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L 45 Wage Arrears and the Distribution of Earnings: What can we learn from Russia?

We examine the implications for estimates of wage relativities and inequality when countries experience wage arrears on a substantial scale, using the Russian labour market as a test case. The increase in wage inequality in Russia during its transition process has far exceeded the increase in wage dispersion observed in other European countries undergoing transition. Russia also has much the largest incidence of wage arrears. Given data on wages and the incidence of wage arrears we show that it is possible to construct counterfactual wage distributions, derived from a variety of different methods. The results suggest that conventional measures of earnings dispersion in Russia would be some 20 to 30% lower in the absence of arrears. Since the incidence of arrears is not random, we then go on to show how wage gaps across gender, education, region and industry are influenced by a failure to allow for wage arrears. If those in arrears are distributed uniformly across the underlying wage distribution, as appears to be the case in Russia, then it may be feasible to use wage information on the subset of those not in arrears and still get close to the underlying population parameters.

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I. Introduction*

Many countries in the developing world, those undergoing the transition from planned to market economic systems and even those in the industrialised west, experience periods in which a substantial proportion of the workforce suffer wage arrears[1]. For research reliant on the distribution of wages, such as estimation of wage inequality, gender pay gaps or the returns to education, this can have important implications, as we show below. Russia is particularly interesting in this regard, since it has experienced well-documented increases in both the incidence of wage arrears and wage inequality over the transition period. Moreover, the availability of data on both these issues facilitates exploration of the linkages between the two that is not always possible in other countries.

Wage inequality in Russia following the end of central planning has risen far more than in Central and Eastern European (CEE) countries undergoing transition. According to estimates based on official statistics, the Gini coefficient for wages in Russia rose from 0.22 before transition to around 0.5 in 1996 [Flemming, Micklewright, 1997]. The level of wage inequality in Russia is also now very high by international standards[2]. Rising earnings dispersion seems to have been the major factor behind

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[1] A glance at the BBC web site: www.bbc.co.uk contains reports on unpaid wages in Argentina, Azerbaijan, , Belarus, Bulgaria, Central African Republic, China, Colombia, Honduras, Iran, Kazakhstan, Kenya, Kosovo, Mexico, Niger and Ukraine as well as Russia over the last 5 years. Following the introduction of the national minimum wage in Britain in 1999, a recent report indicates that some 36% of firms were underpaying their minimum wage workers http://news.bbc.co.uk/1/hi/business/2255947.stm

[2] Over the same period, the Gini indices for wages in CEE grew from levels in the range of 0.2 to 0.25 to levels in the range 0.3 to 0.35. In Chile, the Gini coefficient is around 0.45 and in Turkey around 0.37.

rising inequality in personal incomes. While these trends are well documented, the reasons for the sharp increase in earnings inequality in Russia are not entirely clear [Brainerd, 1998]. One simple explanation of inequality in the wage distribution, in any country, could be the presence of wage arrears. If in any given month a substantial subset of workers, receive only a part of the normal wage, or even no wage at all, then inequality in wages will be extremely high. Wage arrears have been a pervasive feature of Russian economic life since 1994, affecting large sections of the workforce (Lehmann, Wadsworth and Acquisti [1999], show that around 65% of the workforce were owed money at the height of the problem in 1998). Moreover, the withholding of wage payments has been systematic and concentrated heavily on sub-sections of the workforce, particularly in certain regions and industries [see e.g.: Earle, Sabirianova, 2002; Lehmann, Wadsworth, Acquisti, 1999]. An explicit treatment of distributional effects of wage arrears has, however, not yet been undertaken. Most studies of wages in developing and transition economies in general, still tend to ignore the presence of wage arrears without considering the possible consequences[3].

In what follows, we try to estimate what the wage distribution would have looked like in Russia if all workers had been paid in full and on time, in order to establish the "true" parameters of the distribution and adjusted estimates of any between-group differences based on quantiles of the wage distribution. As we argue in the next section there are several reasons for undertaking such an exercise. Essentially, if wage arrears are transitory and liable to occur in times of economic hardship, then the counterfactual establishes the parameters of the "permanent" underlying wage distribution.

Using Russian Longitudinal Monitoring Survey (RLMS) data, covering the years 1994 through 1996 and 1998, we use the results from several different imputation methods to generate predicted wages for those in arrears and hence construct counterfactual estimates of the underlying wage distributions. We find similar results across the various methods. The results suggest that much of the earnings dispersion in Russia occurs amongst the stock of workers affected by wage arrears, and that consequently earnings dispersion may have been some 30% lower if these workers had been paid in full. We then examine the implications

[3] Oglobin [2000] is an exception to this, using a selection equation in his analysis of the mean gender pay gap in Russia.

for estimates of between-group wage differentials commonly addressed in the literature. Since, on average, women seem to be less affected by wage arrears, [cf.: Lehmann, Wadsworth, Acquisti, 1999], the mean gender gap is larger in the counterfactual distributions compared with the observed gender pay gap. We also look at the gender gap across the other quantiles of the earnings distribution, something we cannot do when wage arrears are present on a large scale. In addition, we look at how wage arrears might affect returns to education and relative wage distributions by region and industry.

In the next section we look at the rationale for constructing counterfactual wage distributions in the Russian case. The subsequent section presents the various methods employed to construct counterfactual wage distributions, while section IV discusses data issues. Section V analyses earnings inequality in Russia and the decomposition of its change over time, followed by presentation of the counterfactual results. Section VII then concludes.

II. Economic Reality in Russia and the Construction of Counterfactual Wage Distributions

Why construct counterfactual wage distributions that assume payment of wages in full and on time for all employed members of the workforce? One could argue that an economy may be confronted with a macro constraint that makes it impossible to pay the contracted wage and maintain employment levels at the same time. If mass layoffs are in the short-run politically and economically too costly[4], such an economy may be intrinsically unable to honour all contractual wage claims in any given month. Instead of, for example, imposing an inflationary tax on the entire workforce, the major costs could instead be borne by weaker sub-groups of the workforce by withholding regular wage payments from them. In part the choice of wage arrears over lay-offs has been driven by the policy stance adopted in different transition and developing countries. In Russia, it is clear that wage arrears are an integral part of the labour market experience of many workers. One

[4] Russian labour market legislation stipulates severance pay of three monthly salaries for workers laid off in a mass layoff. Political support for economic reform may be hampered by mass-layoffs.

might conclude that a "non-payment equilibrium" prevails and so the actual wage distribution is what matters and not some elusive counterfactual.

The above lines of reasoning do not preclude, in our opinion, the construction of counterfactual wage distributions for the following reasons. First, even if there is no conscious attempt by policy makers and managers to concentrate the costs of transition on some sub-groups of the workforce, there is no reason to assume that the "non-payment equilibrium" [Earle, Sabirianova, 2000] is the only natural, rational outcome[5]. The political constraint restricting mass layoffs could have been relaxed, as could have labour market legislation that imposes large costs on firms in connection with any layoffs. One could even envisage the counterfactual as that which would emerge in the absence of large shocks. In summary, as long as we can think of sensible counterfactual policy regimes or scenarios it seems legitimate to construct counterfactual wage distributions.

Second, if wage arrears are brought about because of a conscious policy of avoiding mass layoffs or a reluctance to use a general inflationary tax, then we can think of counterfactual wage distributions as reflecting a counterfactual economic policy that encourages the release of labour from unproductive, declining sectors. Such a policy, which has been used in most countries of Central and Eastern Europe despite large initial falls in output, seems to avoid inflationary bottlenecks and reverses the initial output decline. If such a counterfactual economic policy had been chosen, those in work would almost certainly get paid in full and on time[6]. If we construct counterfactual wage distributions we therefore make the assumption that either there are no job losses when all workers get paid in full[7] or the existence of a regime in which large-scale lay-

[5] Desai and Idson [2000] seem to assume this non-payment equilibrium as the natural outcome in the Russian transition period

[6] It may be that there would be differential unemployment levels across the two scenarios. The manner in which unemployment affects the parameters of the wage distribution in Russia is however unclear. The evidence on wage arrears emerging from the analysis in this paper suggests that wage arrears are distributed rather randomly across the wage distribution.

[7] The former is consistent with a bargaining environment where workers are all-powerful and capable of shifting the entire burden of adjustment onto the enterprise. Svejnar [1986] models outcomes of the wage bargain when workers are all powerful. Constructing counterfactual wage distributions that take this trade-off into account is difficult, as we have no reliable estimates of the elasticity of employment demand with respect to wage arrears.

offs are distributed randomly across the wage distribution. Russian workers are poorly organised and unions are weak, so the first scenario is unrealistic, but the random lay-off assumption seems more plausible in a transition context.

Third, if wage arrears are a problem of irregular pay and not of permanently withheld wages, then we have a strong rationale for constructing counterfactual wage distributions that ignore the trade-off between the elimination of wage arrears and employment. We believe that evidence garnered from various sources on the dynamic nature of the arrears process provides this rationale. Aggregate data from Russian Statistical Office (Goskomstat) indicate that since 1996 the stock of wage arrears has been approximately stable, equivalent to two monthly wage bills. At the same time, there is substantial evidence in the RLMS data, which supports the hypothesis of wage arrears as a problem of irregular pay rather than that of permanently withheld wages. Lehmann, Wadsworth and Acquisti [1999], using the RLMS data, document the existence of simultaneous inflows into and outflows from wage arrears. In the data we analyse below, 10% of workers are in arrears at all four interview points and 20% never experience wage arrears. The fact that wage arrears are roughly in a steady state at the end of the sample period and these flow patterns suggest that the amount of contractual wages not paid to (some) workers roughly equals the amount of wage debts paid back to (some) workers in any month. Payroll data from a sample of 19 firms in the city of Ryazan recently collected by one of us also seem to confirm this pattern in Figure A1. At times, the stock of arrears in some firms rises, while falling in others. Moreover, the Figure indicates that wage arrears are eventually paid off, and at different rates across firms. All this implies to us that even though wage arrears are not a purely stochastic phenomenon in the sense that incidence is not entirely random, it seems most workers affected do get paid the wages owed to them eventually.

The RLMS provides a monthly data window as far as wage payments are concerned. This monthly window might be too narrow to obtain an estimate of the "permanent" earnings of those workers affected by the irregularity of pay. Consider a simple thought experiment. Assume an economy where all workers get paid monthly. Let us make the additional assumption that the data window on earnings is the third week of the month in which we undertake the survey. So, we ask: "How much did you get paid in the third week of this month?" Some workers will have been paid their monthly salary in this third week, but many will have been paid in another week of the month. Estimation of monthly earnings on this weekly window will be certainly inefficient, or even misleading. If, in the Russian case, we had a window of, say, two, three or six months, we could obtain better estimates of "permanent" earnings of Russian workers. Counterfactual distributions provide one way of estimating such "permanent" earnings[8].

III. Building Counterfactual Estimates of the Effects of Wage Arrears

Counterfactual wage distributions have been applied to a variety of economic and statistical issues, e.g. minimum wages [DiNardo, Fortin, Lemieux, 1996], item non-response [Biewen, 1999] and international differences in wage inequality [Blau, Kahn, 1996]. The literature suggests several methods of building counterfactuals.

We begin with a simple least squares prediction and then use least squares with the addition of a random residual, both of which use parameters from a wage equation estimated on the sample without wage arrears to predict wages for those in arrears. We then apply a different residual according to the method proposed by Juhn, Murphy Pierce [1993]. We also provide counterfactual estimates of what the wage distribution would look like if everyone were paid on time following the Kernel density approach pioneered by DiNardo, Fortin and Lemieux [1996]. We then employ a variation of the exact matching techniques used by, among others, Heckman, Ishimura and Todd [1997], and Kluve, Lehmann and Schmidt [1999], to assign wages to those in arrears by matching their characteristics to the sub-sample of those who continue to be paid in full but who had a similar labour market pre-treatment history. The last method matches on the propensity score [Lechner, 2000]. These matching estimators may take account of any unobserved heterogeneity that could be missed by the other approaches.

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[8] They give imperfect estimates of "permanent" income since the counterfactuals ignore the losses in earnings over time due to inflation. One should recall, though, that wage arrears are particularly virulent in times of low inflation [Gimpelson, 2001].

OLS methods

Following Oaxaca [1973] we can estimate a wage equation using the sample of those without wage arrears. Using the vector of estimated parameters from the no arrears equation and the observed characteristics of those in arrears we then predict wages, which those in arrears would have received if they had been paid in full. More formally, let B_{NW} be the vector of parameter estimates from the wage equation of the sample without wage arrears and let $X_{i,WA}$ be a vector of characteristics of the i-th person who experiences arrears. Then the predicted wage of this individual, $Y_{i,\ WA}$, will simply be:

$$Y_{i,\ WA} = B'_{NW}\, X_{i,WA}. \tag{1}$$

Since this method gives only a mean prediction and the actual wage equals the sum of the predicted wage and a residual, $y = \hat{y} + \hat{u}$, we can add a residual so as to proxy wage dispersion in full. We do this by first taking the standard error of the regression from the no arrears equation, σ_{NW}, and multiplying each individual observation by a, randomly assigned, standard normal random variable z_i. This random residual is then added to the predicted wage for the arrears sub-group and is given by

$$\varepsilon_{iWA} = z_i \times \sigma_{NW}. \tag{2}$$

Table A1 in the appendix gives the estimates from the OLS real wage equations for the no arrears group used to generate these estimates.

Juhn, Murphy and Pierce

Juhn, Murphy and Pierce [1993] and Blau and Kahn [1996] have suggested that it may be worthwhile trying to take into account unobserved heterogeneity as measured by the percentile ranking of each individual in the residual wage distribution. With a simple transformation of the residual into the product of a standard normal residual, θ, and the residual standard deviation from the wage equation, σ, the predicted wage can be written as

$$Y_{i,\ WA} = B'_{NW}\, X_{i,WA} + \sigma_{NW}\, \theta_{WA}. \tag{3}$$

Applying this method in the context of wage arrears, the counterfactual is then the set of wages that would result if the no arrears wage coefficients and residual standard deviation were given to those currently in arrears. Since many of the observations on the dependent variable in the arrears sample are zero, this technique relies on the assumption of normality in the residuals estimated from this subset[9]. The estimates from the equations used to construct these, and the OLS, estimates are given in Table A1 in the Appendix. It is apparent that the estimated coefficients do vary widely between the arrears and no-arrears groups.

Kernel Density Counterfactuals

DiNardo, Fortin and Lemieux [1996] (hereafter DFL), have suggested that a broader insight may be obtained by taking into account the entire wage structure, allowing the returns to observables and unobservables to vary across the distribution of wages. The principal remains the same, to estimate the wages that those in arrears would receive had they been paid as those paid in full. Given the joint distribution of wages, w, and characteristics, x, the marginal distribution of wages conditional on x can be written $g(w) = \int f(w/x)h(x)dx.$ The conditional expectation, $f(\ )$ is similar to an estimated regression line and the marginal density of x, $h(\ )$ is analogous to the vector of characteristics. Following DFL, using Bayes' law, it can be shown that the counterfactual wage distribution if everybody were paid in full can be obtained by taking the observed wage distribution of the subset of those paid in full and reweighting by a parameter $\Phi(x)$, where $\Phi(x)$ reflects the relative incidence of arrears conditional on characteristics x,

$\Phi(x) = Pr(No\ Arrears)\ /\ Pr(No\ Arrears/x)$. The weights are normalised to sum to one. So,

$$g(w) = \int \Phi(x) f^{\,No\ Arrears}(w/x)h(x/i = No\ Arrears)dx.$$

The integral is approximated using Kernel density estimation, which means that we do not get predictions of individual wages, only the quantiles of the distribution. The numerator in $\Phi(x)$ is the sample proportion of those not in arrears in any year and the denominator is estimated by a logit regression conditional on a set of observed characteristics. The estimates from the logit equations used to construct

[9] This is not always the case in our data.

these estimates (Table A2) confirm the dominance of location and firm characteristics in explaining the incidence of arrears as found in Lehmann, Wadsworth and Acquisti [1999].

Matching Estimators

If there were unobserved heterogeneity amongst those in arrears, then the preceding techniques would fail to account for this. The JMP approach and the DFL density approach perhaps come closest, the latter using the non-parametric structure of the entire distribution. However they implicitly assume that heterogeneity amongst those not in arrears is duplicated amongst those in arrears. If this is not the case, so that those not in arrears are different from those in arrears, the counterfactual estimates could be biased. Moreover, the JMP method uses the standard residuals from the arrears regression to calculate counterfactuals. This standardised residual is usually interpreted as an individual's ranking in the residual wage distribution and as such a measure of unobserved relative skill. However, the outcome we analyse in equation (3) gives an individual's relative ranking in the residual arrears wage distribution, which is hard to interpret as a measure of unobserved skill, unless one is prepared to make the unlikely assumption that the size of non-payment reflects unobserved skill. This, together with our wish to construct counterfactuals untainted by arrears leaves this method open to question.

We therefore experiment with alternative approaches based on the matching estimator literature. The first technique follows Heckman, Ishimura and Todd [1997] in that we also condition, non-parametrically, on "pre-treatment history" in order to minimise biases arising from unobserved heterogeneity. In our case this means conditioning on events **before** wage arrears began, together with a set of current observable, exogenous characteristics, in order to try and capture heterogeneity in the arrears population, i.e. to ensure that the treatment and the control group do not differ systematically. Conditioning on a set of pre-treatment covariates is assumed to be sufficient to allow the assumption of assignment to the treatment group as random, such that unobservables may be ignored. If Y_{i1} is the outcome with treatment and Y_{i0} is the outcome without treatment for individual i and X and H are sets of controls for observable characteristics and "pre-treatment history", then the identification assumption becomes,

$E(Y_{i0} / T = 1, X, H) = E(Y_{i0} / T = 0, X, H)$. Heckman, Ishimura and Todd [1997] find that for this type of matching estimators to work well the same data set should be used for the control and treatment group, the groups should be in the same local labour markets and the data set should contain a rich set of variables relevant to the treatment decision.

Treatment in our study is the experience of wage arrears and the labour market history we condition on, using the panel element of the RLMS, is labour market status one year earlier and if employed, the ranking in the wage distribution of those paid in full. If the individual was out of work one year earlier we create unemployed and inactive categories. If the individual was in arrears one year earlier we create a separate sub-category. We divide last year's wage distribution, excluding arrears, into deciles. Matching proceeds for those sub-groups of the treated and the non-treated who have the same "pre-treatment history", and in addition we match according to age (with a maximum allowed difference of ten years), gender, region (3 groups) and qualifications (3 groups) in the current year. This strategy conforms broadly to the criteria set out by Heckman et al. [1997] required for a good performance of a matching estimator. The assumption made here is that the variables used for matching are not affected by the treatment (arrears)[10].

We assign the wages of those currently paid in full to those in the treatment group, who were placed in the same decile a year ago when both treatment and control groups were paid in full. Those in arrears now who were also in arrears last year or non-employed are given the wages of those currently paid in full who were in the same category one year earlier. In this way, we hope to reduce the difference in unobserved skills and other characteristics that might exist between the individuals experiencing wage arrears and those who are unaffected by them. If more than one person can be matched with the individual we assign the average wage of the matched controls. With this direct matching procedure the set of variables used is much smaller than can be afforded by a regression based technique which is unaffected by empty cells. The matching algorithm is shown in Box A1 in the appendix. Since this approach can only be used when there are at least two consecutive

[10] Whilst within region mobility may be affected by arrears, the regions in the RLMS are so large as to make mobility between regions as a result of arrears unlikely.

years of longitudinal data, we confine our estimates using this approach to 1996 and provide comparisons using the other counterfactual techniques estimated over the same sample.

The approach assumes that individuals do not move rapidly through the earnings distribution. As a check, Table A3 in the appendix presents one and four-year earnings transition matrices using quintiles of the wage distribution. It is apparent that, whilst there is a degree of mobility across earnings quintiles, there is considerably less mobility amongst those not subject to wage arrears. Figure 2 also suggests that those in arrears are drawn from across the entire wage distribution.

Propensity Scores

When performing non-parametric matching we lose around 10% of potential matches for whom a donor from the control group cannot be found. To avoid this, we also employ propensity score matching, where individuals are matched according to the closeness in the estimated probability of experiencing wage arrears. We use the matching algorithm suggested by Dehejia and Wahba [1998][11]. We estimate probit regressions, conditional on the same co-variates as used in the matching approach, take the predicted probability — the propensity score — and match, with replacement, those in arrears with those not in arrears with the nearest propensity score. It can be shown that if Y_{i1} and Y_{i0} are independent of treatment, T, given X and H (that is, given sufficient disaggregation by age, sex and region, for example, as well as by "pre-treatment history"), then the two groups may be treated as the same. In other words, T is *ignorable* given X and H, so that

$$E(Y_{i0} / T = 1, P(X, H)) = E(Y_{i0} / T = 0, P(X, H)) = E(Y_{i0} / P(X, H)).$$

We estimate two variants of the propensity score, one where pre-treatment variables are included in the set of co-variates and one without them. In the latter case the identification assumption becomes,

$$E(Y_{i0} / T = 1, P(X)) = E(Y_{i0} / T = 0, P(X)) = E(Y_{i0} / P(X)).$$

[11] As Kluve, Lehmann and Schmidt [2001] state, "the reduced dimension comes at a cost, however. The propensity score is not known and has to be estimated. Also, in samples of limited size, for some *i* and *j* it may occur that $p(X_i) = p(X_j)$ even if $X_i \neq X_j$, resulting in imperfect balancing of the distributions of covariates." The literature stresses that there seems to be a bias vs. efficiency trade-off between non-parametric and propensity score matching. Smith and Todd [2001] show that estimates from different propensity score matching methods do not vary much as long as the conditioning variables satisfy the requirements set out by Heckman et al. [1997].

IV. Data

Our main data source is the second phase of the Russian Longitudinal Monitor Survey (RLMS), a longitudinal panel of around 4000 households across the Russian federation conducted in the autumn of 1994, 1995, 1996 and 1998. The data contains a set of demographic and establishment characteristics, together with information on the labour market activities of its sample. Despite its relatively small size, the advantage of this source is that we can track individual wages and the incidence of wage arrears over time. We restrict our sample to employees of working age and exclude the military[12]. The survey design does not follow individuals if they move, but does sample new occupants of the same address. There are around 10,000 individual observations in each wave, of which around 4000 are in work in any wave and around 3,500 give wage related information.

The survey questions dealing with wage arrears ask whether, conditional on being in work, an individual was owed money by the firm in the past month or was paid "in kind" with goods produced by the firm, since 75% of this latter group report arrears and the reported wages received of the remainder are assumed to be incomplete. This constitutes our sample of those in arrears in any wave. Some of those in arrears are paid some money, whilst others, around one half of those in arrears, receive nothing[13]. Respondents, both those paid in full and those in arrears, are asked to state the amount of *money* received from their employers after taxin the past month.These are total wage receipts and not contractual wages. There is no distinction made between basic wages and bonus. These wage responses are then deflated by a national price deflator indexed to 100 at January 1998[14]. There is no indication whether wage arrears are estimated before or after tax. We remove

[12] The RLMS is ambiguous on the nature of self-employment, referring instead to the extent of self-ownership in the enterprise where the individual works. We exclude only those who say they own between 51 and 100% of the enterprise.

[13] The RLMS also asks for the total amount owed, together with the number of months since the worker was paid last. It may be that some of those not in arrears are paid more than their monthly wage if arrears are paid back. There may also be some in arrears who were paid in full in the current month. However there is no way of ascertaining these issues from the data.

[14] There are no population weights in the data sets.

outliers from that data, namely those earning in excess of 4000 roubles a month, or less than 50 roubles if the respondents are not in arrears. Standard errors around the quantiles of the observed and counterfactual distributions are generated using the bootstrap method. We also provide some data from a smaller, household survey data set, VTsIOM, undertaken in 1993 in order to provide summary evidence on pay from an earlier period when wage arrears were less prevalent together with data from Poland and Britain as benchmark comparisons[15].

V. Earnings Distributions and Inequality in Russia

The timing of the dramatic rise in inequality during the first years of transition, documented in Brainerd [1998], indicates that most of the rise in inequality occurred before the problem of wage arrears really began. Hyperinflation at the onset of reforms is probably the major contributing factor to the initial rise in inequality. However, as inflation subsided aggregate inequality remained high. Interestingly, the RLMS data indicate that inequality did fall in regions with a low incidence of wage arrears, and rose most in regions with the largest increase in wage arrears. The Gini coefficient in the metropolitan areas, where arrears are lowest, fell from 0.39 to 0.35 between 1994 and 1998, but rose from 0.43 to 0.49 in the Far East, where arrears are highest. It seems important, therefore, to try to analyse to what extent wage arrears have affected the earnings distribution since payment problems began.

In order to demonstrate the effects of wage arrears on the wage distribution, Table 1 gives summary measures of the changes in real monthly wage distribution across our sample period. The data suggest that, by 1998, around two thirds of employees were not receiving a wage complete or on time, and around 40% of these received nothing in the preceding month. Whilst disturbing in itself, this finding of a large number of zero wage observations among the working population means that any conventional measures of inequality based around logarithmic transformations will be of little use here. In what follows therefore, we focus on the real monthly wage distributions and eschew any techniques that rely on logarithmic transformations.

[15] The data for Poland are restricted to full-time workers only, though, as in Russia, part-time working amounts to less than 3% of the Polish workforce.

The Table also shows that real average earnings fell markedly over the sample period, prompted by a series of national economic crises which left inflation soaring and nominal wages failing to keep pace. The earnings distribution also widens over the first half of the sample period, while the evidence for the second half of the sample period is mixed. The coefficient of variation continues to increase, albeit more gently, but the Gini coefficient and the 90 : 50 ratio fall back. By 1996, the Gini coefficient on Russian wages was more than twice that observed in Poland and 60% higher than in Britain.

It is apparent, however, that the Russian results are strongly influenced by wage arrears. Figure 1 tracks the increased skewness of the real monthly wage distribution as the incidence of arrears builds up. The bottom panel of Table 1 confirms that inequality is lower and rises by much less amongst those who receive wages in full during the sample period. The Gini coefficient, for example, is around one third lower if based on the subset of those without wage arrears, in any period. It seems that many individuals appear in low deciles solely because they are not paid at all or paid only part of their wages. So to analyse distributional issues, counterfactual wage distributions for years in which wage arrears are a problem seem to be required.

Table 2 provides a formal decomposition of changes in earnings inequality over the period into between and within-group components[16]. Following Cowell [1995] any generalised entropy measure of inequality can be decomposed

$$I_a = I_{between} + I_{within}$$

where

$$I_{between} = \frac{1}{\theta^2 - \theta}\left[\sum_{j=1}^{k} f_j \left[\frac{\bar{y}_j}{\bar{y}}\right]^{\theta} - 1\right] \quad j = 1,\ldots, k, \text{ population sub-groups}$$

$$I_{within} = \sum_{j=1}^{k} w_j I_j \qquad w_j = g_j^{\theta} f_j^{1-\theta}$$

[16] Fields' [2001] decomposition of the sources of wage inequality relies on a decomposition of the log variance of earnings, which is inappropriate here given the large number of zero wage observations.

f_j is the population share of group j, g_j is the share of group j in total income = $f_i y_i / \bar{y}$ and θ is a choice parameter akin to the degree of inequality aversion. So total within group inequality is a weighted average of inequality in each sub group, though the weights do not add to one unless θ = 1 or 0. This decomposition is sensitive to the choice of parameter θ, so in Table 2 we present estimates based on two different θ values. While the results are somewhat ambiguous, the between group component rises to around 20% of total inequality and then falls back, as the real wage declines experienced by those paid in full eventually begin to narrow the mean wage gap between the two groups. The majority of the change is within group. Inequality is greater (less) among the group in arrears for low (high) values of θ. Low values put less weight on wages above the mean and since there are relatively more high wage observations in the no arrears group, as θ rises, the inequality measure goes up more for the no arrears group. The aggregate results are also ambiguous over the second half of the sample period for similar reasons. Inequality rises or falls depending on the value of θ used. The entropy estimate based on the low θ value falls between 1996 and 1998, because low values put more weight on wages in the lower parts of the distribution and the share of those paid zero wages falls. This is not reflected in the other entropy estimate, which rises as it gives greater weight to wage changes in the upper tail.

The essential feature of Table 2 remains that the pattern of inequality between the two groups is not the same and that the wage distribution is affected by the presence of wage arrears.

We now present our counterfactual estimates of the underlying wage distribution for the years 1994, 1996 and 1998. Table 3 summarises details of the estimated distribution for the different methods used. Figure 3 graphs the counterfactual Kernel densities, the sum of the actual wage of those paid in full and the predicted wage of those in arrears. Table 3 confirms that the mean and various quantiles of the distributions are all higher using any of the counterfactual estimates. The bootstrapped standard errors indicate that the imputed distributions lie within 2 standard errors of each other, with the exception of the OLS I estimates — though these do not contain a random residual and so would be expected to differ. In general then, the counterfactuals indicate that mean wages would have been around 30% higher in 1994 and around 60% higher in 1988 in the absence of wage arrears. Similarly the estimated overall dispersion, as measured by the coefficient of variation, would be around 20% lower in 1994 and some 40% lower in 1998 in the absence of arrears. The counterfactual Gini coefficients are now similar to that observed for Britain and those of the No Arrears sub-group in Table 1.

Table 4 uses the panel element of the data in order to add the exact matching estimator and a second propensity score estimator based on "pre-treatment history" included as additional regressors in the propensity score logit. We compare the results with those using the other methods for the year 1996, based on the sub-sample with valid pre-treatment histories. We also show the distribution of those in the sample who get paid in full and on time (second column). The pattern of results follows that of Table 3. Mean wages would be around 60% higher and thee wage distribution narrower by around 40% in the absence of wage arrears. Apart from the estimates based on simple OLS prediction (OLS I) all other counterfactual distributions have a very similar spread as can be seen from the coefficients of variation and Gini coefficients. It also noteworthy that the quantiles of the no arrears distribution again appear insignificantly different from the counterfactuals, a point to which we return later.

VI. Gender, Region and Education Pay Gaps Revisited

We now examine the implications of these counterfactual estimates for pay gaps between various sub-groups of the workforce. If the incidence of wage arrears is concentrated on sub-groups of the population then pay gaps based on the observed distribution may be biased. Table A2 in the appendix gives marginal effects from logit estimates of the probability of being in arrears[17]. In Table 5 we compare gender pay ratios using the actual distribution, the no arrears distribution and the counterfactual distributions for the year 1996. The observed distribution suggests a mean gender pay gap of around 20% (column 1). The counterfactual estimates, (and the no arrears distribution) suggest that because women are less likely to be observed with wage arrears, then if everyone were paid in full there would be more dispersion in pay between men and women and the gender wage gap would be closer to 30%.

[17] The same estimates are used to generate the counterfactual kernel density estimates.

Table 6 gives mean and median wages of three educational categories (graduate, intermediate and primary) and median ratios relative to the low educational category using the actual, the no arrears and all counterfactual distributions. Since graduates are under-represented among the arrears group, the observed distribution suggests a higher relative return to graduate education than the counterfactual estimates. There is less difference in the estimates of the relative returns for the intermediate group, since the incidence of arrears does not vary much compared with the default group.

We now turn to two dimensions that have the largest explanatory power in the incidence of wage arrears estimates, namely region and industry. We divide the sample into two areas: those living in Moscow and St. Petersburg (Metro), where the incidence of wage arrears is low and wages are high and those living outside the major metropolitan areas where wages are lower and the incidence of wage arrears is high. In Table 7, the actual distribution suggests that there is a 100% median wage gain from living in the metropolitan areas. Accounting for the skewed incidence of wage arrears by region reduces this regional wage premium to around 30%.

In Table 8 we aggregate industries into two sectors, production and services, and note from Table A2 that workers in the former sector are more likely to experience wage arrears than workers in the latter. The actual distribution suggests a median pay penalty in production relative to services. However, since the production sector is affected more by wage arrears, if everyone were paid in full then this would be sufficient to generate a small pay premium in favour of the production sector.

One striking feature of the exercise is that the parameters of the counterfactual wage distributions are very similar to the parameters of the observed wage distributions of those not in arrears. While this does not mean that experience of wage arrears is a random event as confirmed by evidence in Earle and Sabirianova [2002] and Lehmann, Wadsworth and Acquisti [1999], it does suggest that those in wage arrears are drawn reasonably uniformly from throughout the wage distribution. Figure 2 seems to confirm this. For those wishing to study aspects of wage differentials and inequality in Russia, it may, therefore, be feasible to use the subset of those not in arrears and still get close to the true population parameters, subject to an efficiency loss.

VII. Conclusions

It seems apparent from the results above, that estimates of wage inequality and pay gaps in general can be affected strongly in countries that experience bouts of non- or under-payment of wages. Studies that fail to account for wage arrears can over-estimate wage inequality substantially. Pay gaps across sub-groups of the population could be mis-leading if no account is taken of the differing incidence of wage arrears across these sub-groups. Russia, having both one of the highest levels of wage inequality in the world and a large incidence of wage arrears, is a particularly interesting case. Using imputation techniques that could be applicable to any data set for any country with information on wages and wage arrears, we show that wage arrears may have been partly responsible for the failure of inequality to fall back following the unanticipated price shocks in the first half of the nineties. The large share of employees who receive no wages in any month also renders many conventional estimates of inequality based on logarithmic transformations inoperable.

Counterfactual estimates of the wage distribution in the absence of arrears indicate that average earnings would be some twenty to fifty percent higher, depending on the extent of arrears and that earnings dispersion would be lower by similar amounts if everyone were paid in full. This would put Russian wage inequality back towards levels currently experienced in Western countries like Britain and the United States. In the absence of arrears, the gender pay gap could be around 10 percentage points higher than the observed gap. Regional pay differentials would become more compressed and sectoral differentials would narrow in the absence of wage arrears.

In this particular study, it appears that those in arrears are drawn reasonably uniformly from throughout the wage distribution. For those wishing to study aspects of wage differentials and inequality in Russia, it may, therefore, be feasible to use the subset of those not in arrears and still get close to the true population parameters, subject to an efficiency loss.

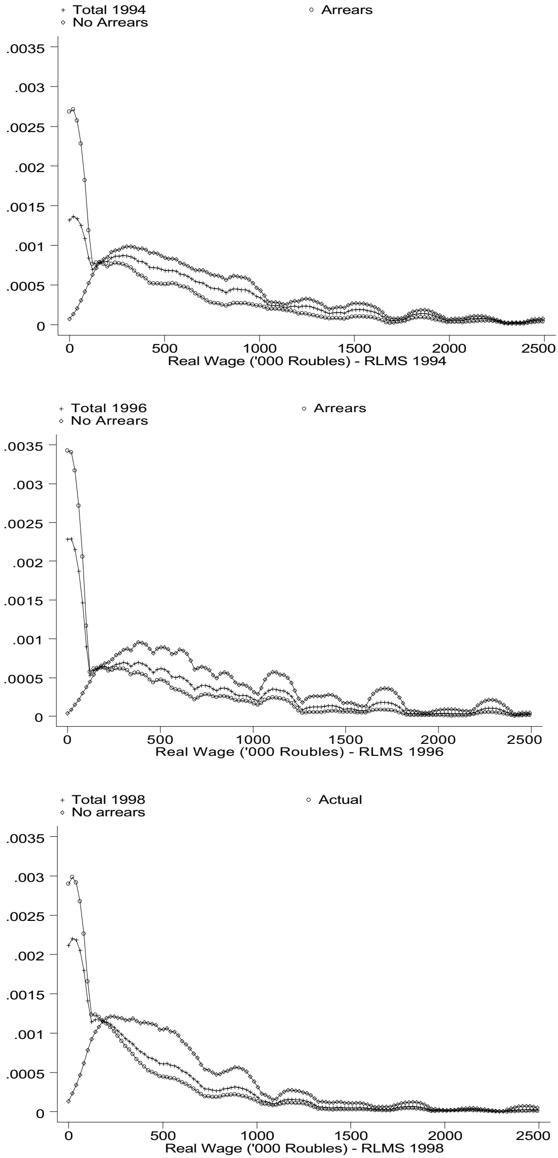

Figure 1. Distribution of Real Wages in Russia

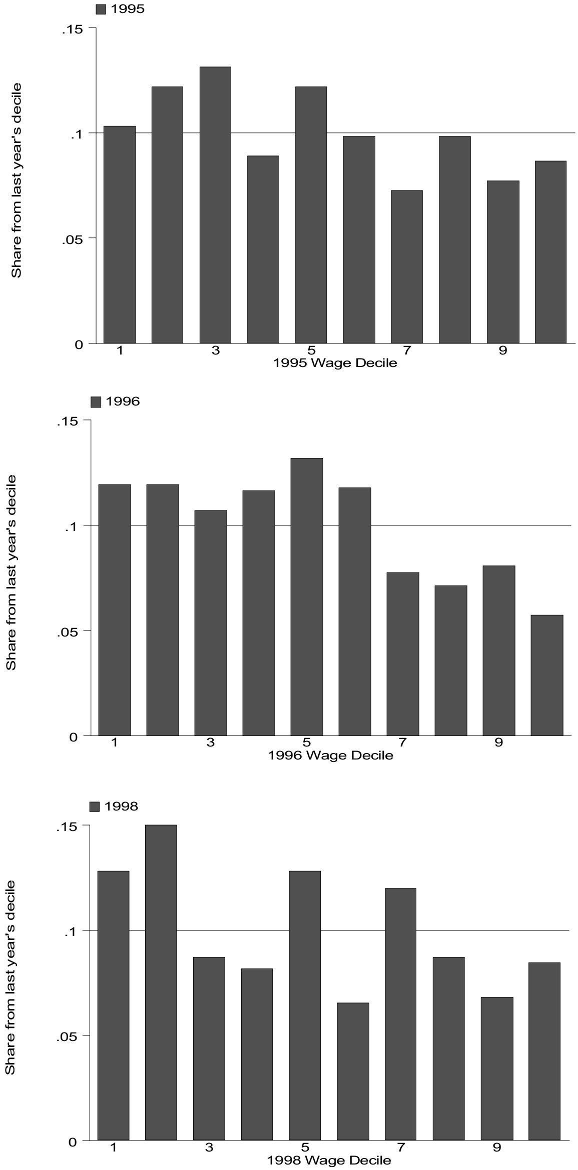

Figure 2. Previous Wage Decile of Those in Arrears

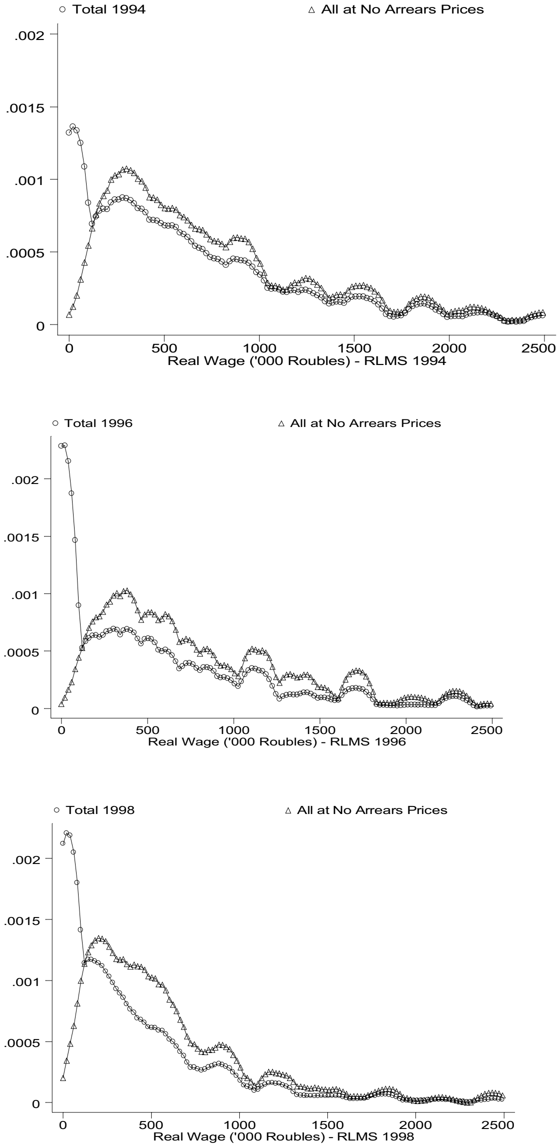

Figure 3. Counterfactual Estimates of Wage Distribution in Absence of Arrears

Table 1. Summary Measures of Real Monthly Wage Distributions

	1993 VTsIOM	1994 RLMS	1996 RLMS	1998 RLMS	1996 Poland	1996 Britain
Total						
Mean	916 (1014)	609 (656)	501 (659)	371 (494)		
90th	1724 (23)	1500 (19)	1376 (14)	907 (11)		
50th	690 (28)	422 (13)	287 (34)	217 (11)		
10th	276 (20)	0	0	0		
90/10	6.25	n/a	n/a	n/a	2.70	8.55
90/50	2.5	3.55	4.79	4.18	1.83	2.20
50/10	2.5	n/a	n/a	n/a	1.48	3.89
Coefficient of variation	1.11	1.11	1.32	1.33	0.62	0.80
Gini	0.407 (.009)	0.547 (.005)	0.637 (.006)	0.619 (.006)	0.239	0.387
% arrears	10 (0.6)	44.4 (0.8)	64.9 (0.9)	67.6 (0.8)	0	0
% no pay	0	19.3 (0.6)	34.6 (0.9)	28.1 (0.8)	0	0
No Arrears						
Mean	944 (1030)	808 (625)	896 (727)	629 (550)		
90th	1724 (24)	1718 (27)	1802 (37)	1273 (25)		
50th	690 (30)	625 (18)	677 (30)	484 (22)		
10th	276 (21)	188 (16)	229 (26)	187 (18)		
90/10	6.25	9.14	7.87	6.81		
90/50	2.5	2.75	2.66	2.63		
50/10	2.5	3.32	2.96	2.59		
Coef. Var	1.12	0.77	0.81	0.87		
Gini	0.407 (.011)	0.420 (.005)	0.415 (.008)	0.428 (.009)		

Note. Wage data indexed to December 1997 prices. Wage observations for population of employees aged 18—69. Standard errors in brackets. Standard errors are bootstrapped over 100 replications for inequality measures, based on delta method approximation using standard normal distribution. Standard errors of proportions are used in percentage rows.

Table 2. Between and Within Group Real Wage Inequality conditional on Arrears

	1993 VTsIOM	1994 RLMS	1996 RLMS	1998 RLMS
Entropy Index ($\theta = 0.5$)	0.298	0.644	0.988	0.882
within arrears	0.003	0.403	0.716	0.651
within no arrears	0.264	0.186	0.132	0.128
between group	0.031	0.056	0.140	0.103
% Share Between Group Inequality	0.3	8.7	14.1	11.7
Entropy Index ($\theta = 2.0$)	0.622	0.545	0.821	0.850
within arrears	0.037	0.185	0.327	0.407
within no arrears	0.584	0.308	0.348	0.339
between group	0.001	0.051	0.147	0.104
% Share Between Group Inequality	0.2	9.4	17.8	12.2
% in Arrears	10	44.4	64.9	67.6

Note. Decomposition based on generalised entropy inequality measure.

Table 3. Counterfactual Real Wage Distributions

	Mean	90th P'centile	Median	10th P'centile	90/10	90/50	50/10	Coef. Var.	Gini
1994									
Actual	629	1538	451	0	n/a	3.4	n/a	1.04	0.532
OLS I	743	1406	607	250	5.6	2.3	2.4	0.73	0.365
	(12)	(32)	(14)	(8)				(.01)	(.006)
OLS II	816	1672	613	190	8.8	2.7	3.2	0.88	0.429
	(17)	(60)	(15)	(8)				(.03)	(.006)
JMP	815	1688	625	203	8.3	2.7	3.1	0.81	0.411
	(15)	(57)	(13)	(11)				(.02)	(.007)
DFL	805	1719	625	188	9.1	2.8	3.3	0.82	0.417
	(16)	(80)	(15)	(5)				(.01)	(.005)
PS I	832	1818	625	188	9.7	2.9	3.3	0.81	0.420
	(17)	(74)	(10)	(7)				(.02)	(.006)
1998									
Actual	384	907	242	0	n/a	3.7	n/a	1.30	0.605
OLS I	517	907	422	212	4.3	2.1	2.0	0.73	0.337
	(14)	(23)	(11)	(10)				(.02)	(.008)
OLS II	594	1210	425	146	8.3	2.8	2.9	0.98	0.443
	(18)	(40)	(12)	(7)				(.05)	(.009)
JMP	607	1211	451	145	8.4	2.7	3.1	0.90	0.430
	(18)	(42)	(18)	(17)				(.03)	(.014)
DFL	588	1210	423	121	10.0	2.9	3.5	0.91	0.433
	(16)	(38)	(13)	(11)				(.03)	(.009)
PS I	609	1247	434	127	9.8	2.9	3.4	0.91	0.449
	(22)	(89)	(23)	(12)				(.03)	(.011)

Source: RLMS authors' calculations.

Note. OLS I is OLS estimate without residuals, OLS II includes residuals, PS I is estimate based on propensity score without conditioning on pre-treatment history. Actual values may vary from Table 1 due to missing observations on covariates used to construct counterfactuals. Bootstrapped standard errors in brackets based on 300 replications.

Table 4. Counterfactual Real Wage Distributions, 1996

	Actual	No Arrears	OLS I	OLS II	JMP	DFL	Match.	PS I	PS II
Mean	512 (14)	897 (26)	762 (21)	858 (30)	860 (26)	845 (32)	889 (30)	887 (32)	861 (36)
90th	1261 (66)	1835 (125)	1351 (65)	1750 (79)	1776 (64)	1720 (71)	1720 (114)	1720 (130)	1802 (129)
50th	339 (18)	688 (14)	635 (21)	630 (25)	674 (19)	630 (37)	688 (37)	688 (23)	631 (31)
10th	0 (10)	229 (20)	304 (10)	227 (24)(22)	194 (9)	221 (12)	229 (18)	229	225
90/10 90/50 50/10	n/a 3.7 n/a	8.0 2.7 3.0	4.4 2.1 2.1	7.7 2.1 2.8	9.2 2.6 3.4	7.8 2.7 2.9	7.5 2.5 3.0	7.5 2.5 3.0	8.0 2.9 2.8
Coef. Var.	1.26 (.03)	0.79 (.02)	0.68 (.02)	0.88 (.05)	0.83 (.03)	0.83 (.03)	0.77 (.03)	0.81 (.03)	0.84 (.03)
Gini	0.617 (.008)	0.405 (.009)	0.332 (.011)	0.423 (.011)	0.411 (.012)	0.411 (.012)	0.392 (.012)	0.409 (.012)	0.423 (.014)

Source: RLMS authors' calculations.

Notes. See Table 3. PS II is estimate based on propensity score conditioning on pre-treatment history. Sample size = 2538, of which 1351 are in arrears and 1187 are paid in full and on time. Bootstrapped standard errors in brackets.

Table 5. Counterfactual Gender Wage Ratios (1996)

	Actual	No Arrears	OLS I	OLS II	JMP	DFL	Match.	PS I	PS II
Men									
Mean	578	1113	922	1076	1043	1009	1078	929	910
Median	344	917	803	803	839	803	917	688	688
90^{th}	1577	2294	1615	2231	2079	1950	2293	1835	1720
10^{th}	0	344	351	279	322	252	321	229	203
Women									
Mean	459	752	633	723	714	704	687	847	821
Median	310	573	533	550	560	550	573	656	619
90^{th}	1126	1605	1080	1425	1498	1456	1261	1720	1720
10^{th}	0	221	262	201	145	184	216	229	203
Gender Ratio									
Mean	0.79	0.68	0.69	0.67	0.68	0.70	0.64	0.91	0.90
50^{th}	0.90	0.62	0.66	0.68	0.67	0.68	0.62	0.95	0.90
90^{th}	0.71	0.70	0.67	0.64	0.72	0.75	0.55	0.94	1.00
10^{th}	n/a	0.64	0.75	0.72	0.45	0.73	0.67	1.00	1.00

Source: RLMS. Sample size = 2193, of which 976 are male and 1217 female.

Table 6. Actual and Counterfactual Education Wage Ratios (1996)

	Actual	No Arrears	OLS I	OLS II	JMP	DFL	Match.	PS I	PS II
Upper									
Mean	594	944	823	923	917	907	902	904	852
Median	394	732	688	688	692	688	722	688	676
Intermed									
Mean	437	831	702	800	772	771	815	865	867
Median	248	631	573	573	573	563	642	653	630
Low									
Mean	448	874	721	804	880	835	824	871	868
Median	229	581	585	569	688	607	574	676	631
Ratio: wrt Low									
Upper	1.59	1.26	1.18	1.21	1.01	1.13	1.25	1.02	1.07
Inter	1.08	1.09	0.98	1.01	0.83	0.93	1.12	0.96	1.00

Source: RLMS. Sample size = 2193, of which 1059 are upper, 759 intermediate and 415 lower. Ratios are based on median values in each group.

Table 7. Actual and Counterfactual Regional Wage Ratios (1996)

	Actual	No Arrears	OLS I	OLS II	JMP	DFL	Match.	PS I	PS II
Metro.									
Mean	758	1073	971	1072	1034	972	1074	1000	971
Median	573	845	821	803	802	803	917	803	788
Other									
Mean	462	847	720	815	824	819	817	861	838
Median	275	654	588	588	650	573	642	676	631
Ratio: wrt other									
Metro.	2.08	1.30	1.22	1.37	1.23	1.40	1.43	1.19	1.25

Source: RLMS. Sample size = 2193, of which 332 are metropolitan, 1702 are elsewhere. Ratios are based on median values in each group.

Table 8. Actual and Counterfactual Industry Wage Ratios (1996)

	Actual	No Arrears	OLS I	OLS II	JMP	DFL	Match.	PS I	PS II
Production									
Mean	491	991	796	884	910	876	897	887	884
Median	281	784	675	642	739	596	748	688	654
Services									
Mean	531	843	730	835	814	813	824	882	839
Median	344	676	603	630	619	653	654	688	631
Ratio wrt services	0.82	1.16	1.12	1.02	1.19	0.91	1.14	1.00	1.04

Source: RLMS. Sample size = 2193, of which 975 are production and 1059 services. Ratios are based on median values in each group.

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Appendix

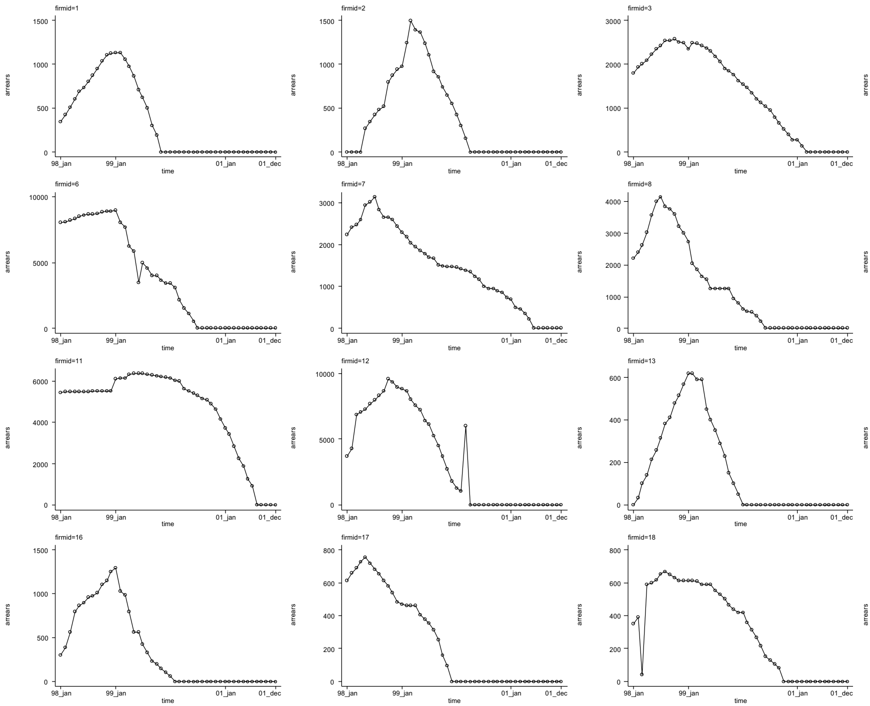
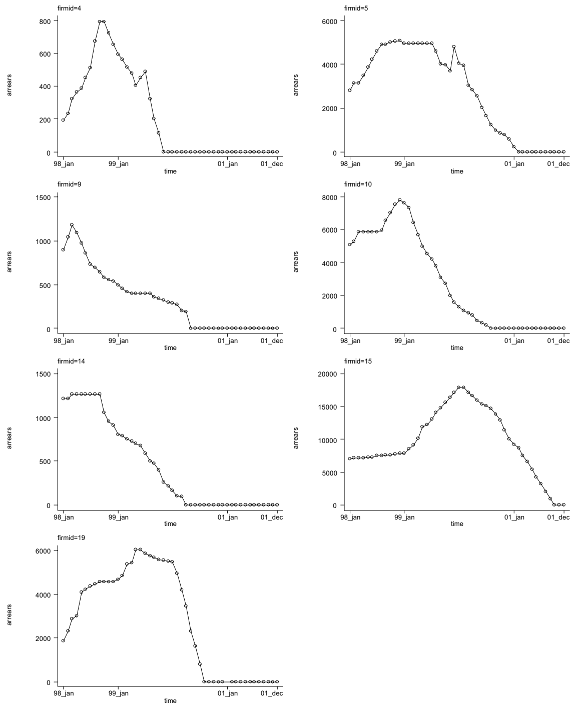


Figure A1. Monthly stock of wage arrears within Russian firms (City of Ryazan — 1998—2001)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Box A1

Exact matching — algorithm and scheme of conditioning on pre-treatment history

Exact matching algorithm

I. Condition on following possible pre-treatment labour market history:
- employed and fully paid and in xth decile of wage distribution
- unemployed
- inactive
- employed and experiencing wage arrears (WA).

II. Match treated individuals to individuals with same pre-treatment history using following observable characteristics:
- gender
- region (4 categories)
- qualifications (6 categories)
- age (maximum allowed difference of 10 years — choose those controls that have the minimum age difference)

Assumption: these variables are not affected by the treatment (WA).
Because treated are more than potential controls, matching is done with replacement.

III. Assign wage of matched control to treated individual, or assign average of wages of matched controls.

Scheme of Conditioning on pre-treatment history by example

Pre-treatment period	***Treatment period***
Potential Control 1 in 95 Employed and fully paid and in 2nd decile of wage distribution	*Potential Control 1 in 96* Employed and fully paid
Treated 1 in 95 Employed and fully paid and in 2nd decile of wage distribution	*Treated 1 in 96* In wage arrears
Potential Control 2 in 95 Unemployed	*Potential Control 2 in 96* Employed and fully paid
Treated 2 in 95 Unemployed	*Treated 2 in 96* In wage arrears

Table A1. OLS Log Real Weekly Wage Estimates for those Not in Arrears

	1994	1996	1998
Female	−0.430	−0.446	−0.417
	(0.033)**	(0.048)**	(0.047)**
Age	0.056	0.057	0.052
	(0.009)**	(0.012)**	(0.012)**
Age2	−0.001	−0.001	−0.001
	(0.000)**	(0.000)**	(0.000)**
University	0.512	0.251	0.456
	(0.051)**	(0.070)**	(0.076)**
Technical	0.302	0.084	0.193
	(0.049)**	(0.069)	(0.074)**
PTU 1	0.090	−0.094	−0.042
	(0.055)	(0.080)	(0.081)
PTU 2	0.052	0.004	−0.035
	(0.065)	(0.093)	(0.100)
Other Quals.	0.052	−0.125	−0.061
	(0.059)	(0.089)	(0.090)
North West	0.088	−0.063	−0.165
	(0.072)	(0.104)	(0.112)
Central	−0.349	−0.313	−0.311
	(0.052)**	(0.069)**	(0.070)**
Volga	−0.509	−0.528	−0.462
	(0.054)**	(0.078)**	(0.081)**
Caucasus	−0.479	−0.310	−0.438
	(0.060)**	(0.090)**	(0.086)**
Urals	−0.229	−0.232	−0.297
	(0.056)**	(0.078)**	(0.079)**
Western Siberia	0.119	0.278	0.281
	(0.065)	(0.098)**	(0.100)**
East	−0.014	−0.098	−0.178
	(0.068)	(0.112)	(0.101)
State	−0.115	−0.162	−0.229
	(0.034)**	(0.051)**	(0.050)**
Agriculture	−0.271	−0.352	−0.190
	(0.094)**	(0.143)*	(0.109)
Manufacturing	0.084	0.149	−0.028
	(0.062)	(0.091)	(0.079)
Construction	0.303	0.459	0.120
	(0.081)**	(0.131)**	(0.132)

	1994	1996	1998
Energy	0.331	0.423	0.313
	(0.072)**	(0.108)**	(0.096)**
Transport	0.287	0.373	0.196
	(0.070)**	(0.102)**	(0.088)*
Retail	0.073	0.162	0.163
	(0.069)	(0.095)	(0.081)*
Finance	0.411	0.634	0.248
	(0.121)**	(0.145)**	(0.130)
Health/Education	−0.098	0.052	−0.186
	(0.058)	(0.087)	(0.076)*
Firm size 11—50	0.040	0.038	0.044
	(0.063)	(0.094)	(0.093)
Firm size 51—100	0.093	0.048	0.110
	(0.072)	(0.109)	(0.105)
Firm size 101—500	0.176	0.127	0.117
	(0.064)**	(0.101)	(0.101)
Firm size 501—1000	0.277	0.171	0.403
	(0.068)**	(0.106)	(0.105)**
Firm size missing	0.109	−0.027	0.090
	(0.064)	(0.090)	(0.093)
Job Tenure 1—2 yrs	0.076	0.177	0.112
	(0.053)	(0.080)**	(0.076)
2—5 yrs	−0.026	0.252	0.117
	(0.048)	(0.068)**	(0.067)
5—10 yrs	0.021	0.107	0.183
	(0.052)	(0.077)	(0.076)**
10—20 yrs	0.081	0.201	0.292
	(0.051)	(0.077)**	(0.082)**
20 yrs+	0.224	0.243	0.215
	(0.060)**	(0.089)**	(0.092)**
Constant	5.470	5.635	5.373
	(0.190)**	(0.255)**	(0.268)**
N	2213	1019	1091
R^2	0.31	0.31	0.31

Standard errors in parentheses ** significant at 5%. Default region is metropolitan Moscow & St. Petersburg. Default industry isther services.

Table A2. Logit Estimates of Probability of Being in Arrears (Marginal Effects)

	1994	1996	1998
Female	−0.070	−0.037	−0.018
	(0.019)**	(0.021)	(0.018)
Age	0.012	0.007	0.008
	(0.005)**	(0.006)	(0.005)
Age2	−0.0002	−0.0001	−0.0001
	(0.00006)**	(0.0001)	(0.0001)
University	0.030	−0.084	−0.086
	(0.029)	(0.031)**	(0.029)**
Technical	0.031	−0.030	−0.061
	(0.028)	(0.029)	(0.029)**
PTU 1	−0.007	0.001	−0.049
	(0.030)	(0.033)	(0.032)
PTU 2	0.018	−0.091	−0.029
	(0.036)	(0.043)**	(0.038)
Other Quals.	0.031	0.054	−0.044
	(0.032)	(0.033)	(0.035)
North West	0.204	0.326	0.382
	(0.042)**	(0.047)**	(0.046)**
Central	0.070	0.119	0.151
	(0.034)**	(0.037)**	(0.034)**
Volga	0.122	0.278	0.319
	(0.034)**	(0.039)**	(0.036)**
Caucasus	0.083	0.247	0.218
	(0.039)**	(0.044)**	(0.040)**
Urals	0.126	0.257	0.259
	(0.035)**	(0.039)**	(0.036)**
Western Siberia	0.145	0.333	0.299
	(0.039)**	(0.044)**	(0.042)**
East	0.252	0.429	0.358
	(0.039)**	(0.049)**	(0.043)**
State	0.079	0.051	0.109
	(0.019)**	(0.022)*	(0.019)**
Agriculture	0.262	0.216	0.074
	(0.045)**	(0.057)**	(0.042)
Manufacturing	0.071	0.156	0.162
	(0.034)**	(0.042)**	(0.031)**
Construction	0.152	0.142	0.183
	(0.042)**	(0.055)**	(0.048)**

	1994	1996	1998
Energy	−0.063	0.047	0.057
	(0.041)	(0.046)	(0.037)
Transport	−0.055	−0.067	−0.022
	(0.039)	(0.047)	(0.036)
Retail	−0.105	−0.143	−0.175
	(0.042)*	(0.048)**	(0.038)**
Finance	−0.254	−0.444	−0.338
	(0.098)**	(0.111)**	(0.078)**
Health/Education	−0.110	0.081	0.130
	(0.032)**	(0.040)**	(0.030)**
Firm size 11—50	0.062	−0.031	−0.031
	(0.038)	(0.045)	(0.041)
Firm size 51—100	0.021	0.056	−0.042
	(0.043)	(0.046)	(0.046)
Firm size 101—500	0.007	0.094	0.030
	(0.038)	(0.042)**	(0.041)
Firm size 501—1000	0.074	0.072	0.009
	(0.041)	(0.045)	(0.043)
Firm size missing	0.042	−0.040	−0.015
	(0.039)	(0.044)	(0.040)
Job Tenure 1—2 yrs	0.007	0.039	−0.027
	(0.032)	(0.037)	(0.032)
2—5 yrs	0.066	0.005	−0.024
	(0.028)**	(0.031)	(0.043)
5—10 yrs	0.069	0.053	−0.027
	(0.030)**	(0.034)	(0.027)
10—20 yrs	0.089	0.074	0.025
	(0.030)**	(0.034)**	(0.032)
20 yrs+	0.102	0.106	0.031
	(0.035)**	(0.038)**	(0.036)
Rural	0.207	0.197	0.182
	(0.025)**	(0.030)**	(0.027)**
N	3962	2884	3336
Log L	−2448	−1590	−1831

Standard errors in parentheses ** significant at 5%.

Table A3. Earnings Mobility in Russia, 1994—1998

a) 1994/95

Total			1995		
1994	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
1	46.5	21.1	12.2	10.8	9.5
2	20.9	37.8	25.3	10.6	5.1
3	17.1	22.5	31.5	21.9	7.0
4	11.1	8.2	22.2	34.8	23.9
5	11.0	5.2	8.2	20.7	54.8

No Arrears			1995		
1994	1	2	3	4	5
1	—	62.5	25.0	—	12.5
2	—	49.8	33.5	10.9	5.0
3	—	21.6	41.6	29.2	7.6
4	—	4.9	24.4	43.2	27.4
5	—	1.5	6.3	23.6	68.5

b) 1995/96

Total			1996		
1995	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
1	58.9	8.0	14.6	11.5	7.1
2	36.8	17.5	29.0	11.5	5.2
3	25.1	7.9	33.8	24.2	9.0
4	21.1	2.5	20.2	32.3	24.0
5	17.2	1.8	8.7	20.2	52.1

No Arrears			1996		
1995	1	2	3	4	5
1	—	—	—	—	—
2	—	21.3	54.6	19.4	4.6
3	—	3.0	49.4	38.1	9.5
4	—	1.0	15.4	48.0	35.6
5	—	1.4	3.2	20.7	74.7

c) 1995/98

Total			1998		
1995	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
1	41.2	17.7	18.2	13.7	8.9
2	30.8	24.6	26.0	13.3	5.3
3	24.9	10.8	29.7	23.9	10.8
4	19.9	7.1	17.9	31.9	23.1
5	14.9	3.4	12.3	24.9	44.6

No Arrears			1998		
1995	1	2	3	4	5
1	—	50.0	16.7	33.3	—
2	—	21.1	43.7	29.6	5.6
3	—	3.5	41.4	41.4	13.8
4	—	2.6	15.7	44.4	37.8
5	—	0.9	8.9	20.5	69.6

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L 45 Wage Arrears and the Distribution of Earnings: What can we learn from Russia? = Леман Х., Водсворт Д. Задолженность по зарплате и дифференциация заработков: чему нас учит российский опыт?: Препринт WP3/2003/03. — М.: ГУ ВШЭ, 2003. — 42 с.

На примере российского рынка труда мы изучаем возможные подходы к оценке относительной заработной платы и неравенства в тех случаях, когда задолженности по заработной плате имеют значительные масштабы. Рост неравенства по заработной плате в течение переходного периода в России был значительнее, чем в других странах с переходной экономикой. В России также чаще всего наблюдались случаи задолженности по заработной плате. С помощью данных по заработной плате и ее задолженности мы показываем, что можно построить условное распределение работников по заработной плате, т.е. такое, каким оно могло бы быть при условии отсутствия задолженностей. В этом случае оценки дифференциации заработков в России были бы на 20—30% меньше. Так как задолженности по зарплате не случайны, это влияет на оценки неравенства в зарплате.

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Препринт WP3/2003/03
Серия WP3
Проблемы рынка труда

Леман Хартмут, Водсворт Джонатан

Задолженность по зарплате и дифференциация заработков: чему нас учит российский опыт?

(на английском языке)

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