Income Shocks, Food Expenditures, Calorie Intake and Body Weight: A multilevel structural equation modelling analysis

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We develop multilevel structural equation models to jointly estimate the extent to which unanticipated income shocks affect household-level food expenditures, and individual-level calorie intake and body weight. Drawing on economic theory, we start by decomposing the income process into shocks that only affect the current period ('transitory shocks', such as getting a bonus) and those that affect the current period as well as all future periods ('permanent shocks', such as a promotion or being made redundant). We then exploit time variation in the second order moments of the income process to estimate the effects of permanent and transitory shocks on household- and individual-level responses to such shocks, accounting for the clustering of individuals' diets within households. We find that – consistent with the economic theory – permanent income shocks have large effects on food expenditure, calorie intake and body weight, with much smaller, often insignificant, effects of transitory shocks.

Key words: Latent variables; Multilevel structural equation model; Multilevel multiple imputation model; Permanent and transitory income shocks

1. Introduction

A large literature examines the effects of income (shocks) or economic conditions on individual health and nutritional outcomes. With the global economic expansion until 2007/08 and the subsequent recession, this remains an important area of research. We examine the welfare implications of income shocks, focussing in particular on individual BMI and nutritional outcomes. More specifically, we examine the effects of household-level permanent and transitory income shocks on individual-level body weight and nutritional intakes. We study this in a unique context, using the Russia Longitudinal Monitoring Survey (RLMS).

2. The empirical framework

2.1 The income process

We model income as a stochastic process. To distinguish between the permanent and transitory components, we use the statistical framework introduced by MaCurdy (1982), and Meghir and Pistaferri (2004). We model real log disposable income as:

$$Y_{h,t} = Z'_{h,t}\beta_t + u^Y_{h,t}, \tag{1}$$

where $Z_{h,t}$ denotes a set of covariates of household h at time t, with a vector of year-specific coefficients β_t. The covariates include indicators for the number of children in the household (0, 1, 2, and ≥3), location characteristics (an urban dummy, indicators for Moscow and St. Petersburg, and the federal districts), a set of indicators for educational attainment of the adult household members, and a quartic polynomial in the age of the adult household members. We define $u^Y_{h,t} = Y_{h,t} - Z'_{h,t}\beta_t$ as the log of real disposable household income net of predictable components, which we decompose into the sum of a permanent ($P_{h,t}$) and transitory ($v_{h,t}$) component:

$$u^Y_{h,t} = P_{h,t} + \varepsilon_{h,t}.$$

We assume that permanent income follows a martingale

$$P_{h,t} = P_{h,t-1} + \eta_{h,t},$$

where $\eta_{h,t}$ are the permanent income shocks that are independently and identically distributed (i.i.d.) across h and t. Examples of such a shock are a promotion, or some technological shock that makes one's skills more or less valuable in the labour market, affecting not only contemporaneous income, but also that in the future. The transitory component is given by $\varepsilon_{h,t}$, which we model as an i.i.d. process. Examples of transitory shocks can be involuntary leave, wage delays, or a bonus. We assume that the permanent and transitory income shocks have mean zero and are uncorrelated: $E(\eta_{h,t}) = E(\varepsilon_{h,t}) = E(\eta_{h,t}\varepsilon_{h,t}) = 0$, for all $h = 1, \dots, H$ and $t = 1994, \dots, 2005$. It follows that unexplained income growth $\left(\Delta u^Y_{h,t} = u^Y_{h,t} - u^Y_{h,t-1}\right)$ can be written as:

$$\Delta u_{h,t}^{Y} = \eta_{h,t} + \Delta\varepsilon_{h,t}. \quad (2)$$

2.2 Income and BMI

We estimate the degree of transmission of income shocks to individual-level BMI. For this, we follow the framework introduced by Blundell, Pistaferri and Preston (2008) and model the residual (unexplained) BMI growth, obtained using the same approach as above and denoted by $\Delta u_{ih,t}^{B}$, where i, h, and t denote the individual, household and year, and the superscript B denotes the BMI residual. We define $i = 1,2$ as the husband and wife respectively.

Note that the income shocks are measured at the household level, whereas the response is measured at the individual level. As we discuss below, our sample is restricted to households with two adult household members. Hence, when we estimate the income process jointly with the model for BMI, we specify two equations, one for each adult. To allow for the fact that it takes time to gain or lose weight, we specify unexplained BMI growth as a function of one year *lagged* income shocks:

$$\Delta u_{1h,t}^{B} = \phi_1^B \eta_{h,t-1} + \psi_1^B \varepsilon_{h,t-1} + \Delta\xi_{1h,t}^{B} \quad (3a)$$

$$\Delta u_{2h,t}^{B} = \phi_2^B \eta_{h,t-1} + \psi_2^B \varepsilon_{h,t-1} + \Delta\xi_{2h,t}^{B}. \quad (3b)$$

This allows for the permanent and transitory income shocks $\eta_{h,t-1}$ and $\varepsilon_{h,t-1}$ to have an impact on BMI with factor loadings ϕ_i^C and ψ_i^C respectively. Note that we estimate different factors loadings for the two household members, allowing for income shocks to differentially affect men and women. The term $\Delta\xi_{ih,t}$ denotes innovations to BMI that are independent of those in income, which may capture factors such as measurement error in BMI, and preference shocks. Furthermore, we allow the contemporaneous levels of innovations in BMI to be correlated: $\sigma_{\xi 12,t} \neq 0$.

We further explore the effects of income shocks on calorie intakes and on dietary quality or composition, as proxied by individual fat and protein intakes. We jointly estimate the income process (2) with the equations for calories, fat and protein (not shown here), allowing for income shocks to have different effects on men and women’s fat and protein intake. However, rather than a lagged effect, we specify the responses as a function of contemporaneous income shocks.

3. Data

We use the Russia Longitudinal Monitoring Survey (RLMS) from 1994 to 2005. Our sample selection process is as follows. First, to obtain a homogeneous sample, we restrict the data to households with two adult members, a husband and wife, both aged between 18 and 60. We exclude households that break up to ensure our sample composition remains the same throughout the observation period. Furthermore, as we model changes in income, expenditures and diet, we drop households that are only observed once. This leads to a sample of 3472 adults nested within 1736 households.

We create a balanced panel, where all households and individuals are represented from 1994 to 2005. For individuals with missing years of data, we impute covariates such as age, education and region using the information from previous waves. We deal with further missing values on income, expenditures, and nutritional intakes, using multiple multivariate imputation, taking account of the hierarchical clustering in the data of years nested within individuals, nested within households.

The imputation model assumes that the data are Missing At Random (MAR). Although we cannot directly test whether the assumption holds, we include several covariates in the imputation model that may affect the missingness, such as the educational level of the two adult household members, a quartic polynomial in the age of both members, the number of children, and a set of location characteristics.

We impute ten complete datasets, using multivariate imputation of chained equations (ICE), also known as Fully Conditional Specification (FCS; van Buuren et al., 1999), or sequential regression multivariate imputation (SRMI; Raghunathan et al., 2001). It accommodates arbitrary missing-value patterns, imputing multiple variables iteratively via a sequence of univariate imputation models, one for each imputation variable, with FCSs of prediction equations (chained equations). We estimate the models of interest on each imputed dataset, and combine the estimates and standard errors using Rubin's (1987) rules to reflect missing data uncertainty.

Our measure of income is the logarithm of real monthly household disposable income, measured over the 30 days prior to the interview. We use individuals' BMI, obtained from measured heights and weights, and nutritional intakes, obtained from 24-hour dietary recalls of each household members' food intake. We further distinguish between expenditures on different types of food groups, including grain, meat, dairy, fruit, sweets, and beverages. Income and expenditures are deflated to December 2000 prices using the national monthly CPI at the date of interview.

4. Results

The income-only model suggests that the variance of permanent shocks is relatively stable over time, whilst there is a clear reduction in the variance of transitory shocks. This is consistent with Gorodnichenko et al. (2010) and with the economic volatility during this period: factors such as wage arrears and involuntary leave were common during the downturn, but reduced substantially during the recovery. As these are temporary changes, they are reflected by an increased variance in transitory shocks.

Table 1: Estimates of the joint income-BMI model

	Men		Women	
	Estimate	Std. err.	Std. err.	Std. err.
Permanent shock: ϕ	4.261	(0.160)	5.914	(0.229)
Transitory shock: ψ	0.080	(0.071)	0.116	(0.079)
Log-Likelihood	-80675			

Notes: Standard errors in parentheses, clustered by household.

The factor loadings obtained from the joint income-BMI model of (2), (3a) and (3b), presented in Table 1, showing that positive shocks to income increase BMI, with larger effects for women than men. This suggests that a 10% positive permanent income shock increases men's BMI by 0.43 units, and women's BMI by 0.59 units, with transitory shocks having little to no effects. Put differently, for the average male and female height of 1.73m and 1.60m respectively, a 10% permanent income shock translates into a weight change of approximately 0.33-1.3kg (men) and 1.5 kg (women) one year later. We next examine whether this may be driven by increases in individual calorie intake in response to income shocks.

Table 2 shows the estimates from the joint income-calorie intake model, suggesting that positive permanent and transitory income shocks increase calorie intake for both men and women, though the effects are larger for men. A 10% positive permanent income shock increases men and women's calorie intake by 75 and 52 calories per day respectively (note that calorie intake is measured in 1000s). Although this may seem like a small change, this refers to the *daily* calorie intake. Hence, as 3,500 calories, on average, equal one pound, it would take men 47 and women 67 days to gain one pound due to a 10% permanent income shock.

Table 21: Estimates of the joint income-calorie intake model

	Men		Women	
	Estimate	Std. err.	Std. err.	Std. err.
Permanent shock: ϕ	0.752	(0.156)	0.518	(0.121)
Transitory shock: ψ	0.100	(0.041)	0.028	(0.031)
Log-Likelihood		-56521		

Notes Calorie intake is measured in 1000's. Standard errors in parentheses, clustered by household.

To explore these results in more detail, we next examine whether these effects may be driven by a change in the quality or composition of the diet, estimating the effects of income shocks on individuals' fat and protein intake as a proportion of the total calorie intake. The results (available from the authors upon request) show that permanent income shocks significantly affect both fat and protein intake for men and women, with no large differences between the genders. In addition, we find that shocks change individuals' diet composition, increasing fat intakes disproportionately, with smaller changes in protein intakes.

To examine whether the change in calorie intake and nutritional composition is consistent with observed changes in household food purchasing behaviour in response to income shocks, we estimate bivariate models of income and food expenditure. As we do not observe expenditures at the individual level, we estimate the model at the household level.

Table 3: Estimates of the income-expenditure model, distinguishing by food group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All food	Grains	Meat	Dairy	Fruit & Veg	Sweets	Drinks
Permanent shock: ϕ	0.789	0.069	0.796	0.879	0.331	0.405	0.704
	(0.176)	(0.052)	(0.113)	(0.097)	(0.116)	(0.080)	(0.092)
Transitory shock: ψ	0.081	-0.013	0.085	0.080	0.188	0.167	0.155
	(0.021)	(0.023)	(0.034)	(0.032)	(0.034)	(0.031)	(0.027)
Log-Likelihood	-30050	-32876	-37166	-35551	-42089	-39622	-38540

Notes: Standard errors in parentheses, clustered by household.

The results, shown in Table 3, suggest that a 10% permanent income shock induces a 7.9% permanent change in expenditures. However, there are strong differences between different food groups: expenditures on grains are fully insured against both permanent and transitory income shocks, with the factor loadings ϕ and ψ insignificantly different from zero. In contrast, spending on meat reacts strongly in response to an income shock. For example, a 10% drop in permanent income leads to an 8.0% drop in spending on meat and an 8.8% drop in spending on dairy.

5. Conclusion

This paper examines the extent to which individuals are affected by income shocks. We exploit time variation in the second order moments of the income process to estimate the BMI response, jointly estimating the decomposition of household income into permanent and transitory shocks and the individual-level response to such shocks, allowing for any clustering of individuals within households. We use a high-quality and unique longitudinal Russian dataset that includes detailed individual and household-level data on incomes, expenditures, dietary intakes, and BMI.

We show that permanent, though not transitory, income shocks significantly affect BMI, as well as calorie intakes. Looking more closely at nutrient intakes suggests that the rise in BMI may be partly driven by a change in diet composition, with income shocks disproportionately increasing fat intakes, with smaller effects on protein intakes. Similar to Stillman and Thomas (2008), these results suggest that income shocks are important determinants of diet, nutrition and health

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