription drug expenditure share by age. Young are individuals below the age of 55 and old are individuals aged 55 to 70. Cross-section, year 2003. Dashed lines are 95% confidence interval.

FIGURE 5

EXPENDITURE SHARE CHANGES FROM AGE 66 TO 68 FOR FULL SAMPLE

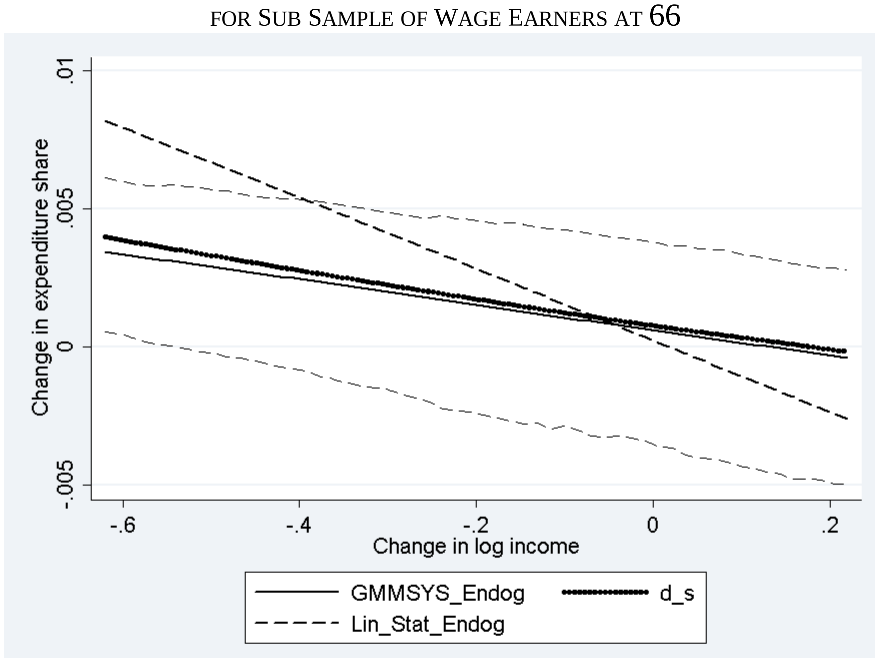


Plot of the predictions from the GMM-SYS estimator and the linear static model with income treated as endogenous. The dotted line is the actual expenditure share changes. The graph only depicts 80% of the distribution of income changes. 10% in the top/bottom has been left out. 95% confidence bands for GMM-SYS predictions are reported. These are bootstrapped using 1,000 replications.

FIGURE 6

EXPENDITURE SHARE CHANGES FROM AGE 66 TO 68

FOR SUB SAMPLE OF WAGE EARNERS AT 66



Plot of the predictions from the GMM-SYS estimator and the linear static model with income treated as endogenous. The dotted line is the actual expenditure share changes. The graph only depicts 80% of the distribution of income changes. 10% in the top/bottom has been left out. 95% confidence bands for GMM-SYS predictions are reported. These are bootstrapped using 1,000 replications.