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Inequality and volatility moderation in Russia: Evidence from micro-level panel data on consumption and income

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ABSTRACT

We construct key household and individual economic variables using a panel micro data set from the Russia Longitudinal Monitoring Survey (RLMS) for 1994–2005. We analyze cross-sectional income and consumption inequality trends and find that inequality decreased during the 2000–2005 economic recovery. The decrease appears to be driven by falling volatility of transitory income shocks. The response of consumption to permanent and transitory income shocks becomes weaker later in the sample, consistent with greater self-insurance against permanent shocks and greater smoothing of transitory shocks. Finally, expenditure and income inequality in Russia are not far apart.

1. Introduction

Modern macroeconomists are increasingly relying on the analysis of environments with heterogeneous agents. Many macroeconomic questions can only be asked (and answered) in the context of multi-agent environments. These richer macroeconomic models require a correspondingly rich set of empirical facts that come from micro data and incorporate information on distributions in addition to the usual aggregates. The goal of this paper is to provide a comprehensive set of cross-sectional and time series stylized facts for the Russian economy and a systematic study of multiple dimensions of inequality.

Since the late 1980s, the Russian economy has been subject to substantial macroeconomic volatility, with a long phase of severe output contraction, periods of high and variable inflation, and a subsequent period of recovery. At the same time, Russia has tremendous regional diversity. The combination of these factors presents unique opportunities for studying both cross-sectional and time-varying dimensions of inequality. Fortunately, high quality data are available to explore these opportunities: a large, nationally representative panel study of Russian households, the Russia Longitudinal Monitoring Survey (RLMS).

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This paper includes multiple dimensions of inequality, with particular focus on consumption and income. We construct key variables describing the economic behavior of Russian households and individuals and analyze their cross-sectional dispersion and time series patterns. Specifically, we create time-varying distributions of individual earnings and labor supply, as well as household-level income, expenditure, and consumption.

We would like to highlight two main results. First, almost all measures of cross-sectional inequality in income and consumption started falling during 2000–2005, after staying relatively high during 1994–1998. Second, the measured fall in inequality is mostly due to the moderation of the transitory shocks to household income and consumption.

The recent period of falling inequality was preceded by an initial rise in the early 1990s that accompanied Russia's transition from a centrally planned to market economy (e.g., Commander et al., 1999; Galbraith et al., 2004). However, the level of inequality at the end of our sample is still higher than it was during the socialist era. Interestingly, poor households do not appear to fall behind during the economic recovery — the lower tail of the expenditure distribution does not diverge from the middle as the economy expands. The latest level of inequality that we find is typical for a middle income country. For example, the Gini coefficient in 2005 was about 0.38–0.40, which is just slightly above the mean value of Gini coefficients for after-tax household income and consumption from upper middle income countries.[1,2] Our findings are generally consistent with previous studies that document changes in income inequality in Russia in the 1990s (Commander et al., 1999; Jovanovic, 2001; Lehmann and Wadsworth, 2007; Milanovic, 1999; Flemming and Micklewright, 2000; etc.).

Some features that set the Russian economy apart from more developed countries turn out to be important for the analysis of inequality. One such feature is home production of food. Our results indicate that home-grown food has a large equalizing effect on income and consumption. The effect is large because poorer rural households are the ones that grow a lot of food for own consumption. Another unique feature of the Russian economy is its geographic diversity. Accounting for regional differences in the cost of living (that vary by a factor of 2.7 in Russia) is shown to have a sizeable equalizing effect (see Section 6). Other important features of the Russian transition, such as underreporting of income, wage payment delays, irregularities in government transfer payments, and forced in-kind substitutes in lieu of wage payments also explain some of the inequality trends.

The comparison of income and expenditure inequality reveals further differences from developed economies, where expenditures are usually distributed more equally than income. This turns out not to be the case for Russia, where expenditure inequality is almost as high as income inequality. We argue that the relatively high expenditure inequality reflected peculiar patterns of consumption smoothing during the downturn. Households facing irregular wage and transfer payments, high inflation and undeveloped financial markets used less conventional mechanisms such as food storage to smooth consumption. Food inventories were built up when income was received to insure against inflation and irregular wage payments.

Looking at the inequality dynamics between groups, we have found almost no evidence of convergence or divergence between groups based on observables, such as education, location, household composition, and age. The reduction in inequality during economic recovery resulted mostly from the moderation in the residual volatility of income and consumption growth.

We examine the reasons for the observed fall in residual income volatility by exploiting the panel dimensions of the data (see Section 5). In particular, we decompose the income process into permanent and transitory components and estimate their effect on consumption. We find that the fall in residual income volatility is mostly due to a fall in the variance of transitory income shocks.[3] Over time, consumption response to both permanent and transitory income components becomes weaker. This is consistent with better insurance against income shocks and better consumption smoothing later in the mid 2000s.

The rest of the paper is organized as follows. In Section 2, we describe the data, provide basic information on the levels of consumption, income, and labor market participation, and compare these statistics with official data. In Section 3, we document the trends in inequality in individual labor market outcomes over 1994–2005. In Section 4, we construct and report consistent time series for a variety of measures of consumption and income inequality at the household level. Section 5 decomposes the income process into transitory and permanent components and investigates the interaction of consumption and income inequality at the household level. In Section 6, we examine the role of regional disparities in generating inequality. Our concluding remarks are in Section 7.

2. Data overview

2.1. Sample and variables

The analysis in this paper uses the RLMS, which is a panel dataset with detailed information on income, consumption, household demographics, and labor supply. The RLMS is organized by the Population Center at the University of North Carolina in cooperation with the Russian Academy of Sociology. The data are collected annually, and our panel includes ten

[1] The RLMS, like most household surveys, may underrepresent very rich individuals. The studies that attempt to adjust for the super-rich typically document much higher levels of inequality (e.g., Aivazian and Kolenikov, 2001; Guriev and Rachinsky, 2008). The cross-country comparisons of inequality are still valid to the extent that all countries underrepresent the super-rich in their surveys.

[2] The comparisons are made using the Inequality Database of the World Institute for Development Economics Research.

[3] Stillman (2001) finds that RLMS expenditures respond strongly to transitory shocks during 1994–1998.

waves during the period 1994–2005, with the exception of 1997 and 1999, when the survey was not administered.[4] There were 8343–10,670 individuals who completed the adult (age 14 and over) questionnaire and 3750–4718 households who completed the household questionnaire in each round. These individuals and households reside in 32 oblasts (regions) and 7 federal districts of the Russian Federation.[5]

The RLMS sample is a multi-stage probability sample of dwellings. The response rate is relatively high: it exceeds 80 percent for households and about 97 percent for individuals within the households. The sample attrition is generally low compared to similar panel surveys in other countries, partly owing to lower mobility and infrequent changes of residences.[6] To account for the panel attrition, all statistics reported in this study are weighted using the RLMS sample weights that adjust not only for sample design factors but also for deviations from the census characteristics. For comparability with other countries in this volume, we restrict our estimation sample to households in which at least one individual is 25–60 years old. Appendix C shows the size and composition of the estimation sample.

We use variable definitions that are consistent across different survey waves. We provide thorough treatment of missing values, influential observations, non-response, and other common problems of micro data. We also take into account important Russia-specific phenomena that influence our variable definition and data analysis such as wage payment delays in the 1990s, production of food at home, high regional diversity in cost of living, as well as peculiarities of the transition to a market economy. The detailed procedures of variable construction are documented in Appendix A.

2.2. Economic conditions

Economic conditions in Russia affect our interpretation of income and consumption data in important ways. During the 1994–2005 period, Russia continued its transformation from a centrally planned system into a market economy. New integrated markets have emerged and new institutions of private ownership and property rights have been established.

This transition to a market economy was accompanied by extreme macroeconomic disturbances, both real and nominal. Our sample period features two distinct phases: the downturn in 1994–1998 and the post-1998 period of rapid recovery. Panel A of Fig. 1 shows that the early 1990s, following price liberalization in 1992, was a period of high inflation: the end-year inflation rate in 1994 was 214 percent. The 1998 inflation spike (84 percent) corresponds to the government default on sovereign debt and the abrupt devaluation of the national currency, the ruble. In the downturn, real per-capita income and expenditures fell by about 40 percent (see panels B–D). Employee compensation and public transfers were paid irregularly, and were delayed by 3 to 5 months, on average. In the recovery phase, real per-capita income and expenditure growth was around 9 percent annually, and inflation stayed relatively low (10 to 20 percent).

2.3. Composition of income

The composition of household income during the sample period remained relatively stable, although there are important differences with Western industrialized economies. Panel B of Fig. 1 shows the trends in household after-tax monthly disposable income per capita, yD, and its labor component, yL, during 1994–2005. Labor income is by far the largest income source; it accounts for 82 percent of household disposable income on average. In addition to labor income, yD includes income derived from financial assets (negligible), net private transfers (3 percent), and public transfers (14 percent). Net private transfers are contributions in money and in kind received from friends, relatives, and charitable organizations minus contributions given to individuals outside the household unit. Although net private transfers should not (and do not) affect average disposable income, gross private transfers are significant; private transfers received amount to 9 percent of disposable income, making them a potentially important channel of risk-sharing. Average public transfers are also large and amount to 14 percent of disposable income. The share of public transfers has increased since 2001, as evidenced by the growing gap between yD and yL in panel B.

2.4. Composition of expenditures

Household consumption is constructed from numerous disaggregated categories of expenditures. Non-durable consumption, c, includes 50 subcategories of food, alcoholic and non-alcoholic beverages, tobacco products, clothing and footwear, gasoline and other fuel, rents and utilities, and 15–20 subcategories of services such as transportation, repair, health care services, education, entertainment, recreation, insurance, etc. Durable consumption is based on purchases made of durable items within the last 3 months. All consumption measures are converted to a monthly base. To keep the coverage of con-

[4] In all plots, except for Fig. 2, the 1997 and 1999 values are 2 point linear interpolations of the data points in adjacent years. We could not use 1992–1993 survey waves due to incompatible data definitions for key variables.

[5] Russia had 89 regions and 7 federal districts as of December 1, 2005. The RLMS sample consists of 38 randomly selected primary sample units (municipalities) that are representative of the whole country.

[6] To deal with attrition, RLMS replenishes its sample on a regular basis by adding new dwellings, especially in the areas of high mobility such as Moscow and other large cities. To maintain the panel, RLMS partially attempts to collect information on those who moved out of the sample dwellings but live in the same location. More details on sample design, attrition, and replenishment are available at http://www.cpc.unc.edu/projects/rlms.

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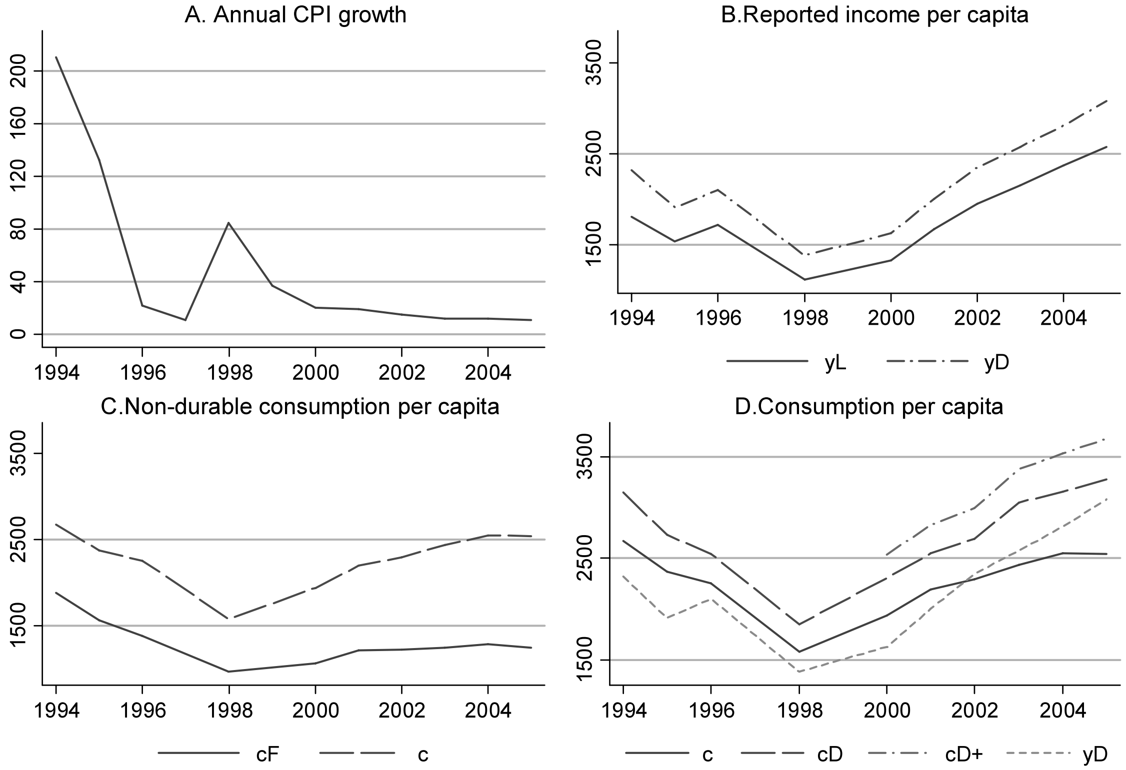

Notes: Panel A shows annual inflation rate using national end-year CPI from official sources. In remaining panels, all measures are average monthly RLMS aggregates per capita in constant December 2002 prices (deflated using national monthly CPI and the date of interview). yL = after-tax household average labor earnings; yD = after-tax household disposable income = yL + net private transfers + financial income + government transfers; cF = household expenditures on food, beverages, and tobacco last week (multiplied by 30/7); c = household non-durable expenditures; $cD = c$ + expenditures on durables; $cD+ = cD$ + imputed services from housing.

Fig. 1. Trends in household income and consumption.

sumption consistent across years, we exclude expenditure categories that became available only in recent years, such as washing supplies, personal hygiene items, books, sporting equipment, internet, and wireless phone services.[7]

Food is the biggest expenditure category for most households. The share of food purchases in aggregate non-durable expenditures starts from a high of nearly 70 percent in 1994 and gradually falls to 49 percent in 2005 (see Fig. 1C). One peculiar feature of Russian households is that many of them grow agricultural products on their subsidiary plots for own consumption. In 1994, about 10 percent of total food consumption (by market value) was home-grown, and by 2005 the share of food grown at home fell to 5 percent. Despite declining in aggregate importance, home production of food significantly affects measures of inequality, because it is concentrated among the poorer rural households (see Section 4).[8]

In addition to our baseline measure, c, Fig. 1D also reports an alternative consumption measure cD, which equals to non-durable expenditure plus durables purchased within the last 3 months (divided by 3). The share of durables was around 14 percent of aggregate expenditures, cD, during 1994–2002, but it has increased significantly after 2003. Expenditures on durables tend to be concentrated at high income levels: 76 percent of households report no durable purchases within the last 3 months. Because the observed durable purchase history is short and durable inventory data are not available, we use only non-durable consumption, c, rather than cD, for inequality measurement.

For 2000–2005, our dataset has a self-reported market value of owner-occupied housing. If we take the annual housing services flow to be 5 percent of its market value, the share of owner-occupied housing will equal roughly 11 percent of total

[7] The share of excluded expenditure categories is about 3 percent of total consumption expenditures in 2001–2004 and 5 percent in 2005. The 2 percentage point increase in 2005 is explained by adding expenditures on internet and cell phones in the 2005 RLMS questionnaire. The omitted expenditure categories do not affect the measures of consumption inequality.

[8] Although we observe expenditures only for a few months in a given year, our results should not be affected by seasonality in any significant way. First, our measures of inequality are not sensitive to controlling for seasonal effects by using monthly dummies (data are collected over 4 months, and we know in which month the data are collected for a given household). Second, in Gorodnichenko et al. (2009b), we find that the level of consumption based on monthly expenditures in the RLMS is similar to the one based on annual expenditures in the Household Budget Survey.

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consumption, $cD+$. The share of housing consumption is relatively stable over time because the aggregate market value of housing is growing at roughly the same rate as aggregate expenditures, cD (see Fig. 1D). The growth in housing value is mostly due to the price change, as the quality of surveyed residences improved little.

2.5. Income underreporting

Two data facts lead us to believe that the aggregate income obtained from RLMS is likely to be underestimated. First is the negligible share of capital income. This could be due to income underreporting but also due to the underrepresentation of very rich individuals in the RLMS. To get a sense of the underestimated capital income, we can take the estimate of personal wealth of Russian billionaires and millionaires (1.4 times national GDP) from Guriev and Rachinsky (2008) and multiply it by a typical rate of return on a diversified financial portfolio (6 percent). If this is correct, the super-rich should earn about 8.4 percent of GDP, which we miss in our data.

The second fact is that in our sample reported income is consistently below reported expenditures (Fig. 1D). This gap cannot be attributed to dissaving, as most households have negligible stocks of financial assets. We believe that respondents may understate income for fear of disclosure of their responses to tax authorities. Consistent with this, Gorodnichenko et al. (2009a) find that the gap between income and consumption is significantly larger in districts where respondents believed that other people do not pay their taxes. Over time, the gap between consumption and income seems to narrow, and the narrower gap may correspond to the effect of the 2001 tax reform, credit market development, and other factors (see Gorodnichenko et al., 2009a).

2.6. Comparison with national accounts

We first compare income and expenditure levels between RLMS and official National Income and Products Accounts (NIPA). To make comparisons with national statistics, one must be careful to use compatible data definitions. The RLMS measure of household disposable income (yD) is after taxes and transfers *given*, and it excludes in-kind consumption, such as owner-occupied housing and home-grown food. The corresponding NIPA measure is disposable income for the "household account" after taxes and transfers minus in-kind consumption (Goskomstat, 2007a). Similarly, the RLMS measure of consumption that we select for comparison purposes (cD) corresponds to the NIPA measure of household final consumption expenditures on durable and non-durable goods and services without imputed in-kind expenditures (Goskomstat, 2007a). For comparability purposes, we use the full unrestricted RLMS sample.

Panels A and B of Fig. 2 compare yD and cD (per capita) with their counterparts from NIPA. Consumer expenditures in RLMS and NIPA are close during most of the sample period,[9] while reported disposable income in RLMS is up to 30 percent lower than the official figures. The big discrepancy in income levels across the two sources is expected, since NIPA expenditure and income data are internally consistent and adjusted for underreporting,[10] and RLMS reported income is much lower than expenditures. Despite the mismatch in levels, the growth rates of NIPA and RLMS income series are fairly close.

Expenditure levels match very well between RLMS and NIPA (panel B). This contrasts sharply with similar comparisons for the U.S. where household surveys tend to underestimate national aggregates by more than 30 percent. The analogous comparisons for the UK produce a less significant discrepancy of 5 percent (Attanasio et al., 2004). The match in expenditure levels in Fig. 2B is somewhat surprising, since RLMS likely underrepresents very rich households that consume out of capital income. It is possible, however, that the official statistics make an insufficient adjustment for shadow economic activity, making the discrepancy between NIPA and RLMS expenditures smaller than one may have expected.

Starting in 2003, RLMS consumption expenditures show slower growth than NIPA expenditures. As explained above, this difference in trends may indicate the growing gap between the RLMS sample and the super-rich individuals. Part of the gap may also arise due to an upward trend in consumption of goods that RLMS data does not consistently track, such as internet and cell phone services. However, new consumption categories are not enough to account for the post-2003 growth gap: new goods added to RLMS over the years constitute at most 5 percent of aggregate expenditures. Finally, a small portion of the gap (up to 1.6 percent of aggregate expenditures per capita) can be explained by the replacement of one of the wealthiest oil-based regions in the North by the middle income region in Siberia in the 2003 RLMS sample (this was the only episode of regional sample replacement during the 1994–2005 period).

Overall, RLMS appears to be a reliable data source for examining the inequality trends in labor market outcomes, reported income, consumption, with the common caveats of income underreporting and underrepresentation of the super-rich.

[9] The 1998 discrepancy can be explained by the fact that RLMS has been conducted just after the August financial crisis while NIPA's numbers are averaged over the year.

[10] NIPA eliminates the discrepancy between reported income and consumption by construction. Disposable income is constructed as a sum of household aggregate expenditures and savings, and the difference between imputed disposable income and the officially reported income is included in the income accounts as unobserved labor compensation.

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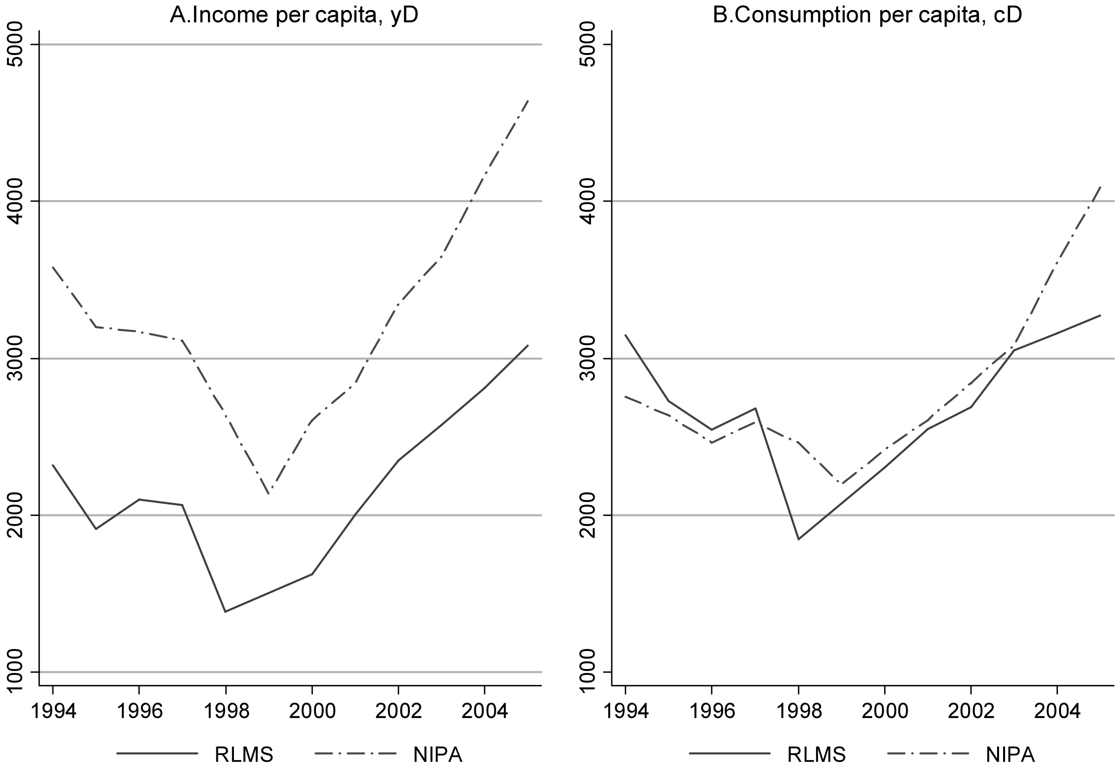

Notes: For comparability purposes, the following RLMS measures are selected: *yD* in panel A and *cD* in panel B. The RLMS sample is unrestricted. All RLMS measures are per capita and deflated using monthly CPI and the date of interview. All NIPA measures are deflated using annual average CPI. RLMS income and consumption for 1997 are imputed using the lagged RLMS value multiplied by the 1997 growth rate from NIPA.

Fig. 2. Comparison of RLMS with official statistics.

3. Inequality in labor market outcomes

Since labor income is the most prevalent income source, the inequality in labor market outcomes is crucial for understanding the overall income inequality. This section looks at the dynamics of inequality in individual wages and labor supply, emphasizing the key differences between major population groups.

3.1. Aggregate labor market trends

We start with an overview of aggregate trends in wages and employment. Several studies observed that during the downturn period in Russia, the decline in employment and hours of work was small while the wage decline was large relative to the output decline, in contrast to Central and Eastern European transition economies (Boeri and Terrell, 2002; World Bank, 2003). We find that the post-1998 economic growth was also accompanied by significant wage adjustments and relatively small changes in employment and working hours.

Hourly real wage level experienced dramatic movements, down 48 percent, or 10 percent per year, during the downturn and up 87 percent, or 9 percent per year, during the recovery (Fig. 3A). Panel A of Fig. 3 shows last month wage rate, wm, defined as the ratio of labor earnings received last month from all regular jobs to actual hours worked, and compares it to average wage rate (available 1998–2005), w, which is the ratio of average monthly labor earnings in the last 12 months to usual hours of work per month. The last month wage rate, wm, is higher than the average wage rate, w, partly because actual hours are lower than usual hours. Male wages appear to be more responsive to output fluctuations: male wages declined faster in downturn, but they also grew more rapidly in recovery.

In contrast to wages, hours of work do not vary considerably over time (Fig. 3B). Even in the downturn, an average employed person (with positive hours) worked more than 40 h per week. The response of hours to the 1998 financial crisis was minimal. Usual hours of work, h, are relatively high (48 h in all jobs for males), and they are bigger than actual hours, hm, because of temporary absence from work due to illness, vacation, maternity leave, involuntary unpaid leave, and other reasons. Females typically work 5–6 h less per week than males. The share of full-time workers does not change much in response to output fluctuations; it increases slightly over time for both genders, with a somewhat larger overall rise for females during 1994–2005 (Fig. 3C).

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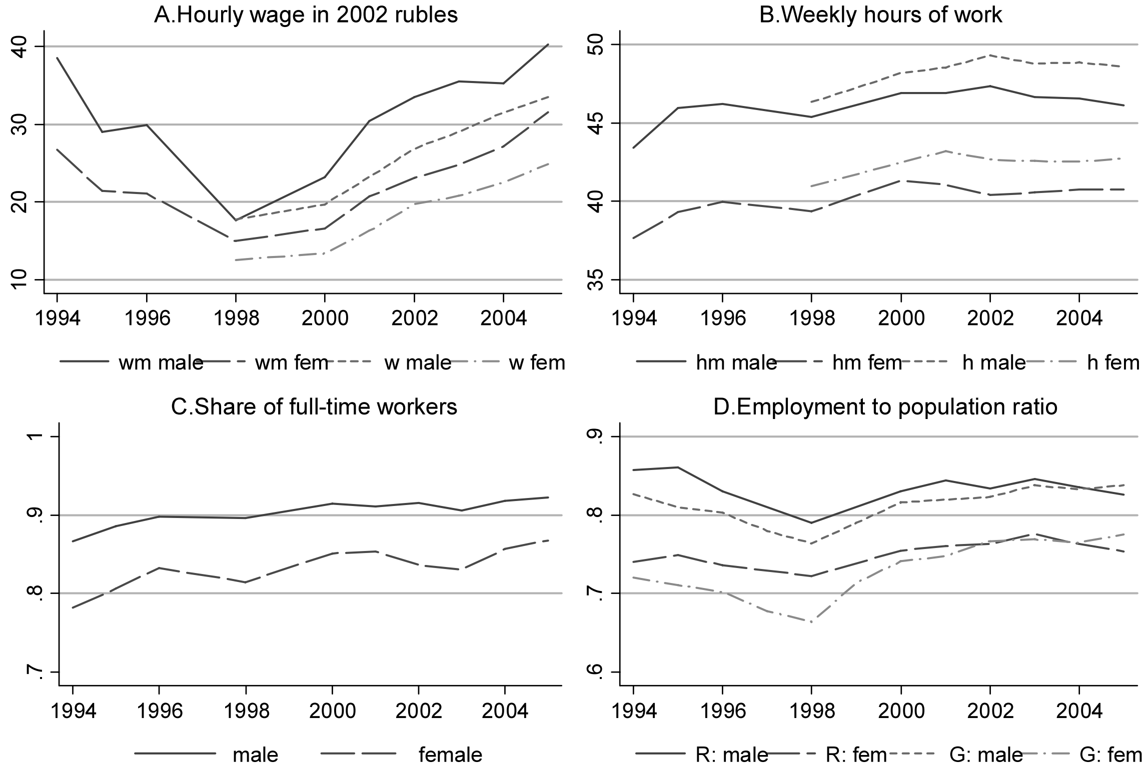


Notes: *wm* = hourly wage rate based on earnings received last month; *w* = average hourly wage rate; *hm* = hours worked last month; *h* = usual hours of work per month. All wages are deflated with national monthly CPI. Workers are considered full-time if actual hours at primary job were more than 120 h in the reference month. Panel D compares employment–population ratios in the RLMS sample (R:) and official Goskomstat statistics (G:). Both ratios are calculated for age group 25–59.

Fig. 3. Trends in labor supply.

Employment-to-population ratio in Russia is high by international standards. However, it declined significantly for males from 94–96 percent in 1985–1990 to 86 percent in 1994, and then down to 79 percent in 1998 (RLMS 2000, retrospective questions). In the growth period, the ratio did not revert to pre-crisis levels and stayed relatively constant at 83–84 percent for 25–59 age group (Fig. 3D). On average, the employment rate for females is 8 percentage points lower than that for males, which is a smaller gender gap compared to 14 percentage points in the U.S. for the same age group (U.S. Bureau of Labor Statistics, 2006). Fig. 3D also shows that the official employment rate is lower than that in RLMS in the 1990s, but the difference between the two data sources vanishes in later years.

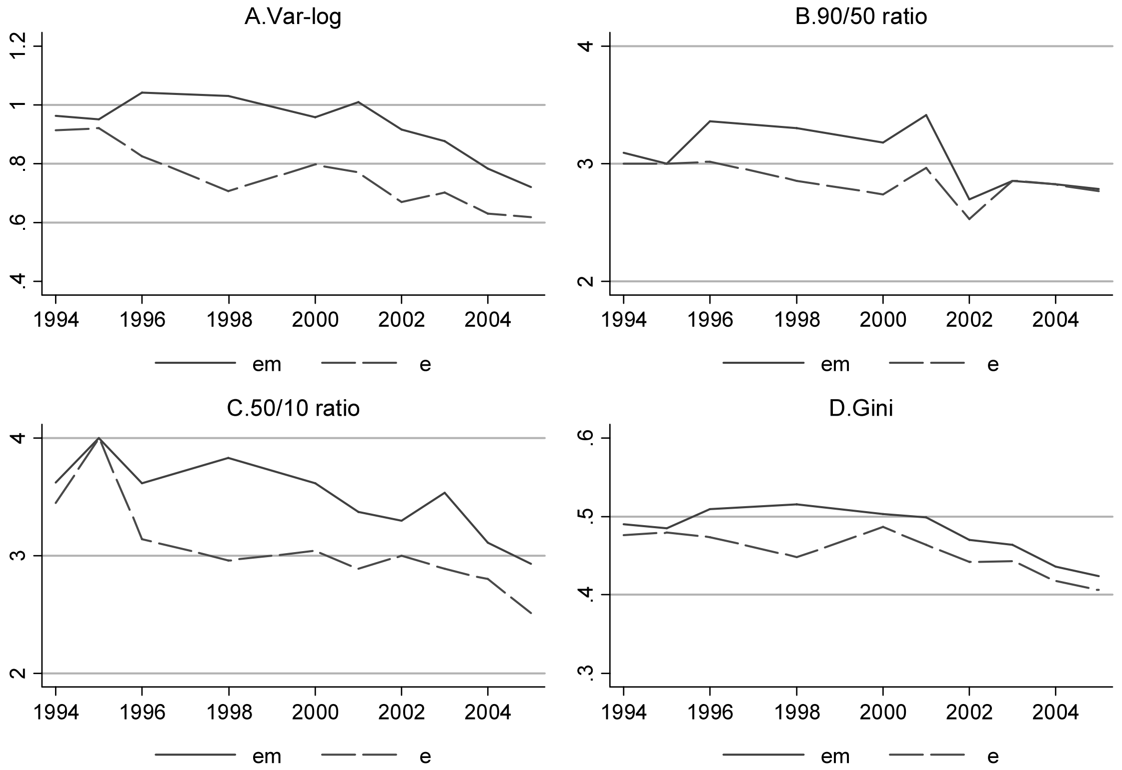
3.2. Earnings and wage inequality

Our sample starts in 1994, in the middle of an economic contraction in Russia that lasted almost a decade. Available evidence suggests that earnings inequality increased in the years preceding our sample period. This increase was associated with the transition to a market economy (Commander et al., 1999). We estimate that the Gini coefficient for earnings increased from 0.28 in 1985 and 0.32 in 1990 to 0.48 in 1995 (RLMS 2000, retrospective questions).[11] The 90/50 ratio climbed from 2.2 in 1990 to 3 in 1995, while the 50/10 ratio rocketed from 2 to 4 in just five years.

During our sample period, however, earnings inequality ceased to grow, as can be seen in Fig. 4. This figure depicts four different measures of inequality for two definitions of individual earnings (last month earnings, *em*, and average monthly earnings, *e*) in 1994–2005.[12] According to most measures in Fig. 4, inequality in individual earnings has been declining over the sample period. The Gini coefficient for average monthly earnings declined from 0.48 in 1995 to 0.41 in 2005, and the

[11] This dynamics of the Gini coefficient is consistent with other studies. For example, Flemming and Micklewright (2000) report an increase in the Gini coefficient for per capita income from 0.27 in 1989 to 0.41 in 1994 based on the Household Budget Survey. They note, however, that inequality could have been larger in the Soviet period after accounting for significant in-kind subsidies (e.g., free housing).

[12] The observations on average earnings are available starting in 1998. For 1994–1996, we construct average earnings from the data on last month earnings and answers to questions about accumulated overdue wage amounts and number of months of overdue pay, following the method proposed by Earle and Sabirianova (2002). See Appendix A for details.



Notes: *em* = individual labor earnings received last month; *e* = average individual labor earnings per month. Var-log is the variance of log earnings. All earnings are after-tax.

Fig. 4. Basic inequality in individual earnings.

variance of logs decreased by 0.17. The decline in earnings inequality is more pronounced in the bottom half of earnings distribution: while the 90/50 ratio hardly changed over the sample period, the 50/10 ratio fell sizably from 4 to 2.5. These changes in inequality statistics are very large compared to relatively slow dynamics of inequality measures in developed countries.

It may seem unusual that inequality at the bottom of the distribution was declining during an economic contraction. One explanation is that the timing of contraction (that started around at least as early as 1991) differed by income groups: for example, the dramatic rise in 50/10 ratio prior to our sample period suggests that low income workers suffered the most during the first years of market reforms. Several factors may have contributed to the decline in earnings inequality at the bottom of the distribution that continued after 1998: oil-driven growth that created labor demand in low-skill industries such as mining and construction, enhanced competition for workers (e.g., the number of employers increased dramatically), improved compensation in the public sector, etc. Each of these factors deserves a separate study.

Although the inequality indices remained higher than their pre-transition levels, the overall inequality decline is quite remarkable, and the reasons for it merit further research. This trend is consistent with international macroeconomic data showing a negative contemporaneous correlation between income inequality and economic growth for less developed countries (Barro, 2000).

Many Russians may be surprised to find that inequality has declined given the emergence of the conspicuous wealthy elite and a popular belief in the rising gap between rich and poor. We note, however, that adding the super-rich to the RLMS data will not affect the Kuznets ratios in Fig. 4. There still might be a valid concern that upwardly mobile high earners may have left the addresses surveyed by the RLMS interviewers, and that those who stayed are self-selected low earners. Some of the issues with panel attrition are addressed within the survey itself by adding new dwellings to the sample and adjusting the sample weights.[13]

[13] To assess the importance of non-random exit from the survey on the measures of inequality, we re-weighted observations by giving a larger weight to observations with a higher probability of exit. The adjusted weight is calculated as $L.weight \times 1/(1 - Pexit)$, where *L.weight* is the sample weight from the previous round and *Pexit* is the probability of exit from the survey estimated from a flexible probit regression that includes a wide range of controls for individual characteristics (pseudo-$R^2 = 0.08$). We found that adjustment for non-random exit barely changes the magnitude and the trend slope of earnings inequality.

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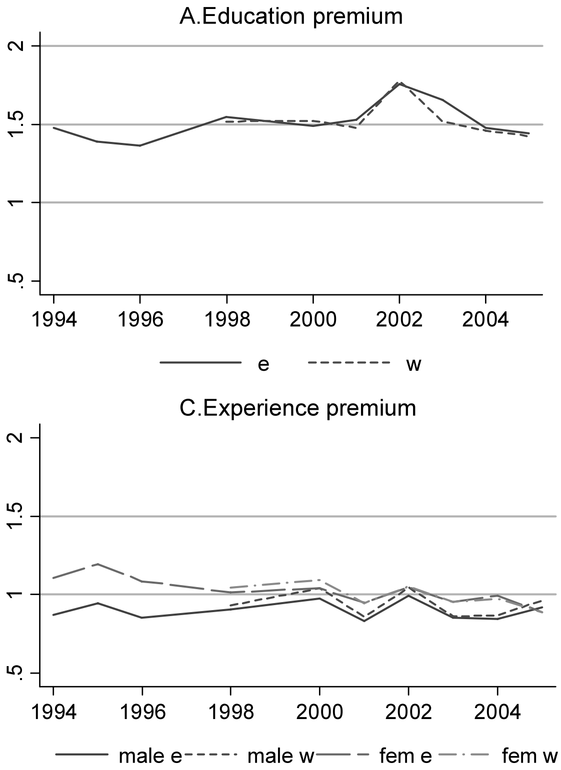

Notes: e = average labor earnings per month, w = average hourly wage rate. All earnings are after-tax. Education premium is the average wage of university educated males divided by the average wage of non-university-educated males. Gender premium is the average wage of males divided by the average wage of females. Experience premium is the average wage of age group 45–55 divided by the average wage of age group 25–35. The variance of residuals is from Eq. (1).

Fig. 5. Wage premia.

3.3. *Comparison of inequality measures based on alternative definitions of earnings*

Earnings received last month in Fig. 4 are much more variable than average monthly earnings. Part of the reason is irregular and delayed wage payments, which were a widespread phenomenon during 1994–1998.[14] Wage arrears tend to exaggerate earnings inequality (Lehmann and Wadsworth, 2007). For example, in 1996–1998 over 30 percent of respondents reported receiving less than one week of pay in the past month, and about 4 percent received more than two months of back pay. At the peak of wage arrears in late 1998, 62 percent of Russian workers reported overdue wages averaging 4.8 monthly salaries per affected worker (Earle and Sabirianova Peter, 2009). Consistent with this, the difference in dispersion between the two definitions of earnings was the largest in 1996–1998. Wage arrears subsided in later years, although they did not disappear entirely: about 12 percent of all employees reported delays in wage payments in 2005. Because of wage arrears as well as seasonal and irregular employment, last month earnings still show higher inequality than average monthly earnings in later years.

We think that the presence of large and time-varying wage arrears makes average monthly earnings a more stable and informative measure of inequality levels and trends. Accordingly, for the remainder of the paper, we select average earnings as the baseline for calculating measures of income inequality. We refer readers interested in dynamics based on actual earnings received last month to the extended working paper version of the present study (Gorodnichenko et al., 2009b).

3.4. *Wage premia*

The analysis of between-group wage inequality reveals several interesting results. Fig. 5 reports aggregate trends in wage premium associated with education, gender, and experience. The male education (college/non-college) premium in average monthly earnings, e, is substantial (about 50 percent on average), although it is smaller than the current education

[14] Other reasons for excessive volatility of earnings in 1994–1998 include unpaid involuntary leaves and forced in-kind payments in lieu of wages owed. The use of involuntary leave peaked in 1996, when 15.8 percent of employees had average leave duration of about eight weeks. In-kind substitutes for money wages peaked in 1998, with 15.4 percent of workers affected (World Bank, 2003). Workers receiving in-kind payments are typically at the bottom of the earnings distribution, which tends to generate additional dispersion.

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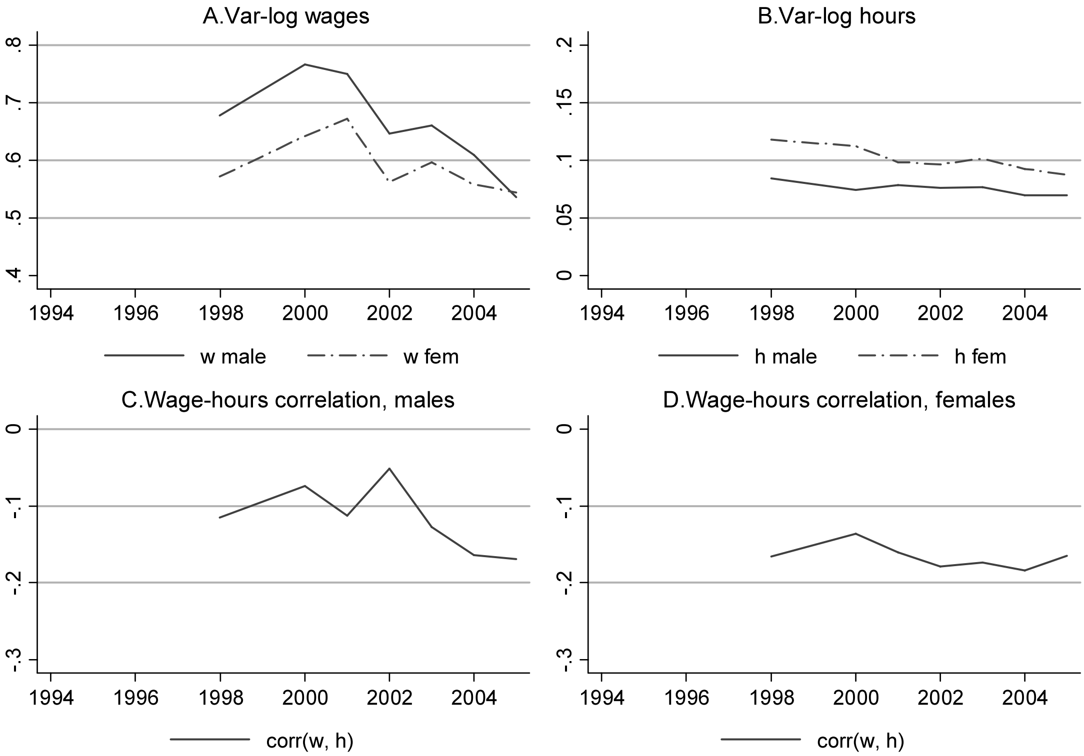

Notes: w = average hourly wage rate; h = usual hours of work per month.

Fig. 6. Inequality in labor supply.

premium in the U.S. (e.g., Autor et al., 2008; Eckstein and Nagypal, 2004). The gender premium in hourly wage rate, w, is 35–47 percent. The level is comparable to the U.S. gender premium in the 1970s (e.g., Blau and Kahn, 2000).[15]

Remarkably, the male experience premium is negative, and it is below the female experience premium (Fig. 5C). The age–earnings profile reaches its peak at age 33 for males (44 for females), whereas male earnings growth in the U.S. continues until much later ages (e.g., Heckman et al., 2008). This unusual earnings profile may be partly attributed to the obsolescence of skills of Soviet-era workers.[16] Another explanation for the negative experience premium is that a period of extreme economic volatility generated a wage premium for more mobile and adaptive younger workers.

The residual inequality trends down over time, which is expected since the overall inequality is declining while the various wage premia for observable characteristics stay roughly constant (Fig. 5D). By way of comparison, the residual wage inequality has an upward trend in the U.S. (e.g., Autor et al., 2008; Lemieux, 2006).

3.5. Gender differences in labor market outcomes

Fig. 6 presents gender comparisons of inequality in hourly wages and hours worked. Wage inequality is higher among males than females, which is found in the U.S. data too (e.g., Eckstein and Nagypal, 2004). Measures of wage inequality for both genders trend down over time, although the decline in inequality is more pronounced for males (this is again consistent with a higher responsiveness of male wages to output fluctuations). Consequently, the differences in wage inequality between genders become less noticeable by the end of the sample period (Fig. 6A).

Hours worked are considerably less variable than wages (note that panels A and B have different scale). Females have slightly more variable hours, perhaps due to higher prevalence of part-time work. Dispersion of hours appears stable over time.

The bottom two panels of Fig. 6 show the correlations between hours and wages for males and females. These correlations are negative for both genders, which could indicate that income effect dominates substitution effect. It could also be due to a downward bias induced by a measurement error in hours, known as "division bias" (e.g., Borjas, 1980). There is no clear time trend in the correlation between wages and hours for either gender.

[15] The share of population with a college degree in RLMS is 15.9 percent.

[16] Consistent with this, Guriev and Zhuravskaya (2009) find evidence of a big shift in life satisfaction by cohort: individuals who finished their education just before the transition report much lower life satisfaction than similar individuals who finished their education just after. This jump in life satisfaction could, perhaps, reflect brighter lifetime earnings prospects of workers educated under the new regime.

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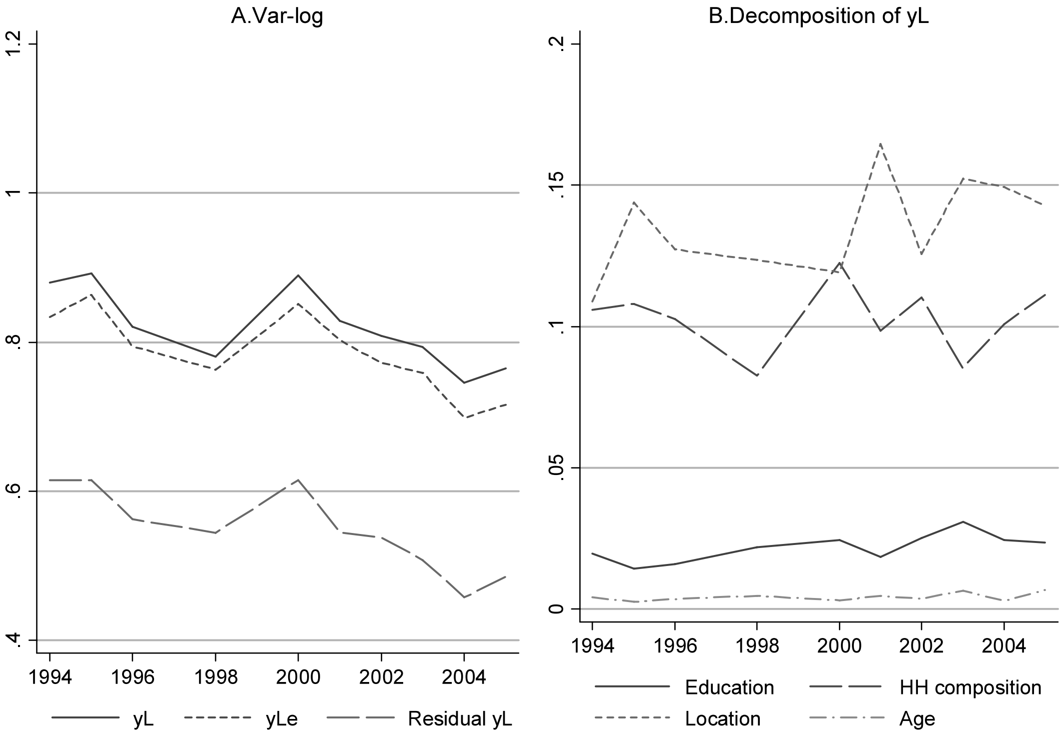


Notes: All earnings are after-tax and deflated using national monthly CPI. *yL* = household labor earnings per month adjusted for non-response, *yLe* = equivalized (with an OECD equivalence scale) household labor earnings per month adjusted for non-response, residual *yL* is the residual from Eq. (1). Panel B reports the variance of each observable component of Eq. (1).

Fig. 7. Household earnings inequality and its decomposition.

Overall, the observed group differences in labor market outcomes behave similarly to developed countries, with the exception of the negative male experience premium. We now turn to the analysis of inequality across households.

4. Inequality in household income and consumption

This section analyzes the aggregate trends in income and consumption inequality at the household level. We first examine inequality in household labor earnings and then show the contributions to inequality from financial income, government transfers, and home production. We also compare income inequality to consumption inequality and discuss possible reasons for the observed differences.

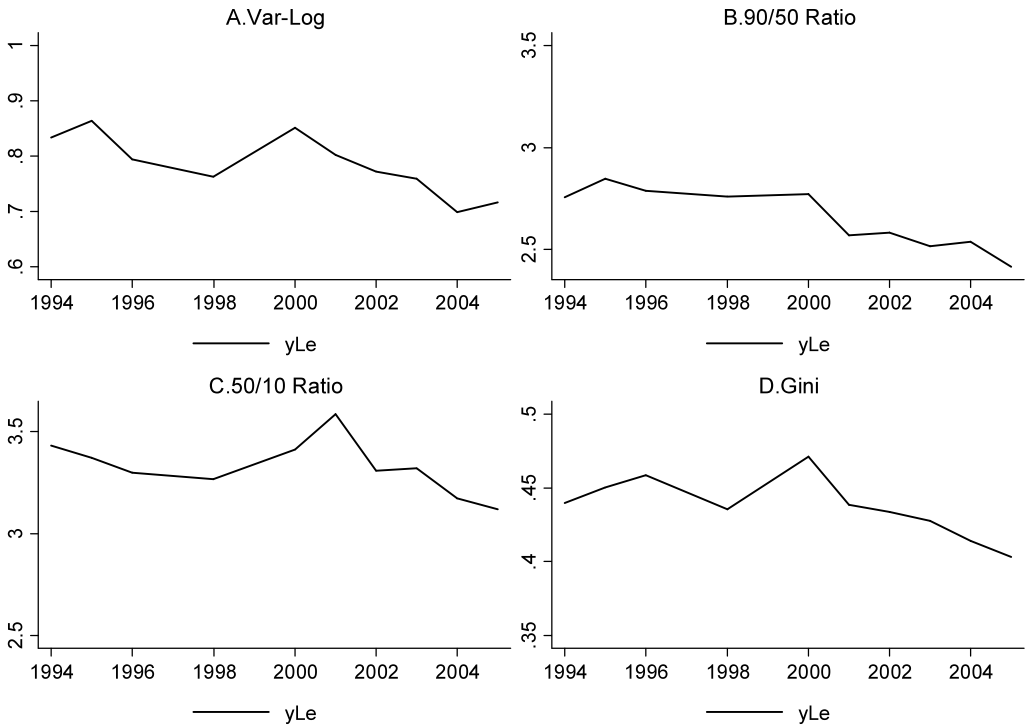
4.1. Inequality in household labor earnings

Household labor earnings, *yL*, are aggregated from individual responses on after-tax average labor earnings (see Appendix A for details). We note that Russian households are rather large and often include multiple generations of adults and extended family. The average number of adult members (14+) is 2.6, and it is not rare for a household to have more than two earners (see Appendix C for the sample composition of households). Fig. 7A shows that the dispersion (Var-log) in household labor earnings is trending downward over time.

The variance of the log of labor earnings can be decomposed into parts accounted for by observable components based on the following regression:

$$\ln(yL_{ht}) = \beta_{0t} + \beta_{1t} D_{ht}^{H} + \beta_{2t} D_{ht}^{L} + \beta_{3t} D_{ht}^{E} + f_t(a_{ht}) + u_{ht}, \tag{1}$$

where yL_{ht} is labor earnings of household h in year t, β_{0t} is year-specific intercept, D_{ht}^{H} is a set of dummies for household composition (e.g., categories for size, number of children, and number of seniors), D_{ht}^{L} is a vector of location characteristics such as an urban dummy, a dummy for Moscow and St. Petersburg, and 7 dummies for federal districts, D_{ht}^{E} denotes a set of dummies for educational attainment of the head of household, $f_t(a_{ht})$ is a quartic polynomial in age of household head, and u_{ht} is the error term (see Appendix A for details on how these components are constructed). The equation is estimated separately for each year. The observables explain a significant portion of inequality; however, the residual inequality remains large (46–62 percent, as shown in Fig. 7A). The relative magnitude of residual inequality is similar to the one in developed countries. Fig. 7B plots the contributions of observable components to the overall dispersion of household labor earnings.



Notes: All earnings are after-tax, equivalized using an OECD equivalence scale, and deflated using national monthly CPI. *yLe* = equivalized household average labor earnings per month adjusted for non-response.

Fig. 8. Basic inequality in equivalized household earnings.

Location and household composition factors contribute the most to the observed inequality; education contributes some but age contributes close to zero. Because of its importance for inequality in Russia, we will consider the effect of location on inequality in more detail in Section 6.

4.2. Comparisons of earnings inequality trends for individuals and households

It is informative to compare the dispersion of earnings at the individual level (e on Fig. 4A) and the household level (yL on Fig. 7A). In general, one would expect the distribution of household earnings to differ from the distribution of individual earnings due to the presence of multi-generational, multi-earner households. In RLMS, 56 percent of working households have more than one earner, and over 10 percent of working households have three earners or more. The resulting distribution of household earnings is strongly correlated with the number of earners in the household. For example, 85 percent of households in the lowest per capita earnings quintile are single-earner, while 27 percent of households in the highest per capita earnings quintile have three earners or more.

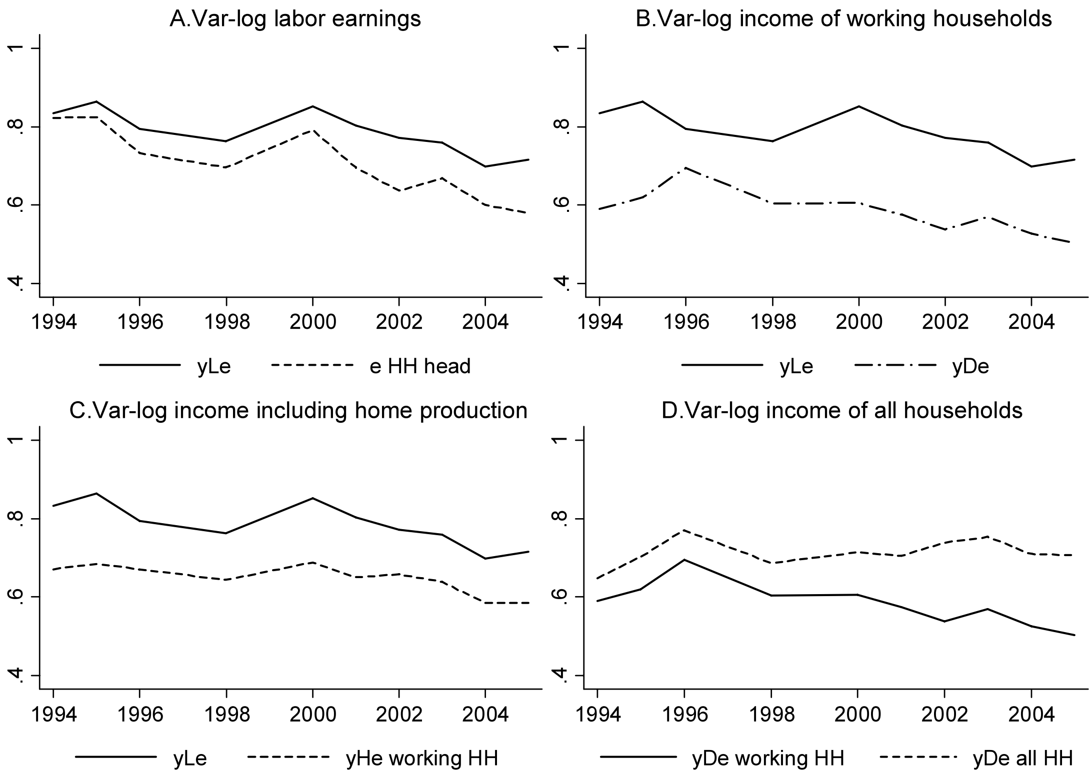
With the exception of 1994 and 1995, the dispersion of yL is larger than the dispersion of e throughout the sample period. The trends in household and individual inequality are diverging: household earnings inequality falls more slowly over time than individual earnings inequality (e.g., compare Fig. 4A to Fig. 7A). The divergence in inequality trends between individual earnings and household earnings appears to be driven by the increasing correlation of earnings among household members. The increasing variance in the number of secondary earners also contributes to the relatively higher dispersion of yL compared to e.

4.3. Inequality in equivalized labor earnings

To account for the effect of household size on earnings inequality, we compute the equivalized household labor earnings, yLe, using the OECD equivalence scale.[17] The dispersion for log equivalized earnings is almost the same as raw dispersion because equivalized earnings are negatively correlated with household size (Fig. 7A).[18] Fig. 8 presents several alternative

[17] The OECD equivalence scale assigns a value of 1.0 to the head of the household, a value of 0.7 to each additional adult (17+), and a value of 0.5 to each child.

[18] Let $yL = yLe \cdot s$, where s is household size. Then $\mathrm{Var}(\ln yL) = \mathrm{Var}(\ln yLe) + \mathrm{Var}(\ln s) + 2\mathrm{Cov}(\ln yLe, \ln s)$. Our calculations show that the second and third terms on the right-hand side nearly cancel each other out, leaving $\mathrm{Var}(\ln yL) \approx \mathrm{Var}(\ln yLe)$.



Notes: All income measures are after-tax and deflated using national monthly CPI. Household-level income measures are equivalized using an OECD equivalence scale; *eHH head* = average labor earnings of the head of household; *yLe* = equivalized household average labor earnings per month adjusted for non-response; *yDe* = equivalized disposable household income = *yLe* + private transfers + financial income + government transfers; *yHe* = *yLe* + income from home production. Panels A, B, C are constructed on a consistent sample of working households with non-zero labor earnings. Var-log is the variance of the logarithm of income.

Fig. 9. From wages to disposable income.

measures of inequality in household labor earnings per adult equivalent. Similar to Fig. 7A, the Gini coefficient and both Kuznets ratios for household equivalized earnings exhibit a downward trend in the recovery period. As explained above, the downward trend in household earnings inequality is less pronounced than the downward trend for individual earnings inequality.

4.4. From earnings to disposable income

Income inequality changes as we expand the definition of household income. Fig. 9A shows that the earnings dispersion increases when we add secondary earnings (*eHH head* vs. *yLe*). Again, we observe that inequality in household labor earnings moderates less than inequality among primary earners. Fig. 9B compares inequality in *yLe* with inequality in *yDe*, equivalized disposable income. The distribution of disposable income is much more equal than the distribution of earnings, primarily due to the effects of government transfers.

Financial income (not shown) is negligible in our sample and has virtually no effect on income inequality. By contrast, income from home production of food (which includes both own consumption valued at market prices and sales of home grown food) has a large equalizing effect on earnings distribution, as shown in panel C.[19]

The dispersion of disposable income of families with one or more wage earners exhibits a downward trend since 1996. However, adding non-working families (about 11 percent of the sample) not only shifts the overall income inequality up, but also alters the time trend (see Fig. 9D). This probably has to do with irregular government transfers during the early years of the sample. In the early years, many recipients of public transfers reported zero income in the past month, and thus were selected out of the sample. Over time, as public transfers became more regular, more non-working households report small positive income, which drives up income inequality in the pooled sample of working and non-working households.

[19] A related study by Gottschalk and Mayer (2002) shows that income adjusted for the value of home production is more equally distributed than unadjusted income in the U.S.

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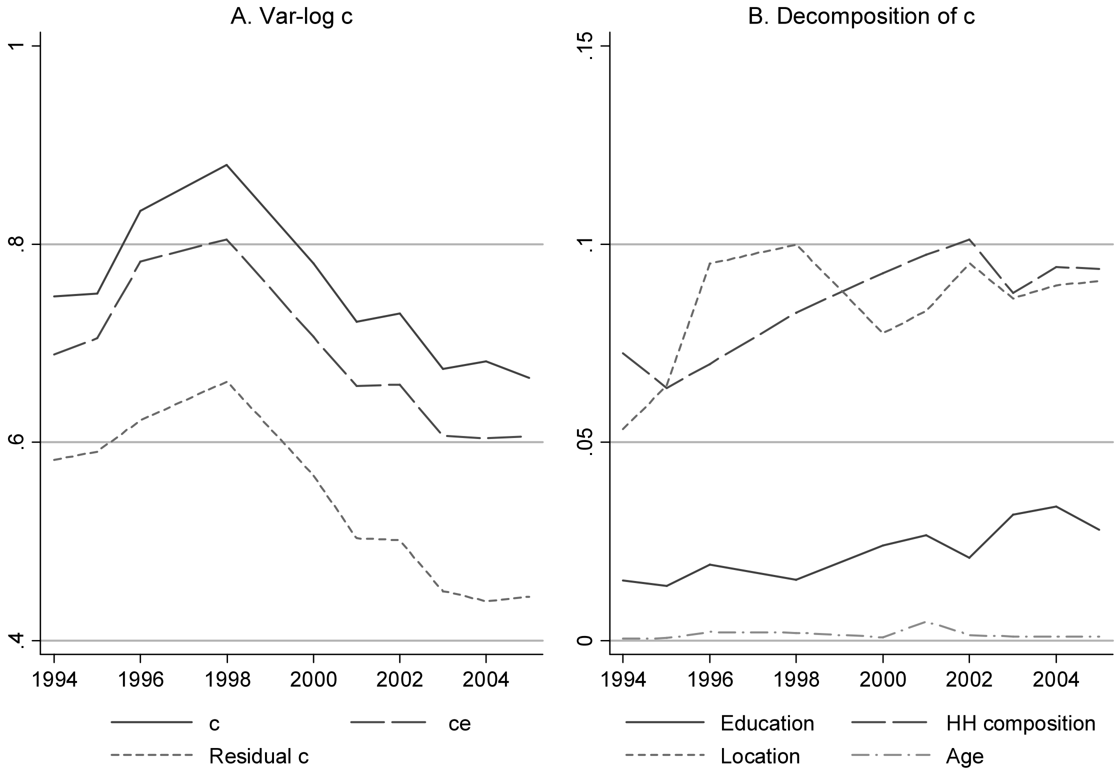


Notes: c = household non-durable expenditures last month; $ce = c$ equivalized using an OECD equivalence scale; residual c is the residuals from Eq. (1). Panel A reports the variance of log. Panel B reports the variance of each observable component from Eq. (1).

Fig. 10. Consumption inequality and its decomposition.

4.5. Inequality in consumption

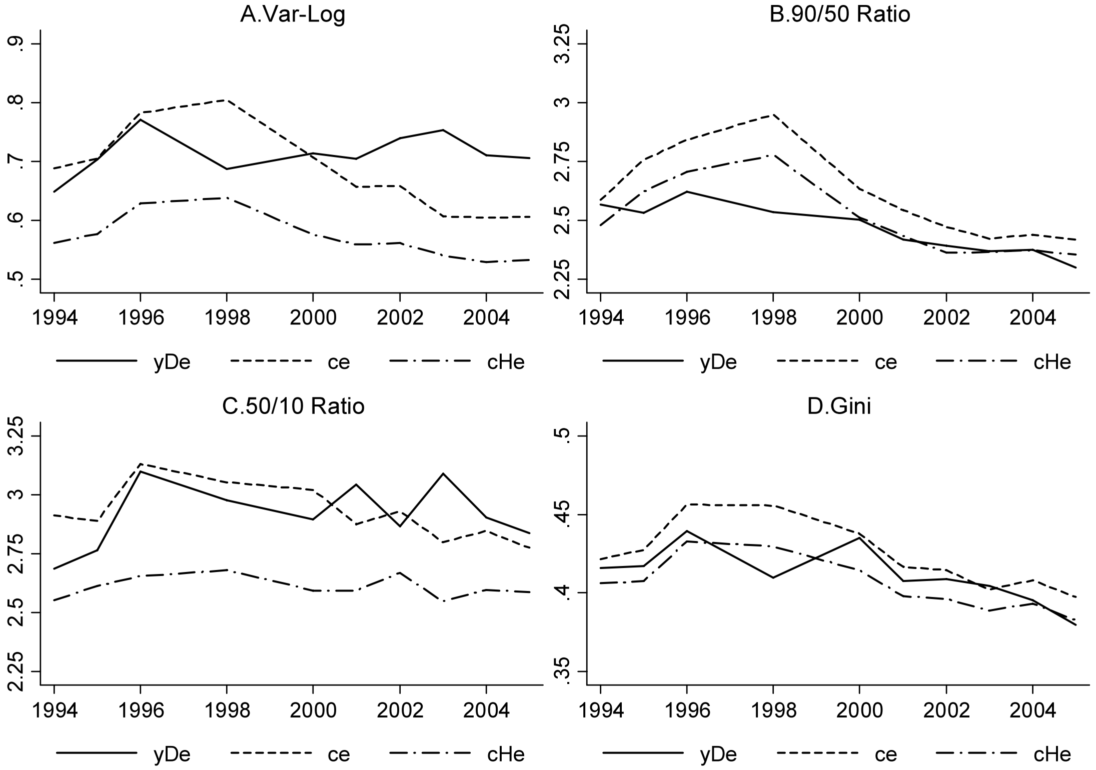
Fig. 10A presents the dispersion of our benchmark measure of consumption, non-durable expenditure for all households, working and non-working. We see that the dispersion of non-durable consumption increases significantly during the downturn and falls rapidly during the economic recovery. Other consumption variables, such as expenditure on non-durables plus durables, follow this trend very closely, although their variance may have different magnitude.

Fig. 10B also presents decomposition of non-durable consumption inequality based on Eq. (1). Similarly to household earnings decomposition in Fig. 7, the dispersion of equivalized consumption is slightly lower than the dispersion of raw consumption. The residual consumption inequality is large and follows the same time pattern as the raw measure of consumption inequality (Fig. 10A). As was the case with income decomposition, the largest observable contributors to consumption inequality are household composition and location. Education of household head explains some of the consumption inequality, but age explains almost none (Fig. 10B). By contrast, in the U.S. inequality across households typically grows with age. The lack of correlation between measures of inequality and age in Russia is also reflected in the flat life-cycle inequality profiles (see the last subsection of Section 4 for details).

4.6. Comparison of income and consumption inequality

Fig. 11 compares various measures of consumption and income inequality. While income inequality in the pooled sample of working and non-working households does not fall over time, consumption inequality rises during the downturn and falls during the recovery. One remarkable result is that consumption inequality actually exceeds income inequality in 1996–1998, which seems to be at odds with consumption smoothing. This fact may be driven by the tendency of Russian households to store food as a means of short-term consumption smoothing. Then expenditure would actually equal consumption plus "saving" in the form of food inventory change.

Why was food storage likely to spike in 1996–1998? We think that irregularly paid wages and transfers as well as volatile and unpredictable inflation made real household monthly income highly variable (e.g., note the difference between last month earnings and average earnings inequality in Fig. 4). In perfect financial markets, these income variations would be smoothed by changing the stock of household financial assets. However, most households in our sample do not hold significant financial assets, perhaps due to undeveloped financial markets or the low real rate of return associated with



Notes: *yDe* = equivalized disposable household income based on average labor earnings; *ce* = equivalized household non-durable expenditures last month; *cHe* = *ce* + consumption of home-grown food. All measures are equivalized using an OECD equivalence scale and deflated with national monthly CPI.

Fig. 11. From disposable income to consumption.

rampant inflation (recall Fig. 1A). Instead, short-term consumption smoothing may have been done by adjusting food inventories: households that received several months of back pay purchased large quantities of storable food (i.e., flour, sugar, etc.) for future consumption. In this case we can have households that spend little and consume from their food inventories as well as households that spend a lot on food, but do not consume all of it. Thus, the presence of food storage can make expenditure inequality exaggerate consumption inequality. Consistent with this hypothesis, statistical decomposition of residual expenditure variance shows that its transitory volatility peaked in 1996–1998 (see Section 5).

In addition, income inequality may be subject to its own biases that would make it seem low relative to consumption inequality. As previously discussed in Section 2, income is likely to be underreported. To the extent that income underreporting varies by income level, underreporting can introduce a bias in measures of cross-sectional income inequality. For example, if higher income households report a smaller fraction of their income than the average household, cross-sectional measures of income inequality will be biased downwards. In particular, a downward bias in income inequality can explain why the 90/50 ratio in Fig. 11B is higher for consumption than for income throughout the entire sample period.[20]

4.7. *Expenditure inequality versus consumption inequality*

Compared to the U.S., expenditure inequality in Russia is puzzlingly high relative to income inequality. For example, Heathcote et al. (2008) report that in the U.S. consumption inequality is three times lower than income inequality.[21] By contrast, expenditure and income inequality measures in Russia are roughly comparable (see Fig. 11).

Part of the explanation for the apparently high expenditure inequality in Russia is that expenditure only partially captures the actual consumption. As noted in Section 2, many Russian households grow food on subsidiary plots and thus consume more food than their expenditure numbers suggest. Although the aggregate amount of food produced at home is fairly small (5–10 percent of non-durable expenditure), food production is concentrated among rural and poorer households. This can make expenditure inequality significantly overstate the true consumption inequality. It turns out that adjusting consumption

[20] Gorodnichenko et al. (2009a) argue that income underreporting declined after 2001. In this case, the attenuation of income reporting bias towards the end of our sample period would make the true fall in income inequality even larger than that in Figs. 7–9.

[21] Specifically, variance of the log of equivalized non-durable consumption is 0.24; variance of the log of equivalized household earnings is 0.75.

for home-grown food produces a large equalizing effect on consumption distribution for all four measures of inequality, as can be seen in Fig. 11, line *cHe*. The impact of home-grown food on consumption inequality is particularly large at the lower end of the consumption distribution (compare panel B to panel C). Section 6 additionally shows that accounting for differences in the cost of living by location (i.e. using region-specific price deflators) reduces consumption inequality even further (see Fig. 14A).

4.8. Summary of key findings on inequality over time

Thus far, we find that compared to its pre-transition level, inequality first rose and subsequently fell. In the sample of working households, we observe a sizeable decline in both income and expenditure inequality beginning the mid 1990s. In the sample of all households, the expenditure inequality fell rapidly, but the decline in income inequality was much less pronounced. In terms of levels, the expenditure inequality in Russia is found to be high relative to income inequality. The distinction between expenditure and consumption turns out to be crucial in understanding the inequality level in Russia. Expenditure can be a noisy measure of consumption when households accumulate large inventories of goods (particularly food) as a form of saving. Importantly, expenditure is not a complete measure of consumption for households that heavily rely on home production. The concentration of food production among poorer households explains a substantial equalizing effect of home-produced food on consumption inequality.

4.9. Inequality over the life cycle

In this section, we examine the age profile of inequality. In doing this, one needs to separate out the age effect on inequality from time effects and cohort effects. These effects are collinear unless one imposes additional restrictions (e.g., Heathcote et al., 2008). Since none of the restrictions is entirely satisfactory, we present decompositions of age, cohort, and time effects under alternative identifying assumptions.

Suppose that the cross-sectional moment $M(a,t)$ depends on age, a, time, t, and cohort effects, $t-a$, through a linear function. An inequality–age regression can separately identify one of these three effects, and the combined effect of the other two. We first perform inequality–age regressions controlling for time effects and assuming that there are no cohort effects. This specification confounds age effects with cohort effects, and the two cannot be separately identified. We regress the inequality moments on the set of age and time dummies:

$$M(a,t)=\sum_a \beta_a D(a)+\sum_t \beta_t D(t)+\varepsilon_{a,t}.$$

Fig. 12A shows the pattern of age dummies β_a, taking $M(a,t)$ to be variance of the log measure of inequality. In almost all cases, the age–inequality profiles are essentially flat, with the exception of a slight decline in inequality among the oldest workers. The flat life cycle inequality profile can be interpreted as age effects and cohort effects roughly canceling each other out (or, both can be zero). The flat profile of age dummies is consistent with income and consumption decompositions on Figs. 7 and 10, where age was found to have almost no explanatory power. Theoretically, the life-cycle inequality profile can also be flat in an environment where permanent income shocks are small. This seems unlikely to apply to Russia. Section 5 shows that the variance of permanent income shocks is at least 3 times larger in Russia than it is in the U.S.

We now turn to a different specification that assumes away time effects and regresses the cross-sectional inequality moments on age and cohort dummies:

$$M(a,t)=\sum_a \beta'_a D(a)+\sum_{t-a} \beta'_{t-a} D(t-a)+\varepsilon'_{a,t-a}.$$

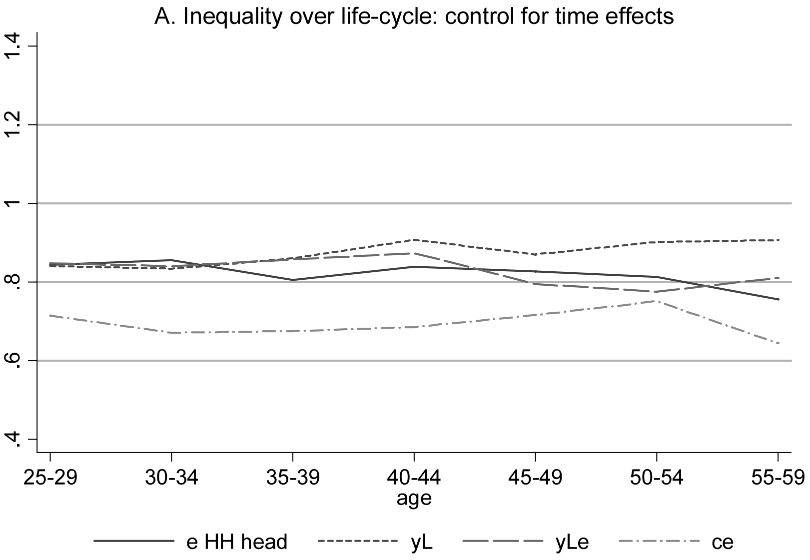
Fig. 12B reports the age coefficients β'_a from the above regression. Now the age–inequality profiles are downward-sloping because time effects are confounded with age effects. In other words, if income and consumption inequality falls over time for a fixed cohort, the regression model categorizes this as an age effect. Our results potentially point to large time effects on inequality.

So far, our analysis of inequality measures relied on repeated cross-sections. In the next section, we will exploit the panel dimension of the data and investigate to what extent changes in income inequality translate into changes in consumption inequality.

5. Time series decomposition and interaction of income and consumption inequality

To understand the dynamics of inequality and the interactions between consumption and income, we need to identify the sources of uncertainty faced by households and to assess households' ability to smooth consumption. As a first pass, we exploit the panel aspect of RLMS and decompose the residual variability in consumption and income into permanent and transitory components. Specifically, we use a statistical model

$$\ln(s_{ht})=X_{ht}\beta_t+u^{(s)}_{ht}, \tag{2}$$



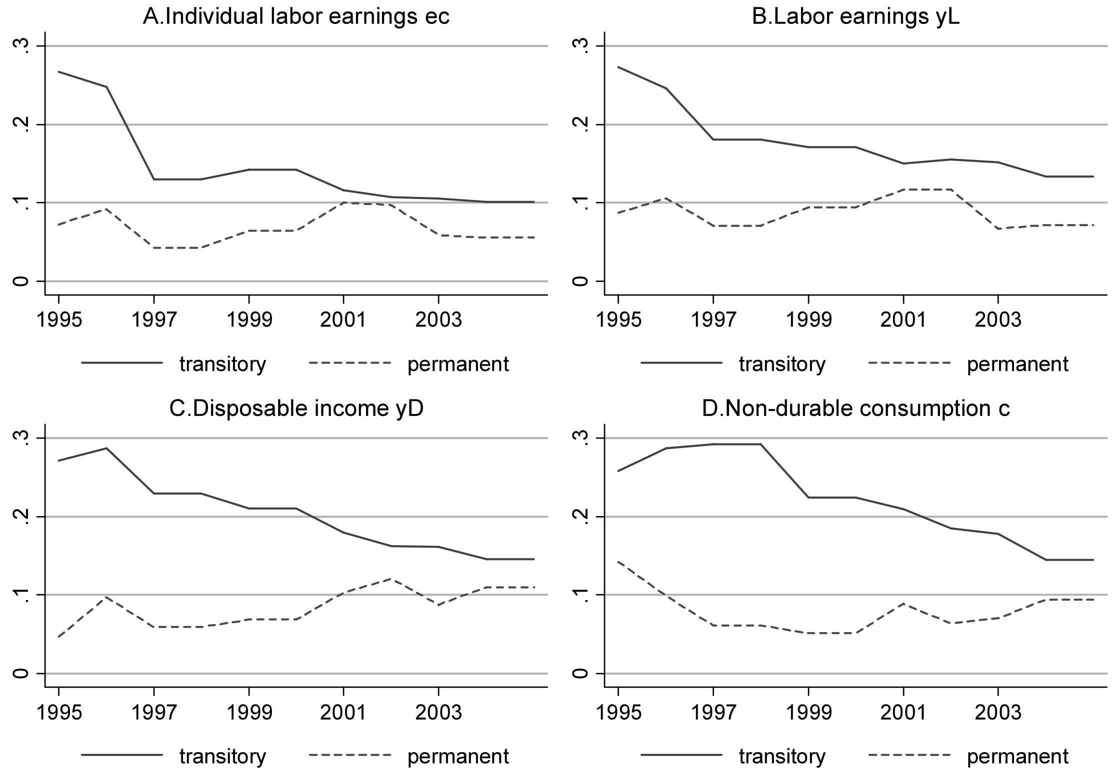
Notes: Panel A depicts age profiles for the Var-log controlling for year effects. Panel B depicts age profiles for the Var-log controlling for cohort effects. All measures are deflated with national monthly CPI. *eHH head* = average labor earnings per month of the head of household; *yL* = household average labor earnings per month adjusted for non-response; *yLe* = *yL* equivalized with an OECD equivalence scale; *ce* = household non-durable expenditures equivalized with an OECD equivalence scale.

Fig. 12. Inequality over the life-cycle.

where s_{ht} is the variable of interest, such as income or consumption, and X_{ht} is the same set of controls as in Eq. (1). We decompose the residual term $u_{ht}^{(s)}$ into the sum of a transitory component and a permanent component that follows a random walk process:

$$u_{ht}^{(s)} = \alpha_{ht} + \varepsilon_{ht},$$
$$\alpha_{ht} = \alpha_{h,t-1} + \eta_{ht}, \tag{3}$$

where $\varepsilon_{ht} \sim (0, \sigma_{\varepsilon,t}^2)$ is the transitory component and $\eta_{ht} \sim (0, \sigma_{\eta,t}^2)$ is the innovation in the permanent component. Note that the variances of the transitory and permanent components are allowed to be time-varying. Using the covariance matrix



Notes: The figure reports the time series of estimated variance of permanent and transitory components. The estimated process is $u_{ht} = \alpha_{ht} + \varepsilon_{ht}$, $\alpha_{ht} = \alpha_{h,t-1} + \eta_{ht}$, where ε_{ht} is the transitory component and η_{ht} is the permanent component. In all specifications, u_{ht} is the residual from projecting the relevant measure of income or consumption on our baseline vector of observable characteristics of households. *e* is average labor earnings of household head, *yL* is household average labor earnings per month, *yD* is disposable household income based on average labor earnings, and *c* is household non-durable expenditures last month. Values in 1998 and 2000 are adjusted for the fact that the permanent component is accumulated over two years. For both permanent and transitory components, 1997 and 1999 values are set equal to 1998 and 2000 values respectively.

Fig. 13. Permanent-temporary component decompositions.

for the first difference of $u_{ht}^{(s)}$ and an equally weighted minimum distance estimator, we estimate the time series for $\sigma^2_{\varepsilon,t}$ and $\sigma^2_{\eta,t}$. The estimation procedure is described in more detail in Appendix D.

5.1. Variance of innovations to income

The estimates of $\sigma^2_{\varepsilon,t}$ and $\sigma^2_{\eta,t}$ are reported in Figs. 13A–C. Each panel uses a separate income measure: individual labor earnings (e) in panel A, household labor earnings (yL) on panel B, and household disposable income (yD) on panel C. The time pattern for variances is similar for all three income measures: the variance of innovations in the permanent component, $\sigma^2_{\eta,t}$, remained relatively stable while the variance of transitory component, $\sigma^2_{\varepsilon,t}$, declined considerably.[22] It appears that the fall in residual income inequality is primarily due to moderation of the transitory component.

The variances $\sigma^2_{\varepsilon,t}$ and $\sigma^2_{\eta,t}$ for permanent and transitory components of income are at least three times larger than comparable estimates for the U.S. (Heathcote et al., 2008, Table A.1). We do not think that this is due to differences in residual income inequality levels $u_{ht}^{(y)}$ between Russia and the U.S. — the residual variance of log household earnings is 0.5 for the U.S. and is less than 0.6 for Russia (see Fig. 7). Rather, the comparison seems to point to different sources of residual income inequality between Russia and the U.S. In Russia, residual inequality appears to be driven by high volatility of both transitory and permanent income shocks. By contrast, in the U.S., the combination of high $u_{ht}^{(y)}$ and low $\sigma^2_{\eta,t}$ points to the dispersion of unobserved household fixed effects, α_{h0}, as playing a larger role.[23]

[22] In addition to individual and household labor earnings and disposable income reported in Fig. 13, we find that other income measures such as household earnings with income from home production have a similar trend.

[23] For example, suppose that errors have no time series volatility: let residual income variance be wholly due to household fixed effects. Then, the permanent-temporary decomposition will show zero variance for both ε and η. By contrast, if regression errors have a lot of time variation, this will lead to high variance in ε, or η, or both. In sum, the *level* of residual inequality is not necessarily related to the variances in the permanent-temporary

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5.2. Variance of innovations to consumption

We use the same statistical procedure to perform the decomposition of household consumption. This decomposition is useful partly because it provides indirect evidence on the effects of food storage. One should expect periods with food inventory fluctuations to have large unexplained transitory movements in expenditure. This is precisely what Fig. 13D shows during 1996–1998.

It is also remarkable that the permanent component of consumption is as volatile as the permanent component of income (Fig. 13D). This result seems consistent with the finding that the time series volatility of consumption typically exceeds the time series volatility of output for developing countries (Aguiar and Gopinath, 2007). The high volatility of consumption relative to income in Russia contrasts with recent trends in the U.S., where a dramatic increase in income inequality did not cause a commensurate increase in consumption inequality. Such divergence between the two inequality measures in the U.S. has been explained by developments in financial markets that allow more risk sharing and consumption smoothing (Krueger and Perri, 2006) and by the changes in the persistence of income shocks (Blundell et al., 2008). Russia, too, witnessed significant advancements in financial markets (especially, consumer credit) towards the end of our sample period, yet we do not observe a divergence between consumption and income variance decompositions.[24] The high variance of permanent consumption innovation is even more puzzling given that Russian households had a variety of consumption smoothing tools such as saving, food storage, home production, variable labor supply, and extended family. On the other hand, the negative correlation between wages and hours and low savings can also indicate the lack of insurance against income shocks (Heathcote et al., 2007).

5.3. Response of consumption to income innovations

To look at possible changes in consumption smoothing patterns over time, we examine the response of consumption to innovations in the permanent and transitory components of income. We continue to assume that the income process is given by Eq. (3) and re-estimate the income equation jointly with a consumption equation that captures the impact of income innovations on residual consumption growth. We model the sensitivity of consumption to income components as in Blundell et al. (2008):

$$\Delta u_{ht}^{(c)} = \phi_t \eta_{ht} + \psi_t \varepsilon_{ht} + \xi_{ht} - \xi_{h,t-1}. \tag{4}$$

The left-hand side of (4) is the growth rate of residual household consumption. The first term on the right-hand side is the product of the permanent income innovation, η_{ht}, and the "loading" factor ϕ_t that measures the responsiveness of consumption to η_{ht}. Similarly, the second term, $\psi_t \varepsilon_t$, measures the response of consumption growth to a temporary income innovation, ε_{ht} given ψ_t capturing the sensitivity of consumption to ε_{ht}. The term $\xi_{ht} \sim (0, \sigma^2_{\xi,t})$ absorbs measurement errors and unobserved household heterogeneity not attributed to income growth and other observables. See Appendix D for detailed description of the estimation procedure.

Blundell et al. (2008) interpret loadings close to one[25] as indicating the lack of insurance against innovations in income. In contrast, if loadings are close to zero, then households have enough instruments (e.g., access to credit markets, self-insurance) to insulate consumption from income shocks. Loadings between zero and one can be interpreted as partial insurance.[26]

Table 1 presents the results from jointly estimating income Eq. (3) and consumption Eq. (4). The loading on the transitory component, ψ_t, is relatively small and falling over time, consistent with households being able to smooth temporary income shocks. The loading on the permanent income component, ϕ_t, is much larger, perhaps, indicating imperfect consumption insurance against permanent shocks. Nevertheless, ϕ_t is falling over time, consistent with an overall improvement in consumption insurance.

It is informative to compare the estimates in Table 1 to those reported in Blundell et al. (2008) for the 1978–1992 U.S. data with similar estimation methodology. The 2005 estimates of ϕ_t and ψ_t from our Table 1 are close to those reported in Blundell et al. (2008, Table 7): $\phi \approx 0.64$, $\psi \approx 0.053$. Thus the sensitivity of consumption to income innovations is about the same for Russian households in 2005 and U.S. households in 1978–1992. This result is puzzling given the apparent difference in consumption smoothing and insurance possibilities between the two countries. Compared to the U.S., Russian households have a much higher variance of transitory and permanent income innovations: Table 1 averages are $\sigma^2_{\varepsilon,t} = 0.204$, $\sigma^2_{\eta,t} = 0.088$ versus $\sigma^2_{\varepsilon,t} \approx 0.051$, $\sigma^2_{\eta,t} \approx 0.013$ for the U.S. (Blundell et al., 2008, Table 6).

decomposition. The ratio of $\sigma^2_{\eta,t}$ to the variance of fixed effects α_{h0} is almost 3 times higher in Russia than it is in the U.S. (0.22 versus 0.08 as reported in Storesletten et al., 2004). Consequently, fixed effects are a relatively less important source of residual inequality in Russia.

[24] Consumer credit more than doubled every year between 2002 and 2006 (Goskomstat, 2006b).

[25] Loading coefficients cannot exceed 1 because this would violate household lifetime budget constraint.

[26] Blundell et al. (2008) show that under certain restrictions the permanent income hypothesis implies $\phi = 1$ and $\psi = 0$. That is, consumption should change by the same percentage as the change in the permanent income ($\phi = 1$), and it should not respond at all to transitory components ($\psi = 0$).

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Table 1
Estimates of consumption response to income innovations.

Year	Variance of innovation in a component of income		Loadings on components		Variance of residual consumption growth rate due to				
					Innovations in components of income			Measurement errors and unobserved household heterogeneity $\sigma^2_{\xi,t}$	Total
	Transitory $\sigma^2_{\varepsilon,t}$	Permanent $\sigma^2_{\eta,t}$	Transitory ψ_t	Permanent ϕ_t	Transitory $\psi_t^2\sigma^2_{\varepsilon,t}$	Permanent $\phi_t^2\sigma^2_{\eta,t}$	Total $\sigma^2_{cy,t}$		
1995	0.257	0.069	0.125	0.908	0.0040	0.061	0.065	0.490	0.555
1996	0.305	0.069	0.125	0.908	0.0048	0.062	0.067	0.494	0.561
1998	0.238	0.092	0.174	0.801	0.0072	0.066	0.074	0.512	0.586
2000	0.213	0.115	0.151	0.561	0.0048	0.041	0.046	0.489	0.535
2001	0.184	0.093	0.040	0.568	0.0003	0.030	0.031	0.404	0.435
2002	0.166	0.107	0.028	0.559	0.0001	0.034	0.034	0.353	0.386
2003	0.169	0.071	0.036	0.629	0.0002	0.028	0.028	0.339	0.367
2004	0.153	0.085	0.032	0.718	0.0002	0.044	0.044	0.310	0.354
2005	0.153	0.085	0.032	0.718	0.0002	0.044	0.044	0.289	0.334
Average	0.204	0.088	0.083	0.708	0.0024	0.046	0.048	0.409	0.457

The much more volatile income of Russian households makes potential welfare gains from consumption insurance much higher in Russia. Using our estimates, we can compute the variance of consumption growth that is due to innovations in income (Table 1, column 8),

$$\sigma^2_{cy,t} = \phi_t^2\sigma^2_{\eta,t} + \psi_t^2\sigma^2_{\varepsilon,t}.$$

The above variance can be used to estimate welfare gains from consumption insurance. Lucas (1987) shows a household with risk aversion parameter γ would be willing to sacrifice up to $\frac{1}{2}\gamma\sigma^2_{cy,t}$ share of their income to have a perfectly smooth consumption path. The Blundell et al. (2008) parameters yield $\sigma^2_{cy,t} \approx 0.0056$, while our Table 1, column 8 estimates of the same are 5–14 times larger. This means that Russian households should be willing to give up a 5–14 larger income share than the US households to achieve perfect consumption smoothing (assuming the same risk aversion parameter).[27] Intuitively, this result obtains because variance of consumption that is attributable to variance in income is much larger in Russia than it is in the U.S.

Interestingly, most of the variance in residual consumption growth is not attributable to income. Income innovations can only explain between 14 and 22 percent of variance in non-durable consumption growth (compare Table 1, columns 9 and 10). There may be several reasons for this. For example, consumption out of irregular unreported income and changes in food inventories would both be categorized as unexplained consumption growth. In addition, our chosen observables do not exhibit much time variation, but both consumption and income vary a lot over time, perhaps due to high occupational mobility. Finally, measurement errors and preference shocks could also contribute to unexplained consumption growth.

Overall, our findings suggest that income and consumption volatility was high in the early years of our sample, and that the ranking of households in the income distribution has been stabilizing in recent years. Despite recent improvements, households have had limited ability to smooth income shocks with financial assets, savings or other insurance instruments and the benefit from providing access to such insurance probably remains substantial.

6. The role of location in inequality trends

In the context of the Russian economy, geography deserves a special consideration as it can help with understanding of the observed inequality trends. Russia is a large and diverse country, both geographically and economically. For example, monetary income per capita in the richest Russian region (the city of Moscow) is 10.4 times larger than per-capita income in the poorest region (the Republic of Ingushetia) in 2005 (Goskomstat, 2007b). A similar maximum-to-minimum ratio across states in the U.S. is only 1.8 (U.S. Census Bureau, 2007).

Location is the most important explanatory variable for the dispersion of earnings and consumption (see Figs. 7 and 10). The substantial dispersion of the regional component of inequality may be associated with the large geographic variation in the cost of living. The 2005 ratio in the cost of fixed consumer goods between the most expensive region and the least expensive region was 2.7 (Goskomstat, 2006a). With such inter-regional diversity, using a common national CPI may overstate the extent of inequality in both income and consumption. Indeed, using regional CPI and accounting for the regional differences in the cost of living move the magnitude of inequality down, but this adjustment does not affect the time trend (see Fig. 14A).

The regional dispersion of expenditure may also be affected by uneven distribution of amounts of food grown at home between urban and rural households. While big city residents purchase more than 95 percent of their food at the store, residents of small towns and villages purchase about 80 percent at the store (less in early years) and grow the rest on

[27] This result has an important caveat: if households smooth consumption with food storage, this would induce strong response of expenditure to transitory income shocks, but will not necessary imply non-smooth consumption.

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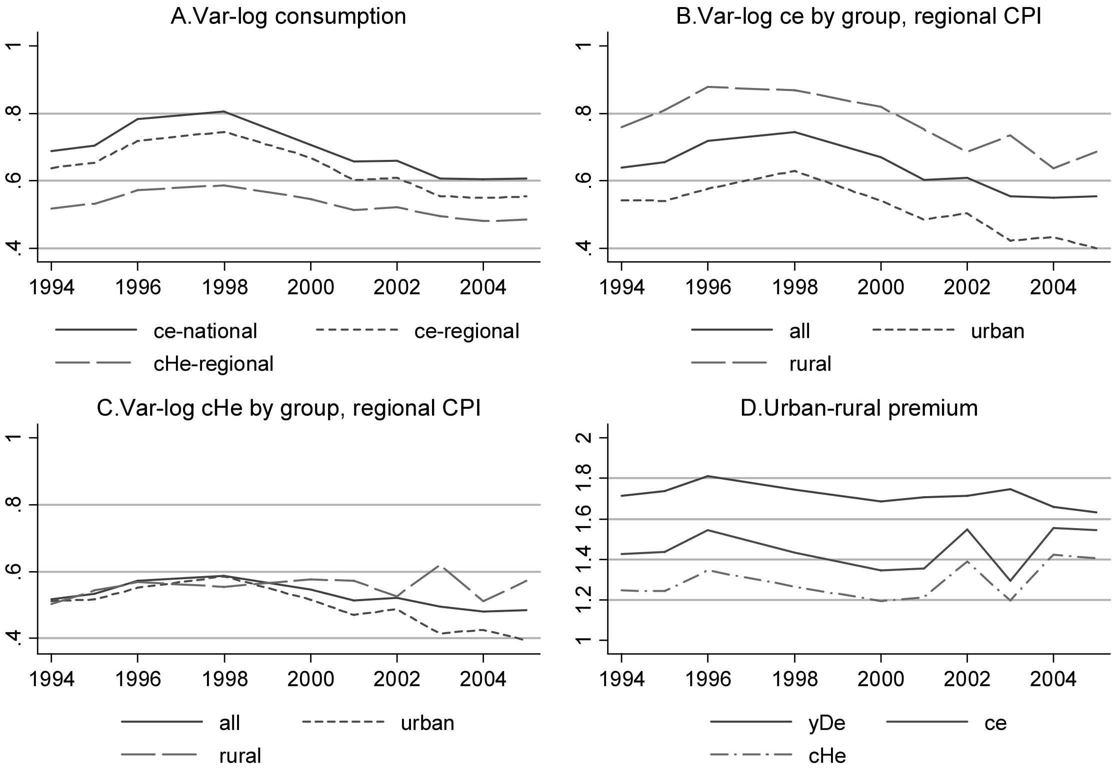

Notes: Rural location is defined as villages and small towns. *yDe* = equivalized disposable household income based on average labor earnings; *ce* = equivalized household non-durable expenditures last month; *cHe* = *ce* + equivalized consumption of home-grown food. All measures are equivalized using an OECD equivalence scale and deflated with regional CPI unless indicated otherwise.

Fig. 14. Within-group and between-group inequality.

their subsidiary plots. Consequently, rural households are likely to have a larger discrepancy between expenditure inequality and consumption inequality. Panels B and C of Fig. 14 implicitly confirm this. The panels depict the variance of the log of non-durable expenditures for the two groups and the pooled sample using regional deflators, with and without food grown at home. Expenditure inequality is apparently much higher among the rural population (panel B). By contrast, inequality in consumption that includes food purchased and grown at home is much more similar across urban and rural households (panel C).

While time trends in expenditure inequality for the two groups are similar, trends in consumption inequality diverge during economic recovery. In particular, consumption inequality among rural households shows no downward trend (panel C). This difference in trends is consistent with transition of rural households from subsidiary farming to professional farming, which could have made the amount of food grown for own consumption more unequally distributed.

Economic consequences of downturn and recovery may have differed between urban and rural populations. One would expect rural households to fall behind during the transition due to the lack of access to large and diverse labor markets that big cities offer and also because of possible migration of the ablest workers to cities.

Surprisingly, our data do not point to much divergence in the mean levels of income and consumption of the two groups until 2002. Fig. 14D shows that the relative levels of equivalized disposable income (*yDe*), expenditures (*ce*), and consumption (*cHe*) stay fairly constant during 1994–2001. It is possible that rural households were already behind when our sample began — recall the discussion in Section 2. On the other hand, the relative consumption level of urban household was at its all-time high in 2002, 2004 and 2005, suggesting that rural households did lag behind as the economic recovery progressed. Particularly, the growth of durable consumption was stronger among urban households. The role of food grown at home in equalizing consumption is strikingly apparent in Fig. 14D. Urban households, who spend 45 percent more than rural households, enjoy only 29 percent higher consumption, on average (compare *ce* and *cHe* lines).[28]

[28] Market value of home production probably overstates its net contribution to household welfare because of the cost of capital goods and materials and decreased leisure. Selling food is also likely to involve high transaction costs, making net income from home production lower than its value at market prices.

Comparisons of group income and consumption differences reveal two important facts. First, we do not find substantial evidence of convergence or divergence between urban and rural populations over time. This fact is interesting in its own right. One would expect the rural population to fare worse in transition due to a limited choice of jobs, low occupational mobility, and migration of high earners to cities. The lack of divergence between urban and rural populations is therefore surprising. Our second finding is that income underreporting problem is more severe for rural households. On average, urban households report roughly 71 percent more disposable income than rural households, but their total expenditure is just 45 percent higher.

7. Conclusions

We investigate the levels and the time trends of consumption and income inequality in Russia. The paper makes a number of contributions on issues of inequality measurement. We explain, for example, why consumption that includes home production, avoids underreporting of resources available to households, and is adjusted for regional variation in the cost of living should be a preferred inequality measure for Russian economy. We find that compared to its pre-transition level, inequality first rose and subsequently fell. The rise in inequality appeared to have happened during the price liberalization in the early 1990s while the fall started after 2000. The level of inequality in Russia is now very similar to that in the U.S. (e.g., Krueger and Perri, 2006).

We uncover several important facts about inequality in Russia. First, poor households appear to gain from recent economic growth. Second, changes in key observable characteristics of households have a small contribution to the dynamics of consumption and income inequality. The variance of permanent and transitory income components is much larger in Russia than in developed countries. Because of this, the fluctuations of consumption that are attributable to income shocks are larger in Russia as well. There are probably substantial gains from introducing insurance schemes to smooth consumption fluctuations. Third, recent moderation in consumption and income inequality appears to be driven by the decline in the volatility of transitory shocks. Fourth, unlike developed economies, expenditure inequality in Russia is high relative to income inequality.

Our results also point out some inconsistencies between RLMS and NIPA. In particular, comparisons of consumption levels across data sources suggest that there may be an insufficient adjustment for shadow economic activity in the official statistics. The growth rate of consumption in NIPA has recently become higher than that in RLMS. Similar discrepancies have been found in other developing economies (e.g., Deaton, 2005).

Our analysis highlights several phenomena that merit further research. The negative experience premium for Russian males looks anomalous compared to positive experience premiums in other countries. We are also puzzled by the finding that the response of consumption to income shocks is similar between the U.S. and Russia despite the different levels of financial development in the two countries. We think that this puzzle can motivate further research on the role of consumer durables in consumption smoothing. There is recent theoretical work showing that income shocks can mostly be absorbed by durable consumption (e.g., Leahy and Zeira, 2005; and Stacchetti and Stolyarov, 2007). The panel structure of RLMS provides a natural data set for investigating the role of durable expenditure as a propagation mechanism for income shocks.

Appendix A. Data description

A.1. Description of RLMS sample

This study uses ten rounds of the Russian Longitudinal Monitoring Survey (RLMS) that was conducted in 1994–1996, 1998, and 2000–2005. RLMS was not conducted in 1997 and 1999. Time-series reported on the figures are linearly interpolated for missing annual data points.

The RLMS sample consists of the 38 randomly selected primary sample units (municipalities) that are representative of the whole country. They are located in 32 regions (or constituent subjects of the Russian Federation) and 7 federal districts. Russia had 89 constituent subjects and 7 federal districts as of December 1, 2005.

A.2. Sample restrictions

We restrict our sample to households in which at least one individual is 25–60 years old. The head of the household in the selected sample is the oldest working-age male or the oldest working-age female if no working-age males are present. If more than one person of the same age-gender is qualified for the head, then the reference person (or the first person surveyed in the roster files) is chosen.

A.3. General notes

1. All income variables are *after tax*.
2. All income and consumption variables are constructed on a *monthly basis*.

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3. Summary statistics are weighted with individual and household sample weights provided in the RLMS.
4. When a household purchased the item but did not report the amount of the purchase, the missing amounts are imputed by regressing the log of expenditure on the complete interaction between year dummies and federal district dummies, controlling for the size of the household (5 categories), number of children 16 years old or younger (4 categories), number of elderly members 60+ (3 categories), and urban location. Because of the log dependent variable, the predicted values of expenditures are adjusted as $y = \exp(\frac{1}{2}\sigma^2)\exp(\widehat{\log y})$. The subcategories with the largest number of missing values include utilities (2.12 percent of the sample), gasoline and motor oil (1.63 percent), transportation services (1.54 percent), and contributions to non-relatives (1.35 percent). Missing values for other subcategories are trivial.
5. Similar regression-based imputations are performed for missing subcategories of non-labor income and income from home production. Imputations of labor income are described in Table A.1. Although the share of missing values for each individual subcategory of non-labor income and expenditures is very small, altogether missing values affect about a third of surveyed households. Our imputation procedure is an improvement over the existing RLMS practice that treats missing values as zeros in computing aggregate income and expenditures.

Table A.1
Variable description and notes.

	Variable name	Definition	Notes
		Individual earnings and labor supply	
hm	Actual hours of work last month	= hours worked last month at primary job + hours worked last month at secondary job + hours spent last month on regular individual economic activities (activities for which an individual is paid for regularly, such as sewing a dress, assisting with repairs, selling goods in a market or on the street, etc.)	Unusually high hours are top coded at 480 h per month (16 h per day*30 days)
h	Usual hours of work per month	= 4 times usual hours in a typical week at primary job + 4 times usual hours in a typical week at secondary job + hours spent last month on regular individual economic activities	*h* is available in 1998–2005 only. Unusually high hours are top coded at 480 h per month (16 h per day*30 days)
status	Working status	= *full-time* if actual hours at primary job $\geqslant 120$, *part-time* if actual hours at primary job < 120, *not working* if a respondent did not work last month at primary job, was not on a temporary leave, and was not engaged in regular individual economic activities	
em	Actual labor earnings last month	= money received last month from primary job + money received last month from secondary job + money received last month from regular individual economic activities + payments in kind received last month from primary job + payments in kind received last month from secondary job	The variable is highly volatile during the period of wage arrears since a worker may not receive any money last month or receive back payments for several months at once
e	Average labor earnings per month	*1998–2005, all employees*: = monthly average (over the last 12 months) after-tax labor earnings of an employee at primary job + money received last month from additional jobs for all employees in 1998–2005 *1994–1996, employees with wage arrears*: = total accumulated wage debt divided by the number of months of overdue wages + money received last month from additional jobs for employees with wage arrears at primary job in 1994–1996 *1994–1996, employees with no wage arrears*: = monetary portion of *wa* for employees with no wage arrears *All years, self-employed*: = monetary portion of *wa* for self-employed (or individuals reporting place of work other than an organization), including those involved in regular individual economic activities in all years.	1. *e* does not include payments in kind 2. Average monthly earnings are available for an employee at primary job in 1998–2005 3. Implausibly low earnings below ½ of the official minimum monthly wage are recoded into missing (0.47 percent of positive earnings) 4. Implausibly high earnings are also recorded into missing if the residuals exceed five standard deviations from the mean after controlling for occupational categories, hours of work, age, age squared, years of schooling, and individual fixed effects (0.13 percent of positive earnings) 5. For household aggregation purposes, if a respondent worked last month at least one hour but has missing average earnings, missing values are imputed using occupational categories, hours of work, gender, age, age squared, years of schooling, urban location and federal district dummies (the share of imputed earnings is 7.8 percent)
wm	Hourly wage rate last month	$= em/hm$	
w	Average hourly wage rate	$= e/h$	*h* is available in 1998–2005 only; *w* is calculated for non-imputed earnings

(*continued on next page*)

Table A.1 (*continued*)

	Variable name	Definition	Notes
		Household income	
yL	Average labor earnings per month adjusted for non-response		Labor earnings of working-age non-respondents are imputed as predicted earnings times the predicted probability of working using the full set of interactions between the four age groups (18–60) and two gender groups and controlling for urban and federal district dummies for each year separately
yH	Labor earnings plus income from home production	$= yL + 0.9H$, where H is average monthly income from home-grown food in the last year defined as the sum of physical quantity of produced food items (minus items given away) multiplied by their median price in a given region, 0.9 is the assumed labor share of home food production	Median prices are obtained in two steps. First, the household-specific market price of individual food item is calculated by dividing the cost of purchase by the amount purchased in the last 7 days. Then the median price of individual food items is computed for each region (*oblast*) and year
yL+	Labor earnings plus net private transfers	$= yL +$ private transfers received last month − private transfers given to individuals outside the household unit last month	"Private transfers received" include received alimonies and 11 subcategories of contributions from persons outside the household unit, including contributions from relatives, friends, charity, international organizations, etc. "Private transfers given" include alimonies paid and various contributions in money and in kind given to individuals outside the household unit (6 categories)
y	Household income before government transfers	$= yL +$ net private transfers + financial income received last month	Financial income includes dividends on stocks and interest on bank accounts
yD	Disposable household income	$= y +$ public transfers	Public transfers include government pensions, state child benefits, stipends, unemployment benefits, and government welfare payments
		Household consumption	
cF	Market expenditures on food, alcohol and tobacco	Monthly expenditures on food, alcohol, and tobacco are computed as the sum of expenditures on individual items in the reference week multiplied by $30/7 = 4.286$	Items include 50 categories of food at home and away from home, alcoholic and non-alcoholic beverages, and tobacco products. See Appendix B for details of computation
c	Non-durable expenditures	Sum of expenditures on non-durables in the last 30 days. Non-durable items include food, alcohol, tobacco, clothing and footwear, gasoline and other fuel expenses, rents and utilities, and 15–20 subcategories of services (such as transportation, repair, health care services, education, entertainment, recreation, insurance, etc.)	
cD	Aggregate expenditures	$= c +$ expenditures on durables in the last 3 months/3. Durable items include 10 subcategories such as major appliances, vehicles, furniture, entertainment equipment, etc.	
cH	Non-durable expenditures plus consumption of home-grown food	$= c +$ consumption of home-grown food, where the last term is calculated as average monthly quantities of consumed home-grown food items multiplied by their median price in a given region	Median prices are determined in the same way as in *yH*
cD+	Aggregate expenditures plus services from housing	$= cD +$ imputed services from housing	Imputed services from housing are calculated as 5 percent of the current housing market value divided by 12
		Adjustments to income and consumption	
equiv	OECD equivalence scale	This equivalence scale assigns a value of 1.0 to the first adult household member, a value of 0.7 to each additional adult, and a value of 0.5 to each child 16 years old and younger	
cpi_t	National monthly CPI	All income and consumption variables are deflated in prices of 2002 using monthly national CPI	If the date of interview is in the first half of month, the previous month CPI is used. If the date of interview is in the second half of month, the current month CPI is used

(*continued on next page*)

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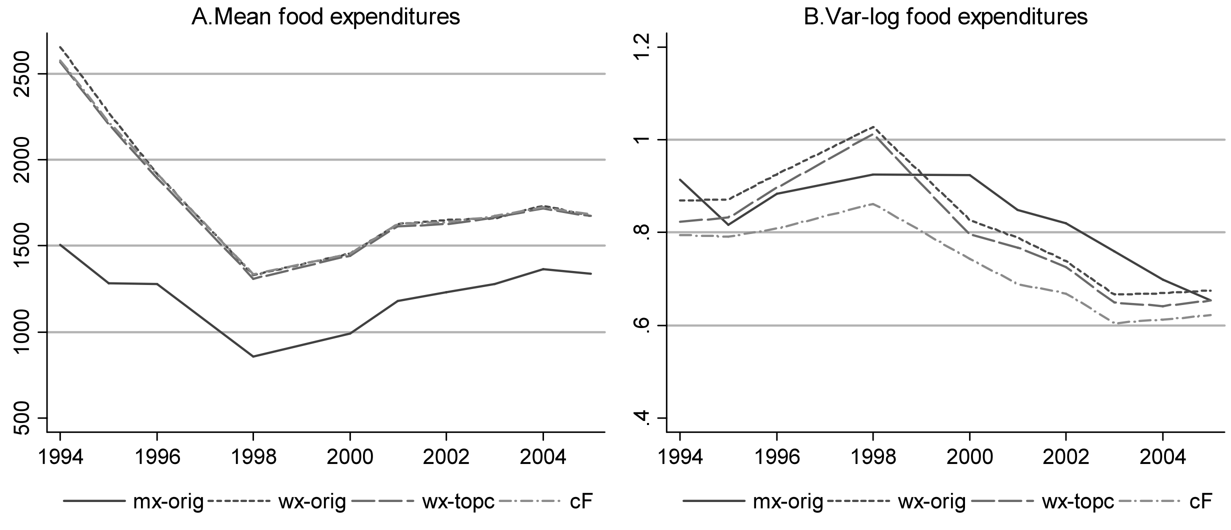
Table A.1 (*continued*)

	Variable name	Definition	Notes
$cpiR_t$	Regional deflator	Deflator that combines monthly national CPI, December to December regional CPIs, and the regional value of fixed basket of goods and services	To adjust for monthly inflation, the flow variables are expressed in December prices of each year by using a country average monthly CPI and the date of interview. Next, the annual (December to December) CPI for each 32 oblasts (regions) is applied to convert the flow variables into prices of December 2002. Finally, these real values are adjusted for regional differences in the cost-of-living by using the regional value of fixed basket of goods and services
		Control variables	
D^H	Household composition	Vector of household composition variables: 4 categories for the number of children 16 years old and younger (0, 1, 2, and 3+), 3 categories for the number of seniors 60 years old and older (0, 1, and 2+), and 5 categories for the number of household members (1, 2, 3, 4, and 5+)	
	Demographics	A female dummy and continuous age variable a	
D^E	Schooling	A set of dummies for educational attainment of the head of household (incomplete secondary, secondary, vocational, technical, and university)	
D^L	Regional variables	A set of dummies for 7 federal districts, a dummy for Moscow and St. Petersburg, and a dummy for urban location	



Note: All reported measures are per adult equivalent.

Fig. B.1. Mean and variance of food expenditures.

Appendix B. Constructing food expenditures

This appendix describes the steps in constructing our measure of food expenditures:

1. RLMS food data contain information on the physical quantity and monetary value of last week purchases for 50 categories of food at home and away from home, alcoholic and non-alcoholic beverages, and tobacco products. We first create *wx-orig* as the sum of expenditures on these individual items multiplied by $30/7 = 4.286$. Missing values for this measure are treated as zero.
2. The RLMS questionnaire also asks about the total sum of food purchases in the last 30 days (*mx-orig*). We discard this measure because of a potentially large measurement error, higher probability of underreporting, and ambiguity in the question (e.g., it is likely to exclude beverages and tobacco). We note, however, that the two measures of food expenditures have similar variance (compare *wx-orig* and *mx-orig* in Fig. B.1B).

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3. When a household purchased the item but did not report the quantity of the purchase, the missing quantities are imputed by regressing the log of expenditure on the complete interaction between year dummies and federal district dummies, controlling for the size of the household (5 categories), number of children 16 years old or younger (4 categories), number of elderly members 60+ (3 categories), and urban location. Because of the log dependent variable, the predicted values of expenditures are adjusted as $y = \exp(\frac{1}{2}\sigma^2)\exp(\widehat{\log y})$. Missing values for food items are generally trivial.
4. We use top coding of unreasonably high prices in excess of 3 interquantile ranges above the median prices in a given location as well as unreasonably high amounts (quantities) of food purchases (the top 99th percentile), conditional on the household structure and location. Top coding and imputations do not change the mean value and only slightly reduce the variance (see *wx-topc* in Fig. B.1).
5. It is very well known that inequality measures, especially those based on logarithms, are very sensitive to very low values. For that reason, we eliminate the bottom 1 percent of total food consumption (from purchases and home production) in constant 2002 prices (about 12 percent of the cost of the reference basket of 25 major food items reported by Goskomstat in 2002). While this procedure does not change the mean value of food expenditures, it predictably reduces the variance (see line *cF*).

Appendix C. Sample composition

Table C.1
Sample composition.

	Full sample	Restricted sample	Estimation sample
Year			
1994	9.34	9.61	9.66
1995	8.89	9.09	9.07
1996	8.82	8.94	8.75
1998	9.00	9.01	8.91
2000	9.42	9.24	9.23
2001	10.64	10.35	10.42
2002	10.97	10.74	10.81
2003	11.09	10.92	10.96
2004	11.07	11.17	11.21
2005	10.75	10.92	10.99
Region			
Moscow and St. Petersburg	11.28	11.17	11.31
North West	6.89	7.33	7.37
Central	19.09	18.17	18.26
Volga	17.72	17.42	17.39
South	11.73	12.13	11.93
Urals	14.17	14.60	14.59
Siberia	9.41	9.45	9.41
Far East	9.71	9.73	9.73
Number of household members			
1	18.39	7.58	7.18
2	27.74	24.28	24.16
3	25.34	30.83	31.07
4	18.06	23.49	23.72
5+	10.47	13.82	13.87
Number of children < 16			
None	56.99	45.63	45.25
1	28.26	35.02	35.32
2	12.23	15.99	16.09
3+	2.53	3.36	3.34
Urban (excluding small towns)	68.91	69.55	70.01
Number of observations	42,541	31,969	31,409

Notes: Restricted sample includes households in which at least one individual is 25–60 years old. Estimation sample includes households with non-missing values on disposable income. The sample composition is unweighted.

Appendix D. Time series decomposition of income and consumption growth

D.1. Permanent-temporary decomposition

The procedure decomposes *residual* variation of income and consumption $u_{ht}^{(s)}$ into temporary and permanent components, where s denotes a measure of income or consumption. Using the notation in the body of the paper, the residual $u_{ht}^{(s)}$ from regression (1) can be decomposed into the sum of a transitory component and a random-walk permanent component:

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$$u_{ht}^{(s)} = \alpha_{ht} + \varepsilon_{ht},$$
$$\alpha_{ht} = \alpha_{h,t-1} + \eta_{ht},$$

where $\varepsilon_{ht} \sim (0, \sigma_{\varepsilon,t}^2)$ is the transitory component and $\eta_{ht} \sim (0, \sigma_{\eta,t}^2)$ is the innovation in the permanent component.

Given $u_{ht}^{(s)}$, we form a vector of changes in the residual $\Delta u_{ht}^{(s)} = \eta_{ht} + \varepsilon_{ht} - \varepsilon_{h,t-1}$ (that equals the annual growth rate of s_{ht}). The full vector of growth rates for household h and measure s_{ht} is $g_h = [\Delta u_{h,1}^{(s)} \Delta u_{h,2}^{(s)} \ldots \Delta u_{h,T}^{(s)}]'$ where $t = 0$ is the first year in the panel and T is the last. The covariance matrix of vector g_h, which has $T(T-1)/2$ unique empirical moments, is

$$V \equiv \frac{1}{H} \sum_{h=1}^{H} (g_h - \bar{g})(g_h - \bar{g})',$$

where $\bar{g} = \frac{1}{H} \sum_{h=1}^{H} g_h$ is the average value of the change in the residual and H is the number of households in the sample.

Let Λ be the vector of parameters we to be estimated (i.e., the year-specific variances of innovations in permanent and transitory components of s_{ht}) and let $V(\Lambda)$ be the corresponding covariance matrix. Under the assumptions of our statistical model,

$$V(\Lambda) = \begin{bmatrix} \sigma_{\eta,1}^2 + \sigma_{\varepsilon,1}^2 + \sigma_{\varepsilon,0}^2 & -\sigma_{\varepsilon,1}^2 & 0 & \cdots & 0 & 0 \\ -\sigma_{\varepsilon,1}^2 & \sigma_{\eta,2}^2 + \sigma_{\varepsilon,2}^2 + \sigma_{\varepsilon,1}^2 & -\sigma_{\varepsilon,2}^2 & \ddots & 0 & 0 \\ 0 & -\sigma_{\varepsilon,2}^2 & \sigma_{\eta,3}^2 + \sigma_{\varepsilon,3}^2 + \sigma_{\varepsilon,2}^2 & \ddots & 0 & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & \ddots & \sigma_{\eta,T-1}^2 + \sigma_{\varepsilon,T-1}^2 + \sigma_{\varepsilon,T-2}^2 & -\sigma_{\varepsilon,T-1}^2 \\ 0 & 0 & 0 & \ddots & -\sigma_{\varepsilon,T-1}^2 & \sigma_{\eta,T}^2 + \sigma_{\varepsilon,T}^2 + \sigma_{\varepsilon,T-1}^2 \end{bmatrix}.$$

Two identification issues are apparent from the above expression for $V(\Lambda)$. First, $\sigma_{\varepsilon,0}^2$ is not identified separately from $\sigma_{\eta,1}^2$. Second, $\sigma_{\varepsilon,T}^2$ is not identified separately from $\sigma_{\eta,T}^2$. We follow the common practice of addressing these identification issues by imposing $\sigma_{\varepsilon,T}^2 = \sigma_{\varepsilon,T-1}^2$ and $\sigma_{\varepsilon,1}^2 = \sigma_{\varepsilon,0}^2$. After imposing these constraints, the vector of parameters to be estimated becomes $\Lambda = \{\sigma_{\varepsilon,1}^2, \sigma_{\varepsilon,2}^2, \ldots, \sigma_{\varepsilon,T-1}^2, \sigma_{\eta,1}^2, \sigma_{\eta,2}^2, \ldots, \sigma_{\eta,T}^2\}$.

Vector Λ is estimated by minimizing the distance between theoretical and empirical moments

$$\hat{\Lambda} = \arg\max_{\Lambda} \bigl(vech\bigl\{V - V(\Lambda)\bigr\}\bigr)' \bigl(vech\bigl\{V - V(\Lambda)\bigr\}\bigr),$$

where the weight matrix is set to be the identity matrix.

D.2. Estimating consumption response to income innovations

The approach to estimating the response of consumption to income components is similar to that in Blundell et al. (2008). The procedure uses (auto)covariances of income and consumption growth rates. As before, the residual in the income equation is assumed to follow the process

$$u_{ht}^{(y)} = \alpha_{ht} + \varepsilon_{ht},$$
$$\alpha_{ht} = \alpha_{h,t-1} + \eta_{ht}.$$

The residual consumption growth

$$\Delta u_{ht}^{(c)} = \phi_t \eta_{ht} + \psi_t \varepsilon_{ht} + \xi_{ht} - \xi_{h,t-1},$$

is decomposed into three parts: the influence of permanent income innovation, the influence of temporary income innovation and unobserved household heterogeneity. Let $g_h = [\Delta u_{h,1}^{(y)}, \Delta u_{h,1}^{(c)}, \ldots, \Delta u_{h,T}^{(y)}, \Delta u_{h,T}^{(c)}]$ denote the vector of income and consumption growth rates for household h. As before, define the empirical covariance matrix

$$V \equiv \frac{1}{H} \sum_{h=1}^{H} (g_h - \bar{g})(g_h - \bar{g})'.$$

Let Λ be the vector of parameters we to be estimated (i.e., the year-specific variances of innovations in permanent and transitory components of income and transitory components in consumption as well as loadings ϕ_t and ψ_t) and let $V(\Lambda)$

be the vector of theoretical moments (i.e., the model equivalent of V). Under our statistical model, with $T = 3$ (for example) we have

$$V(\Lambda) = \begin{bmatrix} \sigma^2_{\eta,1}+\sigma^2_{\varepsilon,1}+\sigma^2_{\varepsilon,0} & \phi_1^2\sigma^2_{\eta,1}+\psi_1^2\sigma^2_{\varepsilon,1} & -\sigma^2_{\varepsilon,1} & 0 & 0 & 0 \\ \phi_1^2\sigma^2_{\eta,1}+\psi_1^2\sigma^2_{\varepsilon,1} & \phi_1^2\sigma^2_{\eta,1}+\psi_1^2\sigma^2_{\varepsilon,1}+\sigma^2_{\xi,1}+\sigma^2_{\xi,0} & -\psi_1\sigma^2_{\varepsilon,1} & -\sigma^2_{\xi,1} & 0 & 0 \\ -\sigma^2_{\varepsilon,1} & -\psi_1\sigma^2_{\varepsilon,1} & \sigma^2_{\eta,2}+\sigma^2_{\varepsilon,2}+\sigma^2_{\varepsilon,1} & \phi_2^2\sigma^2_{\eta,2}+\psi_2^2\sigma^2_{\varepsilon,2} & -\sigma^2_{\varepsilon,2} & 0 \\ 0 & -\sigma^2_{\xi,1} & \phi_2^2\sigma^2_{\eta,2}+\psi_2^2\sigma^2_{\varepsilon,2} & \phi_2^2\sigma^2_{\eta,2}+\psi_2^2\sigma^2_{\varepsilon,2}+\sigma^2_{\xi,2}+\sigma^2_{\xi,1} & -\psi_2\sigma^2_{\varepsilon,2} & -\sigma^2_{\xi,2} \\ 0 & 0 & -\sigma^2_{\varepsilon,2} & -\psi_2\sigma^2_{\varepsilon,2} & \sigma^2_{\eta,3}+\sigma^2_{\varepsilon,3}+\sigma^2_{\varepsilon,2} & \phi_3^2\sigma^2_{\eta,3}+\psi_3^2\sigma^2_{\varepsilon,3} \\ 0 & 0 & 0 & -\sigma^2_{\xi,2} & \phi_3^2\sigma^2_{\eta,3}+\psi_3^2\sigma^2_{\varepsilon,3} & \phi_3^2\sigma^2_{\eta,3}+\psi_3^2\sigma^2_{\varepsilon,3}+\sigma^2_{\xi,3}+\sigma^2_{\xi,2} \end{bmatrix}.$$

Again, there are two identification issues. First, $\sigma^2_{\varepsilon,0}$, $\sigma^2_{\xi,0}$ are not identified separately from $\sigma^2_{\eta,1}$. Second, $\sigma^2_{\varepsilon,T}, \sigma^2_{\xi,T}$ are not identified separately from $\sigma^2_{\eta,T}$. We impose $\sigma^2_{\varepsilon,T} = \sigma^2_{\varepsilon,T-1}$, $\sigma^2_{\varepsilon,1} = \sigma^2_{\varepsilon,0}$, $\sigma^2_{\xi,T} = \sigma^2_{\xi,T-1}$, $\sigma^2_{\xi,1} = \sigma^2_{\xi,0}$. Thus, our vector of parameters becomes

$$\Lambda = \left\{\sigma^2_{\varepsilon,1}, \sigma^2_{\varepsilon,2}, \ldots, \sigma^2_{\varepsilon,T-1}, \sigma^2_{\eta,1}, \sigma^2_{\eta,2}, \ldots, \sigma^2_{\eta,T}, \sigma^2_{\xi,1}, \sigma^2_{\xi,2}, \ldots, \sigma^2_{\xi,T-1}, \phi_1, \phi_2, \ldots, \phi_T, \psi_1, \psi_2, \ldots, \psi_T\right\}.$$

We estimate Λ by minimizing the distance between theoretical and empirical moments

$$\hat{\Lambda} = \arg\max_{\Lambda}\big(vech\{V - V(\Lambda)\}\big)'\big(vech\{V - V(\Lambda)\}\big),$$

where the weight matrix is set to be the identity matrix.

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