Partial Insurance, Information and Consumption Dynamics

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Executive summary

This paper uses panel data on household consumption and income to evaluate the degree of insurance to income shocks. Our aim is to describe the transmission of income inequality into consumption inequality. Our framework nests the special cases of self-insurance and the complete markets assumption. We assess the degree of insurance over and above self-insurance through savings by contrasting shifts in the cross-sectional distribution of income growth with shifts in the cross-sectional distribution of consumption growth, and analyzing the way these two measures of household welfare correlate over time. We combine panel data on income from the PSID with consumption data from repeated CEX cross-sections in a structural way, i.e. using conventional demand analysis rather than reduced form imputation procedures. Our results point to some partial insurance but reject the complete markets restriction. We find a greater degree of insurance for transitory shocks and differences in the degree of insurance over time and across education. We also document the importance of durables and of taxes and transfers as a means of insurance.

Key words: Consumption, Insurance, Inequality.
JEL Classification: D52; D91; I30.

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1 Introduction

Under complete markets agents can sign contingent contracts providing full insurance against idiosyncratic shocks to income. Moral hazard and asymmetric information, however, make these contracts hard to implement, and in fact they are rarely observed in reality. Even a cursory look at consumption and income data reveals the weakness of the complete markets hypothesis. Thus volatility of individual consumption is much higher than the volatility of aggregate consumption, a fact against full insurance (Aiyagari, 1994). Moreover, there is a substantial amount of mobility in consumption (Jappelli and Pistaferri, 2001). Indeed, the growth in consumption inequality over the 1980s is used in Blundell and Preston (1998) to identify growth in permanent (uninsured) income inequality over this period in the UK. Formal tests of the complete markets hypothesis (see Attanasio and Davis, 1996), find that the null hypothesis of full consumption insurance is soundly rejected.[1] Attempts to salvage the theory by allowing for risk sharing within the family and no risk sharing among unrelated families have also failed (Hayashi *et al.*, 1996). At least for developed economies, full risk sharing seems to be convincingly rejected.

Reflecting this evidence, the modern theory of intertemporal consumption behavior is developed and tested under the assumption of incomplete markets (Hall, 1978). In the permanent income hypothesis, for instance, the only mechanism available to agents to smooth income shocks is personal savings. In the extreme formulation of this model contracts or other formal or informal arrangements are absent altogether and quadratic preferences are assumed; permanent shocks to income are permanent shocks to consumption.[2]

Models that feature a myriad of markets and those that allow for just personal savings as a smoothing mechanism are clearly extreme characterization of individual behavior and of the economic environment faced by the consumers. Deaton and Paxson (1994) notice this and envision "the construction and testing of market models under partial insurance", while Hayashi *et al.* (1996) call for future research to be "directed to estimating the extent of consumption insurance over and above self-insurance".

[1] Notable exceptions are Altug and Miller (1990) and Mace (1991). In these papers, however, failure to reject the null hypothesis of full consumption insurance is likely to be due to econometric and sample selection issues. See, e.g., Nelson (1994).

[2] Even with precautionary saving, permanent shocks to labour income will typically be almost fully transmitted into consumption (see below).

In this paper we address the issue of whether partial consumption insurance is available to agents and estimate the degree of insurance over and above self-insurance through savings. We do this by contrasting shifts in the distribution of income growth with shifts in the distribution of consumption growth, and analyze the way these two measures of household welfare correlate over time. Our research is related to other papers in the literature, particularly Hall and Mishkin (1982), Altonji *et al.* (2002), Deaton and Paxson (1994), and Blundell and Preston (1998).

We document a number of key findings. Using data from a combination of the Panel Study of Income Dynamics (PSID) and the Consumers Expenditure Survey (CEX), we find a strong growth in both permanent and transitory income shocks during the early 1980s. The variance of permanent shocks thereafter levels off. There is strong evidence against full insurance for permanent income shocks but not for transitory income shocks, except for the low income subsample where transitory shocks seem less insurable. Further there is evidence of partial insurance of permanent income shocks; the results point to much of this partial insurance occurring through the adjustment of durable expenditures. Finally we show that taxes and transfers provide an important insurance mechanism for permanent income shocks.

We use the term *partial insurance* to denote smoothing devices other than credit markets for borrowing and saving. There is scattered evidence on the role played by such devices on household consumption. Theoretical and empirical research have analyzed the role of extended family networks (Kotlikoff and Spivak, 1981; Attanasio and Rios-Rull, 2000), added worker effects (Lundberg, 1985), the timing of durable purchases (Browning and Crossley, 2001a), progressive income taxation (Mankiw and Kimball, 1992), personal bankruptcy laws (Fay *et al.*, 2002), insurance within the firm (Guiso *et al.*, 2002), financial markets (Davis and Willen, 2001), and the role of government public policy programs, such as unemployment insurance schemes (Engen and Gruber, 2001; Browning and Crossley, 2001b), Medicaid (Gruber and Yelowitz, 1999), and food stamps (Blundell and Pistaferri, 2002).

While we do not take a precise stand on the mechanisms (other than savings) that are available to smooth idiosyncratic shocks to income, we emphasize that our evidence can be used to uncover whether some of these mechanisms are actually at work, how important they are quantitatively, and how they differ across households and over time. Our approach is justified by the fact that "although it is possible to examine the mechanisms [providing partial insurance against income shocks], their multiplicity makes it attractive to look directly at the magnitude that is supposed to be smoothed, namely consumption" (Deaton, 1995).

In the literature to date no structural model has been estimated to address the issue of partial insurance directly. Yet, uncovering partial insurance mechanisms is likely to matter for a number of reasons. First, the presence of mechanisms that allow households to smooth idiosyncratic shocks has a bearing on aggregation results (see Blundell and Stoker, 2002). Second, it may help to understand the characteristics of the economic environment faced by the agents. This may prove crucial when evaluating the performance of macroeconomic models, especially those that explicitly account for agents' heterogeneity. Moreover, it is important to understand to what extent changes in welfare systems affect smoothing abilities, and the consequences of this for private saving behavior. This is important as far as the efficient design of welfare policy is concerned. Finally, the evaluation of changes in welfare requires knowledge of the extent of smoothing or insurance available to consumers. This is particularly relevant in the US, where quantitatively large changes in the structure of relative prices (most notably, wages) have occurred over the last three decades. Much research exists about the rise in wage inequality, and we shall have very little to add about this. Less evidence exists on consumption inequality (Cutler and Katz, 1992; Dynarski and Gruber, 1997). We show that consumption inequality follows very closely the trends in permanent wage inequality documented, among others, by Moffitt and Gottschalk (1994).

A study of this kind requires in principle good quality longitudinal data on household consumption and income. It is well known that the PSID contains longitudinal income data but the information on consumption is scanty (limited to food and few more items). Our strategy is to impute non-durable consumption to all PSID households combining PSID data with consumption data from repeated CEX cross-sections in a structural way. Previous studies (Skinner, 1987) impute non-durable consumption data in the PSID using CEX regressions of non durable consumption on consumption items (food, housing, utilities) and demographics available in both the PSID and the CEX. These equations do not correspond to what is studied in demand analyses. In contrast, our approach starts from a standard demand function for food at home (a consumption item available in both surveys); we make this depend on prices, total non durable expenditure, and a host of demographic and socio-economic characteristics of the household. Under monotonicity of food demands these functions can be inverted to obtain a measure of non durable consumption in the PSID.

The paper continues with an illustration of the model we estimate and of the identification strategy we use (Section 2). In Section 3 we discuss data issues and the imputation procedure. Section 4 contains a discussion of the results and a critical analysis of our finding. Section 5 concludes. The Appendixes discuss technical details about the approximation of the Euler equation used in the empirical section, identification in the presence of measurement error, estimation details and the imputation procedure.

2 Income and Consumption dynamics

2.1 The income process

The unit of analysis is a household, comprising a couple and, possibly, their children. Our sample selection focuses on income risk and we do not model divorce, widowhood, and other household breaking-up factors. We recognize that these may be important omissions that limit the interpretation of our study. However, by focusing on stable households and the interaction of consumption and income we are able to develop a complete identification strategy. We also confine our analysis to links between labor income and consumption that become less important during retirement. Consequently we only select households during the working life of the husband.

We assume that the main source of uncertainty faced by the consumer is income (defined as the sum of labor income and transfers, such as welfare payment). We also assume that labor is supplied inelastically. The income process we consider is:

$$y_{i,a,t} = Z'_{i,a,t}\varphi + P_{i,a,t} + v_{i,a,t} \tag{1}$$

where a and t index age and time, respectively, $y = \log Y$ is the log of real income, and Z a set of observable income characteristics. Equation (1) decomposes current income into a permanent component $P_{i,a,t}$ and a transitory or mean-reverting component, $v_{i,a,t}$. By writing $y_{i,a,t}$ rather than $y_{i,t}$ we emphasize the importance of cohort effects in the evolution of earnings over the life-cycle and, more importantly, across generations entering the labor market in different time periods (and thus facing different economic environments and opportunities). In keeping with this remark, we study consumption decisions separately for different cohorts.

For consistency with previous empirical studies (MaCurdy, 1982; Abowd and Card, 1989; Moffitt and Gottschalk, 1994; Meghir and Pistaferri, 2002), we assume that the permanent component $P_{i,a,t}$ follows a martingale process of the form:

$$P_{i,a,t} = P_{i,a-1,t-1} + \zeta_{i,a,t} \tag{2}$$

where $\zeta_{i,a,t}$ is serially uncorrelated, and the transitory component follows an MA(q) process, where the order q is to be established empirically:

$$v_{i,a,t} = \sum_{j=0}^{q} \theta_j \varepsilon_{i,a-j,t-j}$$

with $\theta_0 \equiv 1$. It follows that income growth is:

$$\Delta y_{i,a,t} = \Delta Z_{it}' \varphi + \zeta_{i,a,t} + \Delta v_{i,a,t} \tag{3}$$

The covariance restrictions implied by (3) are explored in the next Section.

2.2 Self Insurance and Consumption Growth

Consider the optimization problem faced by household i. The objective is to:

$$\max E_{a,t} \sum_{j=0}^{L-a} (1+\delta)^{-j} u\left(C_{i,a+j,t+j}; D_{i,a+j,t+j}\right) \tag{4}$$

subject to the intertemporal budget constraints and the initial and terminal conditions on financial assets:

$$A_{i,a+j+1,t+j+1} = (1+r)\left(A_{i,a+j,t+j} + Y_{i,a+j,t+j} - C_{i,a+j,t+j}\right) \tag{5}$$

$$A_{i,a,t} \text{ given} \tag{6}$$

$$A_{i,L,t+L-a} = 0 \tag{7}$$

The term $D_{i,a+j,t+j}$ includes observable and unobserved taste shifts. We set the end of the life-cycle at age L and assume that there is no interest rate uncertainty. If preferences are of the CRRA form ($u(C) = \frac{C^{1-\gamma}-1}{1-\gamma}$), credit markets are perfect and $r = \delta$, then one obtains the approximate Euler equation (see Appendix A.1 for more details on the approximation):

$$\Delta c_{i,a,t} \cong \Gamma_{b,t} + \Delta Z'_{it}\vartheta + \xi_{i,a,t} + \pi_{i,a,t}\zeta_{i,a,t} + \alpha_a \pi_{i,a,t}\varepsilon_{i,a,t} \tag{8}$$

where $c = \log C$ is the log of real consumption, α_a a weight that is an increasing function of age, $\Gamma_{b,t}$ a parameter that varies over time and by cohort (indexed by b), $\xi_{i,a,t}$ captures idiosyncratic shocks to tastes over the life cycle, and $\pi_{i,a,t}$ is the share of future labor income in the present value of lifetime wealth. The term $\Gamma_{b,t}$ is the slope of the consumption path for different year of birth cohorts.[3] In the empirical analysis we assume that α_a is a known constant rather than a parameter to estimate.

For individuals a long time from the end of their life with the value of current financial assets small relative to remaining future labor income, $\pi_{i,a,t} \simeq 1$, and permanent shocks pass through more or less completely into consumption whereas transitory shocks are (almost) completely insured against through saving. Precautionary saving can provide effective insurance against permanent shocks only if the stock of assets built up is large relative to future labor income, which is to say $\pi_{i,a,t}$ is appreciably smaller than unity, in which case there will be some smoothing of permanent shocks through self insurance. From here onwards we assume $\pi_{i,a,t} \cong \pi_{b,t}$, so that it is approximately constant within a cohort at any specific age; furthermore, y and c should be interpreted as the income and consumption components after removing demographic characteristics and aggregate effects. The terms $Z_{i,a,t}$ and $\Gamma_{b,t}$ will thus be omitted from now on. The remainder of this section considers the case $\pi_{b,t} \simeq 1$ in which no part of permanent shocks is insured through precautionary saving. We defer a discussion of the consequences of removing this assumption to Section 4.4.

We assume that ζ, v, and ξ are mutually uncorrelated processes. The only source of serial correlation, if present, arises from the transitory component $v_{i,a,t}$. Equations (3) and (8) can be used to derive the following covariance restrictions

$$\operatorname{cov}(y_{a,t}, y_{a+s,t+s}) = \begin{cases} \operatorname{var}(\zeta_{a,t}) + \operatorname{var}(\Delta v_{a,t}) & \text{for } s = 0 \\ \operatorname{cov}(\Delta v_{a,t}, \Delta v_{a+s,t+s}) & \text{for } s \neq 0 \end{cases} \tag{9}$$

where var (.) and cov (., .) denote cross-sectional variances and covariances, respectively (the index i is consequently omitted). These moments are computed with respect to individuals belonging to an

[3] Innovations to the conditional variance of consumption growth (precautionary savings) are captured by $\Gamma_{b,t}$.

homogenous group (i.e., individuals born in the same year, with the same level of schooling, etc.). The covariance term $\text{cov}(\Delta v_{a,t}, \Delta v_{a+s,t+s})$ depends on the serial correlation properties of v. If v is an $MA(q)$ serially correlated process, then $\text{cov}(\Delta v_{a,t}, \Delta v_{a+s,t+s})$ is zero whenever $|s| > q+1$. Note also that if v is serially uncorrelated ($v_{i,a,t} = \varepsilon_{i,a,t}$), then $\text{var}(\Delta v_{a,t}) = \text{var}(\varepsilon_{a,t}) + \text{var}(\varepsilon_{a-1,t-1})$.

The moment restriction for $q = 0$ in (9) can be recovered from repeated cross-section data as well. This observation underlies the analysis in Blundell and Preston (1998). In particular they show that

$$\begin{aligned} \text{var}(\Delta y_{a,t}) &= \Delta \text{var}(y_{a,t}) \\ &= \text{var}(\zeta_{a,t}) + \Delta \text{var}(\varepsilon_{a,t}) \end{aligned} \tag{10}$$

in which case the change in the growth of the variance of log income can be used to recover the variance of the permanent shock and the change in the variance of the transitory shock.

The restrictions on consumption growth from (8) are as follows:

$$\text{cov}(\Delta c_{a,t}, \Delta c_{a+s,t+s}) = \text{var}(\xi_{a,t}) + \text{var}(\zeta_{a,t}) + \alpha_a^2 \text{var}(\varepsilon_{a,t}) \tag{11}$$

for $s = 0$ and zero otherwise (due to the martingale assumption). The equivalent repeated cross-section moment used in Blundell and Preston is given by

$$\begin{aligned} \text{var}(\Delta c_{a,t}) &= \Delta \text{var}(c_{a,t}) \\ &= \text{var}(\zeta_{a,t}) \end{aligned} \tag{12}$$

for small α_a and with no permanent taste shocks to consumption. The simple difference between the growth in the variance of income and the growth in the variance of consumption then identifies the growth in the variance of transitory shocks to log income.

Finally, the covariance between income growth and consumption growth at various lags is:

$$\text{cov}(\Delta y_{a,t}, \Delta c_{a+s,t+s}) = \begin{cases} \text{var}(\zeta_{a,t}) + \alpha_a \text{cov}(\Delta v_{a,t}, v_{a,t}) \\ \alpha_{a+s} \text{cov}(\Delta v_{a,t}, v_{a+s,t+s}) \end{cases} \tag{13}$$

for $s = 0$, and $s \neq 0$ respectively. Blundell and Preston show that for small α_a

$$\begin{aligned} \text{cov}(\Delta y_{a,t}, \Delta c_{a,t}) &= \Delta \text{cov}(y_{a,t}, c_{a,t}) \\ &= \text{var}(\zeta_{a,t}) \end{aligned} \tag{14}$$

which allows identification of the variance of the permanent shock with one overidentifying restriction per period.

The availability of panel data has several advantages over a repeated cross-sections analysis. In the latter case identification requires assuming that consumption and income are cross-sectionally orthogonal to past shocks (see also Deaton and Paxson, 1994). This allows one to replace the unobservable $\text{var}(\Delta c_{a,t})$ with $\Delta \text{var}(c_{a,t})$. Moreover, even if this assumption holds true, the model is identified only under a set of restrictive assumptions, such as finite horizon, lack of serial correlation in transitory shocks, and absence of measurement error in consumption and income data. Our panel data approach can handle all these complications (see below). In general, panel data provide more overidentifying restrictions *vis-à-vis* repeated cross-section and thus can afford more flexibility.

To see the advantage of panel data, note for instance that identification of the variances of shocks to income requires only panel data on income, not consumption. In the simple case of serially uncorrelated transitory shock[4]:

$$\text{var}\left(\zeta_{a,t}\right) = \text{cov}\left(\Delta y_{a,t}, \Delta y_{a-1,t-1} + \Delta y_{a,t} + \Delta y_{a+1,t+1}\right) \quad (15)$$

$$\text{var}\left(\varepsilon_{a,t}\right) = -\text{cov}\left(\Delta y_{a,t}, \Delta y_{a+1,t+1}\right) \quad (16)$$

2.3 Partial insurance

We now consider the possibility of partial insurance and suppose there are mechanisms (that we do not model explicitly here but were discussed above) that allow insurance of a fraction $\left(1-\phi_{b,t}\right)$ and $\left(1-\psi_{b,t}\right)$ of permanent and transitory shocks, respectively. We might expect $\phi_{b,t}$ to be close to unity and $\psi_{b,t}$ close to zero. As noted above, precautionary saving might allow partial insurance of permanent shocks ($\phi_{b,t} < 1$) if assets were large enough relative to future labor income (i.e. $\pi_{b,t} < 1$), but interpersonal insurance mechanisms might also underlie this.[5] For simplicity of notation, we confine ourselves to the case where the transitory shock is serially uncorrelated and there are no taste shocks or idiosyncratic innovations to the variance of consumption growth ($\xi_{i,a,t} = 0$). These extensions are taken up in the empirical analysis.

In the partial insurance case residual income and consumption growth can be written, respec-

[4]See Meghir and Pistaferri (2002) for a generalization to serially correlated transitory shocks and measurement error in income.

[5]If there are no interpersonal mechanisms or transfers of any sort, then $\phi_{b,t} = \psi_{b,t} = \pi_{b,t}$.

tively, as:

$$\begin{aligned}\Delta y_{i,a,t} &= \zeta_{i,a,t} + \Delta\varepsilon_{i,a,t} && (17)\\ \Delta c_{i,a,t} &\cong \phi_{b,t}\zeta_{i,a,t} + \psi_{b,t}\alpha_a\varepsilon_{i,a,t} && (18)\end{aligned}$$

The economic interpretation of the partial insurance parameter is such that it nests the two polar cases of full insurance of permanent shocks ($\phi_{b,t} = \psi_{b,t} = 0$), as contemplated by the complete markets hypothesis, and no insurance ($\phi_{b,t} = \psi_{b,t} = 1$), as predicted by the PIH with just self-insurance through savings. A value $0 < \phi_{b,t} < 1$ ($0 < \psi_{b,t} < 1$) is consistent with partial insurance with respect to permanent (transitory) shocks. The lower the coefficient, the higher the degree of insurance.

The relevant panel data moments are:

$$\begin{aligned}\text{var}(\Delta y_{a,t}) &= \text{var}\left(\zeta_{a,t}\right) + \text{var}(\varepsilon_{a,t}) + \text{var}(\varepsilon_{a-1,t-1})\\ \text{cov}(\Delta y_{a,t}, \Delta y_{a-1,t-1}) &= -\text{var}(\varepsilon_{a-1,t-1})\\ \text{cov}(\Delta y_{a+1,t+1}, \Delta y_{a,t}) &= -\text{var}(\varepsilon_{a,t})\\ \text{var}(\Delta c_{a,t}) &= \phi_{b,t}^2\text{var}\left(\zeta_{a,t}\right) + \psi_{b,t}^2\alpha_a^2\text{var}(\varepsilon_{a,t})\\ \text{cov}(\Delta c_{a,t}, \Delta y_{a,t}) &= \phi_{b,t}\text{var}\left(\zeta_{a,t}\right) + \psi_{b,t}\alpha_a\text{var}(\varepsilon_{a,t})\\ \text{cov}(\Delta c_{a,t}, \Delta y_{a+1,t+1}) &= -\psi_{b,t}\alpha_a\text{var}(\varepsilon_{a,t})\end{aligned}$$

Since $\text{var}(\zeta)$ and $\text{var}(\varepsilon)$ can still be identified from panel data on income (the first three moments above), there are only two parameters left to identify: $\phi_{b,t}$ and $\psi_{b,t}$. Take first the simple case $L - a \to \infty$ and $r \to 0$ ($\alpha_a \to 0$). Then:

$$\phi_{b,t} = \frac{\text{var}(\Delta c_{a,t})}{\text{cov}(\Delta y_{a,t}, \Delta c_{a,t})} \tag{19}$$

identifies the extent of insurance against permanent shocks ($\psi_{b,t}$ is obviously not identified). The availability of panel data results in more efficient estimates because of the availability of overidentifying restrictions. For example:

$$\phi_{b,t} = \frac{\text{cov}(\Delta c_{a,t}, \Delta y_{a,t})}{\text{cov}(\Delta y_{a,t}, \Delta y_{a-1,t-1} + \Delta y_{a,t} + \Delta y_{a+1,t+1})}$$

Thus $\phi_{b,t}$ is generally overidentified. Overidentifying restrictions can be tested using standard methods.

As a matter of interpretation, note that the numerator of (19) captures the variance of shifts in consumption. In a model with no transitory shock effects on consumption, consumption growth volatility depends on the arrival of permanent shifts in income and the availability of insurance mechanisms above self-insurance. The denominator of (19) measures the association between consumption growth and income growth. In a model with no transitory shocks, consumption growth tracks income growth only through its long run component. In the absence of partial insurance mechanisms, the numerator and the denominator will be measuring exactly the same (permanent) variability in income. Recall that in the self-insurance, infinite-horizon case any permanent shift in the variance of the distribution of income is paralleled by an equivalent permanent shift in the variance of the distribution of consumption. With partial insurance, however, the latter is attenuated by the fact that permanent income shocks translate less than one-for-one in consumption; the amount of attenuation (given by the ratio in 19) is exactly measured by the parameter $\phi_{b,t}$.

In the more general case of finite $L-a$ and $r \neq 0$, more complicated expressions are available to identify the coefficients of interest. For instance,

$$\begin{aligned}
\psi_{b,t} &= \alpha_a^{-1} \frac{\text{cov}\left(\Delta c_{a,t}, \Delta y_{a+1,t+1}\right)}{\text{cov}\left(\Delta y_{a+1,t+1}, \Delta y_{a,t}\right)} \\
\phi_{b,t} &= \frac{\text{cov}\left(\Delta c_{a,t}, \Delta y_{a,t} + \Delta y_{a+1,t+1}\right)}{\text{cov}\left(\Delta y_{a,t}, \Delta y_{a-1,t-1} + \Delta y_{a,t} + \Delta y_{a+1,t+1}\right)}
\end{aligned}$$

and $\psi_{b,t}$ and $\phi_{b,t}$ are generally overidentified in this simple model.

Finally, it is very likely that *measurement error* will contaminate the observed income and consumption data. We assume that both consumption and income are measured with multiplicative (independent and quasi-classical) error,[6] e.g.,

$$y^*_{i,a,t} = y_{i,a,t} + u^y_{i,a,t} \tag{20}$$

and

$$c^*_{i,a,t} = c_{i,a,t} + u^c_{i,a,t} \tag{21}$$

where x^* denote a measured variable, x its true, unobservable value, and u the measurement error. In Appendix A.2 we show that the partial insurance parameter $\phi_{b,t}$ remains identified under measurement error.

[6] Quasi-classical in the sense that the variance of the measurement error is not (necessarily) constant over time.

2.4 Information

In the analysis presented so far we have assumed that in the innovation process for income (17) the random variables $\zeta_{i,a,t}$ and $\varepsilon_{i,a,t}$ represent the arrival of new information to the agent i of age a in period t. If part of this random term was known to the agent then the consumption model would argue that it should already be incorporated into consumption plans and would not directly effect consumption growth (18). Suppose a proportion κ_ζ of the permanent shock was know to the consumer. Then the consumption growth relationship (18) would become

$$\Delta c_{i,a,t} \cong \widetilde{\phi}_{b,t}\kappa_\zeta\zeta_{i,a,t} + \psi_{b,t}\alpha_a\varepsilon_{i,a,t}. \qquad (22)$$

In this case the estimated $\phi_{b,t}$ would overstate the extent of partial insurance by the information factor κ_ζ.

The econometrician will treat $\zeta_{i,a,t}$ as the permanent shock. Whereas the individual may have already adapted to this change. Consequently, although transmission of income inequality to consumption inequality is correctly identified, the estimated $\phi_{b,t}$ has to be interpreted as reflecting a combination of insurance and information. This is discussed further in section 4.4 where we interpret our empirical results.

3 The data

Our empirical analysis is conducted on two microeconomic data sources: the 1978-1992 PSID and the 1980-1998 CEX. We describe their main features and our sample selection procedures in turn.

3.1 The PSID

Since the PSID has been widely used for microeconometric research, we shall only sketch the description of its structure in this section.[7]

The PSID started in 1968 collecting information on a sample of roughly 5,000 households. Of these, about 3,000 were representative of the US population as a whole (the core sample), and about 2,000 were low-income families (the Census Bureau's SEO sample). Thereafter, both the original families and their split-offs (children of the original family forming a family of their own) have been followed.

[7] See Hill (1992) for more details about the PSID.

The PSID includes a variety of socio-economic characteristics of the household, including age, education, labor supply, and income of household members. Questions referring to income are retrospective; thus, those asked in 1993, say, refer to the 1992 calendar year. In contrast, many researchers have argued that the timing of the survey questions on food expenditure is much less clear (Hall and Mishkin, 1982; Altonji and Siow, 1987). Typically, the PSID asks how much is spent on food in an average week. Since interviews are usually conducted around March, it has been argued that people report their food expenditure for an average week around that period, rather than for the previous calendar year as is the case for family income. We assume that food expenditure reported in survey year t refers to the previous calendar year, but check the effect of alternative assumptions.

Households in the PSID report their taxable family income (which includes transfers and financial income). The measure of income used below excludes income from financial assets and deflates the corresponding value by the CPI.

Education level is computed using the PSID variable "grades of school finished". Individuals who changed their education level during the sample period are allocated to the highest grade achieved. We consider two education groups: with and without college education (corresponding to 13 grades or more and 12 grades or less, respectively).

Since CEX data are available only from 1980, we construct an unbalanced PSID panel using data from 1978 to 1992 (the first two years are retained for initial conditions purposes). Due to attrition, changes in family composition, and various other reasons, household heads in the 1978-1992 PSID may be present from a minimum of one year to a maximum of fifteen years. We thus create unbalanced panel data sets of various length. The longest panel includes individuals present from 1978 to 1992; the shortest, individuals present for two consecutive years only (1978-79, 1979-80, up to 1991-92).

The objective of our sample selection is to focus on a sample of continuously married couples headed by a male (with or without children). The step-by-step selection of our PSID sample is illustrated in Table 1. We eliminate households facing some dramatic family composition change over the sample period. In particular, we keep only those with no change, and those experiencing changes in members other than the head or the wife (children leaving parental home, say). We next eliminate households headed by a female. We also eliminate households with missing report on education and region,[8] and those with topcoded income. We keep continuously married couples and drop some income outliers.[9] We then drop those born before 1920 or after 1959.

As noted above, the initial 1967 PSID contains two groups of households. The first is representative of the US population (61 percent of the original sample); the second is a supplementary low income subsample (also known as SEO subsample, representing 39 percent of the original 1967 sample). To account for the changing demographic structure of the US population, starting in 1990 a representative national sample of 2,000 Latino households has been added to the PSID database. For the most part we exclude both Latino and SEO households and their splitoffs. However, we do consider the robustness of our results in the low income SEO subsample.

Finally, we drop those aged less than 30 or more than 65. This is to avoid problems related to changes in family composition and education, in the first case, and retirement, in the second. The final sample used in the minimum distance exercise below is composed of 17,788 observations and 1,788 households.

We use information on age and the survey year to allocate individuals in our sample to four cohorts defined on the basis of the year of birth of the household head: born in the 1920s, 1930s, 1940s, and 1950s. Years where cell size is less than 100 are discarded.[10]

3.2 The CEX

The Consumer Expenditure Survey provides a continuous and comprehensive flow of data on the buying habits of American consumers. The data are collected by the Bureau of Labor Statistics and used primarily to revising the CPI. Consumer units are defined as members of a household related by blood, marriage, adoption, or other legal arrangement, single person living alone or sharing a household with others, or two or more persons living together who are financially dependent. The definition of the head of the household in the CEX is the person or one of the persons who owns or rents the unit; this definition is slightly different from the one adopted in the

[8] When possible, we impute values for education and region of residence using adjacent records on these variables.

[9] An income outlier is defined as a household with an income growth above 500 percent, below −80 percent, or with a level of income below $100 a year or below the amount spent on food.

[10] Median (average) cell sizes are 249 (219), 245 (246), 413 (407), and 398 (363), respectively for those born in the 1920s, 1930s, 1940s, and 1950s.

PSID, where the head is always the husband in a couple. We make the two definitions compatible.

The CEX is based on two survey instruments, the Diary sample and the Interview sample. The Diary sample interviews households for two consecutive weeks, and it includes detailed expenditures for food, personal care, and household supplies. The Interview sample follows survey households for a maximum of 5 quarters, although only inventory and basic sample data are collected in the first quarter. The data base excludes expenditures for housekeeping supplies, personal care products, and non-prescription drugs. Our analysis below uses only the Interview sample.

The CEX collects information on a variety of socio-demographic variables, including characteristics of members, characteristics of housing unit, geographic information, inventory of household appliances, work experience and earnings of members, unearned income, taxes, and other receipts of consumer unit, credit balances, assets and liabilities, occupational expenses and cash contributions of consumer unit. Expenditure is reported in each quarter and refers to the previous quarter; income is reported in the second and fifth interview (with some exceptions), and refers to the previous twelve months. For consistency with the timing of consumption, fifth-quarter income data are used.

We select a CEX sample that can be made comparable, to the extent that this is possible, to the PSID sample. Our initial 1980-1998 CEX sample includes 1,249,329 monthly observations, corresponding to 141,289 households. We drop those with missing record on food and/or zero total nondurable expenditure, and those who completed less than 12 month interviews. This is to obtain a sample where a measure of annual consumption is available. A problem is that many households report their consumption for overlapping years, i.e. there are people interviewed partly in year t and partly in year $t+1$. Pragmatically, we assume that if the household is interviewed for at least 6 months at $t+1$, then the reference year is $t+1$, and it is t otherwise. Prices are adjusted accordingly. We then sum food at home, food away from home and nondurable expenditure over the 12 interview months. This gives annual expenditures. We also drop those with zero before-tax income, those with missing region or education records, single households and those with changes in family composition. Finally, we eliminate households where the head is born before 1920 or after 1959, those aged less than 30 or more than 65, and those with outlying income (defined as a level of income below the amount spent on food). Our final sample contains 20,974 households. Table 2 details the sample selection process in the CEX.

The definition of total non durable consumption is similar to Attanasio and Weber (1995). It includes food (at home and away from home), alcoholic beverages and tobacco, services, heating fuel, transports (including gasoline), personal care, clothing and footwear, and rents. It excludes expenditure on various durables, housing (furniture, appliances, etc.), health, and education.

3.3 Comparing the two data sets

How similar are the two data sets in terms of average demographic and socio-economic characteristics? Mean comparisons are reported in Table 3 for selected years: 1980, 1983, 1986, 1989, and 1992.

PSID respondents are slightly younger than their CEX counterparts; there is, however, little difference in terms of family size and composition. The percentage of white is slightly higher in the PSID. The distribution of the sample by schooling levels is quite similar, while the PSID tends to under-representing the proportion of people living in the West. Due to slight differences in the definition of family income, PSID figures are higher than those in the CEX. It is possible that the definition of family income in the PSID is more comprehensive than that in the CEX, so resulting in the underestimation of income in the CEX that appears in the Table.

Trends in food expenditure are initially quite similar, but tend to diverge afterwards. One explanation for this is that the wording of the food expenditure question in the CEX changed several times over this period, resulting in PSID figures being higher than the corresponding CEX figures. In particular, the CEX survey question asks about average monthly expenditure over the last quarter in 1980-81, expenditure in an average week of the last quarter in 1982-87, and reverts to the monthly expenditure question starting in 1988. Some researchers (Garner *et al.*, 1998) have noted that the change in the survey question induces a dramatic underestimation of food expenditure in the CEX in the 1982-87 period.

Food away from home is, in contrast, under-reported in the PSID *vis-á-vis* the CEX. Total food expenditure (the sum of food at home and food away from home, the one usually adopted by researchers) is very similar on average in the two surveys (with a difference that never exceeds about $300), but it has the disadvantage of mixing necessity (food at home) and luxury (food away) consumption.

The last two rows of Table 3 compare the labor market activity of the household head and of the spouse. Both male and female participation rates are slightly higher in the PSID than in the CEX.

3.4 The imputation procedure

In deriving the theoretical restrictions above, we have assumed that a researcher has access to panel data on household income and total non-durable consumption. However, this is a very strong data requirement. In the US, panel data typically lack household data on total non-durable consumption; and those surveys, as the CEX, that contains good quality data on consumption, lack a panel feature. We may however combine the two data sets to impute non durable consumption to PSID households. This of course requires making some assumptions detailed below.

The PSID collects data on few consumption items, mainly food at home and food away from home. Moreover, food data are not available in 1987 and 1988. Our strategy is to write a demand equation for food as a function of prices, demographics, labor supply variables, food away from home and total non-durable expenditure. Within each cohort, variability of food consumption is then explained by variability in those components plus unobserved heterogeneity, measurement error, etc. We can invert this relationship to obtain a measure of the variability in total non-durable consumption, one of the main objects of interest from the previous section. This inversion operation requires consistent estimation of the parameters of the demand function for food and monotonicity of the underlying demand function.

Our paper is not the first to combine CEX data with PSID data to impute a measure of non durable consumption in the PSID (examples include Skinner, 1987; Bernheim *et al.*, 2001; Dynan, 2000). However, we are the first to depart from the "Skinner" methodology by using economic theory rather than a statistical procedure,[11] and also the first to analyze the econometric conditions that define a successful imputation procedure. These are detailed in Appendix A.3.

To make matching of the two data sets feasible, the demand function for food must be invertible with respect to total expenditure. This requires the demand function to be monotonic in total

[11] Skinner (1987) regresses non durable consumption on all the consumption items available in both surveys (food at home, food away from home, utilities, rents, etc.).

expenditure.[12] After some experimentation, we selected a loglinear functional form. The main advantage of the loglinear demand function is that it provides "ready-to-use" predictions for total nondurable expenditure, avoiding, for instance, the problem of negative predicted values faced when using the linear expenditure demand function. The loglinear demand function has also a series of shortcomings, however. In particular, it cannot capture zero expenditures, it does not satisfy adding up if applied to all goods in a demand system, and it does not capture apparent non-linearities in Engel curve relationships. Nevertheless, these shortcomings do not appear particularly relevant here. There are no zeros in food spending, the specification below is applied to just one good, and the Engel curve for food is not far from being log linear.

Formally, we write the following demand equation for food at home in the CEX:

$$f_{i,a,t} = M'_{i,a,t}\mu + \beta c_{i,a,t} + e_{i,a,t} \tag{23}$$

where f is the log of food expenditure (which is available in both surveys), M contains prices, food away from home and a set of demographics and labor supply variables (also available in both data sets), c is the log of total non-durable expenditure (available only in the CEX), and e captures unobserved heterogeneity in the demand for food and measurement error in food expenditure.

We pool all the CEX data from 1980 to 1998. Our specification includes the log of the price of food at home,[13] the interaction of this with region of residence, the log of total nondurable expenditure and its interaction with education dummies and indicators for number of children (no children, one child, two or three children, four children or more), indicators for male and female labor market participation and their interactions with the number of children, food away from home,[14] and a vector of demographics (an age spline, dummies for education and region of residence, year of birth dummies, indicators for number of children as above, family size and its interaction with region dummies, and a dummy for whites). We use national prices rather than time dummies for prediction purposes. Measurement error in nondurable expenditure biases the expenditure elasticity towards zero; we thus instrument this variable with the log of before-tax

[12] While theoretically more appealing, flexible functional forms, such as variants of the AIDS model of Deaton and Muellbauer (1980), or demand functions that are non-linear in total nondurable expenditure or contain interactions (Banks, Blundell, and Lewbel, 1999), may violate this requirement.

[13] We omit prices of other commodities due to multicollinearity problems.

[14] The inclusion of labor market participation variables and food away from home is justified by a conditional demand approach.

income (and interactions with demographics).[15] Standard errors are corrected for time clustering. The estimation results are reported in Table 4. We test the hypotheses that the expenditure elasticity does not vary with time or cohort and fail to reject the null (p-values above 10 percent in both cases, see bottom of Table 4).

We estimate an expenditure elasticity of 0.66; this declines with education and increases with the number of children. The main effect is tightly estimated, and so are most of the interactions.[16] The estimate of the price elasticity is -0.46, and is precisely measured. Interaction of the price variable with region dummies are insignificant. Other demographics have the expected sign. Labor market participation reduces expenditure on food at home (more strongly so for females); the effect of male participation is insignificant but becomes stronger in the presence of more children; food at home and food away from home are substitutes.[17]

Armed with the estimated demand parameters, we invert the demand equation for food and obtain a measure of total nondurable expenditure in the PSID matching on observable characteristics that are common to the two data sets. As explained in Appendix A.3, a good inversion procedure should produce a variance of (imputed) consumption in the PSID that is higher than the variance of consumption in the CEX by an additive factor (the variance of the error term of the demand equation scaled by the squared expenditure elasticity). If this factor is constant over time the *trends* in the two variances should be identical.

Trends in the variance of consumption are indeed remarkably similar in the two data sets, as Figure 1 shows (variances are smoothed *via* a rolling third-order moving average). Between 1980 and 1986 the variance of PSID imputed consumption and the variance of CEX row consumption are growing at a similar rate. Afterwards, they are flat. The levels differ by a common factor, see Appendix A.3. This evidence provides confidence in our use of imputed data to estimate the parameters of interest discussed in Section 2.

[15]This is important as far as replicating trends in consumption variance is concerned (see Appendix A.3).

[16]The expenditure elasticity is lower in the OLS case.

[17]We could not find powerful and sensible exclusion restrictions to instrument labor market participation variables and food away from home.

4 The results

We organize the empirical analysis in three parts: repeated cross-sections evidence (section 4.1), unrestricted consumption-income autocovariance estimation from the PSID (section 4.2), and minimum distance estimation using longitudinal data on household income and predicted consumption (section 4.3). We then discuss our findings and a variety of experiments (Section 4.4).

4.1 Consumption Inequality and Income Uncertainty - Repeated Cross-Section Evidence from the CEX

Before presenting estimates of the consumption model based on longitudinal PSID data on income and imputed consumption, it is worth discussing the results of a straightforward replication of the strategy used in Blundell and Preston (1998). To this purpose, we use (10), (12), and (14) to estimate the variance of the permanent shock and the change in the variance of the transitory shocks from repeated CEX cross-sections. We use data from 1980 to 1992.

Table 5 reports simple estimates of the variance of log consumption, the variance of log income, and their covariance for all years and for four year of birth cohorts (born in the 1920s, 1930s, 1940s and 1950s).[18] Figure 2 graphs income and consumption variances and their covariance over the life cycle (we smooth trends using a rolling MA(3)). For the two middle cohorts the variance of consumption increases throughout the sample period (both variance grow very moderately in the second half of the 1980s). For the youngest cohort the variance of income is flat while the variance of consumption actually declines. Finally, for the oldest cohort both variances increase in the early 1980s and decline afterward. Trends in covariances resemble those for the consumption variance (the level is higher).

Table 6 reports optimal minimum distance estimates of $\Delta var\,(v)$ and $var\,(\zeta)$ for three different models: a fully stationary model in which these variances are restricted to being identical across the whole data period, a non-stationary model where the variances shift between 1986 and 1987, and a non-stationary model where the variances shift between 1984 and 1985 and between 1988 and 1989.

We first comment on the results obtained in the whole sample, without distinguishing by year

[18] These are the variances of deviations of consumption and income per household member from the cohort-specific cross-sectional means. The covariance is the covariance of such residuals.

of birth. The first and most restrictive model shows an increase in the variance of transitory shocks to log income (income instability), associated with a small variance of the permanent shock. The results for the second model in which there is one jump in parameters between 1986 and 1987, show that the variance of the permanent shock is high in the first half of the sample period and statistically insignificant around zero in the second. The final and least restrictive specification confirms this pattern, but also shows that transitory uncertainty accelerates in 1981-84 and 1989-92, while it remains flat in 1985-88.

The evidence by cohort is somewhat similar. For all cohorts but the oldest transitory income uncertainty increases throughout the 1980s. The variance of the permanent shock is generally higher in the early 1980s then in the late 1980s or early 1990s. For the individuals born in the 1920s the shifts in transitory uncertainty appear to be a cyclical phenomenon.

This evidence squares quite well with the figures presented above. However, there is an inherent bias in repeated cross-section analyses that neglect the possibility of insurance over and above savings. Suppose α_a is small, $q = 0$, and that there is partial insurance with respect to permanent shocks as in Section 2.3. Then the difference in difference strategy used in Blundell and Preston (1998):

$$\Delta\text{var}\left(y_{a,t}\right) - \Delta\text{var}\left(c_{a,t}\right) = \left(1 - \phi_{b,t}^2\right)\text{var}\left(\zeta_{a,t}\right) + \Delta\text{var}\left(\varepsilon_{a,t}\right)$$

fails to identify shifts in transitory uncertainty unless $\phi_{b,t} = 1$ and there is no insurance of permanent shocks. In general, it provides an upward biased estimate. By the same token, with partial insurance $\Delta\text{var}\left(c_{a,t}\right) = \phi_{b,t}^2\text{var}\left(\zeta_{a,t}\right)$ and $\Delta\text{cov}\left(c_{a,t}, y_{a,t}\right) = \phi_{b,t}\text{var}\left(\zeta_{a,t}\right)$ are downward biased estimates of the variance of permanent shocks (a possible explanation for why those variances are quite small throughout Table 6).[19] The model we estimate below uses panel data and allows for partial insurance as well as other generalizations, such as measurement error.

4.2 Autocovariance Estimates of Consumption and Income: Longitudinal Evidence from the Matched PSID

The PSID data set contains longitudinal records on income and imputed consumption. We remove the effect of deterministic effects on log (imputed) consumption and income by separate regressions

[19] The bias when using $\Delta\text{cov}\left(c_{a,t}, y_{a,t}\right)$ is generally lower than $\Delta\text{var}\left(c_{a,t}, y_{a,t}\right)$ as long as $\phi_{b,t} < 1$. In fact, in most cases $\text{cov}\left(c_{a,t}, y_{a,t}\right)$ grows more rapidly than $\text{var}\left(c_{a,t}, y_{a,t}\right)$.

of these variables on a set of observable family characteristics (a quartic in age, education dummies, year dummies, race dummies, family size, number of children, dummies for self-employment and employment status, and region dummies). These variables reflect deterministic growth in consumption and income (information). We then work with the residuals of these regressions (we run different regressions for different cohorts/education groups), $c_{i,a,t}$ and $y_{i,a,t}$.

To pave the way to the formal analysis of Section 4.3, Table 7 reports unrestricted minimum distance estimates of several moments of interest for the whole sample: the variance of unexplained income growth, $\text{var}(\Delta y_{a,t})$, the first-order autocovariances ($\text{cov}(\Delta y_{a+1,t+1}, \Delta y_{a,t})$), and the second-order autocovariances ($\text{cov}(\Delta y_{a+2,t+2}, \Delta y_{a,t})$). Estimates are reported for each year. Table 8 repeats the exercise for our measure of consumption. Finally, Table 9 reports minimum distance estimates of contemporaneous and lagged consumption-income covariances.

Looking through Table 7, one can notice the strong increase in the variance of income growth, especially in the early 1980s. Also notice the strong blip in final year (in 1992 the PSID converted the questionnaire to electronic form and imputations of income done by machine). The absolute value of the first-order autocovariance also exhibits an inverted ∪-shape. Second- and higher order autocovariances are small and only in few cases statistically insignificant. At least at face value, this evidence seems to tally quite well with a canonical MA(1) process, as implied by a traditional income process given by the sum of a martingale permanent component and a serially uncorrelated transitory component.[20]

Table 8 shows that the variance of imputed consumption growth increases quite strongly in the early 1980s, peaks in 1984 and then it is essentially flat afterwards. Note the high value of the variance which is clearly the result of our imputation procedure. The variance of consumption growth captures in fact the genuine association with shocks to income, but also the contribution of taste shocks and measurement error. The absolute value of the first-order autocovariance of consumption growth should be a good estimate of the variance of the imputation error. This is in fact quite high and approximately stable over time. Second-order consumption growth autocovariances are mostly statistically insignificant and economically small.

Table 9 looks at the association, at various lags, of unexplained income and consumption growth.

[20]Since evidence on second-order autocovariances is mixed, in estimation we allow for MA(1) serial correlation in the transitory component.

The contemporaneous covariance should be informative about the effect of income shocks on consumption growth if measurement error in consumption are orthogonal to measurement error in income. This covariance increases in the early 1980s and then bounces around afterwards.

The covariance between current consumption growth and future income growth $\mathrm{cov}(\Delta c_{a,t}, \Delta y_{a+1,,t+1})$ should reflect the extent of insurance with respect to transitory shocks. Note that in the pure self-insurance case and with infinite horizon, the impact of transitory shocks on consumption growth is the annuity value $\frac{r}{1+r}$. With a small interest rate, this will be indistinguishable from zero, at least statistically. The addition of partial insurance $\psi_{b,t} < 1$ makes this even more likely. In fact, this covariance is hardly statistically significant and economically close to zero. The formal analysis below confirms this.

The covariance between current consumption growth and past income growth $\mathrm{cov}(\Delta c_{a,t}, \Delta y_{a-1,,t-1})$ plays no role in the PIH model with perfect capital markets, but may be important in alternative models where liquidity constraints are present. Also in this case, however, estimates are close to zero at least for this sample.

To sum up, the evidence presented in this section suggests that the income process

$$\Delta y^*_{i,a,t} = \zeta_{i,a,t} + \Delta v_{i,a,t} + \Delta u^y_{i,a,t}$$

(with the permanent shock ζ and measurement error u^y being mutually and serially uncorrelated and the transitory shock v possibly MA(1)) fits the data sufficiently well. Additionally, there is weak evidence that transitory shocks impact consumption growth or that liquidity constraints are empirically important. We now turn to formal minimum distance estimation of the insurance and variance parameters.

4.3 Partial Insurance

We estimate the parameters that characterize the income and consumption process by optimal minimum distance. Technical details are in Appendix A.4.

We report the results of a simple non-stationary model where the parameters vary across cohorts or education groups (depending on the specification adopted) and time: in particular, we assume that they shift at some point over the 1980s (consistent with most of the Figures discussed above).

There are several parameters to estimate: the variances of the permanent and transitory income shocks (σ_{ζ}^2 and σ_{ε}^2, respectively), the MA coefficient θ of the transitory shock, the variance of taste shocks (σ_{ξ}^2) and imputation error (σ_u^2), the partial insurance coefficient for the permanent shock (ϕ) and for the transitory shock (ψ). We assume $L - a \to \infty$ and thus the annuitization factor $\alpha_a = \frac{r(1+r-\theta)}{(1+r)^2}$, where θ is the MA(1) parameter of the transitory income component. We set $r = 0.05$.

Table 10 reports the results of the model for the whole sample, four year of birth cohorts (born in the 1950s, 1940s, 1930s, and 1920s), and two education groups (with and without college education).

Starting with income growth parameters, note that the variance of the permanent shocks generally declines after 1985 (with the single exception of those with college education), while the variance of transitory shocks generally increases (with the single exception of those born in the 1940s). Transitory shocks also become more persistent. Some of the shifts are quite dramatic: for instance the variance of permanent shocks halves for the oldest cohort and the variance of the transitory shock doubles for the cohort born in the 1930s. Note finally that the variance of permanent shocks declines (and the variance of transitory shocks increases) with the year of entry in the labor market and with education.

Turning to consumption parameters, note that the imputation error absorbs a large amount of the cross-sectional variability in consumption in the PSID, anything between 0.08 and 0.12. The variance of the imputation error σ_u^2 is always precisely measured. The variance of taste shocks is also sizable and generally well measured.

In the whole sample the estimate of ϕ, the partial insurance coefficient for the permanent shock, provides evidence in favor of partial insurance and rejects both the complete markets assumption ($\phi = 0$) and the traditional self-insurance hypothesis (where $\phi = 1$). In contrast, the evidence on ψ accords with a simple PIH model with infinite horizon. In no case do we reject the null that there is full smoothing with respect to transitory shocks ($\psi = 0$). Finally note that the insurance coefficient ϕ almost doubles between the early 1980s and the late 1980s-early 1990s, suggesting that the degree of insurance has declined over this period. This may also reflect the nature of the permanent shocks that occurred over this period rather than a change in the insurance mechanisms themselves.

When the sample is stratified by year of birth or education, we find qualitatively similar results: there is evidence for partial insurance with respect to the permanent shocks, full insurance with respect to transitory shocks, and a decline in the insurance opportunities of permanent income shocks that occurred after 1984. The evidence across cohorts does not reveal any economically interesting heterogeneity in the degree of insurance available to consumers, perhaps because of small cell sizes that inflate standard errors; those with college education appear to be more able to smooth consumption in the face of permanent shocks to income. For individuals without college education there is no evidence for insurance against permanent income shocks in the second half of the sample period.

Finally, the χ^2 goodness of fit statistics reveal some support for our model specification despite its simplicity for certain of the periods and household types.

4.4 Discussion: Information, Insurance and Measurement

In this section we provide further interpretation of our results and discuss potential sources of bias in our estimates. For simplicity, we focus on the case of $\phi_{b,t}$, the partial insurance coefficient with respect to the permanent shocks, and on the results for the 1985-92 period. Those for 1979-84 are qualitatively identical and hence omitted. Table 11 reports the results of various sensitivity checks on our assumptions concerning information and the origin of insurance. Table 12 reports additional sensitivity analysis results on measurement issues: our imputation procedure, sample selection, and estimation methods used.

4.4.1 Information

As discussed in section 2.4, it is conceivable that what appears to the researcher as an unpredictable innovation is in fact known to the individual who may have advance notice of events such as promotions, layoffs, absences from work, etc. Although we still correctly measure the degree by which income inequality is transmitted into consumption inequality, in the absence of extra information we cannot distinguish between genuine uninsured uncertainty and income variability known to the individual. The main consequence of acknowledging the discrepancy of information that exists between the consumer and the econometrician is that $\phi_{b,t}$ can be biased downward to reflect superior information of households, rather than insurance.

While we cannot test for superior information directly, we can provide some suggestive evidence by restricting the set of predictors ΔZ_{it} of income growth in (3). In column (2) of Table 11 we predict income growth using just time dummies, education dummies and an age polynomial, and obtain an estimate of ϕ of 0.31. The full set of predictors in the basic specification gives an estimate of 0.52 (see "Baseline" column). Thus enriching the information set available to consumers produces larger estimates of ϕ as predicted by the information story. This exercise relies on arbitrary assumptions about the information used by consumers and must be taken with caution.

Along similar lines, it can be argued that the timing of the PSID survey question on food is generating a downward biased estimate of $\phi_{b,t}$. This is the case if food reported in survey year t refers to the current year rather than $t-1$ and thus include advance information on income innovations (to which PIH consumers do not respond). Since food is typically asked in the first quarter of year t, a possible correction is to assume that households have some advance information about income innovations at time t when they decide their consumption at $t-1$, as in Hall and Mishkin (1982). Alternatively, one can make the assumption that the PSID food expenditure data reported at t refers to a typical week of that year. We re-estimate our model changing the timing of the food question. The results (see column 3, Table 11) show that this adjustment produces some effects (less evidence for insurance), but does not change the whole picture dramatically. We still reject the PIH and complete insurance and we still find evidence for full insurance of transitory shocks and (albeit more limited) partial insurance of permanent shocks.

4.4.2 Distinguishing Permanent and Transitory Shocks in Income

Suppose that individual are not able to distinguish between transitory and permanent income shocks, i.e., instead of (3) they observe:

$$\Delta y_{i,a,t} = \Delta Z_{it}'\varphi + \varsigma_{i,a,t} - \rho_1 \varsigma_{i,a-1,t-1} - \rho_2 \varsigma_{i,a-2,t-2}$$

and the Euler equation in the infinite horizon case is:

$$\Delta c_{i,a,t} \cong \Gamma_{b,t} + \Delta Z_{it}'\vartheta + \xi_{i,a,t} + \phi_{b,t}\Theta\left(r, \rho_1, \rho_2\right) \varsigma_{i,a,t}$$

where $\Theta(r, \rho_1, \rho_2) = 1 - \frac{\rho_1}{1+r} - \frac{\rho_2}{(1+r)^2}$. Column (4) of Table 11 reports the results of this specification. The partial insurance coefficient estimate is smaller than in the baseline case (0.33 vs. 0.52), implying that agents' inability to distinguish short-run from long-run shocks in income cannot explain the downward bias (if any) in the estimate of $\phi_{b,t}$ in the general model.

4.4.3 Insuring Income Shocks through Durables, Housing and Education

Consider that the PIH could hold with respect to total consumption rather than non-durable consumption, the measure we use. The main consequence of this is that the Euler equation contains an omitted variable, the growth in the fraction of total consumption that is devoted to non-durable expenditure. If general $\phi_{b,t}$ will reflect, at least in part, the sensitivity of durable expenditure to income shocks. It is possible to correct for this by extending our analysis to a measure of consumption that includes durable expenditure. This is available in the CEX and our imputation procedure can easily handle such extension. In column (5) of Table 11 we add expenditure on health and education to our measure of consumption. The results are essentially the same as in the baseline specification. In column (6) we use a comprehensive measure of consumption that includes durables and nondurables; this has a rather dramatic effect on our results, we now find no evidence for partial insurance with respect to permanent shocks and again evidence for full insurance as far as transitory shocks are concerned.[21]

These results suggest that most of the insurance we estimate in the baseline model arises from optimal durable choice and timing, as argued, among others by Browning and Crossley (2001a).[22] It also appears to dismiss the relevance of the information story discussed above.

4.4.4 The Insurance Value of Taxes and Transfers

To see the impact of public insurance, suppose we exclude transfers (of any kind) from our measure of income. If taxes and transfers provide insurance for permanent income shocks, the insurance parameter in this specification should fall by an amount that reflects the degree of insurance. This

[21] Total consumption includes food (at home and away from home), alcoholic beverages, tobacco, housing (utilities, fuels and public services, mortgage interests, property tax, maintenance and repairs, rents, other lodging, domestic services, textiles, furniture, floor coverings, appliances), clothing and footwear, transports (new and used cars, other vehicles, gasoline, vehicle finance charges and insurance, maintenance and repairs, rentals and leases, public transports), personal care, entertainment, health (insurance, prescription drugs, medical services), reading and education, cash contributions, and personal insurance (life insurance and retirement).

[22] In column (7) this story is confirmed for the sample that includes low income households.

happens because still consumption incorporates any insurance value of taxes and transfers but the new measure of income no longer does. The results of this experiment are reported in the last column of Table 11. A comparison of column (1) and column (8) shows that the estimated insurance parameter declines from 0.52 to 0.30. That is by excluding transfers the partial insurance coefficient drops by 40%, an estimate of the insurance provided by private and public transfers. This insurance can also be seen through the change in the estimated variance of permanent shocks. With taxes and transfers excluded, the variance of permanent shocks is indeed much higher.

4.4.5 Precautionary Asset Accumulation

The assumption $\pi_{i,a,t} \simeq 1$ made in Section 2.2 could be violated in the presence of precautionary asset accumulation. This could be particularly relevant for cohorts close to retirement, and it would signal partial insurance even when this is absent. However, focusing on young cohorts allows us to address this point directly, because young individuals a long time from retirement have very little precautionary assets to rely on. Nevertheless, one can notice that for the oldest cohort (where the bias should be more severe) we find a very high partial insurance coefficient (see Table 10), while for young cohorts the insurance coefficient is similar to that estimated for the whole sample. Finally, while we cannot separately identify precautionary saving effects (π) from insurance effects (ϕ), we still pin down the degree of transmission of income shocks into consumption.

4.4.6 The Specification of Imputation Error

Our imputation procedure requires that the variance of predicted consumption differ from the variance of true consumption only by an additive term (which is estimated, see σ_u^2 in Table 10). But if in addition to this there is a scaling factor, the latter is generally not separately identifiable from the partial insurance parameter $\phi_{b,t}$. Thus the estimate of $\phi_{b,t}$ will be biased (upward, if the problem resembles that discussed in Appendix A.3). However, we have checked that this is not the case (see the discussion in the Appendix). As a further check, in column (2) of Table 12, we use PSID food data directly without imputing; the estimate of the partial insurance coefficient in this column (0.33) should be scaled by the food expenditure income elasticity (0.66, from Table 4) giving, e.g., $\frac{0.33}{0.66} = 0.5$, which isn't far from the coefficient estimated with imputed data in the "Baseline" column. This is evidence that our imputation procedure is not responsible for the results.

4.4.7 Low Incomes and Young Households

In column (3) of Table 12 we include families from the poverty subsample of the PSID. Two results are worth mentioning: the estimate of ϕ is slightly higher reflecting less insurance opportunities in this sample, and we now reject full insurance with respect to transitory shocks (an estimate of ψ of 0.13, similar to the 0.2 benchmark found by other researchers, Hall and Mishkin, 1982). In fact, in this subsample alone there is not much evidence for insurance altogether. In column (4) we focus on this subsample and find that we cannot reject the null that $\phi = 1$, while still finding evidence of less than full insurance with respect to the transitory shock.

In column (5) we include those aged 20-29, and find results that are similar to the baseline scenario.

In column (6) we use the sum of food at home and the monetary value of food stamps as our measure of consumption; the coefficient on the permanent shock is lower than in column (2), suggesting that food stamps provide insurance, but the difference is unlikely to be statistically significant. However, when we add the low income subsample (see column 7) the coefficient is much lower and suggests an important insurance role for food stamps. These issues are explored more in depth in Blundell and Pistaferri (2002). Overall, the results suggest that transfer programs appear partially successful in providing insurance only for marginal populations (low income groups) and/or marginal components of household consumption (food). This should not be seen as diminutive of the role and value of transfer programs, because helping low income households to afford an adequate consumption of food, health and shelter is precisely the objective of these programs.

4.4.8 Estimation Methods

As said above, the parameters of all our models are estimated by OMD. In general, the choice is between a non-linear least squares procedure (equally weighted minimum distance, or EWMD) and a non-linear generalized least squares procedure (optimal minimum distance, or OMD). Altonji and Segal (1996) show that EWMD dominates OMD even for moderately large sample sizes. We find no dramatic differences between OMD and EWMD, however (see the last column of Table 12). There is a small downward bias in the variance of the permanent income shock but the estimate of the insurance coefficient is similar to that reported in the baseline specification, and so is the evidence for full insurance of transitory shocks.

5 Conclusions

The extensive research on the dynamics of income inequality in recent years has not been paralleled by comparable research on consumption inequality. The existing research has either reached contrasting conclusions (some papers find an increase in consumption inequality, while others find little or no change),[23] or made little attempt to interpret the empirical findings using traditional consumption theory.[24]

This paper used individual panel data on consumption and income to evaluate the degree of consumption insurance with respect to income shocks. Our framework allowed for self-insurance, in which consumers smooth idiosyncratic shocks through saving. It also considered the complete markets assumption in which all idiosyncratic shocks are insured. These two models sit amidst a wide range of missing insurance opportunities. We were able to assess the degree of insurance over and above self-insurance through savings. We did this by contrasting shifts in the cross-sectional distribution of income growth with shifts in the cross-sectional distribution of consumption growth, and analyzing the way these two measures of household welfare correlate over time. Our identification strategy was applied to a semi-structural model of consumption behavior. A major innovation of our study was to combine panel data on income from the PSID with consumption data from repeated CEX cross-sections in a structural way, i.e. using conventional demand analysis rather than reduced form imputation procedures. We also allowed for heterogeneity in a very general way.

Our results show a strong growth in both permanent and transitory income shocks in the US during the early 1980s. The variance of permanent shocks levels off thereafter. We find strong

[23] Thus Cutler and Katz (1992) find evidence that consumption inequality increases in parallel with income inequality, while Slesnick (1994) shows that consumption inequality has historically fallen and raised only slightly in recent years.

[24] Thus Dynarski and Gruber (1997) regress consumption growth on income growth (instrumented to avoid the downward bias due to measurement error), and interpret the coefficient on income growth as measuring the extent of insurance against income shocks (i.e., as the discrepancy between income and consumption inequality). While their analysis is valuable, the interpretation of their estimates outside a structural consumption model is problematic. The modern theory of consumption makes a sharp distinction between the effect of anticipated and unanticipated income growth (and between transitory and permanent income growth), which is absent in their analysis.

evidence against full insurance for permanent income shocks but not for transitory income shocks. Interestingly, this latter result needs adapting for the low income subsample where transitory shocks seem less insurable. Further there is evidence of partial insurance of permanent income shocks; the results point to much of this partial insurance occurring through the adjustment of durable expenditures. We also find differences in the degree of insurance over time, although we are unable to distinguish changing insurance opportunities from changing nature of shocks. Finally we show that taxes and transfers provide an important insurance mechanism for permanent income shocks.

Our results have implications for both macroeconomics and labor economics. The macroeconomic literature has long been concerned with explaining why modern economies depart from the complete markets benchmark. Recent work has examined the role of asymmetric information, moral hazard, heterogeneity, etc., and asked whether the complete markets model can be amended to include some form of imperfect insurance. This issue has not been subject to a systematic empirical investigation. Insofar as lack of smoothing opportunities implies a greater vulnerability to income shocks, our research can be relevant to issues of the incidence and permanence of poverty studied in the labor economics literature. Studying how well families smooth income shocks, how this changes over time in response to changes in the economic environment confronted, and how different household types differ in their smoothing opportunities, is an important complement to understanding the effect of redistributive policies and anti-poverty strategies.

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Table 1
Sample selection in the PSID

	# dropped	# remain
Initial sample (1968-1992)	145,940	145,940
Interviewed prior to 1978	52,408	93,532
Change in family composition	18,570	74,962
Female head	23,779	51,183
Missing values and topcoding	308	50,875
Change in marital status	5,882	44,993
Income outliers	2,407	42,586
Born before 1920 or after 1959	8,510	34,076
Poverty subsample	12,600	21,476
Aged less than 30 or more than 65	3,674	17,778

Table 2
Sample selection in the CEX

	# dropped	# remain
Initial sample	141,289	141,289
Missing expenditure data	1,351	139,938
Present for less than 12 months	76,773	63,165
Zero before-tax income	2,131	61,034
Missing region or education	5,084	55,986
Marital status	24,025	31,960
Born before 1920 or after 1959	7,071	24,889
Aged less than 30 or more than 65	2,968	21,921
Income outliers	947	20,974

Table 3
Comparison of means, PSID and CEX

	1980		1983		1986		1989		1992	
	PSID	CEX	PSID	CEX	PSID	CEX	PSID	CEX	PSID	CEX
Age	42.96	43.71	43.36	45.01	43.83	46.03	43.97	45.26	45.91	47.01
Family size	3.61	3.95	3.52	3.74	3.48	3.64	3.44	3.61	3.42	3.55
# of children	1.32	1.47	1.25	1.26	1.21	1.19	1.19	1.17	1.14	1.15
White	0.91	0.89	0.92	0.88	0.92	0.88	0.93	0.89	0.93	0.88
HS dropout	0.21	0.20	0.18	0.19	0.16	0.18	0.14	0.14	0.13	0.15
HS graduate	0.30	0.32	0.31	0.33	0.32	0.30	0.32	0.31	0.31	0.30
College dropout	0.49	0.48	0.51	0.48	0.53	0.52	0.54	0.56	0.56	0.55
Northeast	0.21	0.20	0.21	0.25	0.22	0.21	0.22	0.23	0.22	0.23
Midwest	0.33	0.28	0.31	0.26	0.30	0.27	0.30	0.28	0.30	0.29
South	0.31	0.29	0.31	0.28	0.30	0.27	0.31	0.27	0.30	0.26
West	0.15	0.24	0.17	0.21	0.18	0.25	0.18	0.23	0.18	0.22
Family income	32,759	29,078	37,907	35,587	45,035	43,473	52,919	50,690	61,911	55,956
Food at home	3,683	3,501	3,905	3,305	4,176	3,501	4,557	4,266	5,098	4,565
Food away	759	1,165	936	1,334	1,118	1,695	1,281	1,881	1,507	1,857
Total food	4,442	4,666	4,841	4,639	5,294	5,196	5,838	6,146	6,604	6,422
c	9.74	9.47	9.77	9.58	9.85	9.70	9.92	9.83	10.04	9.88
Husband's particip.	0.96	0.97	0.94	0.92	0.93	0.91	0.94	0.93	0.93	0.88
Wife's particip.	0.69	0.67	0.71	0.67	0.74	0.71	0.78	0.73	0.77	0.73

Table 4
The demand for food in the CEX

This table reports IV estimates of the demand equation for (the logarithm of) food at home in the CEX. We instrument the log of total nondurable expenditure (and its interaction with age and education dummies) with the log of family before-tax income (and its interaction with age and education dummies).

Variable	Estimate	Variable	Estimate
$\ln c$	0.6590 (0.0280)	Family size	0.0665 (0.0038)
$\ln c$∗One child	0.0722 (0.0228)	Family size*Northeast	0.0118 (0.0036)
$\ln c$∗Two children	0.0517 (0.0299)	Family size*Midwest	−0.0030 (0.0044)
$\ln c$∗Three children+	0.0817 (0.0281)	Family size*South	0.0091 (0.0036)
$\ln c$∗HS dropout	0.0077 (0.0315)	Born 1955-59	−0.2067 (0.0433)
$\ln c$∗HS graduate	0.0115 (0.0261)	Born 1950-54	−0.1605 (0.0372)
$\ln p$	−0.4559 (0.0630)	Born 1945-49	−0.1219 (0.0324)
$\ln p$∗Northeast	−0.0234 (0.0439)	Born 1940-44	−0.0913 (0.0257)
$\ln p$∗Midwest	0.0555 (0.0355)	Born 1935-39	−0.0666 (0.0229)
$\ln p$∗South	−0.0615 (0.0445)	Born 1930-34	−0.0323 (0.0158)
Aged 36-40	0.0243 (0.0096)	Born 1925-29	−0.0059 (0.0137)
Aged 41-45	0.0276 (0.0150)	Male participant	−0.0113 (0.0096)
Aged 46-50	0.0154 (0.0215)	Female participant	−0.0607 (0.0085)
Aged 51-55	0.0064 (0.00254)	Male part.*# of children	−0.0124 (0.0056)
Aged 56-60	−0.0106 (0.00270)	Fem. part.*# of children	0.0065 (0.0045)
Aged 61-65	−0.0457 (0.0350)	One child	−0.6269 (0.2247)
High school dropout	0.0027 (0.3019)	Two children	−0.3713 (0.2979)
High school graduate	−0.0657 (0.2553)	Three children+	−0.6591 (0.2766)
Northeast	−0.0285 (0.0184)	White	0.0817 (0.0100)
Midwest	−0.1073 (0.0142)	Food away/1000	−0.0534 (0.0042)
South	−0.0395 (0.0217)	Constant	1.5459 (0.2607)
P-value test that β does not vary with time			0.1056
P-value test that β does not vary with cohort			0.1184

Table 5
Consumption and income variances and covariances, CEX 1980-1992

	Born 1920s			*Born 1930s*		
	var(c)	var(y)	cov(c, y)	var(c)	var(y)	cov(c, y)
1980	0.2315	0.4860	0.4230	0.2184	0.4479	0.4009
1981	0.2500	0.5567	0.4789	0.2523	0.4618	0.4616
1982	0.2470	0.5874	0.4836	0.2344	0.4830	0.4591
1983	0.2678	0.5657	0.5358	0.2472	0.5424	0.5194
1984	0.2729	0.6053	0.5375	0.2712	0.6245	0.5412
1985	0.3060	0.7733	0.5836	0.2652	0.6013	0.4999
1986	0.2706	0.6963	0.5069	0.2970	0.6008	0.6067
1987	0.2849	0.7177	0.6205	0.2422	0.5404	0.4194
1988	0.2522	0.6562	0.4788	0.3014	0.7079	0.5498
1989	0.2765	0.4751	0.4691	0.3213	0.5681	0.5624
1990	0.2379	0.7406	0.4769	0.2840	0.6094	0.5154
1991	0.2757	0.4989	0.5591	0.2982	0.7166	0.6482
1992	0.3240	0.6334	0.5004	0.2747	0.6677	0.5030

	Born 1940s			*Born 1950s*		
	var(c)	var(y)	cov(c, y)	var(c)	var(y)	cov(c, y)
1980	0.2115	0.3646	0.3933	0.1155	0.2654	0.1562
1981	0.1921	0.4107	0.3609	0.2499	0.4438	0.3563
1982	0.2137	0.4904	0.4281	0.2291	0.4793	0.4194
1983	0.2030	0.4892	0.4060	0.3005	0.5715	0.4979
1984	0.2187	0.4915	0.4289	0.2438	0.5166	0.5005
1985	0.2371	0.4488	0.4198	0.2552	0.4765	0.4337
1986	0.3031	0.5443	0.5784	0.2678	0.5970	0.5374
1987	0.2263	0.5521	0.4638	0.2356	0.5250	0.4220
1988	0.2889	0.5664	0.4959	0.2262	0.5008	0.4373
1989	0.2461	0.5467	0.4791	0.2569	0.5514	0.4470
1990	0.2975	0.6343	0.5268	0.2252	0.5131	0.4243
1991	0.2931	0.5672	0.5028	0.2454	0.5756	0.4315
1992	0.2657	0.6230	0.4724	0.2286	0.5184	0.4204

Table 6
Repeated cross-section estimates of income shock variances, CEX 1980-1992

	Time period	*Whole sample*	*Born in the 1920s*	*Born in the 1930s*	*Born in the 1940s*	*Born in the 1950s*
$\Delta \text{var}(v)$	1981-1992	0.0057 (0.0013)	0.0001 (0.0031)	0.0094 (0.0028)	0.0095 (0.0021)	0.0064 (0.0026)
	1981-1986	0.0086 (0.0031)	0.0152 (0.0068)	0.0094 (0.0062)	0.0097 (0.0046)	0.0068 (0.0067)
	1987-1992	0.0028 (0.0032)	−0.0189 (0.0082)	0.0095 (0.0068)	0.0094 (0.0054)	0.0061 (0.0048)
	1981-1984	0.0158 (0.0051)	0.0291 (0.0108)	0.0197 (0.0105)	0.0133 (0.0072)	0.0053 (0.0115)
	1985-1988	−0.0026 (0.0043)	−0.0186 (0.0097)	−0.0044 (0.0094)	0.0059 (0.0070)	0.0062 (0.0070)
	1989-1992	0.0105 (0.0052)	0.0010 (0.0144)	0.0230 (0.0113)	0.0117 (0.0091)	0.0068 (0.0079)
$\text{var}(\zeta)$	1981-1992	0.0040 (0.0009)	0.0020 (0.0022)	0.0060 (0.0018)	0.0086 (0.0014)	0.0037 (0.0016)
	1981-1986	0.0085 (0.0020)	0.0058 (0.0043)	0.0089 (0.0040)	0.0098 (0.0032)	0.0172 (0.0039)
	1987-1992	−0.0004 (0.0020)	−0.0031 (0.0057)	0.0029 (0.0043)	0.0073 (0.0034)	−0.0073 (0.0033)
	1981-1984	0.0104 (0.0034)	0.0126 (0.0073)	0.0103 (0.0068)	0.0057 (0.0050)	0.0349 (0.0072)
	1985-1988	0.0030 (0.0028)	−0.0062 (0.0066)	0.0062 (0.0060)	0.0126 (0.0043)	−0.0101 (0.0058)
	1989-1992	−0.0003 (0.0032)	0.0055 (0.0099)	0.0013 (0.0069)	0.0039 (0.0057)	−0.0017 (0.0050)

Table 7
The autocovariance matrix of income growth

Year	var(Δy_t)	cov($\Delta y_{t+1}, \Delta y_t$)	cov($\Delta y_{t+2}, \Delta y_t$)
1980	0.0973	-0.0238	-0.0031
	(0.0104)	(0.0043)	(0.0042)
1981	0.0853	-0.0292	-0.0049
	(0.0082)	(0.0040)	(0.0038)
1982	0.0826	-0.0279	-0.0065
	(0.0062)	(0.0041)	(0.0034)
1983	0.0918	-0.0219	-0.0103
	(0.0084)	(0.0041)	(0.0048)
1984	0.0938	-0.0344	-0.0044
	(0.0068)	(0.0043)	(0.0033)
1985	0.1269	-0.0411	-0.0022
	(0.0183)	(0.0079)	(0.0045)
1986	0.1131	-0.0398	-0.0130
	(0.0081)	(0.0059)	(0.0042)
1987	0.1214	-0.0389	0.0028
	(0.0103)	(0.0055)	(0.0047)
1988	0.1008	-0.0354	-0.0033
	(0.0088)	(0.0047)	(0.0035)
1989	0.1014	-0.0309	-0.0028
	(0.0079)	(0.0069)	(0.0041)
1990	0.1028	-0.0332	-0.0082
	(0.0103)	(0.0056)	(0.0055)
1991	0.0950	-0.0375	
	(0.0072)	(0.0050)	
1992	0.1454		
	(0.0095)		

Table 8
The autocovariance matrix of consumption growth

Year	var(Δc_t)	cov($\Delta c_{t+1}, \Delta c_t$)	cov($\Delta c_{t+2}, \Delta c_t$)
1980	0.2605	-0.1375	0.0011
	(0.0225)	(0.0198)	(0.0109)
1981	0.2728	-0.1235	0.0017
	(0.0241)	(0.0159)	(0.0104)
1982	0.2792	-0.1391	0.0067
	(0.0234)	(0.0188)	(0.0107)
1983	0.3088	-0.1426	-0.0012
	(0.0269)	(0.0158)	(0.0104)
1984	0.3348	-0.1470	-0.0186
	(0.0299)	(0.0259)	(0.0187)
1985	0.3264	-0.1399	NA
	(0.0301)	(0.0194)	
1986	0.3094	NA	NA
	(0.0234)		
1987	NA	NA	NA
1988	NA	NA	NA
1989	NA	NA	NA
1990	0.3426	-0.1149	-0.0062
	(0.0335)	(0.0125)	(0.0108)
1991	0.3416	-0.1694	NA
	(0.0239)	(0.0206)	
1992	0.3203	NA	NA
	(0.0238)		

Table 9
The consumption-income growth covariance matrix

Year	cov($\Delta y_t, \Delta c_t$)	cov($\Delta y_t, \Delta c_{t+1}$)	cov($\Delta y_{t+1}, \Delta c_t$)
1980	0.0022	0.0075	0.0026
	(0.0065)	(0.0063)	(0.0064)
1981	0.0146	-0.0044	-0.0080
	(0.0057)	(0.0053)	(0.0051)
1982	0.0156	-0.0018	-0.0066
	(0.0059)	(0.0067)	(0.0044)
1983	0.0248	-0.0083	-0.0052
	(0.0070)	(0.0064)	(0.0069)
1984	0.0264	-0.0108	-0.0012
	(0.0070)	(0.0052)	(0.0065)
1985	0.0156	0.0026	-0.0068
	(0.0059)	(0.0068)	(0.0051)
1986	0.0229	NA	0.0036
	(0.0057)		(0.0079)
1987	NA	NA	NA
1988	NA	NA	NA
1989	NA	0.0064	NA
		(0.0070)	
1990	0.0028	-0.0018	0.0046
	(0.0083)	(0.0053)	(0.0076)
1991	0.0131	-0.0057	-0.0080
	(0.0059)	(0.0061)	(0.0066)
1992	0.0178	NA	NA
	(0.0066)		

Table 10
Minimum distance partial insurance and variance estimates

This table reports minimum distance estimates of the parameters of interest: θ is the MA(1) coefficient of the transitory component of income, σ_u^2 the variance of the measurement error in consumption, σ_ξ^2 the variance of idiosyncratic taste shocks/innovation to the conditional variance of consumption growth, σ_ζ^2 the variance of permanent shocks to income, σ_ε^2 the variance of transitory shock to income, ϕ and ψ the partial insurance coefficients with respect to permanent and transitory income shocks, respectively. We assume $L - a \to \infty$, and an interest rate of 5 percent.

	Born 1950s		*Born 1940s*		*Born 1930s*		*Born 1920s*	
	79-84	85-92	79-84	85-92	79-84	85-92	79-84	85-92
σ_u^2	0.1056	0.0959	0.0806	0.0991	0.0759	0.0924	0.1086	0.1164
	(0.0160)	(0.0084)	(0.0059)	(0.0102)	(0.0063)	(0.0091)	(0.0068)	(0.0103)
σ_ξ^2	0.0242	0.0276	0.0180	0.0166	0.0116	0.0478	0.0129	0.0283
	(0.0240)	(0.0089)	(0.0034)	(0.0117)	(0.0038)	(0.0109)	(0.0046)	(0.0140)
θ	−0.0877	0.1166	0.1798	0.0979	0.1635	0.2036	0.1249	0.1855
	(0.3278)	(0.0563)	(0.0541)	(0.0529)	(0.0623)	(0.0442)	(0.0490)	(0.0285)
σ_ζ^2	0.0266	0.0192	0.0157	0.0142	0.0162	0.0144	0.0172	0.0090
	(0.0131)	(0.0024)	(0.0025)	(0.0020)	(0.0023)	(0.0023)	(0.0029)	(0.0031)
σ_ε^2	0.0212	0.0247	0.0235	0.0219	0.0197	0.0377	0.0314	0.0507
	(0.0123)	(0.0023)	(0.0026)	(0.0023)	(0.0024)	(0.0032)	(0.0033)	(0.0043)
ϕ	0.1875	0.4572	0.4444	0.5071	0.0995	0.3537	0.3438	0.7893
	(0.2885)	(0.1132)	(0.0974)	(0.1590)	(0.0986)	(0.2134)	(0.1199)	(0.3957)
ψ	−0.1373	0.0104	0.1268	0.2747	−0.0252	0.0754	−0.0861	−0.1471
	(0.3926)	(0.0945)	(0.0860)	(0.1344)	(0.1115)	(0.1085)	(0.0850)	(0.0837)
χ^2	16.97	118.89	86.82	123.74	108.86	159.37	111.45	211.26
	[0.2577]	[0.0074]	[0.0977]	[0.0031]	[0.0026]	[0.0000]	[0.0015]	[0.0000]

	Whole sample		*No College*		*College*	
	79-84	85-92	79-84	85-92	79-84	85-92
σ_u^2	0.1085	0.1195	0.1069	0.1160	0.0894	0.1111
	(0.0053)	(0.0072)	(0.0069)	(0.0105)	(0.0060)	(0.0084)
σ_ξ^2	0.0182	0.0390	0.0125	0.0243	0.0212	0.0314
	(0.0033)	(0.0079)	(0.0044)	(0.0125)	(0.0036)	(0.0087)
θ	0.1403	0.1158	0.1871	0.1423	0.0498	0.1158
	(0.0418)	(0.0272)	(0.0429)	(0.0297)	(0.0639)	(0.0470)
σ_ζ^2	0.0210	0.0199	0.0162	0.0127	0.0202	0.0230
	(0.0021)	(0.0019)	(0.0027)	(0.0019)	(0.0026)	(0.0026)
σ_ε^2	0.0283	0.0417	0.0399	0.0513	0.0178	0.0268
	(0.0022)	(0.0023)	(0.0034)	(0.0032)	(0.0022)	(0.0022)
ϕ	0.3058	0.5170	0.4146	1.0808	0.2213	0.3196
	(0.0631)	(0.1121)	(0.1196)	(0.2449)	(0.0739)	(0.0997)
ψ	0.0601	0.0637	0.0636	0.0451	−0.0883	0.0768
	(0.0665)	(0.0603)	(0.0705)	(0.0617)	(0.1078)	(0.0952)
χ^2	95.37	127.53	105.07	110.75	80.14	119.54
	[0.0285]	[0.0016]	[0.0054]	[0.0269]	[0.2143]	[0.0066]

Table 11
Sensitivity analysis:
Information, Durables, and Transfers

The first column reports the results of the baseline specification. In column (2) we predicts $\ln y$ just with year dummies, an age polynomial, and education dummies. In column (3) we assume that food expenditure reported at t refers to t (not $t-1$). In column (4) we assume that people do not distinguish between transitory and permanent shocks. In column (5) we add health and education expenditure to our measure of nondurable consumption. In column (6) we use a measure of total consumption. Column (7) repeats the experiment performed in column (6) but adds the SEO subsample. Finally, in column (8) we use a measure of income that excludes transfers.

	Baseline	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ_u^2	0.1195	0.1246	0.1184	0.1221	0.1020	0.3647	0.4166	0.1185
	(0.0072)	(0.0073)	(0.0104)	(0.0071)	(0.0062)	(0.0219)	(0.0222)	(0.0073)
σ_ξ^2	0.0390	0.0396	0.0449	0.0385	0.0340	0.1189	0.1468	0.0398
	(0.0079)	(0.0079)	(0.0155)	(0.0079)	(0.0067)	(0.0236)	(0.0237)	(0.0081)
θ	0.1158	0.1797	0.1247		0.1156	0.1166	0.1188	0.1113
	(0.0272)	(0.0340)	(0.0257)		(0.0271)	(0.0270)	(0.0197)	(0.0353)
σ_ζ^2	0.0199	0.0278	0.0204		0.0199	0.0198	0.0198	0.0446
	(0.0019)	(0.0020)	(0.0020)		(0.0019)	(0.0019)	(0.0017)	(0.0046)
σ_ε^2	0.0417	0.0286	0.0435		0.0418	0.0419	0.0500	0.0607
	(0.0023)	(0.0019)	(0.0024)		(0.0023)	(0.0023)	(0.0022)	(0.0045)
ϕ	0.5170	0.3063	0.7424	0.3306	0.4912	0.9241	0.9912	0.2978
	(0.1121)	(0.0787)	(0.1352)	(0.0467)	(0.1040)	(0.1976)	(0.1881)	(0.1161)
ψ	0.0637	-0.0225	-0.0587		0.0586	0.0991	0.2267	0.0591
	(0.0603)	(0.0854)	(0.0673)		(0.0554)	(0.1045)	(0.0790)	(0.0972)
ρ_1				0.4316				
				(0.0179)				
ρ_2				0.0616				
				(0.0160)				
σ_ς^2				0.0796				
				(0.0029)				
χ^2	127.53	130.21	119.72	130.79	126.15	127.65	136.53	102.02
	[0.0016]	[0.0009]	[0.0003]	[0.0010]	[0.0020]	[0.0015]	[0.0003]	[0.0882]

Table 12
Sensitivity analysis:
Imputation, Sample Selection, and Estimation

The first column reports the results of the baseline specification. In column (2) we use food expenditure as our measure of consumption. In column (3) we include the SEO subsample. Column (4) reports the results for the SEO subsample alone. In column (5) we include those aged 20-29. In column (6) we use the sum of food at home and the monetary value of food stamps as our measure of consumption. Column (7) repeats the experiment performed in column (6) but adds the SEO subsample. Finally, in column (8) we report EWMD estimates.

	Baseline	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ_u^2	0.1195	0.0574	0.1362	0.1489	0.1211	0.0561	0.1168	0.1409
	(0.0072)	(0.0034)	(0.0073)	(0.0120)	(0.0072)	(0.0036)	(0.0036)	(0.0113)
σ_ξ^2	0.0390	0.0181	0.0476	0.0482	0.0379	0.0154	0.0210	0.0395
	(0.0079)	(0.0037)	(0.0079)	(0.0129)	(0.0080)	(0.0035)	(0.0034)	(0.0152)
θ	0.1158	0.1172	0.1194	0.1088	0.1311	0.1097	0.1242	0.0960
	(0.0272)	(0.0267)	(0.0196)	(0.0271)	(0.0251)	(0.0273)	(0.0193)	(0.0388)
σ_ζ^2	0.0199	0.0197	0.0197	0.0184	0.0193	0.0192	0.0194	0.0312
	(0.0019)	(0.0019)	(0.0017)	(0.0025)	(0.0018)	(0.0019)	(0.0017)	(0.0039)
σ_ε^2	0.0417	0.0422	0.0500	0.0514	0.0427	0.0419	0.0509	0.0449
	(0.0023)	(0.0023)	(0.0022)	(0.0031)	(0.0022)	(0.0023)	(0.0022)	(0.0037)
ϕ	0.5170	0.3289	0.5710	0.8247	0.5554	0.3142	0.2085	0.4674
	(0.1121)	(0.0767)	(0.1092)	(0.2141)	(0.1130)	(0.0759)	(0.0687)	(0.1278)
ψ	0.0637	0.0397	0.1327	0.1823	0.0960	0.0223	0.0737	−0.0038
	(0.0603)	(0.0411)	(0.0453)	(0.0702)	(0.0565)	(0.0393)	(0.0307)	(0.0772)
χ^2	127.53	136.69	123.48	92.04	128.89	131.76	137.15	127.60
	[0.0016]	[0.0002]	[0.0033]	[0.2570]	[0.0012]	[0.0007]	[0.0002]	[0.0015]

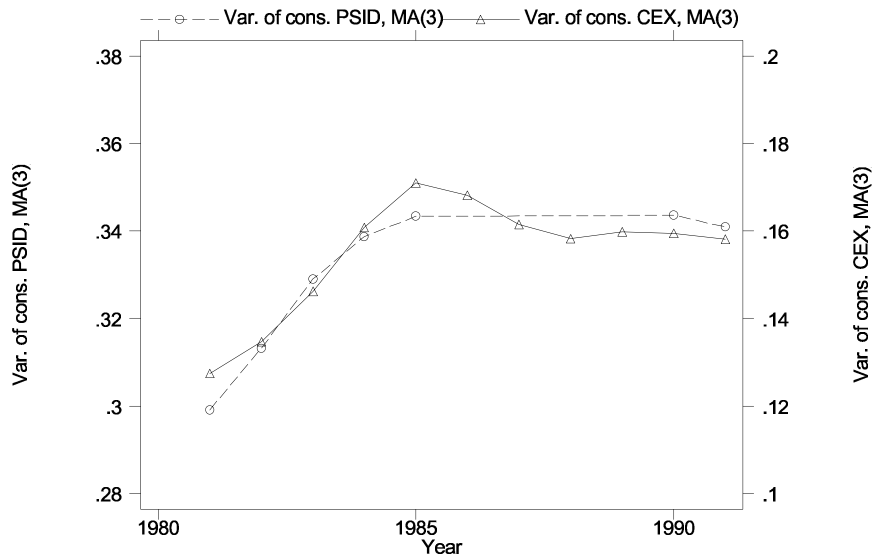

Figure 1: The variance of consumption, PSID and CEX.

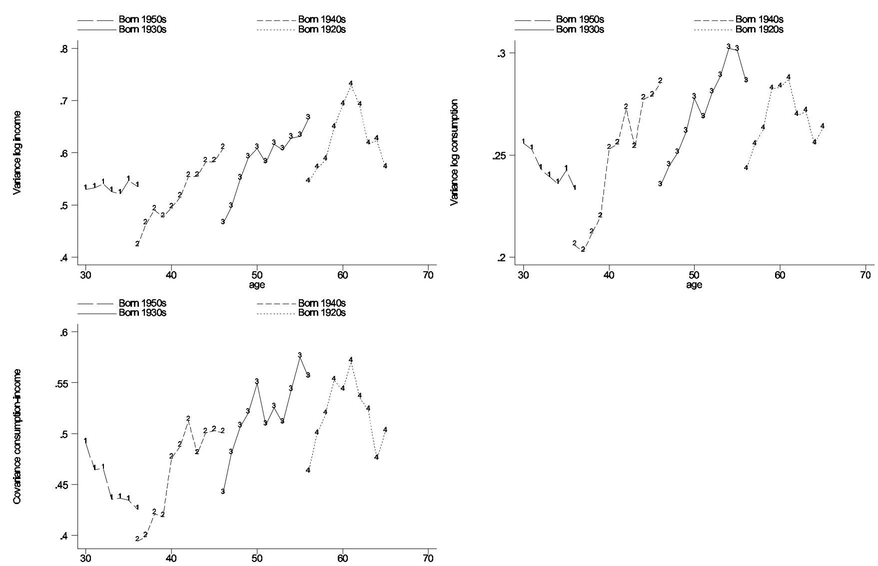

Figure 2: Cohort profiles of the variances of log income and log consumption and their covariance, CEX 1980-1992.

A.1 Appendix: The Euler Equation Approximation

Consider:

$$\ln \sum_{k=0}^{T-t} X_{t-k} = \ln X_t + \ln \left[1 + \sum_{k=1}^{T-t} \exp(\ln X_{t-k} - \ln X_t) \right]$$

Taking a Taylor expansion around $\ln X_{t+k} = \ln X_t + \sum_{i=0}^{k} \delta_{t+i}$, $k = 1, ..., T-t$ with $\delta_t = 0$,

$$\ln \sum_{k=0}^{T-t} X_{t-k} \simeq \ln X_t + \ln \left[1 + \sum_{k=1}^{T-t} \exp(\sum_{i=0}^{k} \delta_{t+i}) \right]$$
$$+ \sum_{k=1}^{T-t} \frac{\exp(\sum_{i=0}^{k} \delta_{t+i})}{\left[1 + \sum_{k=1}^{T-t} \exp(\sum_{i=0}^{k} \delta_{t+i}) \right]} (\ln X_{t+k} - \ln X_t)$$
$$\simeq \sum_{k=0}^{T-t} \alpha^{\delta}_{t+k,T} \ln X_{t+k} - \sum_{k=0}^{T-t} \alpha^{\delta}_{t+k,T} \ln \alpha^{\delta}_{t+k,T}$$

where $\alpha^{\delta}_{t+k,T} = \exp(\sum_{i=0}^{k} \delta_{t+i}) / \left[1 + \sum_{k=1}^{T-t} \exp(\sum_{i=0}^{k} \delta_{t+i}) \right]$.

Take the simple consumption income model

$$\Delta c_{t+k} = \phi \xi_{t+k} + \phi \omega_{t+k}$$
$$\Delta y_{t+k} = \gamma_{t+k} + \Delta \varepsilon_{t+k} + \zeta_{t+k}.$$

The intertemporal budget constraint is

$$\sum_{k=0}^{T-t} q_{t+k} C_{t+k} = \sum_{k=0}^{L-t} q_{t+k} Y_{t+k} + A_t$$

where T is death, L is retirement and q_{t+k} is appropriate discount factor $\prod_{i=1}^{k}(1 + r_{t+i})$, $k = 1, ..., T-t$ (and $q_t = 1$). Using the above approximation

$$\sum_{k=0}^{T-t} \alpha^{\phi\omega - r}_{t+k,T} [\ln C_{t+k} - \ln q_{t+k} - \ln \alpha^{\phi\omega - r}_{t+k,T}]$$
$$\simeq \pi_t \sum_{k=0}^{L-t} \alpha^{\gamma - r}_{t+k,L} [\ln Y_{t+k} - \ln q_{t+k} - \ln \alpha^{\gamma - r}_{t+k,L}]$$
$$+ (1 - \pi_t) \ln A_t - [(1 - \pi_t) \ln a_t + \pi_t \ln \pi_t]$$

where $\pi_t = \frac{\sum_{k=0}^{L-t} q_{t+k} Y_{t-k}}{\sum_{k=0}^{L-t} q_{t+k} Y_{t-k} + A_t}$.

Taking differences in expectations and allowing for revisions to ω gives

$$\begin{aligned}
\phi\xi_t &\simeq \pi_t[\zeta_t + \alpha_{t,L}^{\gamma-r}\varepsilon_t] \\
&\quad + \sum_{k=0}^{T-t}(E_t - E_{t-1})(\alpha_{t+k,T}^{\phi\omega-r}\sum_{i=1}^{k}[\phi\omega_{t+i} + r_{t+i}]) \\
&\quad - \sum_{k=0}^{T-t}(E_t - E_{t-1})(\alpha_{t+k,T}^{\phi\omega-r}\ln\alpha_{t+k,T}^{\phi\omega-r}) \\
&= \pi_t[\zeta_t + \alpha_{t,L}^{\gamma-r}\varepsilon_t] \\
&\quad + (E_t - E_{t-1})\ln\left[1 + \sum_{k=1}^{T-t}\exp(\sum_{i=0}^{k}[\phi\omega_{t+i} + r_{t+i}])\right]
\end{aligned}$$

For large $L-t$ we may be prepared to assume that $\alpha_{t,L}^{\gamma-r}$ is small enough to be ignored and $\pi_t \simeq 1$. The terms on the second line are common within the cohort and therefore do not affect the evolution of variances.

A.2 Appendix: Measurement error

In the light of our imputation procedure, let's assume that both consumption and income are measured with multiplicative (independent and quasi-classical) error,[25] e.g., $y^*_{i,a,t} = y_{i,a,t} + u^y_{i,a,t}$ and $c^*_{i,a,t} = c_{i,a,t} + u^c_{i,a,t}$, where x^* denote a measured variable, x its true, unobservable value, and u the measurement error. Equations (17) and (18) then rewrite as:

$$\Delta y^*_{i,a,t} = \zeta_{i,a,t} + \Delta\varepsilon_{i,a,t} + \Delta u^y_{i,a,t} \tag{24}$$

$$\Delta c^*_{i,a,t} \cong \phi_{b,t}\zeta_{i,a,t} + \psi_{b,t}\alpha_a\varepsilon_{i,a,t} + \Delta u^c_{i,a,t} \tag{25}$$

Consider first the case $L-a\to\infty$, $r\to 0$, and $\alpha_a \to 0$. Assume that measurement error in income is orthogonal to measurement error in consumption. Note that the "measured" ratio (19) $\frac{\text{var}\left(\Delta c^*_{a,t}\right)}{\text{cov}\left(\Delta y^*_{a,t},\Delta c^*_{a,t}\right)}$ no longer identifies $\phi_{b,t}$ because of measurement error in consumption. However, the expression:

$$\phi_{b,t} = \frac{\text{cov}\left(\Delta c^*_{a,t}, \Delta y^*_{a,t}\right)}{\text{cov}\left(\Delta y^*_{a,t}, \Delta y^*_{a-1,t-1} + \Delta y^*_{a,t} + \Delta y^*_{a+1,t+1}\right)} \tag{26}$$

still identifies the partial insurance parameter $\phi_{b,t}$. Similarly:

$$\phi_{b,t} = \frac{\text{cov}\left(\Delta c^*_{a,t}, \Delta c^*_{a-1,t-1} + \Delta c^*_{a,t} + \Delta c^*_{a+1,t+1}\right)}{\text{cov}\left(\Delta c^*_{a,t}, \Delta y^*_{a,t}\right)}$$

showing that $\phi_{b,t}$ is again overidentified. Under the martingale assumption for consumption, $var\left(u^c_{a,t}\right)$ can be identified using the covariance of current and lagged consumption growth:

$$\text{var}\left(u^c_{a,t}\right) = -\text{cov}\left(\Delta c^*_{a+1,t+1}, \Delta c^*_{a,t}\right) \tag{27}$$

[25] Quasi-classical in the sense that the variance of the measurement error is not (necessarily) constant over time.

However, $var\left(\varepsilon_{a,t}\right)$ and $var\left(u^y_{a,t}\right)$ cannot be told apart, and $\psi_{b,t}$ thus remains unidentified. If $L-a$ is finite and $r \neq 0$, then:

$$\phi_{b,t} = \frac{\text{cov}\left(\Delta c^*_{a,t}, \Delta y^*_{a,t} + \Delta y^*_{a+1,t+1}\right)}{\text{cov}\left(\Delta y^*_{a,t}, \Delta y^*_{a-1,t-1} + \Delta y^*_{a,t} + \Delta y^*_{a+1,t+1}\right)} \tag{28}$$

This identifies the partial insurance parameter $\phi_{b,t}$. Once more, $var\left(\varepsilon_{a,t}\right)$ and $var\left(u^y_{a,t}\right)$ cannot be separately identified and $\psi_{b,t}$ remains unidentified. It is possible however to put an upper bound on $\psi_{b,t}$ using the fact that:

$$\psi_{b,t} \leq \alpha_a^{-1} \frac{\text{cov}\left(\Delta c^*_{a,t}, \Delta y^*_{a+1,t+1}\right)}{\text{cov}\left(\Delta y^*_{a+1,t+1}, \Delta y^*_{a,t}\right)}.$$

Thus it is possible to argue that the estimate of $\psi_{b,t}$ is upward biased due to measurement error in income.

A.3 Appendix: The imputation procedure

Consider the demand equation for food at home (23) in the CEX:

$$f_{i,\text{CEX}} = M'_{i,\text{CEX}}\mu + \beta c_{i,\text{CEX}} + e_{i,\text{CEX}}$$

Define *imputed* consumption in the CEX by inverting assuming $e_{i,\text{CEX}}$ and $\widehat{\beta} \neq 0$:

$$\widehat{c}_{i,\text{CEX}} = \frac{\left(f_{i,\text{CEX}} - M'_{i,\text{CEX}}\widehat{\mu}\right)}{\widehat{\beta}}$$

where a caret indicates a consistent estimate. The corresponding *imputed* measure of consumption in the PSID is

$$\widehat{c}_{i,\text{PSID}} = \frac{\left(f_{i,\text{PSID}} - M'_{i,\text{PSID}}\widehat{\mu}\right)}{\widehat{\beta}}$$

To understand under which conditions moments of imputed PSID consumption mirror those of "true" consumption, we are confronted with a (non-standard) measurement error problem of the form:

$$\widehat{c}_{i,\text{CEX}} = \frac{\beta}{\widehat{\beta}} c_{i,\text{CEX}} + M'_{i,\text{CEX}} \frac{(\mu - \widehat{\mu})}{\widehat{\beta}} + u_{i,\text{CEX}}$$

and $u_{i,\text{CEX}} = \frac{e_{i,\text{CEX}}}{\widehat{\beta}}$. Consider for simplicity the univariate regression case:

$$\widehat{c}_{i,\text{CEX}} = \frac{(\mu - \widehat{\mu})}{\widehat{\beta}} + \frac{\beta}{\widehat{\beta}} c_{i,\text{CEX}} + u_{i,\text{CEX}}$$

and define with $\overline{x} = \frac{\sum_{i=1}^N x_i}{N}$ and $var\left(x\right) = \frac{\sum_{i=1}^N (x_i - \overline{x})^2}{N}$ the sample cross-sectional mean and variance of the variable x. Let us consider two cases of interest.

The first case is when $c_{i,\text{CEX}}$ is measured without error. In this case, plim $\widehat{\beta} = \beta$ and plim $\widehat{\mu} = \mu$. It follows that:

$$\text{plim } \bar{\hat{c}}_{\text{CEX}} = \text{plim } \bar{c}$$

and:

$$\text{plim var}\left(\widehat{c}_{\text{CEX}}\right) = \text{plim var}\left(c\right) + \frac{1}{\beta^2}\text{plim var}\left(e\right)$$

Thus the sample mean of predicted CEX consumption converges to the same limit of the sample mean of true consumption, while the sample variance of predicted CEX consumption converges to the limit of the variance of true consumption up to an additive term. The latter decreases with the value of the expenditure elasticity. If the demand for food at home is relatively inelastic ($\beta \rightarrow 0$) the additive term may be potentially quite large.

As for PSID imputed consumption, it is easy to prove that:

$$\text{plim } \bar{\hat{c}}_{\text{PSID}} = \text{plim } \bar{c} + \frac{1}{\beta}\left[\text{plim } \overline{f}_{\text{PSID}} - \text{plim } \overline{f}_{\text{CEX}}\right]$$

and:

$$\begin{aligned} \text{plim var}\left(\widehat{c}_{\text{PSID}}\right) &= \text{plim var}\left(c\right) + \frac{1}{\beta^2}\text{plim var}\left(e\right) \\ &+ \frac{1}{\beta^2}\left[\text{plim var}\left(f_{\text{PSID}}\right) - \text{plim var}\left(f_{\text{CEX}}\right)\right] \end{aligned} \tag{29}$$

Thus the sample mean of imputed PSID consumption converges to the limit of the sample mean of true consumption up to an additive term (the mean difference in the input variable available in both surveys, e.g., food consumption). If food consumption is on average the same in the two data sets, the sample mean of imputed PSID consumption converges to the same limit of the sample mean of true consumption. Otherwise, the sample mean of imputed PSID consumption may overestimates or underestimate the sample mean of true consumption.

Note also that the sample variance of imputed PSID consumption differs from the variance of true consumption because of two factors: the variance of food heterogeneity scaled by the square of the income elasticity and the difference between the variance of food consumption in the two data sets, again scaled by the square of the income elasticity.[26] Our minimum distance procedure is designed to estimate this factor using, e.g., (27).

In the second case, $c_{i,\text{CEX}}$ is measured with classical error: $c^* = c + v$. It follows that plim $\widehat{\beta} = \frac{\beta}{\lambda}$ and plim $\widehat{\mu} = \mu + \beta\frac{(\lambda-1)}{\lambda}\text{plim } \bar{c}$, where $\lambda = \frac{\text{plim var}(c^*)}{\text{plim var}(c)} \geq 1$. Repeating the same steps above:

$$\text{plim } \bar{\hat{c}}_{\text{CEX}} = \text{plim } \bar{c} = \text{plim } \overline{c^*}$$

[26] It also follows that the variances of first differences var $\left(\Delta\widehat{c}_{\text{CEX}}\right)$ will exceed var $\left(\Delta c\right)$ by the term $\frac{\text{var}(\Delta e)}{\beta^2}$, and that var $\left(\Delta\widehat{c}_{\text{CEX}}\right)$ will exceed var $\left(\Delta c\right)$ by the term

$$\frac{\text{var}\left(\Delta e\right)}{\beta^2} + \frac{1}{\beta^2}\left[\text{plim var}\left(\Delta f_{\text{PSID}}\right) - \text{plim var}\left(\Delta f_{\text{CEX}}\right)\right].$$

and:

$$\begin{aligned} \text{plim var}\left(\widehat{c}_{\text{CEX}}\right) &= \lambda \text{plim var}\left(c\right) + \left(\frac{\lambda}{\beta}\right)^2 \text{plim var}\left(e\right) \\ &= \lambda^2 \text{plim var}\left(c^*\right) + \left(\frac{\lambda}{\beta}\right)^2 \text{plim var}\left(e\right) \end{aligned}$$

As for PSID imputed consumption,

$$\begin{aligned} \text{plim } \overline{\widehat{c}}_{\text{PSID}} &= \text{plim } \overline{c} + \frac{\lambda}{\beta}\left[\text{plim } \overline{f}_{\text{PSID}} - \text{plim } \overline{f}_{\text{CEX}}\right] \\ &= \text{plim } \overline{c^*} + \frac{\lambda}{\beta}\left[\text{plim } \overline{f}_{\text{PSID}} - \text{plim } \overline{f}_{\text{CEX}}\right] \end{aligned} \tag{30}$$

and:

$$\begin{aligned} \text{plim var}\left(\widehat{c}_{\text{PSID}}\right) &= \lambda \text{plim var}\left(c\right) + \left(\frac{\lambda}{\beta}\right)^2 \text{plim var}\left(e\right) \\ &+ \left(\frac{\lambda}{\beta}\right)^2 \left[\text{plim var}\left(f_{\text{PSID}}\right) - \text{plim var}\left(f_{\text{CEX}}\right)\right] \\ &= \lambda^2 \text{plim var}\left(c^*\right) + \left(\frac{\lambda}{\beta}\right)^2 \text{plim var}\left(e\right) \\ &+ \left(\frac{\lambda}{\beta}\right)^2 \left[\text{plim var}\left(f_{\text{PSID}}\right) - \text{plim var}\left(f_{\text{CEX}}\right)\right] \end{aligned} \tag{31}$$

In general, the presence of classical measurement error makes the discrepancy between moments of imputed consumption and moments of true consumption worse than in the case where c is measured without error.

This discussion suggests the use of an instrumental variable procedure in the attempt of minimizing the impact of biases in the estimated coefficients β and μ (see Table 4 for the results).

Table 3 shows that our imputed PSID consumption overestimates CEX consumption by about 25 percent in the initial year. The amount of overestimation declines somewhat in the following years. The fact that imputed consumption in the PSID is on average higher than raw consumption in the CEX may have various explanations. First, despite our focus on homogeneous samples, the demographic characteristics in the PSID may still be quite different than those in the PSID (see Table 3). The second possibility is that the input variable (food expenditure) is measured differently in the two data sets, and measurement of this variable may have changed over time. This is in fact the case in the CEX, as we noticed in the main text. Finally, our IV procedure may not eliminate the bias in the parameters of the demand equation due to measurement error in non-durable expenditure. In this case, overestimation is expected.

Despite these difference, it is worth noting that while the matching of mean consumption is desirable, it is not necessary, in that the scope of the empirical analysis is to estimate models for the variance of consumption and its covariance with income.

To see whether measurement error is an issue in our imputations procedure, we finally compute the slope of the relationship between $var\left(\widehat{c}_{\text{PSID}}\right)$ and $var\left(c^*_{\text{CEX}}\right)$ in two cases: OLS and IV. The OLS slope is 1.15, the IV is 0.99.[27] The OLS intercept is also larger than the IV intercept. These findings are indeed

[27]These are obtained by simple OLS regressions of var $\left(\widehat{c}^{OLS}_{\text{PSID}}\right)$ and var $\left(\widehat{c}^{IV}_{\text{PSID}}\right)$ on var $\left(c^*_{\text{CEX}}\right)$.

predictable by the analysis above. To see this point, recall that equation (31) and (29) refer to the OLS and IV case, respectively, if consumption in the CEX is measured with classical error and a valid instrument is available. From the comparison of these two equations two things can be noticed. First, the slope of the relationship between $var\left(\widehat{c}_{\text{PSID}}\right)$ and $var\left(c^{*}_{\text{CEX}}\right)$ is unity in the IV case and greater than one in the OLS (biased) case. Second, the intercept of the relationship is greater in the OLS case than in the IV case. Both predictions appear to be supported.

While this evidence can only be taken as suggestive, it provides some useful information. First, an IV adjustment seems warranted. Second, once the adjustment is made, the moments of imputed PSID consumption mirror closely those of "true" consumption (see Figure 1).

A.4 Appendix: Estimation details

The two basic vectors of interest are:

$$\mathbf{c}_i = \begin{pmatrix} \Delta c_{i,1} \\ \Delta c_{i,2} \\ \dots \\ \Delta c_{i,T} \end{pmatrix} \text{ and } \mathbf{y}_i = \begin{pmatrix} \Delta y_{i,1} \\ \Delta y_{i,2} \\ \dots \\ \Delta y_{i,T} \end{pmatrix}$$

where, for simplicity, we indicate with 0 the first year in the panel (1978) and with T the last (1992), and the reference to age has been omitted. Conformably with the vectors above, define:

$$\mathbf{d}_i = \begin{pmatrix} d_{i,1} \\ d_{1,2} \\ \dots \\ d_{i,T} \end{pmatrix}$$

where $d_{i,t} = 1\left\{y_{i,t},\ c_{i,t} \text{ are not missing}\right\}$. This means that only complete observations on these two variables are used. This notation allows us to handle the problem of unbalanced panel data in a simple manner.

Stacking observations on Δy and Δc for each individual we obtain the vector:

$$\mathbf{x}_i = \begin{pmatrix} \mathbf{c}_i \\ \mathbf{y}_i \end{pmatrix}$$

Now we can derive:

$$\mathbf{m} = vech\left\{\sum_{i=1}^{N}\left(\mathbf{x}_i\mathbf{x}_i'\right) \oslash \mathbf{d}_i\mathbf{d}_i'\right\}$$

where $\oslash$ denotes an elementwise division. The vector $\mathbf{m}$ contains the estimates of $cov\left(\Delta y_t, \Delta y_{t+s}\right)$, $cov\left(\Delta y_t, \Delta c_{t+s}\right)$, and $cov\left(\Delta c_t, \Delta c_{t+s}\right)$, a total of $T\left(2T+1\right)$ unique moments). To obtain the variance-covariance matrix of $\mathbf{m}$, define conformably with $\mathbf{m}$ the individual vector:

$$\mathbf{m}_i = \left(\mathbf{x}_i\mathbf{x}_i'\right) \oslash \mathbf{d}_i\mathbf{d}_i'$$

The variance-covariance matrix of $\mathbf{m}$ that can be used for inference is:

$$\mathbf{V} = \left[\sum_{i=1}^{N}\left(\mathbf{m}_i - \mathbf{m}\right)\left(\mathbf{m}_i - \mathbf{m}\right)' \circledast \left(\mathbf{d}_i\mathbf{d}_i'\right)\right] \oslash \mathbf{D}\mathbf{D}'$$

where $\mathbf{D} = vech\left\{\sum_{i=1}^{N} \mathbf{d}_i \mathbf{d}_i'\right\}$ and $\circledast$ denotes an elementwise product. The square roots of the elements in the main diagonal of $\mathbf{V}$ provide the standard errors of the corresponding elements in $\mathbf{m}$.

What we do in the empirical analysis is to estimate models for $\mathbf{m}$:

$$\mathbf{m} = f(\mathbf{\Lambda}) + \mathbf{\Upsilon}$$

where $\mathbf{\Upsilon}$ captures sampling variability and $\mathbf{\Lambda}$ is the vector of parameters we are interested in (the variances of the permanent shock and the transitory shock, the partial insurance parameters, etc.). For instance the mapping from $\mathbf{m}$ to $f(\mathbf{\Lambda})$ is:

$$\begin{pmatrix} \text{var}(\Delta c_1) \\ \text{cov}(\Delta c_1, \Delta c_2) \\ \dots \\ \text{cov}(\Delta c_1, \Delta c_T) \\ \dots \end{pmatrix} = \begin{pmatrix} \phi^2 \text{var}(\zeta_1) + \psi^2 \alpha^2 \text{var}(\varepsilon_1) + \text{var}(\xi_1) + \text{var}(\eta_1^c) + \text{var}(\eta_0^c) \\ -\text{var}(\eta_1^c) \\ \dots \\ 0 \\ \dots \end{pmatrix} + \mathbf{\Upsilon}$$

We solve the problem of estimating $\mathbf{\Lambda}$ by minimizing:

$$\min_{\mathbf{\Lambda}} (\mathbf{m} - f(\mathbf{\Lambda}))' \mathbf{A} (\mathbf{m} - f(\mathbf{\Lambda}))$$

where $\mathbf{A}$ is a weighting matrix. Optimal minimum distance (OMD) imposes $\mathbf{A} = \mathbf{V}^{-1}$, equally weighted minimum distance (EWMD) imposes $\mathbf{A} = \mathbf{I}$, and variance-weighted minimum distance (VWMD) requires that $\mathbf{A}$ is a diagonal matrix with the elements in the main diagonal given by $diag\left(\mathbf{V}^{-1}\right)$.

For inference purposes we require the computation of standard errors. Chamberlain (1984) shows that these can be obtained as:

$$\widehat{var\left(\widehat{\mathbf{\Lambda}}\right)} = \left(\mathbf{G}'\mathbf{A}\mathbf{G}\right)^{-1} \mathbf{G}'\mathbf{A}\mathbf{V}\mathbf{A}\mathbf{G} \left(\mathbf{G}'\mathbf{A}\mathbf{G}\right)^{-1}$$

where $\mathbf{G} = \frac{\partial f(\mathbf{\Lambda})}{\partial \mathbf{\Lambda}} \Big|_{\mathbf{\Lambda}=\widehat{\mathbf{\Lambda}}}$ is the Jacobian matrix evaluated at the estimated parameters $\widehat{\mathbf{\Lambda}}$. The validity of the overidentifying restrictions can be tested by constructing the test statistic:

$$J = \left(\mathbf{m} - f\left(\widehat{\mathbf{\Lambda}}\right)\right)' \mathbf{V}^{-1} \left(\mathbf{m} - f\left(\widehat{\mathbf{\Lambda}}\right)\right)$$

in the OMD case. See Chamberlain (1984) for more details. Under the null hypothesis that the model is valid, the test statistic J is distributed χ^2 with degrees of freedom equal to $[T(2T+1) - rank(\mathbf{G})]$. This test statistics is reported at the bottom of Tables 10 and 11.