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ABSTRACT

The Labeling Effect of a Child Benefits System: Evidence from Russia 1994-2015*

Impacts of child benefits and earned incomes on child wellbeing are identified for Russia. To predict earnings, a counter-factual commodity price model is constructed using information on local industrial composition and the evolution of world prices during 1994-2015 for six key commodity exports. Discontinuity in benefits eligibility at age 16 is exploited to predict the probability of receipt. Child benefits are found not to be spent differently from earned incomes or to influence child health differentially. Benefits do not observably crowd out private transfers to households containing children. Earned incomes and child health appear to be little related.

JEL Classification: H3, I12, O12, O5, R11

Keywords: child benefits, commodities prices, child wellbeing, Russia, labour supply, program evaluation

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1 Introduction

Much of the older literature examining uses of social transfer incomes relies on very strong identification assumptions. For example, Kooreman (2000) exploits variation in child benefits levels across years in the Netherlands to infer that a greater fraction of a Dutch Guilder obtained from child benefits is spent on children than is a Guilder of other household incomes. This is referred to as a labeling effect, and attributed to behavioral responses from the name of the income source. Lundberg, Pollack, and Wales (1997) find that a discrete change in the allocation of UK child benefits from fathers to mothers increased household expenditures on children's clothing. In this paper, the 1994-2015 Russian Longitudinal Monitoring Study (RLMS) from Russia is employed to compare the causal effects of child benefits and earned incomes, respectively, on two types of outcomes relevant to child wellbeing: household expenditures and child health. Discontinuity in benefits eligibility at age 16 and variation in incomes due to world commodity price changes during 1994-2015 are exploited for identification.

If households view child benefit payments as earmarked for children in some way that other incomes are not, providing these benefits will be more effective in improving the living standards of children than more generic forms of incomes support to low-income households, such as social assistance. For policymakers, understanding how benefits are allocated is very important but the implied estimation problem is difficult. Child benefits are one of few government transfers in which the recipient is not the target beneficiary. Instrumentation for a single constructed variable, such as the fraction of household incomes obtained in child benefits, may not to overcome the identification problem.

In early empirical studies, exogeneity of household earned incomes is often assumed. These studies generally examine whether or not the fraction of incomes obtained from child benefits affects expenditures, after accounting for earnings. However, accounting for the potential endogeneity of benefits receipt using administrative rules will not overcome the identification problem if there is mismeasurement of the non-benefits incomes variable. Similarly, changes across two periods in administrative rules might not provide a credible source of identification in the absence of account for pre-existing trends in household expenditure patterns. Recent insights from regression discontinuity

designs and from instrumental variables identification strategies have the potential to greatly improve inference about how households spend incomes from different sources. Using these techniques, analyses of nationally-representative expenditure and wellbeing data may complement those of randomised control trials of cash transfers (see, for example, Araujo, Bosch, and Schady (2016), Baird, McIntosh, and Özler (2016) and Haushofer and Shapiro (2018)).

Amongst the behavioural explanations most commonly advanced when labeling effects are found, perhaps the most common is that individuals earmark money towards intended uses because of moral suasion. To avoid shame or perceived stigma from others, those receiving food stamps or child benefits optimally choose to spend money on food or children, respectively (see, for example, Devaney and Fraker (1986), Breunig and Dasgupta (1999), Smith, Berning, Yang, Colson, and Dorfman (2016), Hener (2015)). Beatty, Blow, Crossley, and O'Dea (2014) also find labeling effects of the UK fuel benefit. Behavioral experiments suggest that, subjects in lab settings do not make decisions consistent with the fungibility of money (see, for example, Abler and Marklein (2017)). Sahn and Gerstle (2004) employ the 1994 Romanian Integrated Household Survey and observe that child benefits are spent on goods accruing to children and on increasing their caloric intakes. However, labeling effects are not always observed. Case and Deaton (1998) find that pensions are spent much as are other household incomes in South Africa. Edmonds (2002) finds no evidence of labeling effects of the Slovenian child benefit. The presence or absence of moral suasion effects may depend greatly on cultural context.

Misreporting of incomes and differential variability of incomes by source are both also potential explanations when labeling effects are measured. Survey respondents may better remember benefits amounts than they do earned incomes. They might also be more honest about reporting incomes from government sources. Benefits information is verifiable and should not have negative taxation consequences for individuals. If apparent labeling effects are in fact a result of differential reporting errors across income sources, improved identification strategies may change inference. However, differential reliability of incomes by source are an explanation for real behavioural differences in the use of funds from different sources. In this case, improved identification strategies should not eliminate previously-measured differences in the use of incomes by source.

The labeling effects literature is strongly related to that examining differences in household resource allocation priorities across the sexes, and to the development of models of the household

which allow for more than one decisionmaker (see, for example, Browning, Bourguignon, Chiappori, and Lêchene (1994), Hoddinott and Haddad (1995), Fortin and Lacroix (1997), Chiappori, Fortin, and Lacroix (2002), Lundberg and Pollack (1993), Anderson and Eswaren (2009), Lyssiotou (2017)). Duflo (2003) finds that grandfathers allocated pension incomes differently than did grandmothers in in South Africa in the early 1990s. Policy changes which reallocated benefits payments from fathers to mothers provide exogenous variation in the fraction of household incomes in the hands of mothers. Adults of one sex may also may be particularly sensitive to labeling effects of benefits, so that observed changes in expenditure patterns around administrative changes may confound labeling effects with those of gendered preferences.

In general, changes in potential wages and benefits are expected to have impacts on labour supply (see, for example, Bertrand and Mullainathan (2003)). Simple models of labour supply, such as Becker (1965) and Gronau (1977), predict that positive income shocks will reduce optimal market labour supply. This might change leisure time, which could then affect demand for leisure-related goods and services (see, for example Browning and Meghir (1991), Schirle (2015)). Holford (2015) finds a negative impact of the UK Education Maintenance Allowance on parental labour supply. Labour supply changes may directly affect expenditure patterns. Changes in benefits eligibility might be large enough to impact household composition, particularly in the case of large transfers such as pensions.

There are several attractive features of the Russian context and data which greatly facilitate investigation of how households spend incomes from child benefits and earnings. In the RLMS data, the employment rate of females aged 18-55 was 73% in 1994 and 71% in 2015. Child benefits monies are seldom the only incomes held by women. Large changes in the prices of commodities produced in Russia occurred during the 1994-2015 sample period. However, labour supply of both men and women is very income inelastic. Labour supply responses to incomes or benefits should not then be a major channel through which observed expenditure changes occur. Russia produces several different internationally-traded commodities, and these provide large numbers of jobs in some communities. Commodity price changes and geospatial heterogeneity in the composition of employment can be used to identify local changes in earned incomes, conditional on labour supply. Child benefits eligibility is partly determined by the ages of children. Although this means that households anticipate

the termination of benefits, consumption smoothing responses are relatively unlikely. Savings rates amongst households with children are negligible in this sample. The extensive site-level information contained in a separate community survey permits controls for non-earnings factors that may be influenced by commodity price changes.

The paper proceeds as follows. In Section 2, the data and summary statistics are introduced. Identification and estimation are discussed in Section 3. The hypothesis that child benefits are spent similarly to other earned incomes is tested, and impacts on child health and wellbeing are examined. Section 4 concludes.

2 Background, data and summary statistics

The RLMS consists of two panels, a four wave panel running between 1992 and 1994 and a (continuing) 20 wave panel running between 1994 and 2015. Both are nationally representative samples of Russian households and individuals. The second panel contained 3974 households in 1994. The sample has been replenished and increased over time. In 2015 the sample size was 6872 households. The use of sample weights helps account for attrition due to moving and mortality.

The RLMS data were collected primarily to assess the health and labour market consequences of economic transition. Interviewers obtain detailed information on the working lives of individuals and on household incomes and expenditures. The 1994-2015 panel contains yearly information on prices of basic commodities and the availability of services in each of 169 secondary sampling sites in the RLMS. A majority of studies of poverty, pensions, and subjective wellbeing in Russia in the 1990s employ these data (see, for example, Mroz and Popkin (1995), Ravallion and Lokshin (2002), Sheidvasser and Benitez-Silva (1999), Senik (2004), Lokshin and Ravallion (2005), Richter (2006), Frijters, Geishecker, Haisken-DeNew, and Shields (2006)).

Universal child benefits were introduced in Russia in 1991. Previously, only very poor families had received financial assistance for help with children. The Soviet government anticipated that economic changes would have strong negative effects on family budgets. These new benefits were to be paid out by the regional governments of Russia. Prior to the introduction of child benefits, maternity leave benefits had been the main Soviet policy aimed towards families with children (see, for example,

Malkova (2018)).

Regional budget crises in Russia almost immediately compromised payment of these and other benefits. Denisova, Kolenikov, and Yudaeva (2000) find that in 1996 only 33% of eligible families received child benefits. Using the 1994-1996 rounds of the Russian Longitudinal Monitoring Survey (RLMS), Jensen and Richter (2004) find that the pension payment crisis had a large negative impact on living standards of pensioners, and effectively tripled poverty rates amongst this group.

From 1994, child benefits payments were made in the form of a single monthly payment for families. Benefits levels, though initially universal, have consistently been structured according to the age of children. The age groupings used are 0-1.5, 1.5-6, and 6-16. Maternity benefits and benefits to non-working mothers with children under 1.5 years are financed by the Social Insurance Fund, but are also often referred to as child benefits. Because of this, all benefits to families with children are here considered child benefits.

Late payment and non-payment of child benefits accompanied the fiscal crises of the mid 1990s in Russia. This is evident from Figure 1, which plots the OLS-predicted probability of receiving benefits as a function of year dummies. The sample is all households containing at least one member under age 18. The benefits receipt probability can be compared between the full sample of households containing at least one member aged 12 to 17 (inclusive), and those containing at least one member aged 12 to 15 (inclusive). This probability is generally higher where there is at least one member aged 12 through 15. In the multivariate analysis, the addition of controls for numbers of children under 12 will help ensure that this is a strong predictor of benefits receipt propensities.

In the second half of the 1990s regional regions began adopting new strategies to deal with the fiscal burden of paying child benefits. Some governments began to target benefits at poor families in 1995, with several others following suit in subsequent years. In 1998 the Russian State Duma passed legislation conforming to the prevailing practise. This legislation proclaimed that only families with incomes below the regional subsistence level could receive child benefits. Regions (oblasts and autonomous republics) maintained the right to impose further restrictions. It was anticipated that targeting would help clear benefit arrears by limiting coverage to families most in need of support. In 1994, the median monthly child benefit level per child, when received, was 336 June 1992 roubles. This represented about 6% of median total household incomes amongst households containing at

least one child under age 18.

Incomes rose substantially in the 2000s. The fraction of incomes derived from transfers varied widely during 1994-2015. The relationship between earned incomes and total incomes (including all transfers) is plotted in Figure 2. These are OLS-predicted incomes from a regression containing only year dummies. In 1994, mean food expenditures (excluding eating out) comprised 50% of total expenditures in the month prior to the RLMS interview in this sample. By 2015 this had declined to about 26%.

By the 2000s, means testing of child benefits had become pervasive across regions. Different regions used different criteria, usually an incomes test combined with various means tests relating to the age composition of the household. For a comprehensive discussion of these targeting schemes, take-up rates, and of the effectiveness of targeting criteria, see Denisova, Kolenikov, and Yudaeva (2000). Kolosnitsyna and Philippova (2017) examine the impact of child benefits in reducing poverty in Russia since 2003. They find that benefits were initially not well-targeted towards the most vulnerable households and that there was substantial leakage of benefits to the less poor. Later in the 2000s targeting rules were relaxed so that more middle-income families again qualified.

One constant amongst the many eligibility criteria and targeting schemes undertaken by different regions is that age 16 has remained the cutoff for benefits receipt. Because receipt after the 16th birthday was very exceptional across all regions during this period, there is a large discontinuity in the probability that a household receives benefits as a child crosses this threshold. Amongst the sample of households containing at least one member under age 18, comparing households with and without members under 16 will yield insights about how child benefits impact expenditure patterns.

Expenditure patterns appear to differ little by whether or not households contain a child this age. In Panel A of Table 1, expenditures on health, alcohol and tobacco, services and recreation, and durables and clothing are shown to be similar in households with and without children under age 16. In 1994, home production amounts were slightly greater in households with no under-16s. This difference had been eliminated by 2015. Assistance to households was greater in 2015 if there were children under 16 present. These differences are statistically significant at the 10% level.

Assets and dwelling characteristics differ only slightly across households by whether or not they contain a member under age 16. Table 2 illustrates. The probability of living in a house, and owning

a washing machine or a car is a bit higher in households containing a person under age 16. However, these households are not necessarily wealthier. Living spaces are very similar in size, at just under 40 metres squared per family. Dwellings in which under-16s reside are slightly less likely to be owned or to have central heating. Probabilities of having a landline telephone are similar across household types. Home ownership rates are very high, at nearly 90% in the full sample. This reflects the privatisation of enterprise-owned housing stocks in the early 1990s, and explains why a majority of households have no monthly expenditure on mortgages or rent.

Although adult and child clothing expenditure are not distinguishable in the RLMS, children above age 6 are posed questions about school attendance, recent health problems, exercise and subjective health, and their height and weight. Parents provide this information for children under this age. They are also asked to give subjective health rankings. If child benefits do improve the wellbeing of children in ways different from earned household incomes, these types of outcomes may be at least as important to consider as child clothing or other assignable expenditures. Even if adults were found to spend child benefits money disproportionately on children's clothing or health care, there may be no benefit to children's health or wellbeing. New clothing may more reflect parental desire to signal social status than a response to needs of children.

Summary health statistics for children do not suggest a strong relationship between age-eligibility for benefits and health. These are shown for children aged 2-17 (inclusive) in Table 3. While children under age 16 report more health problems in the preceding month, other measures of wellbeing do not differ across this age threshold. The incidence of overweight, "good" or better subjective health evaluation, and probability of having been hospitalised in the past three months are statistically the same on either side of the age threshold.

3 Estimation

The empirical strategy is similar in spirit to Acemoglu and Angrist (2000), who instrument both for endogenous state-level compulsory schooling and for individual schooling in a wage equation. Bartik (1993) interacts local industry shares with national industry growth rates to form an instrument for local growth, and the strategy here is not dissimilar. Estimation accounts for endogeneity in

earned incomes by exploiting 1994-2015 commodity price variation, and geographical heterogeneity in the composition of industry. For each of the 169 secondary sampling units ('sites') included in the RLMS, a base year industry-specific employment composition is used to create a time-varying counterfactual prediction of incomes in the site in the year. This counterfactual is employed to predict total earned incomes of a household. The exclusion restriction is that there is no systematic correlation between world commodity price changes and other changes in households which might impact their expenditures. This includes labour supply and household composition changes. Identification of each of the two endogenous variables will be discussed in turn.

3.1 Identification

3.1.1 Child benefits

Identification of child benefits effects comes from administrative rules governing eligibility. Child benefits are normally ascribed to mothers Normally, benefits can be received for children under age 16. Benefits are higher for single mothers and for children of fathers who do not pay alimony. Only in exceptional circumstances are benefits allocated for children aged 16 and 17 in full time study.

There are two other major discontinuities in benefits receipt levels which are not exploited in estimation. These changes in benefits levels correspond to other lifestyle transitions which might directly impact either child wellbeing or household expenditures. Mothers with children under aged 18 months receive a maternity leave benefit. This money is recorded in the RLMS as child benefits money. However, a new birth involves many changes in earnings potential, the value of leisure, and access to non-labour incomes. Another discontinuity in benefits receipt amounts occurs at age 6. This age corresponds closely to the school start age, 7, in Russia, which may coincide for women with a change in hours of work, use of daycare facilities, or in household expenditure patterns. For these reasons, only the discontinuity in receipt propensities between households containing individuals aged under 16 and under 18 is exploited for identification.

The data span years in which late payment and non-payment of all types of government transfer incomes occurred. In the late 1990s, delays in payment of pension and child benefits incomes were large, and many delayed payments were never paid (see, for example, Jensen and Richter (2004)). The

extent of these deviations from administrative rules governing benefits receipt varied substantially across regions and time. As well, different targeting schemes were introduced at different times across provinces. To account for these features in estimation, all multivariate estimation will take account of year effects and site fixed effects. These controls will help ensure that only variation around age 16 in receipt propensities is exploited to predict the probability of having obtained any child benefits money in the month prior to the RLMS interview.

The firststage regression explaining whether or not a household obtained child benefits income, $ANYBEN$ in the month prior to the RLMS interview may be written as:

$$\begin{aligned} ANYBEN_{hst} &= \alpha + \gamma * HNCHU16_{st} + \beta * \widehat{H_{st}} + \sum_{r=1}^{R} \delta_h * HHCOMP_{hst} \\ &+ \sum_{w=1}^{W} \delta_h * HHWEALTH_{hst} + \sum_{x=1}^{X} \delta_h * HHDWELL_{hst} \\ &+ \gamma * PLEVEL_{st} + \mu_s + \lambda_t + \epsilon_{st} \end{aligned}$$

In household h of site s in year t, the number of children aged 12 through 15, $HNCHU16$, is used to predict whether or not any child benefits were received in the month prior to the interview. Numbers of children under 4 and aged 4 through 11 are employed as controls. This firststage regression answers the question: "Conditional on having at least one child under age 18, how does the probability of obtaining child benefits alter if at least one child is under age 16?" Standard errors are clustered at the household level. Predicted incomes from the counterfactual commodities model, $\widehat{H_{st}}$, to be discussed below, also predict the probability of receiving a benefit.

Both the sample and the household composition variables contained in $HHCOMP$ are selected to facilitate identification. These variables accounting for the age composition of children comprise the numbers of children aged under 4, aged 4 through 11 and aged 12 through 17 (inclusive). Amongst adults, variables are defined separately by sex. Age-earnings profiles of men and women generally differ. As well, women become eligible for state pensions in Russia five years before men do. The six age-sex groups are: aged 18-23, 24-state pension age, and older than pension age.

Goods prices are important determinants of expenditure choices, and so proper account of spatial and intertemporal changes in prices is potentially important for inference. All incomes and expenditure measures are deflated to real 1992 roubles to account for nationwide inflation during the period. However, local prices plausibly varied both across time and space, and these changes may be correlated with world commodities prices or in the real value of the benefit. For example, Filmer, Friedman, Kandpal, and Onishi (2018) find that targeted cash transfers reduced wellbeing of young children in non-recipient households in the Philippines by increasing the price of protein-rich foods. For this reason, the extensive food price data included in annual site-specific community questionnaires is exploited to construct a measure of local price levels. Mean expenditures on 25 budget lines in a site in 1994 form the basket of goods for which a Laspeyres price series is constructed. This series takes the form $\sum_{n=1}^{25} p_n \bar{X}_{n,1994} = PLEVEL_{st}$. The component prices and quantities included in the index are discussed in more detail in Data Appendix A.

The inclusion of the local price index, $PLEVEL$, in estimation should help account for site-year variations in purchasing power, but there are likely other time-varying factors that confound inference. Community price information is available only for food items. This remains the largest single budget line for households. There are, however, other important components of prices that remain unknown. One of these is housing.

Extensive information on characteristics of dwellings is collected in the RLMS. These $HHDWELL$ variables are employed as controls in all estimation. Interviewers collected information on total living space, dwelling type, and the presence of central heating, piped cold and hot water water, sewerage and land-line telephones. This information also helps account for household wealth, or 'permanent income'. In this way, exogenous income effects can be more plausibly identified.

In addition to variables describing dwelling characteristics, RLMS interviewers gather information on consumer durables possessed by households. The data collected varies across years, as might be expected given the long period spanned by these data. However, $HHWEALTH$ control variables can be constructed for those assets for which information is collected in all periods. These indicator variables are dummies indicating possession of a car, a colour television, a fridge, a washing machine, and ownership of the dwelling in which the interview RLMS takes place.

3.1.2 Earned incomes

The reasons for instrumentation of the earned incomes variable are multiple. Earned incomes might be less well reported than benefits incomes. This might be attributable both to differential ability to recall incomes from these two sources, and also due to differential incentives to correctly report these incomes. Measurement error will tend to bias coefficients towards zero in estimation, a result of attenuation. Reverse causality and unobserved heterogeneity are also possible sources of endogeneity bias. Individuals may work more to pay for family health shocks, new consumer durables, or new housing. Household unobservables such as status consciousness may be correlated both with earnings and with expenditure patterns.

Earned incomes effects are identified by combining information on the geographical distribution of industry and the large changes in world natural resource prices during the 21 years spanned by the data. Oil, gas, coal and gold mining, and softwood and wheat production are six internationally-traded commodities which account for substantial fractions of employment in Russia. The long period covered by these data and the geographical heterogeneity in resource endowments within regions facilitates identification. The evolution of world prices for these six commodities is shown in Figure 3. The strength of earnings predictions from the counterfactual commodities model will depend partly on the observable heterogeneity in price trends.

To create the counterfactual predicted incomes of households in a site in a year, the fraction of individuals employed in the oil and gas, mining, and agricultural product industries, respectively, in a base year is first calculated. These are the industries, amongst the 30 industry codes defined in the data, for which international prices might have direct impacts on local wages. This base year share of individuals employed in each industry in each site is multiplied by the mean World Bank Pink Sheet price for the respective commodity in the year (World Bank (2018)).

A year and site-specific predictor of earned incomes are created by summing across all sectors within sites and years. The inclusion of site-specific fixed effects in all estimation ensures that the geographical contribution to predicted incomes occurs only through the time variation in commodities prices. The relative importance of each commodity to the local labour market is reflected in the industry-specific employment measure.

The matrix of predicted earned incomes in each year provides exogenous variation in site-specific incomes. For secondary sample unit sites numbered 1 to 169 and for d different commodities, where m refers to the base year level of employment in site s for the commodity in question:

$$\begin{bmatrix} m_{11} \cdots & m_{1d} \\ \vdots & \\ m_{s1} \cdots & m_{sd} \end{bmatrix} \begin{bmatrix} p_{11} \cdots & p_{1t} \\ \vdots & \\ p_{d1} \cdots & p_{dt} \end{bmatrix} = \begin{bmatrix} h_{11} \cdots & h_{1t} \\ \vdots & \\ h_{s1} \cdots & h_{st} \end{bmatrix}$$

The elements H_{cd} represent the fraction of employed workers in an industry times price per unit of industrial output in the base year. Information on units of each commodity produced in each site in any year is not available, but this is not a problem for construction of the counterfactual. The time-invariant value of baseline year employment is subsumed into the site fixed effect.

Let H_{st} describe the matrix of the counterfactual commodities model, where both world prices and the base year importance of a commodity to earned incomes in a site are component parts:

$$H_{st} = \begin{bmatrix} h_{11} \cdots & h_{1t} \\ \vdots & \\ h_{s1} \cdots & h_{st} \end{bmatrix}$$

In contrast with most applications of instrumental variables, the instrument in this case is predicted. The variables contained in the matrix H_{st} constitute the counterfactual. To emphasize this point $\widehat{H_{st}}$ is written. This variable predicts what total earned incomes from the d commodities would have been in each year for each site, assuming the base year level of employment in each of these commodities sectors. More details on the construction of the counterfactual commodities model are contained in Data Appendix A.

The first-stage regression predicting earned incomes of household h in site s in year t is:

$$
\begin{aligned}
EARNED_{hst} &= \alpha + \gamma * \widehat{H_{st}} + \delta * HNCHU16_{hst} + \sum_{r=1}^{R} \delta_h * HHCOMP_{hst} \\
&\quad + \sum_{w=1}^{W} \delta_h * HHWEALTH_{hst} + \sum_{x=1}^{X} \delta_h * HHDWELL_{hst} \\
&\quad + \gamma * PLEVEL_{st} + \mu_s + \lambda_t + \epsilon_{st}
\end{aligned}
$$

The instrument $\widehat{H_{ct}}$ should not introduce bias into estimation. If $E(H_{st}) * E(u_{st}) \neq 0$, the exclusion restriction will only be satisfied for $E(H_{st}|\mu_s, \lambda_t) * E(u_{st}) = 0$, where u_{st} is the residual in the second stage. If this variable is a poor predictor of $EARNED_{st}$, the instrument will be weak, and coefficients biased.

This firststage regression for earnings is conditioned on the number of children aged 12-15, which is also potentially endogenous in this context. This dummy variable $HNCU16$ forms the second instrument. In general, instrumentation for more than one endogenous variable in a regression is complicated by the necessity of simultaneously satisfying all exclusion restrictions. Without multiple, disparate, sources of identification, identification will not be possible.

The firststage regression results for earned incomes are presented in Panel A of Table 4. Incomes are measured in real June 1992 roubles. In the specification of column (1) only earned incomes are instrumented. In each site and for each year, earned incomes have been predicted using the counterfactual commodities model. A simple dummy variable is included to indicate whether or not the household received any child benefits in the month prior to the survey. The F-statistic on this firststage is 13.6. The counterfactual commodities model is a strong predictor of household earned incomes, conditional on local prices levels, site, year and household composition variables.

The difficulty of instrumenting for two endogenous variables becomes apparent when the probability of receiving any benefit is also instrumented with the number of children in the household aged 12 -15 (inclusive). Results are presented in column (2) of Panels A and B. These disparate sources of exogenous variation facilitate reasonably strong prediction of both endogenous variables. The F-statistic on the age threshold instrument in the firststage for child benefits receipt is 81, indicating that identification of this endogenous variable is not weak. The coefficient predicting earned incomes

is little different from that in column (1), although the F-statistic for the two instruments that must now predict the firststage has fallen to 8.4. The number of children aged 12 to 15 in the household turns out to not be a strong predictor of earned incomes, *ceteris paribus*. The addition of household dwelling characteristics (column (3)), household wealth controls (column (4)) and labour supply controls (column (5)) does little to alter the signs or significance of either of the two instrumented variables.

The F-statistic for the instrument for child benefits receipt is greater than 10 in all specifications. The Cragg-Donald F-statistic for the joint predictive power of instruments is 7.9 in the latter, preferred, specification. This suggests that weakness in predicting earned incomes is not likely to be causing bias in the coefficients of interest. Because the probability of benefits receipt is precisely predicted, a finding of no statistically significant causal effect will not be attributable to a lack of statistical power.

The counterfactual commodities model instrument does help predicting the probability of benefits receipt. Poorer households are more likely to receive benefits under the targeting which began in the late 1990s (Panel B). This remains the case after accounting for household dwelling characteristics (column (3), wealth controls (column (4)) and labour supply (column (5)).

3.2 Main regressions

Both expenditure and child wellbeing outcomes are investigated. The main regressions take the form:

$$\begin{aligned} OUTCOME_{hst} &= \alpha + \sigma * \widehat{EARNED}_{hst} + \delta * \widehat{ANYBEN}_{hst} + \sum_{r=1}^{R} \delta_h * HHCOMP_{hst} \\ &+ \sum_{w=1}^{W} \delta_h * HHWEALTH_{hst} + \sum_{x=1}^{X} \delta_h * HHDWELL_{hst} \\ &+ \gamma * PLEVEL_{st} + \mu_s + \lambda_t + \epsilon_{st} \end{aligned}$$

The budget lines examined comprise: health, tobacco and alcohol, clothing and consumer durables, services and recreation, and gifts and loans to non-residents. Of these, perhaps only tobacco and

alcohol expenditures and gifts and loans to other households are truly adult-assignable (excludable for children). If households do spend child benefits disproportionately on children, less of this money should be spent on such budget lines than of earned incomes. The treatment of outliers is discussed in Data Appendix A. Estimation results are presented in Table 5.

For the full sample of households containing at least one member under age 18, there is no robust difference in health expenditures across income sources (Panel A). In the OLS specification (column (1)), measured income effects are generally much smaller than those obtained when incomes are instrumented using the counterfactual commodities model (columns (2)-(6)). In the OLS specification, the benefits dummy suggests a negative and statistically significant conditional correlation between expenditures on health and benefits receipt. This observed correlation may be attributable to poorer households being more officious about benefits takeup, as well as to endogeneity and attenuation of the earned incomes variable. The lack of effect of child benefits receipt is consistent across specifications which instrument both for earned incomes and benefits receipt (columns (3)-(6)). The inclusion of controls for the nature of the residential dwelling (column (4)), and for household wealth (column (5)), do not alter the coefficients of interest.

Results are also robust to the inclusion of controls for hours worked by the different age-sex groups resident in the household. In the preferred specification, these controls are included (column (6)). The marginal propensity to consume on health (MPC) from earned incomes are unaltered, at about 0.1.

Expenditures on alcohol and tobacco appear to be invariant to earned incomes. The MPC from earned incomes is not statistically different from zero in any specification. There are several potential explanations. Home-made alcohol may be a very important component of alcohol consumption in Russia. The low-grade filterless "papyrus" cigarettes smoked by a majority of Russian males are very inexpensive. Both alcohol and tobacco consumption are habitual.

The finding that child benefits are not used for alcohol or tobacco expenditures is consistent with recent evidence. In a meta-analysis of 19 studies of cash transfers from Latin America, Africa and Asia, Evans and Popova (2017) show that households do not tend to spend cash transfers on alcohol and tobacco 'temptation' goods to any greater or lesser degree than incomes from other sources. Raschke (2016) finds similar results in Germany.

The marginal propensity to consume on services and recreation are highest of all the non-food budget lines considered. In OLS estimation, this propensity appears much smaller (column (1)) than in estimation which controls for the potential endogeneity of earned incomes and for attenuation bias due to measurement error (columns (2)-(6)). Expenditure on services and recreation is negatively conditionally associated with receipt of the child benefit (column (1)). This is consistent with poorer households being more likely to receive the benefit and also spending less on this budget line. The statistical significance of the child benefits dummy is eliminated after accounting for the endogeneity of earned incomes (column (2)). Child benefits receipt has no measurable differential impact on expenditures on services and recreation.

Expenditures on consumer durables, luxury items and clothing in the month prior to the RLMS interview do not appear to be strongly causally related to household incomes levels. The MPC from earned incomes is not different from zero in the preferred specification. This is perhaps because consumer durables expenditure is much more 'lumpy' than is other spending, although the value of this variable is zero in only about 1/7 of observations. In some specifications with instrumentation for both endogenous variables, child benefits appear to cause a reduction, significant at the 10% level in spending on this budget line. However, this finding is not robust across specifications.

Over the 1994-2015 period, the fraction of an additional rouble expended on loans and gifts to non-household members is about 0.1, similar to that for health care. Money from child benefits allocated to this budget line is conditionally less in poorer households (Panel E, column (1)). However, the conditional correlation disappears once the endogeneity of benefits receipt and earned incomes have both been taken into account using instrumentation. Earned incomes matter for assistance to other households. Child benefits matter in the same way.

In Data Appendix B, the potential crowding out of private transfers, savings and home production by benefits receipt is examined. To summarise, only for home production is receipt sometimes found to cause a change in behaviour. The sources of this change are investigated using the available time use diary data spanning 1994-1998. Consumption of neither staples nor perishable foods is found to be impacted by benefits receipt.

The data do not suggest that child benefits are spent differently from earned incomes. There remains a possibility that increased incomes in the hands of women household members because

of the benefit masks a true labeling effect of the benefit. Russian women already earn substantial fractions of household incomes. If women value adult-assignable goods less than do men, we would perhaps have expected to find statistically significant negative effects of child benefits receipt for expenditures on alcohol, tobacco and assistance to other households.

3.3 Child wellbeing measures

The RLMS data contain an extensive interview with all children and their parents. For children under age 6, parents answer questions. Effects of earned and child benefits incomes on child health outcomes can be assessed. The five outcomes examined are: a self-reported subjective health evaluation, having a BMI less than 'overweight', having had no health problem in the 30 days prior to the interview, and whether or not the child was hospitalized in the three months prior to the interview. These represent all child health outcomes measured throughout the survey period. The measurement of each of these outcome variables is described in detail in Data Appendix A.

Estimation is at the individual level and includes a linear variable in age and a dummy for female. Instruments and controls are otherwise identical to those included in the household level estimation. These results are presented in Table 6.

There are several results of note. First, no robust causal impacts on the subjective health evaluation measure (Panel A), the probability of being overweight (Panel B), or on the probability of having been hospitalised in the three months preceding the RLMS interview (Panel D). The results also do not suggest differential impacts of child benefits and earned incomes on children's wellbeing. For these outcomes, the benefits receipt dummy is never statistically significant in the preferred specifications (column (6)). The oft-observed health gradient in incomes does not appear to be a causal relationship for children in Russia during 1994-2015. This finding is consistent with Cesarini, Lindqvist, Ostling, and Wallace (2016), who find that wealth shocks from lottery wins affect neither child development nor mortality outcomes in Sweden.

Children, or their parents, are asked by interviewers to report if there were any health problems experienced by the child in the preceding 30 days. There does not appear to be a measurable impact of earned incomes on the probability of reporting no health problems are found (Panel D). A follow-

up question asks respondents to indicate if a reported health problem was addressed by trained health professionals. Unfortunately, this question was discontinued in the 2009 RLMS. The limited number of observations from 1994-2008 means that this question cannot be observed to gain further understanding of the causal mechanisms relating incomes to health services use.

Since child benefits generally accrue to mothers, the apparent lack of differential impacts of benefits on child health is perhaps unsurprising. Thomas (1990) shows that incomes accruing to women have larger effects on child health than that those accruing to men. In contexts such as Russia, however, where basic nutrition and health services are accessible, the disease environment favourable, parental education levels high, and female participation near-universal, earned incomes are perhaps more plausibly unrelated to child health. If childhood health investments are flows which accumulate, changes in benefits eligibility or parental incomes might little impact the health of older children.

4 Conclusions

This paper compares the impact on children of earned incomes and child benefits money using two plausibly independent sources of exogenous variation for identification. Nationally-representative household survey data spanning 1994-2015 is employed. Geospatial heterogeneity in natural resource endowments is exploited to construct a counterfactual commodities price model which predicts earned incomes, conditional on local price levels and labour supply of household members. Information on price levels and other time-varying site-specific information contained in the RLMS allows isolation of the commodity price-household earnings channel. Exogenous variation in receipt propensities amongst households containing children just younger and just older than age 16 is exploited to identify benefits effects. This is a strong predictor of the probability of benefits receipt. Households may anticipate the termination of benefits as a child reaches age 16, and adjust their spending behaviour. However, household savings rates are negligible in this sample, and so consumption smoothing is unlikely to explain the main results.

The disparate sources of identification and a pseudo-panel structure facilitate identification of the marginal propensity to consume on different budget lines, including adult-specific goods and health.

Responses from an extensive child wellbeing module are compared to those for expenditures.

The 1994-2015 Russian data do not indicate that earned incomes are spent differently from child benefits incomes. Since both sources of income are precisely predicted, these results cannot be attributable to a dearth of statistical power. Households with higher incomes spend more money on health care, services and recreation and assistance to other households. The data also do not suggest that private transfers towards recipient households are crowded out either by benefits or by earned incomes. An additional rouble from child benefits money is spent very similarly to an additional rouble from earned incomes. There appears to be no labeling effect of child benefits in Russia during 1994-2015.

The apparent lack of differential effects of the child benefit does not, however, imply that these benefits are ineffective at reducing poverty. Household incomes may still be very important to the wellbeing of children in the long run. Amongst children aged 2 through 17, earned incomes have no measurable causal impact on the incidence of overweight, a self-reported health evaluation or on the probability of having been hospitalised in the previous three months. However, earned incomes are a strong determinant of expenditures on recreation and services by households containing children. Social capital-related components of child wellbeing may well be improved through the increased spending on this budget line with higher benefits or earnings. These aspects of child wellbeing are difficult to capture in household surveys, but may be particularly important in middle-income countries where nutrition, school attendance, and basic health care access is assured.

The use of long pseudo-panels may help deepen understanding of the channels through which cash transfer effects operate, even at the cost of some reduction in precision. Randomised control trials of cash transfers avoid the need to instrument for non-transfer incomes by ensuring that pre-trial incomes are indistinguishable across treatment and control groups. This mitigates bias in the estimation of causal impacts of transfers, particularly if local price level changes can be taken into account. For many countries, long and nationally-representative pseudo-panels can complement insights from such trials. The period now spanned by the Russian data and the geographic heterogeneity in resource endowments permit instrumentation for two endogenous variables. Even when instrumentation for earned incomes is not possible, exploiting age discontinuities in eligibility may provide valuable insights into how households allocate funds.

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Table 1: Summary statistics for household expenditures 1994-2015

children<16?	no	yes	no	yes	no	yes	no	yes	no	yes
PANEL A:	**health**		**adult**[a]		**Total services**		**Dur., lux., clothes**		**Assist. to hhlds**	
1994:										
	80.1365	68.5911	343.5926	485.3243	1882.3854	2258.3567	1673.2143	3120.3197	560.2425	937.2904
	(27.913)	(10.315)	(42.914)	(27.194)	(272.250)	(118.634)	(249.260)	(263.914)	(165.360)	(145.391)
p-value test eq.	0.697		0.810		0.737		0.663		0.183	
2015:										
	604.3779	794.6840	461.4003	531.5146	7000.7375	6495.5444	3997.4228	3254.5486	693.4755	439.9001
	(125.657)	(46.219)	(62.822)	(20.228)	(1080.954)	(409.022)	(1623.495)	(217.819)	(179.854)	(49.573)
p-value test eq.	0.495		0.690		0.137		0.134		0.971	
PANEL B:	**Assist. from non hh.**		**Home prod.**		**Staple food**		**Perishable food**		**Savings**	
1994:										
	560.3030	913.5126	1133.9899	920.6297	2020.7097	2045.5074	3980.9948	4061.1019	393.4627	729.4185
	(134.338)	(69.445)	(177.419)	(48.461)	(174.773)	(57.613)	(321.760)	(112.939)	(148.016)	(163.576)
p-value test eq.	0.610		0.000		0.029		0.517		0.469	
2015:										
	538.3043	1139.9474	1177.4320	568.1882	1158.1982	1190.1619	3254.8172	3853.7233	846.9420	450.6720
	(116.438)	(94.287)	(336.887)	(55.962)	(74.943)	(27.402)	(201.224)	(83.610)	(302.555)	(68.257)
p-value test eq.	0.010		0.148		0.557		0.146		0.636	

Source: RLMS-HSE 1994-2015. [a] Adult is the sum of alcohol and tobacco expenditures. Household with at least one child under age 18 are included. Standard errors are clustered at the household level.

Table 2: Summary statistics for household assets and physical structure of the dwelling, 1994-2015

Panel A:	**own car**		**dwelling house**		**living space (m^2)**		**washing machine**		**fridge**		**c. sewerage**	
children <16?	no	yes	no	yes	no	yes	no	yes	no	yes		
	0.3214	0.3505	0.1840	0.1974	38.4979	37.5242	0.6591	0.6673	0.6087	0.6063	0.7124	0.6977
	(0.008)	(0.003)	(0.006)	(0.002)	(0.288)	(0.109)	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)
p-value test eq.	0.527		0.000		0.000		0.000		0.000		0.000	
Panel B:	**own colour tv**		**own house**		**central heat**		**cold water**		**hot water**		**h. phone**	
children<16?	no	yes	no	yes	no	yes	no	yes	no	yes		
	0.7702	0.7414	0.9202	0.8751	0.7139	0.7063	0.8604	0.8473	0.6290	0.6203	0.5833	0.5123
	(0.007)	(0.003)	(0.005)	(0.002)	(0.008)	(0.003)	(0.006)	(0.002)	(0.008)	(0.003)	(0.008)	(0.003)
p-value test eq.	0.000		0.000		0.000		0.000		0.000		0.197	

Source: RLMS-HSE 1994-2015. Household with at least one child under age 18. Standard errors are clustered at the household level.

Table 3: Summary statistics for child health, 1994-2015

	No health prob. 30 days?		**BMI $\geq$ 25**		**Health eval "good"**		**Hospital last 3 months**	
Aged $\leq$16?	no	yes	no	yes	no	yes	no	yes
	0.5902	0.6520	0.0427	0.0535	0.6453	0.6171	0.0350	0.0300
	(0.004)	(0.005)	(0.002)	(0.002)	(0.004)	(0.005)	(0.001)	(0.002)
p-value test equality	0.000		0.000		0.000		0.034	

Source: RLMS-HSE 1994-2015. Children residing in households with at least one child under age 18. Standard errors are clustered at the household level.

Table 4: Firststage regressions predicting household earned incomes and child benefits receipt

Panel A. Dependent variable: Household earned income					
commodity model inc.	25.7256***	28.5288***	29.4484***	26.5561***	25.9310***
	(6.889)	(6.913)	(7.142)	(7.348)	(7.363)
no children 12-16		118.3756	138.4354	159.8837	235.5903
		(255.521)	(263.509)	(252.230)	(249.957)
any chben l month	-1824.0964***				
	(217.937)				
no children under 4	-681.5948**	-1107.3772***	-1084.5155***	-1098.2953***	-582.3522*
	(294.116)	(295.793)	(300.129)	(296.591)	(310.206)
no children 4 to 11	376.5179**	209.1652	165.6999	124.2014	201.1878
	(188.364)	(188.631)	(189.825)	(187.485)	(182.629)
no children 12 to 18	530.4666**	312.9780	220.8043	255.7027	236.7770
	(237.068)	(252.018)	(254.651)	(240.622)	(238.203)
constant	-3177.3941***	-3350.0207***	-4399.8088**	-2360.5287	-1204.7839
	(750.054)	(754.438)	(1988.478)	(2033.079)	(2080.353)
R^2	0.139	0.137	0.143	0.153	0.159
No. obs.	28355	28355	27428	27310	27310
Panel B. Dependent variable: Probability household received child benefit					
commodity model inc.		-0.0015***	-0.0014***	-0.0012***	-0.0012***
		(0.000)	(0.000)	(0.000)	(0.000)
no children 12-16		0.0680***	0.0681***	0.0688***	0.0680***
		(0.008)	(0.008)	(0.008)	(0.008)
no children under 4		0.2306***	0.2388***	0.2405***	0.2308***
		(0.009)	(0.009)	(0.009)	(0.009)
no children 4 to 11		0.0888***	0.0914***	0.0930***	0.0919***
		(0.006)	(0.006)	(0.006)	(0.006)
no children 12 to 18		0.0271***	0.0291***	0.0275***	0.0275***
		(0.009)	(0.009)	(0.009)	(0.009)
constant		0.0853***	0.1066***	0.3931***	0.3734***
		(0.023)	(0.028)	(0.047)	(0.047)
R^2		0.174	0.180	0.185	0.186
Additional controls:					
dwelling	no	no	yes	yes	yes
wealth	no	no	no	yes	yes
l. supply	no	no	no	no	yes

Source: RLMS-HSE 1994-2015. Controls for local price levels and household composition are included in all specifications. The specification in column (1) instruments only for earned income. In columns (2)-(5) both earned incomes and benefits receipt propensities are treated as endogenous. Standard errors are clustered at the household level. These are the firststage regressions for expenditures on different household budget lines. * significant at 10% level, ** significant at 5% level, and *** at 1% level.

Table 5: The impact of child benefits and earned incomes on household expenditures

	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Health						
earned	0.0050***	0.0963***	0.1146***	0.1070***	0.1089***	0.1064***
	(0.001)	(0.028)	(0.039)	(0.036)	(0.038)	(0.036)
any chben l month	-58.9458***	120.8222**	452.9589	477.5806	435.6775	321.0896
	(15.062)	(57.858)	(451.148)	(441.100)	(423.245)	(399.027)
F stat	45.793	8.800	5.090	4.435	3.713	3.736
No. obs.	28355	28355	28355	27428	27310	27310
Panel B: Adult (alcohol and tobacco)						
earned	0.0023***	-0.0075	-0.0192	-0.0168	-0.0167	-0.0157
	(0.000)	(0.009)	(0.013)	(0.012)	(0.012)	(0.012)
any chben l month	-3.9029	-22.9839	-252.5956	-245.8747	-253.1041	-213.9558
	(8.585)	(19.893)	(169.168)	(169.017)	(165.001)	(157.475)
F stat	46.190	0.758	5.012	4.328	3.965	3.807
No. obs.	28391	28391	28391	27462	27342	27342
Panel C: Services (including recreation and meals out)						
earned	0.1224***	0.5113***	0.4554**	0.4334***	0.3897**	0.3859**
	(0.026)	(0.160)	(0.178)	(0.168)	(0.169)	(0.165)
any chben l month	-564.0349***	136.0427	-1012.6457	-464.0435	-618.6560	-776.8844
	(127.617)	(327.916)	(2321.140)	(2318.485)	(2176.303)	(2118.254)
F stat	39.977	19.263	5.509	4.561	2.357	2.250
No. obs.	28387	28387	28387	27458	27338	27338
Panel D: Clothing, consumer durables and luxury items						
earned	0.1815***	-0.1078	-0.3021	-0.2926	-0.3572	-0.3438
	(0.034)	(0.139)	(0.221)	(0.208)	(0.227)	(0.218)
any chben l month	24.9676	-565.4670*	-4537.9778	-4800.6216	-5423.6858*	-4868.0563*
	(148.052)	(318.672)	(2934.882)	(2969.126)	(2990.713)	(2823.771)
F stat	23.031	2.636	2.124	2.070	1.395	1.565
No. obs.	28375	28375	28375	27446	27326	27326
Panel E: Assistance to other households						
earned	0.0113***	0.0795*	0.1084*	0.1009*	0.0950*	0.0942*
	(0.003)	(0.047)	(0.061)	(0.057)	(0.057)	(0.056)
any chben l month	-137.6074***	-56.1841	485.3234	510.4888	331.0928	273.6382
	(40.332)	(95.069)	(779.476)	(795.316)	(771.809)	(748.918)
F stat	4.735	9.705	3.929	2.658	2.011	2.037
No. obs.	28391	28391	28391	27462	27342	27342
Additional controls:						
dwelling	no	no	no	yes	yes	yes
wealth	no	no	no	no	yes	yes
l. supply	no	no	no	no	no	yes

Source: RLMS-HSE 1994-2015. Controls for local price levels and household composition are included in all specifications. Year dummies and site fixed effects are also included. In specification (2), instrumentation is for earned income, and in specifications (3)-(6) for both earned incomes and child benefits receipt. Standard errors are clustered at the household level * significant at 10% level, ** significant at 5% level, and *** at 1% level. Household sample weights are employed.

Table 6: The impact of child benefits and earned incomes on health of children aged 2-17 (inclusive)

	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Subjective health score "Very good" or "good"						
earned real inc. 10 000s roubles	-0.0004	-0.0154	0.0509	0.0457	0.0381	0.0375
	(0.001)	(0.020)	(0.058)	(0.050)	(0.043)	(0.040)
any chben l month	-0.0033	-0.0063	0.1201	0.1162	0.1011	0.0997
	(0.002)	(0.005)	(0.094)	(0.087)	(0.075)	(0.069)
F stat	2.643	2.036	1.343	1.306	1.348	1.426
No. obs.	23274	23274	23274	22511	22409	22409
Panel B: Overweight (BMI $\geq$ 25)						
earned real inc. 10 000s roubles	-0.0007	0.0509	0.0203	0.0359	0.0433	0.0397
	(0.001)	(0.039)	(0.082)	(0.076)	(0.079)	(0.073)
any chben l month	0.0008	0.0105	-0.0450	-0.0022	-0.0008	-0.0083
	(0.004)	(0.009)	(0.130)	(0.128)	(0.130)	(0.121)
F stat	2.124	2.131	2.379	1.741	1.661	1.696
No. obs.	19730	19730	19730	19180	19119	19119
Panel C: No health problem in past month						
earned real inc. 10 000s roubles	-0.0042**	0.1211*	0.2969	0.3074	0.3272	0.2955
	(0.002)	(0.065)	(0.223)	(0.204)	(0.220)	(0.190)
any chben l month	-0.0139*	0.0101	0.3552	0.3627	0.3982	0.3273
	(0.007)	(0.015)	(0.371)	(0.360)	(0.378)	(0.325)
F stat	12.466	45.070	23.009	23.439	21.601	24.362
No. obs.	23310	23310	23310	22533	22437	22437
Panel D: Hospitalised in past 3 months						
earned real inc. 10 000s roubles	0.0011	0.0265	0.0290	0.0461	0.0508	0.0517
	(0.001)	(0.021)	(0.061)	(0.057)	(0.060)	(0.055)
any chben l month	0.0051*	0.0100*	0.0153	0.0424	0.0499	0.0518
	(0.003)	(0.005)	(0.115)	(0.115)	(0.119)	(0.110)
F stat	1.902	2.275	1.616	1.380	1.216	1.302
No. obs.	22666	22666	22666	21917	21826	21826

Source: RLMS-HSE 1994-2015. A linear term in age and a female dummy are included in all specifications. All estimates include a full set of controls for: local price levels, household composition, household wealth, and household assets. Year time dummies and their interactions with province dummies are also included. In specification (2), instrumentation is for earned income, and in specifications (3)-(6) for both earned incomes and child benefits receipt. Standard errors are clustered at the household level * significant at 10% level, ** significant at 5% level, and *** at 1% level. Household sample weights are employed.

Figure 1: Predicted probability of receiving child benefit by age of children

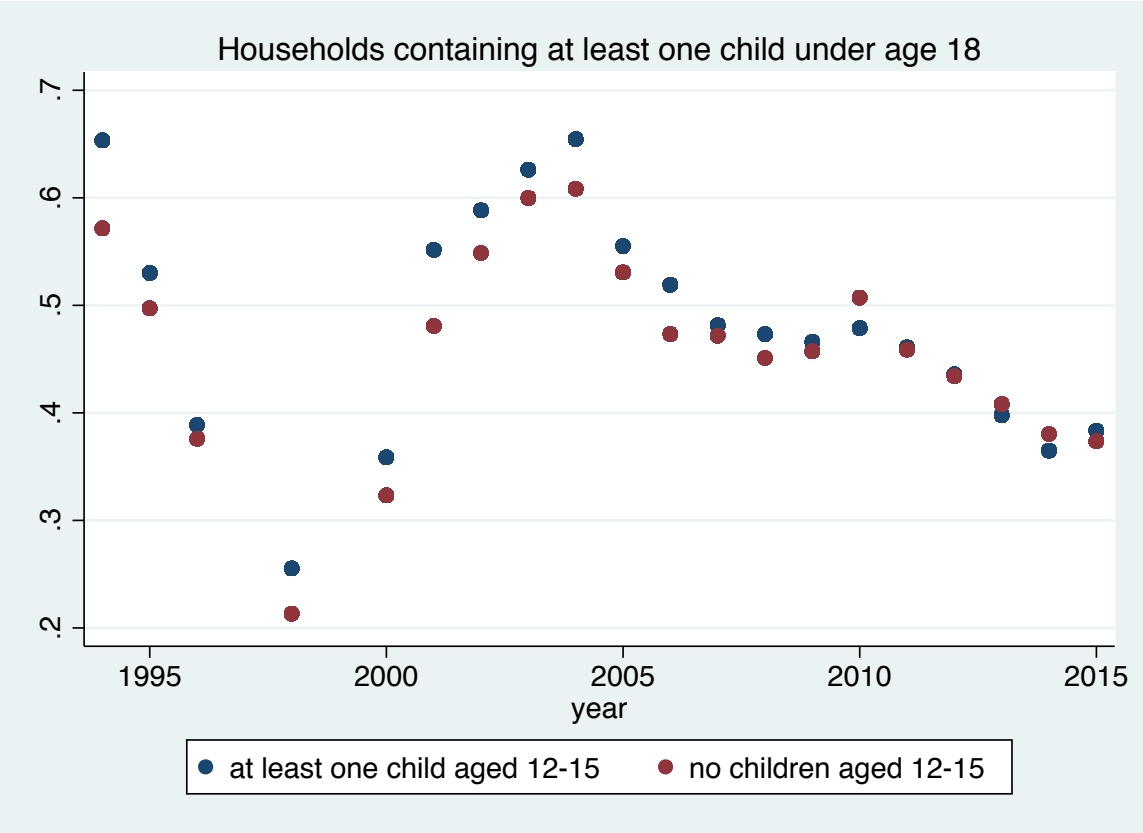


Figure 2: Predicted mean earnings and total household incomes

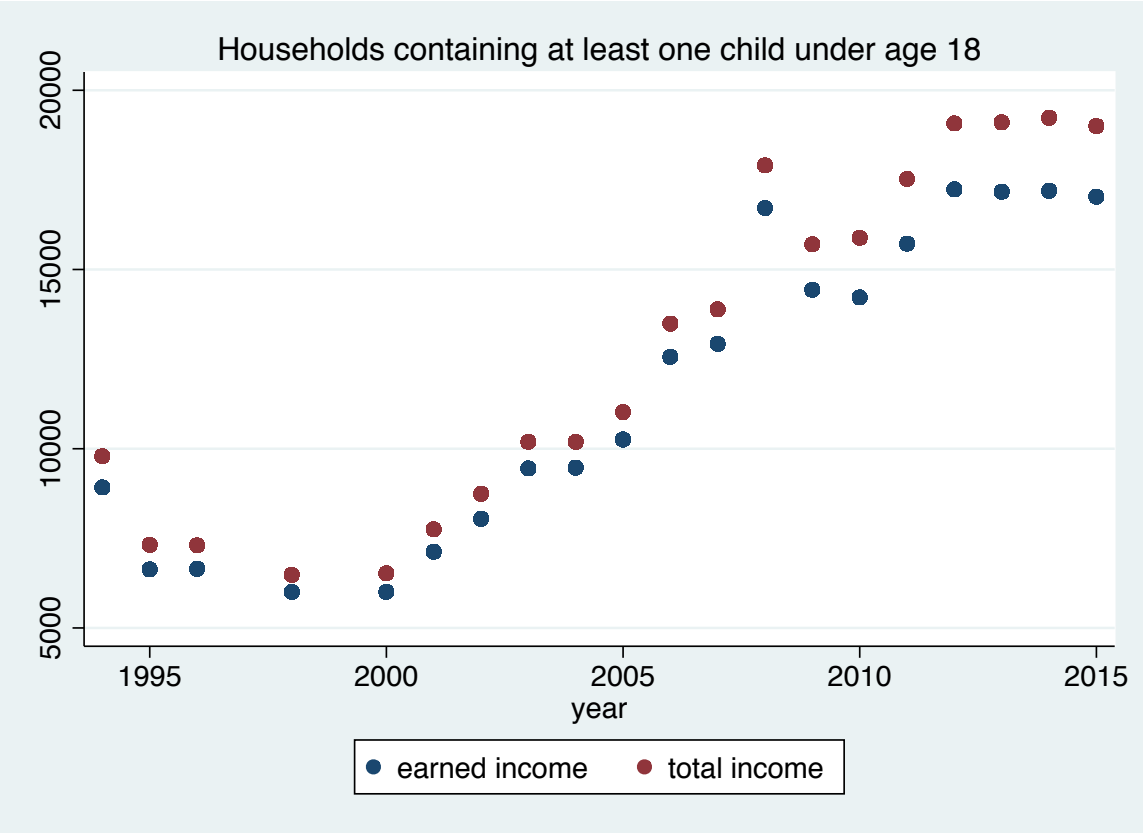
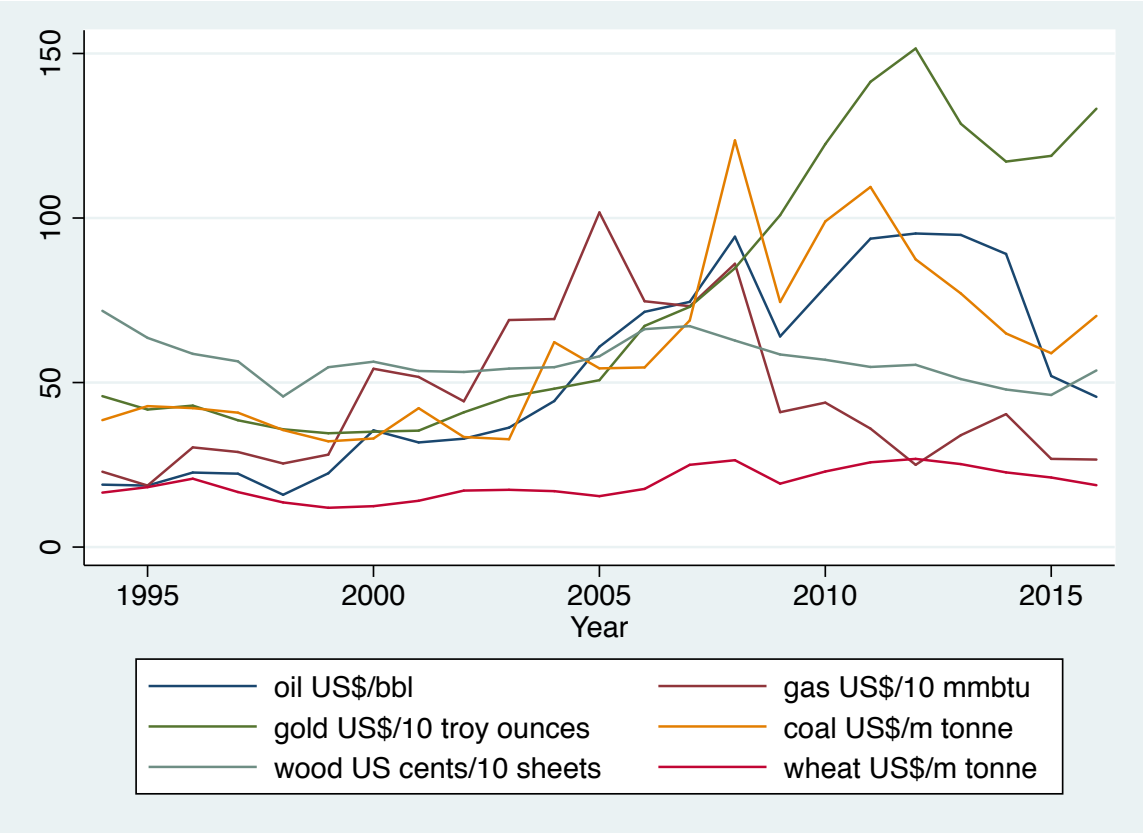


Figure 3: Prices of major commodities produced in Russia (rescaled)



Data Appendix A

Definitions:

Expenditures and incomes:

Consumer Durables, Luxuries and Clothing: The sum of new adult and child clothing expenditures plus all consumer durables (appliances, cars, bicycles, furniture) and all luxuries purchased.
Adult-assignable goods: Alcohol and tobacco.
Health: The sum of all out-of-pocket health expenditures for all household members.
Services: The sum of service and recreation costs plus all other household services, including meals eaten outside of the home.
Assistance to others: The sum of money given or lent to all other households.
Staple foods:potatoes, bread, fats.
Home production: Sum of value of home-made goods sold for cash and values of in-kind output, as calculated by RLMS staff.
Perishables: dairy, eggs, meat, fish, fruit and vegetables.
Savings: savings in an account, and in stocks and bonds.

Child wellbeing outcomes, children aged 2-17 (inclusive):

Subjective health evaluation: "Very good", "good", "average", "poor" or "very poor". "Very good" and "good" take the value 1, zero otherwise.
Body Mass Index: Derived from the BMI score. Overweight is defined as a BMI over 25.
No health problem in last 30 days: No health issue that was either attended by a physician or treated in the home.
Hospitalised in past 3 months: Stayed overnight in either a public or private hospital.

School attendance is nearly universal amongst this age group, and so this outcome is not examined.

Construction of the local price index

Higher incomes may result in local food price inflation, so controlling for price levels may be particularly important for inference. Income and expenditure data have been deflated by RLMS staff to June 1992 roubles, but this will not account for local changes in real food purchasing power.

There are 25 food items included in the basket of commodities in the local Laspeyres price index. These items comprise those for which the greatest mean fraction of household food budgets was spent in 1994. Quantities purchased and prices are measured in the same units, generally kilograms or litres. The mean amounts purchased of each commodity in the base year are multiplied by the simple mean of all prices collected for that commodity.

Yearly community surveys include components devoted to documenting local prices. For each commodity, high and low prices in stores and in the market were collected in each year. Only in 1998, immediately following the August Russian Rouble Crisis, were local price variables somewhat differently. In 1998, two prices were generally collected for each commodity, but store and market prices were not distinguished. The two prices collected in 1998 do not necessarily correspond to 'low' and 'high' prices. For 1998, mean prices are calculated as the simple average of all available prices. Unfortunately, price information was not consistently collected for each commodity in each site in each year as intended by RLMS community survey coordinators. As a result, there are many missing observations in the community level data.

Household level information on amounts paid and quantities bought of different food items can be used as an alternative way of deriving a price per unit in each site in each year. The simple mean per unit price paid by purchasing households can be calculated for each site.

The composition of the food basket used in the construction of the Laspeyres series is shown in Table A1 below:

Household expenditure data may conceal switches to higher quality goods as incomes or benefits rise. In the US context, Hastings and Schapiro (2013) find that consumers switch between qualities of gasoline in response to gasoline price shocks. Several behavioural explanations for the apparent

Table 7: Food basket employed in construction of the site-specific price series

Food item item	mean units purchased in month prior to 1994 RLMS interview	price per unit (real 1992 roubles)
beef	1.85	4607.614
sausage meat	0.17	9122.567
fruit	1.73	2895.092
poultry	0.76	5116.134
pork	0.84	5392.048
sugar	2.21	1961.499
butter	0.49	8503.81
white bread	4.06	1009.01
candy	0.38	10998.34
vodka	0.39	7575.532
eggs (unit)	11.57	229.0635
flour	3.5	899.5516
vegetable oil	0.73	4257.876
fish	0.48	4944.857
milk	2.4	930.4701
tobacco	3.60	661.0094
pasta	0.85	2201.517
cakes	0.35	5083.163
liqueur	0.17	9519.211
black bread	2.02	743.8909
cheese	0.19	7534.571
coffee	0.03	43838.5
potatoes	1.43	930.8727
cream	0.27	4247.795
beverages	0.45	2344.203
groats	0.80	1336.098

lack of fungibility of incomes are tested. Households switch to more expensive calorie sources and to prepared meals as incomes rise. This might also be true for other goods. Because household expenditure data almost never contain information on goods qualities, the availability of extensive child welfare information is potentially very important to assessing child benefits and earned incomes impacts.

Construction of the counterfactual commodities model

To construct the year and site-specific counterfactual commodities model, a measure of industry-specific employment in a base year is necessary for each site. Only from 2006 were respondents asked to report their industry of employment in the RLMS. Within provinces, sites are not named or otherwise identified. Locational information cannot be used to ascertain whether a site contains gas or oil deposits, or the types of minerals mined in the location. For this reason, site-specific employment of individuals aged 18 to retirement age is employed to calculate industry-specific employment rates for each site in the base year.

In the RLMS work questionnaire, industry is reported at the two-digit level. This means that oil and gas is classified as one industry, all mining as another, and agriculture as another. Despite the courseness of this industry definition, heterogeneity in price movements between oil and gas, different types of mine output, and between different agricultural products can be exploited to predict earnings. The 38 primary sampling units (PSUs) are identified by name. These are mainly regions and autonomous republics. Two cities in Komi, Syktyvkar and Usinsk, and two in Krasnojarskij Kray, Krasnoyarsk and Kushchevskij Rajon, are identified as PSUs. For these four, the types of natural resource activities in which people are employed can be more precisely identified than for other PSUs.

For Usinsk, for example, the calculation of the relative importance of oil versus gas is relatively simple. Output of these two commodities is available starting only in 2001 from the regional government of the Komi Republic. Still, the detailed breakdown given of various hydrocarbon volumes permits the shares, by volume, of oil versus gas to be calculated (Komi Republic (2018)). In 2001, the sum of oil, motor gasoline, diesel fuel and fuel oil, in thousand metric tonnes, was 6300.1. The quantity of natural gas, dry gas and stable gas produced was 5059.3. This means that the relative share of oil is 0.555, and that of gas $(1 - 0.555)$. These are the weights assigned to the two respective price series in predicting the evolution of earnings during 1994-2015 in Usinsk.

The counterfactual prediction of earnings from the oil and gas industry for Usinsk is added to that for agriculture (wood and wheat) and mining (coal and gold) to predict earnings in Usinsk for each year. Wheat cannot be produced in Usinsk, or anywhere in the Komi Republic. As a result, the share of wood in the agricultural price series is here 1. Usinsk sits just north of the Tom-Usinsk area

of the Kuznetsk coal basin. There is no gold mining in the immediate vicinity of Usinsk, although Komi is rich in reserves of gold and other minerals. For Usinsk, then, the share of coal prices in the mining series is again 1.

For sites in the remaining 34 PSUs, the weighted average of provincial employment in each of the following commodities is calculated: gold mining, coal mining, oil, gas, wheat and softwood lumber. In this way, the world price variation in specific commodities can be combined with the available site and industry-specific employment information. For each site s and commodity d, the contribution of an industry to the counterfactual commodities predictor in the baseline year is $\widehat{m_{sd}} = k_{rd} * EMP_{esd} + (1 - k_{rd}) * EMP_{esd}$ where e refers to the industry employment rate defined by the two-digit industry code and k is the PSU-specific fraction of output in the base year of the two main commodities produced by that industrial sector. This output is measured by volume, which should reflect industry-specific employment levels more closely than might the value of the output. Prices are normalised for each commodity, with 1994 as the base year.

Treatment of outliers

The treatment of outliers is necessarily somewhat arbitrary. Household incomes totals are recoded as missing if reported incomes for the previous month are less than zero or more than 900 000 real June 1992 roubles. Child benefits amounts are recoded as missing if they are greater than 20 000 roubles. Home production values, which have been imputed by RLMS staff on the basis of reported cash and good production in the household, are recoded as missing if above 50 000 roubles.

Expenditure outliers have been left as originally reported.

Data Appendix B: Crowding out of home production, private transfers and savings

The RLMS data contain particularly detailed information on private transfers and home production. Money and goods accruing to and from other households is recorded. Home production amounts in cash and in kind are estimated for each year by RLMS personnel. This information can be employed to examine whether or not there are any crowding out effects from child benefits and other incomes. Jensen (2004) finds that the expansion of the South African state pension in the early 1990s substantially reduced private transfers from children to their elderly parents. Households might receive fewer roubles in private incomes support when their own incomes are higher. They might also choose to engage less in home production as they purchase more goods and services. With higher incomes, households may spend more on transfers to others outside of the household. Effects might differ across income sources.

Results for private transfers towards households containing children, and for home production, are broadly consistent. No evidence is found that either earned incomes or child benefits money crowd out private transfers towards sample households (Panel A of Table 8). When household incomes rise because of world commodity price changes or benefits, other households do not change the extent of financial flows towards them.

Home production appears not to vary with earned incomes. However, there does seem to be a negative causal relationship between benefits receipt and home production. The value of home production, as assessed by RLMS interviews for cash and kind homemade goods, is more than 1000 roubles lower in households because of child benefits receipt in some of the specifications with instrumentation for both variables of interest (Panel B). When households stop receiving the child benefit because the last child passes the age threshold of 16, they may compensate by increasing the value of their home production.

Since the preferred home production specification controls for labour supply, any increase in time spent on home production is likely obtained from a reduction in leisure. One potential reason for this finding is that child benefits were often received in goods form in the 1990s. These goods were often perishable foodstuffs. This food was the output of domestic food processing industries whose local tax liabilities had been contributed to authorities in kind. Another is that children spend more time growing and processing fruit and vegetables for the winter when they attain age 16, because

their parents need them to compensate for the loss of child benefit money. Further analysis of time use data may yield insights about changes in the behaviour of children around the age of benefits termination.

The data do not suggest that perishable food received as an in-kind child benefit can explain the change in home production observed as a child turns 16. There is no reduction in purchases of perishables as a result of having obtaining the child benefit (Panel C). Similarly here is little evidence that purchases of non-perishable staple foods are impacted either by income shocks or by child benefits receipt. Results for all specifications are presented in Table 8, Panel D. The impact of these monies on staples comprising bread, potatoes and fats is also not found to be statistically significantly different from zero.

If households behave as though child benefits have been labeled for children, saving behaviour might be altered by their receipt. In principle, savings might be made for children's future education or health needs, so these effects might go either way. There is no statistically significant relationship between earned incomes and savings rates amongst this subpopulation. This is shown in Panel E of Table 8. The coefficient on the dummy variable for child benefits receipt is also not statistically different from zero in any specification. Savings rates were very low amongst families with children during this period.

Time use of boys and girls aged 14-17 (inclusive)

The possibility that changes in home production values result from child benefits receipt can be further investigated by examining time spent in home production activities by children around the child benefits receipt threshold. Time use data for the week prior to the RLMS interview was collected in the 1994-1998 rounds of the RLMS for individuals aged 14 and older. There are 5933 children aged 14 through 17 in these data.

The restricted time spanned by these data prohibits separate identification of incomes and child benefits impacts. As well, only 37% of children under age 18 resided in households which had received the benefit in the month prior to the RLMS. In this subsample, the probability that a child is aged 14 or 15 is not a strong predictor of the probability of having received benefits. This is likely because of the payment and arrears crises which affected all government transfers during this period. Nevertheless, the available data do provide some information about whether or not children on either

side of the child benefits threshold engaged in substantially different amounts of home production activities. This is one potential violation of the exclusion restriction which is suggested by a finding that households lower home production output because of receiving the child benefit.

There appears to be no strong relationship in these data between child age and time spent in home production. This is true with or without conditioning on household wealth, dwelling characteristics and time spent in paid work by household members aged 18 and older. Results are presented separately for boys and girls in Table 9. For girls, time engaged in home production does not increase in age (Panel A). This result holds with the inclusion of a full set of site, year, household composition, wealth and dwelling controls. Allowance for a discontinuity at the normal age of termination of the child benefit does not alter this inference, although this is perhaps related to the payments crisis. No conditional association is found between attaining age 16 and time spent in paid work, as measured in the time use survey.

For boys, results are slightly different. There is no robust conditional association between age and home production time, and no discrete jump in home production time at age 16. However, time spent in paid work does change substantially for boys as they age from 14 to 17. For each additional year of age, boys work about 3 hours more per week for pay. Importantly, however, there is no apparent discontinuity in this upwards trend at age 16.

The available time use data support the exclusion restriction for child benefits in the main analysis. There is no apparent difference in home production or paid work activities by children on either side of the age benefits threshold. This suggests that any rise in home production caused by child benefits termination cannot be explained by resulting changes in children's time use. The target beneficiaries do not work more in the home or in the market because these monies cease.

Table 8: The impact of child benefits and earned incomes on home production, savings, transfers from other households

	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Assistance from other households						
earned	0.2458***	0.1358	0.1881	0.1798	0.1955	0.1887
	(0.086)	(0.105)	(0.133)	(0.137)	(0.152)	(0.149)
any chben l month	304.1641**	124.5215	1314.6452	969.4813	932.3692	629.2101
	(130.501)	(215.332)	(1274.536)	(1257.266)	(1219.094)	(1106.709)
F stat	10.778	1.421	8.925	7.611	7.997	7.118
No. obs.	28391	28391	28391	27462	27342	27342
Panel B: Home production in cash and kind						
earned	0.0165***	0.1001*	0.0309	0.0483	0.0553	0.0531
	(0.003)	(0.057)	(0.052)	(0.050)	(0.054)	(0.053)
any chben l month	36.8796	266.6438**	-1133.3810*	-977.1493	-1108.4502*	-1199.3990*
	(32.267)	(106.608)	(620.534)	(612.413)	(612.094)	(614.424)
F stat	17.436	4.945	3.657	1.955	1.964	2.193
No. obs.	27383	27383	27383	26482	26365	26365
Panel C: Staple foods (potatoes, fats, bread)						
earned	0.0030***	-0.0171	-0.0175	-0.0151	-0.0144	-0.0133
	(0.001)	(0.018)	(0.022)	(0.021)	(0.021)	(0.020)
any chben l month	-1.8975	-70.7402*	-129.6953	-55.0279	-54.9378	-13.8230
	(18.682)	(37.592)	(335.211)	(319.234)	(312.756)	(305.338)
F stat	51.334	2.588	13.548	10.977	11.524	9.642
No. obs.	28391	28391	28391	27462	27342	27342
Panel D: Perishables (dairy, eggs, meat, fish, fruit and vegetables)						
earned	0.0169***	-0.0902**	-0.0309	-0.0452	-0.0663	-0.0625
	(0.003)	(0.042)	(0.043)	(0.042)	(0.046)	(0.044)
any chben l month	-73.3508**	-341.6293***	732.9627	904.6940	789.6617	970.4184
	(34.388)	(92.198)	(614.090)	(638.548)	(644.365)	(623.159)
F stat	68.503	10.022	11.062	8.172	5.690	5.316
No. obs.	28391	28391	28391	27462	27342	27342
Panel E: Savings						
earned	0.0178***	0.0758	0.0806	0.0853	0.0870	0.0877
	(0.005)	(0.050)	(0.055)	(0.054)	(0.059)	(0.058)
any chben l month	-20.8597	83.9098	181.0533	166.2365	43.9336	50.4221
	(63.053)	(112.539)	(755.952)	(815.169)	(818.896)	(793.005)
F stat	5.136	1.657	1.356	1.559	1.372	1.381
No. obs.	28384	28384	28384	27456	27336	27336
Additional controls:						
dwelling	no	no	no	yes	yes	yes
wealth	no	no	no	no	yes	yes
l. supply	no	no	no	no	no	yes

Source: RLMS-HSE 1994-2015. Real 1992 roubles. Controls for local price levels and household composition are included in all specifications. Year dummies and site fixed effects are also included. In specification (2), instrumentation is for earned income, and in specifications (3)-(6) for both earned incomes and child benefits receipt. Standard errors are clustered at the household level * significant at 10% level, ** significant at 5% level, and *** at 1% level. Household sample weights are employed.

Table 9: The conditional association between age and hours spent in activities by children aged 14-17 (inclusive), 1994-1998

Panel A: Girls						
Home production						
age	-0.2039	2.7080	3.0136	2.7076	0.4833	0.6383
	(1.139)	(2.324)	(2.391)	(2.512)	(2.724)	(2.772)
< age 16		6.6325	8.0259*	6.5786	4.8638	5.3593
		(4.377)	(4.353)	(4.599)	(5.281)	(5.339)
constant	19.5281	-32.0854	-35.3192	-25.9697	1.4298	5.1204
	(18.690)	(40.167)	(42.529)	(45.936)	(50.981)	(51.269)
R^2	0.274	0.277	0.311	0.324	0.325	0.331
No. obs.	2859	2859	2859	2737	2290	2290
Paid work plus commuting						
age	0.7375	0.7339	-0.2316	0.0298	0.5537	0.4135
	(0.473)	(0.940)	(0.749)	(0.768)	(0.830)	(0.835)
< age 16		-0.0082	-0.9386	-0.7842	-0.6522	-0.7919
		(1.527)	(1.442)	(1.524)	(1.856)	(1.822)
constant	-10.9342	-10.8704	2.9111	-3.8990	-14.4042	-11.7583
	(7.564)	(15.567)	(12.125)	(13.059)	(14.045)	(14.517)
R^2	0.111	0.111	0.157	0.170	0.230	0.240
No. obs.	2833	2833	2833	2712	2258	2258
Panel B: Boys						
Home production						
age	-2.2544**	-1.7254	-0.2762	-0.9325	-0.8987	-0.8736
	(1.122)	(1.918)	(2.067)	(2.094)	(2.348)	(2.343)
< age 16		1.1518	3.1998	2.6377	3.0797	3.1613
		(3.692)	(3.728)	(3.802)	(4.111)	(4.099)
constant	66.0068***	57.1176*	24.4127	36.1112	25.6270	25.7783
	(20.577)	(33.137)	(36.071)	(37.223)	(41.265)	(41.152)
R^2	0.153	0.153	0.186	0.194	0.218	0.225
No. obs.	2905	2905	2905	2843	2458	2458
Paid work plus commuting						
age	3.4301***	4.2212***	3.3425***	3.2652***	3.1118***	3.1814***
	(0.616)	(1.084)	(1.061)	(1.082)	(1.178)	(1.178)
< age 16		1.7227	0.9170	0.9645	0.2911	0.4281
		(1.586)	(1.591)	(1.620)	(1.724)	(1.730)
constant	-57.4139***	-70.7084***	-62.6085***	-60.2456***	-59.5687***	-60.5596***
	(10.459)	(18.318)	(17.891)	(18.358)	(20.063)	(19.916)
R^2	0.240	0.241	0.254	0.260	0.233	0.236
No. obs.	2905	2905	2905	2843	2458	2458
Additional controls:						
hh. adults	no	no	yes	yes	yes	yes
dwelling	no	no	no	yes	yes	yes
wealth	no	no	no	no	yes	yes
l. supply	no	no	no	no	no	yes

Source: RLMS-HSE 1994-1998. OLS estimation. Time use data refer to hours spent in the week prior to the RLMS interview. After 1998, time use data were no longer collected. Standard errors are clustered at the household level * significant at 10% level, ** significant at 5% level, and *** at 1% level. Household sample weights are employed.