Intergenerational Linkages in Consumption Behavior

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ABSTRACT

We investigate familial relationships in consumption patterns using a sample of parents and their children from the Panel Study of Income Dynamics. We find a positive and statistically significant parent-specific effect on children's consumption even after controlling for the effect of parental income. This correlation is found in different measures of consumption, and is not sensitive to private transfers. In contrast, the correlation is not statistically significant between pairs of households that are not related. The evidence is quite strong that income is not the only source of a parental effect in consumption behavior of their offspring.

I. Introduction

It was once thought that economic mobility was high enough that the effects of earnings innovations would be wiped out in three generations (Becker and Tomes 1986). But more recent evidence based on longer panels indicates that intergenerational earnings mobility is less fluid than earlier studies suggest.[1] Economic stratification across generations is just as pronounced if we examine consump-

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1. See, for example, Behrman and Taubman (1990), Solon (1992), Zimmerman (1992), and Mulligan (1997).

tion data, arguably a more accurate measure of economic well-being. Only about 8 percent of the adult children with parents from the lowest consumption quintile make it into the highest quintile.[2]

But while most would agree that the intergenerational correlation in consumption is largely a manifestation of intergenerational correlation in earnings, it is far less clear that income is the only source of this correlation. This paper explores the possible role that preferences and behavior might play in accounting for intergenerational correlations in consumption, using information about parents and their children from the Panel Study of Income Dynamics (PSID). We develop an empirical framework that allows both parental income and other parent-specific effects unrelated to income to be transmitted from one generation to the next. The model is used to assess the relative importance of both types of parental effects in consumption of their children.

Several studies indicate that consumption and wealth accumulation cannot be fully explained by the life-cycle model or commonly considered household characteristics.[3] For example, why does the majority save so little while a minority saves a great deal? A possible shortcoming of standard consumption models is that they treat the household in isolation even though consumption is at least partly a social activity that extends beyond the nuclear family. One obvious link comes from possible income transfers between households, but there are many other ways the extended family can influence a household's consumption. Children might strive to keep up with the consumption of parents and siblings and their well-being might depend on comparisons with these reference groups. Children might acquire consumption-related habits early in life while still living with their parents. They might learn their savings and investment behavior by watching their parents or perhaps acquire an aversion to risk from observing their parents' inclinations or experiences. Such influences could account for some of the unexplained heterogeneity in consumption behavior. Below, we refer to these kinds of nonincome-related influences as "tastes." The goal of the empirical work is to see if parents influence consumption behavior of the children beyond the influence through income.

Despite the potential importance of intergenerational influences for consumption and savings behavior, most of the literature on intergenerational relationships has focused on income or earnings.[4] The three studies we are aware of that investigate intergenerational correlations in consumption all find the parental correlation to be large and statistically significant. Chiteji and Stafford (1999) find intergenerational similarities in portfolio choice. But the authors confine their attention to bank accounts and stock ownership, and their primary focus is on racial differences in wealth accumulation. Mulligan (1997) controls for life cycle and business cycle effects in consumption and finds the intergenerational correlation in time-averaged consumption to be quite large. However, it is not clear whether a significant correlation would remain once parental income was taken into account. Charles and Hurst (2003) examine intergenerational correlations in wealth and find the correlation in income accounts for most, but not all of the observed wealth correlation. Because wealth data

2. Evidence on consumption mobility will be presented in more detail in Table 2 below.
3. See Lusardi (2000) for evidence from the Health and Retirement Survey. Browning and Lusardi (1997) provide a survey of savings and anomalies not explained by standard optimizing models of consumption.
4. Mulligan (1997) surveys many of the studies on income. See also Altonji and Dunn (1994).

are available from the PSID only in five-year intervals from 1984 on, their analysis examines intergenerational correlations at specific points in time. In contrast, our analysis makes use of income and consumption data over the 1968 to 1992 sample to study the average correlation in behavior over time.

The plan of the paper is as follows. Section II contains a general discussion of why one might expect intergenerational correlations in consumption. The data used in the empirical work are described in Section III. In Section IV, we build an intergenerational model that allows for transmissions via income and tastes. The results are reported in Section V and VI. The results confirm an intergenerational transmission in consumption via income, but we also find a correlation in taste between children and their parents even after income is taken into account. Parental tastes explain between 5 and 10 percent of tastes of their children.

II. Possible Explanations for Intergenerational Correlations in Consumption

Parent-child correlation in consumption can be consistent with a variety of channels of intergenerational influence. One such influence could be parental attempts to modify their children's behavior. In Becker and Mulligan (1997), for example, parents devote resources to reducing their children's subjective rate of time preference. Thus, rich people, or people with rich parents, "choose" to be more patient. Furthermore, wealthier parents have greater capacity for undertaking productive human capital investments in their children. Consumption between generations could be correlated to the extent that such investments lead to higher permanent income.

Similarities in consumption behavior between generations also could arise even if parents do not actively influence the behavior of their children. As Becker and Tomes (1986) and Behrman and Taubman (1990) explain, a parent who is especially talented will have a higher-than-average demand for her human capital and hence higher earnings. Her child is likely to be similarly talented (though not identically so if talent regresses to the mean) and therefore would inherit the earnings advantage. Intergenerational correlations in human capital generate corresponding correlations in permanent incomes and hence consumption. Shea (2000) further investigates this relation and finds that most of the intergenerational correlation in income does indeed appear to originate from a correlation in ability rather than from the effects of parental income *per se*. Using adoption data, Das and Sjogren (2002) also find that the intergenerational correlation in income mobility is due more to a correlation in innate abilities than wealth.

A parent-child correlation in consumption also could arise from the unintentional transmission of parental preferences to children. Such preferences could be intratemporal, such as when children acquire their parents' tastes for sports cars or dining out. The preferences also could be intertemporal, as in cases where children observe their parents being thrifty. Children may acquire a taste for saving when parents encourage them to put money into their piggy banks, for example. Parents who enjoy gambling might unintentionally pass on to their children an affinity for risk taking.

Children might develop an interest for investing in the stock market as a result of nightly discussions at the dinner table. Two generations with similar rates of time preference and degrees of risk aversion would then have similarly sloped age-consumption profiles. Family medical history might lead to special awareness for precautionary saving. Heritability of life-span could, at least in principle, generate intergenerational correlations in consumption as well.

Consumption externalities such as the ones discussed in the early literature on the relative income hypothesis (Duesenberry 1949) also can generate intergenerational correlations in consumption. Suppose consumer utility depends on own consumption, C_t, and a reference group's consumption, S_t, and assume $U(C_t,S_t) = u(C_t - \beta S_t)$. If the reference variable S_t is aggregate consumption, then the model is what Abel (1990) referred to as "keeping up with the Joneses." But it seems just as reasonable to suppose that children might use the consumption of their parents or siblings as the reference group. Following the literature, we refer to this "keeping up with their parents" as an "external habit," a form of deliberate imitation.

Suppose habits follow the law of motion, $S_{k,t} = (1 - \theta_k)S_{k,t-1} + C_{k,t}$, where the subscript k denotes child variables. Rather than taking the initial condition $S_{k,0}$ as exogenously determined, as is common practice, think of $S_{k,0}$ as the level of habit that the child inherits from his parents during the years of coresidence. That is, $S_{k,0} \propto C_p$, where C_p is permanent consumption of the parent. Although the importance of the initial habit falls at rate θ_k as the child ages, parental habits will be passed on to their children via $S_{k,0}$. Notice that this effect of the initial habit is obtained whether habits are internal or external to the consumer. We refer to this as the "inherited habit" effect.[5]

The channels discussed above suggest several reasons to expect positive correlations in consumption. Are there other channels that might lead to correlations in the opposite direction? Suppose households are altruistic. The shared budget constraints hypothesis of Becker and Tomes (1986) implies that $C_k = Y_k + Y_p - C_p$, where Y_p and Y_k denote the permanent income of the parent and the children, respectively. With permanent incomes constant, the less my parents consume, the more resources are left over for me, leading to a negative correlation in consumption. One might dismiss this prediction because such an extreme implication for consumption implied by the altruism model was rejected by Altonji, Hayashi, and Kotlikoff (1992). But suppose the motive for intergenerational transfers is exchange, such as discussed in Bernheim, Shleifer, and Summers (1985) or Cox (1987). According to the exchange view, my parents might amass a large estate, or make frequent inter-vivos transfers, to elicit "child services." The excess of Y_p over C_p is then used to make transfers to the child. With parental income constant, an increase in parental consumption also should reduce child consumption. Either motive for transfers thus predicts the same negative intergenerational correlation in consumption, controlling for permanent incomes.

Although intergenerational correlations in consumption can arise for many reasons and trying to identify them is no small task, it also is possible for there to be only weak intergenerational correlations in the data. Mulligan (1997) argues that endogenous parental altruism can cause consumption to regress to the mean, since rich parents who have high opportunity costs might spend less time with their children.

5. The effect of parental habits is to be investigated in a separate paper by the authors.

The influence of wealth on fertility and assortative marriage markets (Becker and Tomes 1986, p. S21) also could weaken the intergenerational correlation.

Other factors also could override familial influences. One is liquidity constraints, since consumption behavior would then be constrained by the availability of resources despite any desire to catch up with or imitate parents. By this reasoning, intergenerational correlations in consumption would be weaker for the poor than for the rich. Another would be proximity of residence. The greater the distance between parents and their children after they form their own household, the less opportunity they will have to observe and imitate the habits of their parents. There are several other factors that could weaken or eliminate intergenerational correlations in consumption, such as competing influences of peers, teachers, or the media. Only by examining appropriate data can we ever learn whether such correlations are empirically important, so with this in mind we turn to a discussion of the PSID.

III. The PSID Data, Splitoffs, and Data Description

Our data come from the Panel Study of Income Dynamics (PSID), a longitudinal survey of U.S. individuals and their families. Household heads and their spouses are reinterviewed each year starting in 1968. We refer to this sample of earliest parents as "main households." In addition, if main household members leave to form households of their own, they are followed and interviewed as well. For example, a split could occur with divorce or separation. We do not consider households that experienced a change in family composition of this sort. Our interest is in those splits that occur when children leave home to set up their own households. We follow the literature by referring to these cases as "child splitoffs," or, more simply, "splitoffs." Because of these splitoffs, the PSID has grown over the years from an initial sample of 4,800 households to one of nearly 10,000 by 1992, the last year of our sample.[6]

In focusing on intergenerational relationships, we follow Altonji, Hayashi, and Kotlikoff (1992) by constructing a data set of parental and splitoff households that satisfies the following three conditions: (1) the parents must be respondents in the first wave of the PSID in 1968; (2) the child splitoffs must have been recorded as children of those earliest parents, and (3) the child must have left the parental household sometime between 1969 and 1992. Table 1 contains selected summary statistics from the resulting data file. There are 842 main households and 1,808 splitoff households, or 2.14 splitoffs per main household. By 1992, both spouses are alive and living together in 56.77 percent of main households; 34.09 percent are single-head households, mostly because the spouse died or dropped out of the sample following divorce or separation. Some have been single-head households since 1968. The remaining 9.15 percent are divorced or separated, but both are still in the sample. In this case, all information is taken from the 1968 head of household's family (usually the father's) for the years following separation. If splitoffs divorce or separate, the

6. The PSID samples households from a "representative" sample and a special "low-income" sample. We consider only the representative sample, and we treat it as self-weighting. We also do not include the additional Latino sample that was added in 1990.

Table 1
Descriptive Statistics

Number of Children Per Main Household	Sample Size	Percent of Sample	Number of Splitoffs	Percent of Sample
1	332	39.43	332	18.36
2	255	30.29	510	28.21
3	137	16.27	411	22.73
4	70	8.31	280	15.49
5	31	3.68	155	8.57
6	6	0.71	36	1.99
7	6	0.71	42	2.32
8	4	0.48	32	1.77
10	1	0.12	10	0.55
Total	842	100	1808	100

Parents' status in 1992	Sample size	Percent of sample	Number of splitoffs	Percent of sample
Parents still married	478	56.77	1,070	59.18
Parents divorced/ separated	77	9.14	159	8.79
Only one parent in sample	287	34.09	579	32.03

	Main Households	Splitoff Households
Number of time series observations	20.92	11.26
Years of Consumption after retirement	2.77	0.12
Average income	60,684	46,168
Average weighted consumption	30,670	22,881
Average food consumption	7,456	5,167
Family size	3.14	2.65
Age in 1992	62.9	35.5
Percent retired by 1992	40.9	3.32
Percent married	81.1	65.6
Percent single female head	14.7	16.9
Age splitoff left home	—	22.9

PSID follows only the original sample member, who is the child of an original PSID family and thus their family information is used throughout. Using the above sample selection criteria, the average main household head in our sample is 62.9 years old in 1992, and by that year 40.9 percent of them have retired. The average age of the splitoffs is 35, and the average age at which they left home is 22.9.

Income data are available in all waves of the PSID. Income refers to noncapital income (that is earnings plus private and government transfer income) of the previous year, so our income data end in 1991. Questions about consumption were asked in all years except 1973, 1988 and 1989. We also cannot use information for 1968 because the question about food consumed outside the home was asked starting in 1969. Following prevailing convention, our consumption variables refer to the year in which the question was asked. After deleting those main households with missing information for some of the years, the average number of usable yearly consumption observations is 20.9. Of these, an average of 2.77 years are spent in retirement. For the splitoff households we have, on average, 11.26 years of consumption information.

We focus on two consumption measures in the empirical work: total food expenditures, and what is referred to below as "weighted consumption." The former is the sum of the amount spent on food consumed both at and away from home, which are measured separately in the PSID. The latter, based on Skinner (1987), is imputed from a linear regression of total consumption taken from the Consumer Expenditure Survey on consumption indicators in the PSID, notably, food consumed in and outside of the home, rent, and house value. The difference between weighted consumption and food, which we refer to as "nonfood" consumption, also will be examined.[7]

Table 2 reports the intergenerational mobility in the distribution of income and both measures of consumption averaged over time. The table reinforces the findings of other studies that average economic well-being (as opposed to economic well-being measured at a point in time) is highly stratified across generations. The distribution of weighted consumption matches up closely with the income distribution. Nearly 40 percent of the children in the lowest quintile of time-averaged consumption have parents who were also in that quintile. Likewise, about 41 percent of the children in the highest quintile have parents who were also in that quintile. In contrast, only a little over eight percent of the children with parents in the lowest consumption quintile made it into the highest consumption quintile after leaving home. Intergenerational mobility, as measured by food consumption, is somewhat less stratified, with 14 percent of splitoffs whose parents were in the lowest quintile making it into the top quintile. Still, 34 percent of the splitoffs in the highest consumption bracket had parents also from that bracket.

Geographic closeness opens up the potential for correlated behavior since splitoffs can more easily imitate and learn from the parents. Panel A of Table 3 shows that immediately following the split, more than 75 percent of the children continue to reside in the same state as their parents. Although this number drops the longer splitoffs remain on their own, even after 20 years, 65 percent of parents and children continue to reside in the same state.

7. As suggested by one of the referees, one could simply think of nonfood consumption as housing consumption. Hamermesh (1984) imputes total consumption based on information from the Retirement History Survey in a similar fashion.

Table 2
Mobility of Income (first row), Weighted Consumption (second row), and Food consumption (third row). Percent of splitoffs quintile by main household quintile

	Splitoffs					Total
Main households	1	2	3	4	5	N
	40.96	24.58	15.25	11.02	8.19	354
1 (lowest)	39.94	23.69	17.63	11.02	7.71	363
	27.35	22.10	20.72	15.75	14.09	362
	21.41	23.10	21.13	19.15	15.21	355
2	24.38	26.59	17.45	19.67	11.91	361
	18.78	20.99	19.06	25.41	15.75	362
	18.03	21.13	21.69	23.10	16.06	355
3	15.24	25.48	24.38	19.11	15.79	361
	24.03	19.61	20.17	19.89	16.13	362
	11.93	18.75	19.89	23.58	25.85	352
4	13.26	15.47	24.03	24.03	23.20	362
	17.73	20.50	23.27	19.39	19.11	361
	7.65	12.46	22.10	23.23	34.56	353
5 (highest)	7.20	8.86	16.34	26.32	41.27	361
	12.19	16.90	16.62	19.67	34.63	361
	354	354	354	354	353	1,769
Total N	362	362	361	362	361	1,808
	362	362	361	362	361	1,808

Table 3 also presents additional indicators of intergenerational correlations. We find a significant intergenerational correlation in total wealth and nonmortgage debt in 1989, but no significant correlation in total debt, including mortgage debt (see Panel B). One implication of the intergenerational transmission of tastes is that there may be similarities in the composition of consumption between parents and the splitoffs. To the extent that dining out is determined by consumer preferences, a significant intergenerational correlation in food consumed outside of the home is suggestive of intergenerational correlations in consumption behavior. The positive correlation reported in Panel C might simply reflect an intergenerational correlation in income. Therefore, we also consider the ratio of food consumed outside the home to total food consumption. As we can see from Table 3 Panel D, the intergenerational correlation of this ratio remains significant in the first 10 years the splitoffs left home. The correlation is nonetheless smaller the longer the splitoffs have been away from home, which accords with the idea that inherited habits might depreciate.

Overall, the crude evidence for intergenerational correlation in consumption appears quite compelling. But these simple statistics do not give any indication about the source of this correlation. In the next section, we go beyond simple correlations and investigate a model that puts more structure on the intergenerational transmission of consumption.

IV. An Econometric Model of Intergenerational Linkages

Our goal is to understand to what extent the intergenerational correlation in consumption is simply a manifestation of income. We begin by setting up some notation. Main households are indexed by $i = 1, \ldots, N$. The i^{th} main household has $K_i \geq 0$ children. Let $x_{i0,t}$ be the value of the variable x for the main household i at time t , and $x_{ij,t}$, $j = 1,\ldots,K_i$ be the value of x for the j^{th} splitoff associated with main household i. Given $x_{ij,t}$, let $\bar{x}_{ij} = \frac{1}{T_{ij}}\Sigma_{t=1}^{T_{ij}} X_{ij,t}$ be the average of $x_{ij,t}$ over the years that the data are available.

We assume that (log) consumption and (log) income are determined by four factors: life cycle effects; business cycle effects; individual-specific time-invariant effects; and individual-specific random effects. We are interested in the intergenerational correlation in the individual-specific effects that are time invariant. As in Altonji, Hayashi, and Kotlikoff (1992), we first regress the log of consumption and the log of income of the main households and the splitoffs on life cycle variables (age, age-squared, family size, marital status, a female head and a retirement dummy) and business cycle variables (an unemployment dummy and year dummies). These auxiliary regressions yield corresponding consumption and income residuals that are orthogonal to business cycle and life-cycle effects. Denote these residuals by $c_{i0,t}$, $c_{ij,t}$, $y_{i0,t}$, and $y_{ij,t}$. Hereafter, we simply refer to these variables as "consumption" and "income."

Our econometric model is specified by (1) an income process for the parents, and one for the splitoffs, (2) a consumption function for parents and one for splitoffs, and (3) the intergenerational transmission of income and tastes.[8]

8. A similar model was used in Altonji and Dunn (2000) to study the intergenerational correlation in earnings and labor supply.

Table 3
Simple Statistics for Main Households and Splitoffs by Years since Splitoff left home

A. Percentage of Splitoffs living in the same State as their Parents

	Full Sample	Restricted Sample
1–5 years after split	77.11	77.13
6–10 years after split	73.92	74.03
11–15 years after split	71.78	71.84
16–20 years after split	69.50	69.48
More than 21 years after split	65.08	65.08

Notes: Full sample: all splitoffs and main households. Restricted Sample: Includes only splitoffs and main households for which there are at least 10 years of splitoff observations on consumption available.

B. Correlations in Asset Measures 1989, Full Sample

	Correlation	p-value
Total wealth	0.148	0.000
Stock ownership	0.142	0.000
Home ownership	0.108	0.000
Total debt	−0.000	0.998
Nonmortgage debt	0.120	0.000

Notes: Wealth and debt are measured in 1996 dollars; stock and home ownership are dummy variables indicating whether the family reports owning any stock or owning a house. Debt is log(debt).

C. Correlations in Food Consumed away from Home

	Full Sample		Restricted Sample	
	Correlation	p-value	Correlation	p-value
1–5 years after split	0.198	0.000	0.197	0.000
6–10 years after split	0.173	0.000	0.183	0.000
11–15 years after split	0.184	0.000	0.186	0.000
16–20 years after split	0.172	0.000	0.171	0.000
More than 21 years after split	0.146	0.000	0.145	0.000

D. Correlations in Food Consumed away from Home relative to Total Food Consumption

	Full Sample		Restricted Sample	
	Correlation	p-value	Correlation	p-value
1–5 years after split	0.152	0.000	0.165	0.000
6–10 years after split	0.105	0.000	0.106	0.000
11–15 years after split	0.027	0.095	0.025	0.132
16–20 years after split	0.040	0.080	0.039	0.088
More than 21 years after split	0.036	0.378	0.033	0.419

Income

We model observed income as follows:

(1) $y_{i0,t} = y_{i0} + z_{i0,t},$
$y_{ij,t} = y_{ij} + z_{ij,t}.$

The variables y_{i0} and y_{ij} are the permanent components of income for the parents and the splitoffs, respectively. With a slight abuse of terminology, we will refer to these as permanent income. The dynamics of income are captured by $z_{i0,t}$ and $z_{ij,t}$. We model these as ARMA (1,1) processes and allow the autoregressive and moving average parameters to be generation specific:

$$z_{i0,t} = \rho_0 z_{i0,t-1} + \varepsilon_{i0,t} + \theta_0 \varepsilon_{i0,t-1},$$

$$z_{ij,t} = \rho_j z_{ij,t-1} + \varepsilon_{ij,t} + \theta_j \varepsilon_{ij,t-1}.$$

Consumption

We posit that consumption is comprised of two mutually uncorrelated components: a systematic component and a transitory component. The systematic component of consumption can be further decomposed into a permanent income and a total taste component.[9] Denote by D_{i0} the total taste of the parents and by D_{ij} the total taste of the splitoffs, respectively. Their consumption functions are

$$c_{i0,t} = a_0 y_{i0} + D_{i0} + e_{i0,t} + k_0 e_{i0,t-1}$$

$$c_{ij,t} = b_0 y_{ij} + D_{ij} + e_{ij,t} + k_j e_{ij,t-1}$$

where $e_{i0,t}$ is the innovation to main household *i's* consumption at time *t*, and $e_{ij,t}$ is similarly defined. We assume that the adjustment of consumption to these innovations takes two periods. Thus, the deviation of actual consumption from its systematic component is a moving average process of order one.

To isolate the pure effect of taste on consumption, we decompose D_{i0} so that it has a permanent income component, and another component, d_{i0}, that is uncorrelated with permanent income. Hereafter, we refer to this latter component as taste. Thus,

$$D_{i0} = f_0 y_{i0} + d_{i0}.$$

This implies that

(2) $c_{i0,t} = a y_{i0} + d_{i0} + e_{i0,t},$

where $a = (a_0 + f_0)$ is the total effect of permanent income on consumption of the main households. To arrive at a consumption equation for the splitoffs, we need to specify the intergenerational transmission of income and tastes.

9. Han and Mulligan (2001), in an otherwise very different model, also emphasize the importance of explicitly recognizing the presence of "taste" heterogeneity in addition to income heterogeneity in analyses of intergenerational mobility.

Intergenerational Linkages

We specify the following intergenerational transmission mechanisms for income and tastes:

(3) $y_{ij} = \phi y_{i0} + u_{ij}$,

(4) $D_{ij} = \gamma_0 d_{i0} + d_{ij}$,

where u_{ij} is the permanent component of income that is splitoff-specific, while d_{ij} is the taste component that is splitoff specific. The parameters ϕ and γ_0 are the effects of parental permanent income and tastes on the income and tastes of the splitoffs, respectively. Allowing d_{ij} itself to have a permanent income (y_{ij}) and a pure taste component (v_{ij}) we have $D_{ij} = \gamma_0 d_{i0} + f_1 y_{ij} + v_{ij}$.

This in turn implies the following consumption equation for the splitoffs:

(5) $c_{ij,t} = \phi b y_{i0} + y_0 d_{i0} + b u_{ij} + v_{ij} + e_{ij,t} + k_j e_{ij,t-1}$

where $b = (b_0 + f_1)$ is the total effect of the splitoff's permanent income on his consumption.

Equations 1–5 define the model. For identification purposes, we assume that (1) permanent and transitory income are uncorrelated, that is $\text{cov}(y_{ij}, \varepsilon_{ik,t}) = 0$, (2) permanent income and transitory consumption are uncorrelated, $\text{cov}(y_{ij}, e_{ik,t}) = 0$, and (3) pure taste is uncorrelated with transitory income and transitory consumption, that is $\text{cov}(d_{ij}, e_{ik,t}) = 0$, $\text{cov}(d_{ij}, \varepsilon_{ik,t}) = 0$ for all i, and for all j, $k = 0, \ldots K_i$. We allow transitory consumption and transitory income to be correlated to accommodate deviations from the permanent income hypothesis, which could arise due to liquidity constraints for example. These assumptions, which amount to treating consumption as the sum of orthogonal components, enable us to identify the intergenerational parameters, ϕ and γ_0. However, we cannot separately identify the direct effect of permanent income on consumption (a_0 and b_0) from the indirect effects (f_0 and f_1) that operate through total tastes.[10] Therefore, we only estimate $a = a_0 + f_0$ and $b = b_0 + f_1$, the total effect of permanent income on consumption of the parents and the splitoffs, respectively.

While in most empirical studies, time invariant effects are not the objects of interest, the focus of this study is precisely to see if the systematic parent-specific effects are correlated with the systematic splitoff-specific effects. One possibility is to separately perform fixed effect estimation of Equations 2 and 5, and then correlate the estimated fixed effect of the parents with the estimated fixed effect of the splitoffs.[11] Another possibility is to simply regress time averaged consumption of the splitoffs on their (time averaged) income and the parents' consumption and income.[12] The main problem with these approaches is that we only have (on average) 11 time series observations for the splitoffs (see Table 1). As is well known, the fixed effect cannot

10. We could have specified $D_{ij} = \gamma_0 d_{i0} + \gamma_1 y_{i0} + f_1 u_{ij} + v_{ij}$, but we also would not be able to identify γ_l and f_1.

11. Performing this correlation yields a correlation coefficient of 0.5, with a p-value of 0.000.

12. To be precise, the regression is $\bar{c}_{ij} = a_0 + a_1 \bar{c}_{i0} + a_2 \bar{y}_{ij} + a_3 \bar{y}_{i0} + error$. Performing such a regression yields an estimate for a_1 of 0.27, and statistically significant. In terms of the parameters of our model, $a_1 = \gamma_0$ and $a_3 = -a \cdot \gamma_0$. A regression of $\bar{c}_{ij}$ on $\bar{c}_{i0}$ yields a highly significant estimated coefficient of 0.43.

be precisely estimated when the number of time periods is short. Furthermore, even if we had a longer panel and the time invariant effects are precisely estimated, the estimated fixed effect is still the sum of an income and a taste effect, and we are interested in whether a pure taste effect remains after controlling for income. As well, estimating the time averaged equation alone would not provide us with the required information to assess the quantitative (not just statistical) importance of the two parental effects, which is an object of independent interest.

We use an estimator that is consistent when the number of cross-section observations is large, even though the time dimension of the panel is short. The approach was used by Altonji and Dunn (2000) in an intergenerational study of labor supply. Abowd and Card (1989), and Baker (1997) also used the same estimator to analyze the dynamics of earnings in the PSID. The idea is to find parameters to match the covariances implied by the model to the sample covariances.[13] More specifically, the ten sample covariances, 16 first order autocovariances, and 16 second order autocovariances provide us with 42 moments (given in Appendix 1) to estimate 20 unknowns.[14] Let D be the 42×1 vector of differences between the sample and the model implied covariances. If the model is correctly specified, D should be a vector with mean zero. The estimates are obtained by minimizing the objective function $D'\Omega D$, where Ω is a weighting matrix. As shown in Chamberlain (1984), this minimum distance estimator is $\sqrt{N}$ consistent for any Ω that is positive definite, where N is the number of observations used to construct the sample moments.

In theory, there exists a weighting matrix Ω that is optimal, in the sense of delivering estimates that are most efficient. As discussed in Altonji and Segal (1996) and Altonji and Dunn (2000), use of the optimal weighting matrix could lead to large finite sample bias in the parameter estimates. Following Abowd and Card (1989) and Altonji and Dunn (2000), we use weighting matrices that do not depend on the parameter estimates. We consider two choices of Ω: an identity matrix, and the inverse of the sample variance of the second moments. The identity matrix weights the moments equally, while the inverse of the variances performs unequal weighting of the moments. The two sets of results are quite similar. To conserve space, we concentrate on the results using the identity matrix (which tend to have larger standard errors).

Because of missing observations and the nonbalanced nature of the panel, the sample used to compute the empirical moments changes with the moment in question. The sample size for the splitoffs is generally larger than for the main households for a given t because each main household can have more than one splitoff. However, data for the splitoffs are available over a shorter span. In consequence, more observations are used to calculate the sample moments for the main households than for the splitoffs.

V. Base Case Results

In our model, the intergenerational transmission of permanent income is captured by the parameter ϕ while γ_0 measures the extent to which there

13. For example, the model implies $\text{cov}(c_{ijt}, y_{i0t-1}) = b\ var(y_{i0})$. The sample analog of the left hand side can be obtained by averaging over all possible cross-products of c_{ijt} and $y_{i0,t-1}$.

14. In the base case, these are a_0, b_0, ϕ, γ_0, var$[d_{i0}]$, var$[d_{ij}]$, var$[y_{i0}]$, var$[y_{ij}]$, var$[\varepsilon_{i0t}]$,var$[\varepsilon_{ijt}]$, var$[e_{i0t}]$, var$[e_{ijt}]$, θ_0, θ_1, ρ_0, ρ_1, k_0, k_1, cov$[e_{i0t}, \varepsilon_{i0t}]$ and cov$(e_{ijt}, \varepsilon_{ijt})$.

remains an intergenerational correlation in consumption after controlling for the parent-child correlation in income. If γ_0 is zero, the parent-child relationship in consumption is just driven by income considerations with little room for intergenerational correlation in tastes.

Table 4 reports what we refer to as "base case" results. These are equally weighted estimates (that is with $\Omega = I$), based on data that include only those splitoffs for whom we have at least ten years of data (which we call the restricted sample). Using food consumption, we obtain a point estimate for ϕ of 0.453, with a standard error of 0.019.[15] Income is therefore transmitted intergenerationally. The statistical significance of ϕ is perhaps not surprising, given the well-documented evidence on the stratification of income. The new and striking result is that γ_0 has a point estimate of 0.224 with a standard error of 0.028. Not only does parental income affect consumption of the splitoffs, the effect of parental tastes is significant even after parental income is taken into account.

The parameters a and b represent the marginal effect of the permanent component of income on consumption. These are estimated to be 0.585 for the main households and 0.544 for the splitoffs, both with tight standard errors. Our ARMA (1,1) estimates for income are (0.777, −0.311) for the main households with standard errors of 0.034 and 0.057. The corresponding estimates for the splitoffs are (0.529, −0.221), with standard errors of 0.092 and 0.090, respectively.[16] Thus, introducing the two parental effects still gives reasonable estimates of the income dynamics and the propensities to consume.

Although the estimates for ϕ and γ_0 are statistically well determined, this does not imply that the effects of parental income and tastes are quantitatively important. This is because the variances of parental tastes and income also matter. The lower panel of Table 4 provides various decompositions to assess the importance of the parental variables. Evaluated at the base case estimates, 5.6 percent of the variation in tastes of the splitoffs is transmitted from parents, and 23.1 percent of the variation in permanent income of the splitoffs is influenced by parental permanent income. Not surprisingly, the parental income effect is larger than the parental taste effect, but the parental taste effect remains nonnegligible even after parental income is taken into account. The combined parental effect accounts for 6 percent of the total consumption, and about 14 percent of the systematic variation in the consumption of the splitoffs.

Results for weighted consumption are reported in the second column of Table 4, while those for nonfood consumption are reported in column 3. Both point estimates for ϕ are around 0.48, while γ_0 is estimated to be 0.450 for weighted consumption, and 0.423 for nonfood consumption. For both measures of consumption, parental tastes account for 22 percent of the child's tastes, and parental permanent income accounts for 27 percent of the child's permanent income.

Notably, the taste effects in the weighted and nonfood consumption measures are significantly larger than the one estimated for food. To the extent that a good part

15. This is in line with estimates for example by Behrman and Taubman (1990); Solon (1992); Zimmerman (1992); and Mulligan (1997).

16. Baker (1997) estimated a more general model for income and obtains autoregressive and moving average parameter estimates of 0.519 and −0.187, respectively, with standard errors of 0.114 and 0.097.

Table 4
Base Case, Splitoffs with 10+ years of data

	Total Food		Weighted Consumption		Nonfood	
	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
a	0.585	0.023	0.846	0.023	0.915	0.025
b	0.544	0.024	0.864	0.025	0.948	0.027
ϕ	0.453	0.019	0.478	0.015	0.479	0.016
γ_0	0.224	0.028	0.450	0.080	0.423	0.067
var $[d_{i0}]$	0.063	0.004	0.026	0.005	0.034	0.005
var $[d_{ij}]$	0.056	0.004	0.024	0.004	0.029	0.005
var $[y_{i0}]$	0.222	0.010	0.212	0.007	0.212	0.007
var $[y_{ij}]$	0.198	0.010	0.179	0.007	0.176	0.007
var $[\varepsilon_{i0t}]$	0.113	0.005	0.114	0.005	0.114	0.005
var $[\varepsilon_{ijt}]$	0.147	0.009	0.158	0.008	0.159	0.008
var $[e_{i0t}]$	0.102	0.005	0.072	0.005	0.073	0.005
var $[e_{ijt}]$	0.162	0.007	0.119	0.006	0.127	0.006
θ_0	-0.311	0.057	-0.320	0.054	-0.320	0.054
θ_j	-0.221	0.090	-0.317	0.066	-0.327	0.065
ρ_0	0.777	0.034	0.798	0.027	0.799	0.027
ρ_j	0.529	0.092	0.659	0.049	0.673	0.047

$corr(e_{i0t},\varepsilon_{i0t})$	0.026	0.023	0.005	0.029	0.006	0.030
$corr(e_{ijt},\varepsilon_{ijt})$	0.097	0.020	0.119	0.023	0.122	0.024
k_0	0.110	0.036	0.198	0.054	0.236	0.058
k_j	0.136	0.025	0.215	0.031	0.243	0.032
$\text{var}[c_{i0t}]$	0.253		0.242		0.289	
$\text{var}[c_{ijt}]$	0.282		0.279		0.322	
Importance of Parental Effects						
$\frac{\gamma_0^2 \text{ var}[d_{i0}]}{\text{var }[d_{ij}]}$	0.056		0.223		0.215	
$\frac{\phi^2 \text{ var}[y_{i0}]}{\text{var}[y_{ij}]}$	0.231		0.272		0.277	
$\frac{\gamma_0^2 \text{ var}[d_{i0}] + b^2\phi^2 \text{ var}[y_{i0}]}{\text{var}[c_{ijt}]}$	0.060		0.147		0.155	
$\frac{\gamma_0^2 \text{ var}[d_{i0}] + b^2\phi^2 \text{ var}[y_{i0}]}{\text{var}[c_{ijt}] - \text{var}[e_{ijt}](1 + k_j^2)}$	0.146		0.264		0.267	

Notes: The results are based on covariance structure estimation of the intergenerational model using the identity matrix as the weighting matrix. The complete moment conditions are given in Appendix 1. The parameters for the intergenerational transmission of income and taste are ϕ and γ_0, respectively.

of food consumption arises as a result of need, it is possible that parental influence is stronger on those components of consumption that the splitoffs have more discretion over. On the other hand, a large component of weighted consumption, and especially nonfood consumption, is housing expenses. If the main household and splitoffs both live in the same city, an unconditional intergenerational correlation in consumption might arise simply because the main household and the splitoffs face the same cost of living. However, cities with high costs of living are also likely to have high wage rates. If cost of living was the only cause of the intergenerational correlation, we would expect the correlation to be much reduced once we control for income. Our finding that the conditional correlation is significant is thus a strong result. It indicates that income is not the only conduit for intergenerational correlation, and that family links can generate a correlation in the unobserved heterogeneity of two households.

VI. Sensitivity Analysis

Our base case results suggest that there is a statistically significant and quantitatively nonnegligible parental influence on consumption of the splitoffs that is unrelated to income. To check the sensitivity of the results, we reestimated the model with a number of modifications made to the base case. To conserve space, we only report results for the main parameters of interest, ϕ and γ_0, as well as two statistics from the decomposition of variances:- one summarizing the importance of parental tastes in the child's taste, and one summarizing the combined effect of parental tastes and income in the systematic component of the child's consumption. These will be labeled "parental taste" and "total parental effect" in Table 5.

A. Private Transfers

Transfers enable households to consume more than their earned resources permit. Our measure of income includes transfers, and it is well-documented that inter-vivos transfers are made predominantly by the rich.[17] The significant estimate for γ_0 might simply be driven by the rich in the sample. We address this issue in a number of ways.

First, we have annual information on whether the splitoffs received help from relatives (not necessarily parents). On average, 5 percent of the respondents received help. The PSID also allows us to identify the year a house was purchased. We then construct a sample of parent-splitoff pairs in which the splitoffs received no financial help when buying a house. Such a sample can loosely be thought of as comprising those that did not receive help towards the down payment of a house. The results in Table 5, rows one and three indicate point estimates for γ_0 of 0.218 for food and 0.552 using weighted consumption, and both estimates are precisely determined. The parental taste effects are 0.053 and 0.28, while the total parental effects are 0.141 and 0.268, respectively.[18]

17. See, for example, Gale and Scholz (1994).

18. If we do not condition on buying a house and estimate a sample of all those not reporting any financial help received, the point estimates for γ_0 are 0.220 and 0.441, respectively.

Table 5
Sensitivity Analyses—Selected Coefficients and Variance Decompositions

	ϕ		γ_0		Importance of Parental Effects	
	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Parental Taste	Total Parental Effect
No help with down payment food	0.444	0.019	0.218	0.029	0.053	0.141
No transfers reported food	0.446	0.027	0.300	0.044	0.110	0.175
No help with down payment weighted consumption	0.470	0.016	0.552	0.108	0.280	0.268
No transfers reported weighted consumption	0.467	0.020	0.616	0.130	0.430	0.288
Low income sample	0.319	0.033	0.184	0.038	0.041	0.085
High income sample	0.172	0.025	0.305	0.061	0.107	0.101
Daughters only	0.378	0.026	0.248	0.047	0.065	0.119
Sons only	0.521	0.027	0.209	0.035	0.052	0.174
Residing in the same state	0.448	0.022	0.286	0.035	0.090	0.178
Not in the same state	0.490	0.052	0.057	0.067	0.003	0.052
Not related—same state	0.196	0.012	0.068	0.016	0.014	0.055
Not related—similar income	0.318	0.018	0.020	0.032	0.000	0.036
Not related—similar schooling	0.194	0.018	0.041	0.025	0.002	0.018
WLS	0.446	0.019	0.213	0.026	0.052	0.121
Trimmed outliers	0.348	0.017	0.236	0.028	0.067	0.120
All splits	0.456	0.017	0.229	0.029	0.057	0.147
Measurement error	0.545	0.055	0.303	0.074	0.124	0.283

Parental taste: $\dfrac{\gamma_0^2 \operatorname{var}[d_{i0}]}{\operatorname{var}[d_{ij}]}$; total parental effect: $\dfrac{\gamma_0^2 \operatorname{var}[d_{i0}] + b^2\phi^2 \operatorname{var}[y_{i0}]}{\operatorname{var}[c_{ijt}] - \operatorname{var}[e_{ijt}](1 + k_j^2)}$

Second, the 1988 wave of the PSID collected detailed information on money and time transfers of PSID families. We focus on whether splitoffs received financial help from parents, and about 15 percent of the sample responded positive. We then reestimate the model using only those parents-splitoffs pairs that responded no help was received in 1988.[19] Using information in one year to split the sample for all years is less than ideal, but is the best that could be done given the data available. With this caveat in mind, the results reported in rows two and four show a point estimate for γ_0 of 0.300 for food and 0.616 for weighted consumption, giving estimates of the parental taste effect of 0.11 and 0.43, respectively.

The results thus indicate that even for the samples in which financial transfers amongst family members are not prevalent, the parental taste effect is statistically well determined. It also appears that there is a stronger parental taste effect in total consumption than food. The point to be emphasized is that an intergenerational taste effect is present in different measures of consumption, not just food. Hereafter, additional sensitivity analysis will be performed taking the more conservative food estimate as our benchmark.

B. Liquidity Constraints

Even if a splitoff has tastes similar to those of his parents, his availability of resources will override his preferences if he faces liquidity constraints. One would expect the parental taste effect to be weaker for a poor than a rich splitoff. To see if this is the case, we use the average income (over time) of the splitoffs to split the sample. If a splitoff's average income is above the median, he is in the "high income" sample. Otherwise, he is in the "low income" sample. The results are reported in rows five and six. The point estimate for γ_0 is 0.305 for the high income sample and 0.184 for the low income sample, with corresponding parental taste effects of 0.107 and 0.041, respectively. This result is consistent with our conjecture that the effect of parental tastes is stronger when the splitoffs are not constrained by the availability of resources. Nonetheless, even in the sample of the low income households, a significant parental taste effect is found.

C. Gender

In our analysis, we use all splitoff observations available, regardless of gender. In contrast, other researchers often confine their sample to sons, for example Altonji, Hayashi, and Kotlikoff (1992) and Mulligan (1997). While we control for single female heads of household, it is conceivable that the intergenerational correlation in tastes differs for daughters and sons. We thus reestimate the model separately for sons and daughters. The results are shown in rows seven and eight. They are very similar to the base case. While γ_0 is smaller for sons, the difference with that of the daughters is small. We can thus conclude that the gender of the splitoff does not matter for our analysis. The parental effect is still significant in the data.

19. We also included a dummy variable in the first step regression to flag observations that received no transfer. The estimate for γ_0 is 0.223 with a standard error of 0.028.

D. Location

Cohabitation provides the environment for imitation and acquisition of tastes. But tastes and habits acquired from the parents also can be unlearned. The effect of parental tastes is less likely to "depreciate" the more frequently the two generations interact. One way to measure the degree of interaction is geographic distance. This leads to the hypothesis that the parental taste effect is stronger the closer the two generations live.

We reestimate the model on two subsamples, depending on whether the parents and the splitoffs live in the same state. As seen from Table 3, over 65 percent of the parents-splitoffs pairs live in the same state even 20 years after the splitoffs left their parents. Inevitably, the "living in the same state" sample is larger than the "not living in the same state." The point estimate for γ_0 is 0.286 for the sample that lives in the same state, with parental tastes accounting for 9 percent of tastes of the splitoffs. For the sample labeled "not in the same state," γ_0 is small and not statistically different from zero (0.057 with a standard error of 0.067). How far two generations live apart does seem to determine the strength of the intergenerational correlation.

E. Strangers

Another way to check whether the correlation in tastes can indeed be attributed to familial relationships is to pair children with strangers rather than their own parents. If we find a correlation in tastes between pairs of strangers similar to the one we find between parents and the splitoffs, we would be concerned that the so-called intergenerational taste effect is merely picking up omitted factors that shape the tastes of the two generations.

We first check our result that kids' and parents' tastes are more highly correlated when they live in close proximity by constructing a sample of parents and children that live in the same state, but are not related. From all possible pairings, we create random subsamples of size similar to the one used in the estimation above. Averaging over ten such subsamples gives estimates of ϕ and γ_0 of 0.196 and 0.068, respectively. Although both are statistically significant, these estimates for stranger pairs living in the same state are much smaller than the ones obtained for related parents and children living in the same state. As well, the parental taste effect is now negligible (0.014).

We also consider two additional samples that combine observations from two generations that are not biologically related, but share other similarities. First, we compute a splitoff's average income over the sample period. Then, we pair parents with (unrelated) splitoffs that come from the same income quintile as their actual children (see Table 2). Secondly, we combine parents with splitoffs that have the same number of years of schooling as their own children. The results of this exercise show that while most of the generation-specific parameters, such as the propensities to consume, are of similar magnitude as in the base case, the intergenerational parameters are much smaller, and more specifically, γ_0 has now become insignificant. Parental tastes explain almost none of the variation in tastes of the splitoffs. It should be remarked that we also tried a number of other criteria to match parents with nonrelated children, including random matching. In many cases, convergence could not be achieved. This is not surprising given that we were looking for intergenerational correlations in unrelated parent-child pairs. In light of these results, we are even more confident that the correlation in consumption we find after controlling for income indeed stems from familial relationships.

F. Outliers and Measurement Errors

We proceed with a final check of the sensitivity of our base case estimates to data irregularities and the choice of the weighting matrix. In the row labeled "WLS," we report estimates using the inverse of the variance of the moments as the weighting matrix. The point estimate of γ_0 is 0.213 and remains statistically significant.

A problem that every user of the PSID has to confront is measurement error. While we provide no solution to this problem, we performed additional estimations to gauge the robustness of the results. First, we removed some outliers from the sample. Specifically, we removed splitoff families whose average income falls into the top or bottom 2.5 percent of the distribution. Apart from a smaller point estimate for ϕ (now 0.348 compared to the base case of 0.453), the results are qualitatively and quantitatively similar to those of the base case. The results in the second to last row of Table 5 are based on data of all the splitoffs, not just those with at least ten years of data. Again, the results are similar to the base case.

An approach sometimes used to deal with measurement error in the PSID is to average the data over time (Solon 1992; Zimmerman 1992). Since we exploit the model's first and second order autocovariance properties to estimate the parameters, we averaged our data to obtain three nonoverlapping "periods" so that second order autocovariances can still be constructed. The estimates based on these time-averaged data are reported in the last row of Table 5. Because one period is now several years, the moving-average terms are not well-determined and dropped from the model. However, the point estimate of our key parameter, γ_0, is 0.303 and remains statistically well determined. Parental tastes now account for 12 percent of tastes of the splitoffs, while the total parental effect is 0.283. These effects are even larger than the base case estimates.

To summarize, our estimates for γ_0 in Table 5 are generally between 0.2 and 0.3 when considering samples of parents and their actual children, with parental tastes explaining roughly 5 to 10 percent of tastes of the splitoffs' food consumption. There is clear and rather robust evidence of an intergenerational correlation in consumption even after controlling for income.[20]

VII. Conclusion

There are many channels through which the consumption of parents and children might be linked. Previous studies in the literature have focused on the intergenerational transmission of income. In this paper, we consider the possibil-

20. If tastes consist of a parental and an individual component, then our intergenerational model implies that siblings' tastes should be correlated to the extent that a parental taste effect exists. In an earlier version of the paper, we consider a test for the presence of a parental effect without direct use of the parental information. We find a siblings taste effect that is statistically significant and larger than the intergenerational one. These results are available upon request.

ity that parental effects unrelated to income—referred to as parental tastes in the analysis—also could be transmitted from one generation to the next. We focused on isolating the systematic effects of the parental variables on consumption of the splitoffs. The main finding is that both parental income and tastes have statistically significant effects on consumption of the splitoffs. For food consumption, between 5 to 10 percent of variations in tastes of the splitoffs are linked to parental tastes. The taste effect remains well-determined (and is in fact larger) for other constructed measures of consumption. Our results are robust to various kinds of transfers, liquidity constraints or the location of parents and their splitoffs. Evidently, the finding on income is consistent with Becker's investment view of human capital and reinforces the importance of income as a channel of intergenerational transmission. The finding concerning parental tastes is consistent with the view that splitoffs imitate their parents or unintentionally acquire their habits.

Our sample is restricted to households with at least ten years of data on income and consumption. It is by examining the data over time that we hope to determine if systematic intergenerational correlations in consumption and income exist. A complementary approach is to look for an intergenerational correlation in consumption via wealth, an exercise undertaken by Charles and Hurst (2003). But to the extent that wealth and income are linked through the budget constraint, we should still be able to identify an effect unrelated to economic well-being whether we use wealth or income for the analysis. Indeed, Charles and Hurst present evidence to suggest that imitating parental behavior and/or inheriting parental preferences could explain the propensities to save of the splitoffs, which corroborate our main finding. Consumption appears not to be an isolated activity as standard theories of consumption posit.

Appendix 1

Estimation Details

For convenience, define $w_{i0t} = e_{i0t} + k_0 e_{i0t-1}$, $w_{ijt} = e_{ijt} + k_j e_{ijt-1}$, $a = a_0 + f_0$ and $\bar{b} = b_0\phi + \gamma_1$.

The 10 moments based on contemporaneous covariance are:

$$A1.\quad \text{var}[c_{i0t}] = a^2\,\text{var}[y_{i0}] + \text{var}[d_{i0}] + \text{var}[e_{i0t}](1 + k_0^2),$$

$$A2.\quad \text{var}[c_{ijt}] = \bar{b}^2\,\text{var}[y_{ij}] + \text{var}[d_{ij}] + \text{var}[e_{ijt}](1 + k_j^2),$$

$$A3.\quad \text{cov}[c_{i0t}, c_{ijt}] = \gamma_0\,\text{var}[d_{i0}] + a\bar{b}\,\text{var}[y_{i0}],$$

$$A4.\quad \text{var}[y_{i0t}] = \text{var}[y_{i0}] + \text{var}[z_{i0t}](0),$$

$$A5.\quad \text{var}[y_{ijt}] = \text{var}[y_{ij}] + \text{var}[z_{ijt}](0),$$

$$A6.\quad \text{cov}[y_{i0,t}, y_{ij,t}] = \phi\,\text{var}[y_{i0}],$$

$$A7.\quad \text{cov}[c_{i0,t}, y_{i0,t}] = a\,\text{var}[y_{i0}] + \text{cov}(e_{i0t}, z_{i0t}),$$

$$A8.\quad \text{cov}[c_{i0,t}, y_{ij,t}] = a\phi\,\text{var}[y_{i0}],$$

$$A9.\quad \text{cov}[c_{ij,t}, y_{i0,t}] = \bar{b}\,\text{var}[y_{ij}],$$

$A10.\quad \text{cov}[c_{ij,t},y_{ij,t}] = \bar{b}\phi\ \text{var}[y_{ij}] + (b_0 + f_1)\ \text{var}(u_{ij}) + \text{cov}[e_{ijt},z_{ijt}].$

For $k = 1$, we have the following 16 autocovariances:

$B1.\quad \text{cov}[c_{i0,t},c_{i0,t-k}] = \text{var}[d_{i0}] + a^2\ \text{var}[y_{i0}] + k_0\ \text{var}[e_{i0}],$

$B2.\quad \text{cov}[c_{ij,t},c_{ij,t-k}] = \gamma_0^2\ \text{var}[d_{ij}] + \bar{b}^2\ \text{var}[y_{ij}] + (b_0 + f_l)^2\ \text{var}[u_{ij}] + \text{var}[v_{ij}] + k_j\ \text{var}[e_{ijt}],$

$B3.\quad \text{cov}[y_{ij,t},y_{ij,t-k}] = \phi^2\ \text{var}[y_{i0}] + \text{var}[u_{ij}] + \text{var}[z_{ijt}](k),$

$B4.\quad \text{cov}[y_{i0,t},y_{i0,t-k}] = \text{var}[y_{i0}] + \text{var}[z_{i0,t}](k),$

$B5.\quad \text{cov}[c_{i0,t},y_{i0,t-k}] = a\ \text{var}[y_{i0}] + \text{cov}[w_{i0,t-k},z_{i0t}]$

$B6.\quad \text{cov}[c_{i0,t-k},y_{i0,t}] = a\ \text{var}[y_{i0}] + \text{cov}[w_{i0,t-k},z_{i0t}],$

$B7.\quad \text{cov}[c_{ij,t},y_{ij,t-k}] = \bar{b}\ \phi\ \text{var}[y_{i0}] + (b_0 + f_l)\ \text{var}[u_{ij}] + \text{cov}[w_{ij,t-k},z_{ijt}],$

$B8.\quad \text{cov}[c_{ij,t-k},y_{i0,t}] = \bar{b}\ \text{var}[y_{i0}],$

$B9.\quad \text{cov}[c_{i0,t},c_{ij,t-k}] = \gamma_0\ \text{var}[d_{i0}] + a\bar{b}\ \text{var}[y_{i0}],$

$B10.\quad \text{cov}[c_{i0,t-k},c_{ij,t}] = \gamma_0\ \text{var}[d_{i0}] + a\bar{b}\ \text{var}[y_{i0}],$

$B11.\quad \text{cov}[c_{i0,t-k},y_{ij,t}] = a\phi\ \text{var}[y_{i0}],$

$B12.\quad \text{cov}[c_{ij,t-k},y_{ij,t}] = \bar{b}\ \phi\ \text{var}[y_{i0}] + (b_0 + f_1)\ \text{var}[u_{ij}] + \text{cov}[w_{ij,t-k},z_{ijt}],$

$B13.\quad \text{cov}[c_{ijt},y_{i0,t-k}] = \bar{b}\ \text{var}[y_{i0}],$

$B14.\quad \text{cov}[c_{i0,t},y_{ij,t-k}] = a\phi\ \text{var}[y_{i0}],$

$B15.\quad \text{cov}[y_{i0,t},y_{ij,t-k}] = \phi\ \text{var}[y_{i0}],$

$B16.\quad \text{cov}[y_{i0,t-k},y_{ij,t}] = \phi\ \text{var}[y_{i0}],$

with $\text{cov}[w_{i0,t},z_{i0t}] = \text{cov}[e_{i0t},\varepsilon_{i0t}](1 + k_0(\rho_0 + \theta_0))$

$\text{cov}[w_{ijt},z_{ij,t}] = \text{cov}[e_{ijt},\varepsilon_{ijt}](1 + k_j(\rho_j + \theta_j))$

$\text{cov}[w_{i0,t},z_{i0t-1}] = k_0\ \text{cov}[e_{i0t},\varepsilon_{i0t}]$

$\text{cov}[w_{i0,t-1},z_{i0t}] = (1 + k_0\rho_0(\rho_0 + \theta_0))\text{cov}[e_{i0t},\varepsilon_{i0t}]$

$\text{cov}[w_{ijt},z_{ij,t-1}] = k_j\ \text{cov}[e_{ijt},\ \varepsilon_{ijt}]$

$\text{cov}[w_{ij,t-1},z_{ij,t}] = (1 + k_j\rho_j(\rho_j + \theta_j))\ \text{cov}[e_{ijt},\ \varepsilon_{ijt}]$

$\text{var}[z_{i0t}](0) = \sigma_{\varepsilon_o}^2(1 + (\rho_0 + \theta_0)^2/(1 - \rho_0^2)),$

$\text{var}[z_{ijt}](0) = \sigma_{\varepsilon_j}^2(1 + (\rho_j + \theta_j)^2/(1 - \rho_j^2)),$

$\text{var}[z_{i0t}](1) = \sigma_{\varepsilon_0}^2((\rho_0 + \theta_0) + (\rho_0 + \theta_0)/(1 - \rho_0^2)),$

$\text{var}[z_{ijt}](1) = \sigma_{\varepsilon_j}^2((\rho_j + \theta_j) + (\rho_j + \theta_j)/(1 - \rho_j^2)),$

For $k \geq 2$, we also have 16 covariances:

$C1.\quad \text{cov}[c_{i0t},c_{i0t-k}] = \text{var}[d_{i0}] + a_2\ \text{var}[y_{i0}],$

$C2.$ $\text{cov}[c_{ijt,t}, c_{ij,t-k}] = \gamma_0^2 \text{var}[d_{ij}] + \bar{b}^2 \text{var}[y_{ij}] + (b_0 + f_1)^2 \text{var}[u_{ij}] + \text{var}[v_{ij}],$

$C3.$ $\text{cov}[y_{ijt,t}, y_{ij,t-k}] = \phi^2 \text{var}[y_{i0}] + \text{var}[u_{ij}] + \text{var}[z_{ijt}](k),$

$C4.$ $\text{cov}[y_{i0t}, y_{i0,t-k}] = \text{var}[y_{i0}] + \text{var}[z_{i0,t}](k),$

$C5.$ $\text{cov}[c_{i0t}, y_{i0,t-k}] = a \text{ var}[y_{i0}],$

$C6.$ $\text{cov}[c_{i0t-k}, y_{i0,t}] = a \text{ var}[y_{i0}] + \text{cov}[w_{i0,t-k}, z_{i0t}],$

$C7.$ $\text{cov}[c_{ijt,t}, y_{ij,t-k}] = \bar{b}\phi \text{ var}[y_{i0}] + (b_0 + f_1) \text{ var}[u_{ij}],$

$C8.$ $\text{cov}[c_{ij,t-k}, y_{i0t}] = \bar{b} \text{ var}[y_{i0}],$

$C9.$ $\text{cov}[c_{i0t}, c_{ij,t-k}] = \gamma_0 \text{ var}[d_{i0}] + a\bar{b} \text{ var}[y_{i0}],$

$C10.$ $\text{cov}[c_{i0t-k}, c_{ij,t}] = \gamma_0 \text{ var}[d_{i0}] + a\bar{b} \text{ var}[y_{i0}],$

$C11.$ $\text{cov}[c_{i0t-k}, y_{ij,t}] = a\phi \text{ var}[y_{i0}],$

$C12.$ $\text{cov}[c_{ijt,t-k}, y_{ij,t}] = \bar{b}\ \phi \text{ var}[y_{i0}] + (b_0 + f_1) \text{ var}[u_{ij}] + \text{cov}[w_{ij,t-k}, z_{ijt}],$

$C13.$ $\text{cov}[c_{ijt}, y_{i0,t-k}] = \bar{b} \text{ var}[y_{i0}],$

$C14.$ $\text{cov}[c_{i0t}, y_{ij,t-k}] = a\ \phi \text{ var}[y_{i0}],$

$C15.$ $\text{cov}[y_{i0t}, y_{ij,t-k}] = \phi \text{ var}[y_{i0}],$

$C16.$ $\text{cov}[y_{i0t-k}, y_{ij,t}] = \phi \text{ var}[y_{i0}],$

with

$$\text{cov}[w_{i0t-k}, z_{i0,t}] = \rho_0^{k-1}(1 + k_0\rho_0)(\rho_0 + \theta_0)\text{cov}[e_{i0t}, \varepsilon_{i0t}]$$

$$\text{cov}[w_{ij,t-k}, z_{ij,t}] = \rho_j^{k-1}(1 + k_j\rho_j)(\rho_j + \theta_j)\text{cov}[e_{ijt}, \varepsilon_{ijt}]$$

Recall that consumption and income are regression residuals from a first step regression with time dummies and are mean zero for any period. Thus, as an example, $\text{var}[c_{i0t}]$can be estimated as follows

$$\text{var}[c_{i0t}] = \frac{1}{NT}\sum_{i=1}^{N_i}\sum_{t=1}^{T} c_{i0t}^2,$$

where $N = \Sigma_{t=1}^{T} N_t$, N_t is the number of main households for which consumption data are available in period t. Likewise, cov $[c_{ij,t}, c_{ij,t-1}]$ is replaced by

$$\text{cov}[c_{i0,t}, c_{ij,t-1}] = \frac{1}{NT}\sum_{i=1}^{N_t}\sum_{t=1}^{T}\sum_{j=1}^{K_{it}} c_{i0,t}c_{ijt-1},$$

where K_{it} is the number of splitoffs associated with main household i at time t, and $N = \Sigma_i\Sigma_t K_{it}N_t$ is now the number of observations for which consumption of the main household and lagged consumption of the splitoffs are both available.

Appendix 2

Notes on the weighted consumption measure

Aside from the usual problems of mismeasurement of consumption, the PSID unfortunately provides only three elements of consumption. These are food consumed at home, food consumed away from home, and the value of food stamps received. Since our model pertains to total consumption, we would prefer to have information on all elements of consumption. Even though this information is not available, there is a way to proxy for total consumption, using just the consumption elements available in the PSID. Jonathan Skinner (Skinner 1987) proposes a technique that relies on a linear regression of total consumption taken from the Consumer Expenditure Survey (CEX) on consumption elements available in the PSID, such as food at home, food consumed away from home, the house value, rent, utility payments, and the number of automobiles (see also Hamermesh 1984). The regression, which is performed for the years 1972/73 and 1983, yields a set of coefficients which can then be used for other years to compute an estimate of total consumption. They appear to be very stable over time, which Skinner shows by predicting 1983 consumption using the coefficients estimated from the 1972/73 regression. The correlation between predicted values using either set of coefficients exceeds 0.98 regardless of the precise specification used. Using only food at home, food away from home, rent, and the house value in a regression yields an $\bar{R}^2$ of 0.9724 for 1972/73, which hardly increases when adding utility payments and automobiles. The problem with including the other elements for our purposes is that utility payments were last asked in the 1987 survey while the number of automobiles per family is last reported in the 1986 survey. However, since the increase in predictive power through the use of these additional elements is small in any case, we construct total consumption measures using Skinner's estimated coefficients from the specification that only includes the four basic elements.

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