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THE GENDER GAP AND WAGE ARREARS IN RUSSIA:

EVIDENCE FROM THE RLMS

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Abstract: Using the RLMS, this paper re-examines the nature of the gender wage gap in Russia between 1994 and 1998 taking into account the pervasiveness of Russia's non-payment institutions. Investigating discrimination 'bands' at different sections of the income distribution and for various important sub-groups we found the following. Using censored regressions that capture the effect of wage arrears and payment in-kind, the wage gap is larger than estimates derived using OLS. The wage gap is distributed unevenly both across the income distribution and between various sub-groups. Specifically, women at the lower end of the income distribution suffer the highest degree of discrimination. However, we find that wage arrears and payment in-kind attenuated wage discrimination, in particular amongst the lowest paid workers. The evidence seems to suggest that Russian enterprise managers assigned importance to equity considerations when allocating wage arrears and payment in-kind.

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1. Introduction

Russia's ongoing transformation into a market economy has given rise to dramatic increases in wage inequality, a substantial decline in female participation rates[1] and the emergence of peculiar and widespread labour market institutions such as wage arrears and payment in-kind. It is not obvious *a priori* how the changing wage structure would combine with the emergence of these institutions in influencing the gender wage differential. Thus, in this paper we add an important strand to the growing literature on the Russian gender pay gap by examining the effects of wage arrears and payment in-kind on the differential across the wage distribution.

To date, there have been several attempts to measure and explain the extent of the gender wage gap in Russia (Silverman and Yanowitch, 1997; Ogloblin, 1999; Reilly, 1999; Brainerd, 1998, 2001; Glinskaya and Mroz, 2000; Newell and Reilly, 1996, 2001; Lehman and Wadsworth, 2001;). A stylised fact emerging from this literature is that the gender wage gap increased during the initial transition period but that there has been little change in the years that followed. However, these studies largely ignore the presence of wage arrears and payment in-kind in their analysis of the wage gap[2] and in most cases don't go beyond 1996.

Any study of the Russian wage structure is incomplete without accounting for the emergence of Russia's unique labour market characteristics. Unprecedented delays in the payment of wages and the widespread use of payment in-kind have become endemic features of the Russian labour market in transition. Wage arrears accumulated rapidly between 1994 and 1998, amounting to 275 per cent of the monthly wage bill of employees in receipt of wage arrears (Russian Economic Trends, 1997, 1). Our household data, from the Russian Longitudinal Monitoring Survey (RLMS), reveal an increase in the incidence of wage arrears from 30 per cent in 1994

[1] For details, see Boeri et al., (1998).
[2] Notable exceptions are Ogloblin (1999) who uses a wage arrears selection equation in his analysis and Lehman and Wadsworth (2001) who construct counterfactual wage distributions in order to reassess the gender pay gap.

to 55% in 1998 and a rise in the incidence of payment in-kind from 7 per cent to 14 per cent during the same period.

Several studies claim that the allocation of wage arrears is differentiated across employees and used strategically by employers. Desai and Idson (1998) suggest that employers tried to reduce the incidence of wage arrears for highly productive workers to retain them in the firm and, as a result, less productive workers became the primary targets for delays in wage payment. Earle and Sabirianova (1999) maintain that firms use wage arrears in a discriminating way against employees who have job specific skills. In the same spirit, Lehman et al. (1999) find that firms allocate wage arrears to the most stable employees. In sum, there has been substantial variation in wage arrears across regions, industries and occupations and male workers, in low skilled positions, in large 'Soviet style' enterprises have proved most vulnerable to accumulating a large volume of wage arrears (Earle and Sabirianova 1999).

A significant number of studies analyse the gender pay differential and the phenomena of wage arrears in separate strands but there have been few attempts to combine these themes by investigating the relationship between wage arrears and the gender wage gap. Specifically, did enterprise managers use wage arrears as a discriminatory tool favouring male workers, or were wage arrears allocated among female employees in a manner that compensated them for the losses arising from higher wage discrimination? Were in-kind payments used to mitigate the effects of the most severe gender wage gaps? Did the allocation of arrears and in-kind payments follow similar patterns across the wage distribution for men and women? Bearing in mind that, ultimately, the effect of wage arrears and payment in-kind on the gender wage differential is an empirical matter this paper sets out to investigate the above questions.

We found that, explicitly incorporating wage arrears and payment in-kind provides important insights into the gender wage gap missing from other studies. Accounting for censored wages, the wage gap itself is more substantial than those derived from OLS estimates. It is distributed unevenly across the income distribution and between various sub-groups. Specifically, women at the lower end of the income distribution

suffer the highest degree of discrimination. However, our analysis indicates that wage arrears and payment in-kind served to attenuate discrimination, in particular amongst the lowest paid workers. The evidence seems to suggest that Russian enterprise managers assigned importance to equity considerations when allocating arrears and payment in-kind.

We proceed as follows. Section 2 provides an outline review of the literature. In section 3, following a brief discussion of the data, we test for selectivity bias and estimate different wage equations. Applying the Oaxaca-Ransom decomposition to various wage specifications, in section 4, we analyse the size and composition of the gender wage gap. We then investigate the wage differentials according to income percentiles and examine the effects of wage arrears and payment in-kind on the gender wage gap. Section 5 concludes the paper.

2. Wage discrimination and wage arrears: related literature

There have been a number of attempts to explain and measure the extent of Russia's gender wage gap since transition began. These studies have largely been based on the Oaxaca-Blinder (1973) decomposition in which wage equations are estimated separately for men and women in order to allow for different rewards by gender to a set of productive characteristics. The male-female average wage differential is explained in terms of the difference in average endowments evaluated at the male (female) pay structure and the difference in returns evaluated at the female (male) average endowment. Thus, in the absence of discrimination, men and women will have the same return for similar endowments, and hence the latter difference is interpreted as 'discrimination'.

This approach has been supplemented in a variety of ways. In the absence of information regarding the true non-discriminatory pay structure Cotton, (1998) proposes estimating a weighted linear combination of the female and male returns; whilst Oaxaca and Ransom (1989) suggest using the estimates from a pooled male-female wage equation. Juhn, Murphy and Pierce (1993) and Blau and Kahn (1996) extend the basic decomposition to study the wage differential over time as a function

of changes in observable characteristics and the associated returns, changes in ranking within the wage distribution and changes in the wage distribution itself.

There is a growing empirical literature relating to the gender wage differential in the transition economies[3]. For Russia, Silverman and Yanowitch (1997) find that the *average* female-male wage ratio was 0.68 but that the pay gap exhibits substantial variation depending on which gender dominates a particular occupational category. Following Juhn et al (1993), Reilly (1999) examines the evolution of the gender pay gap in Russia between 1992 and 1996. He finds that women's relative wages remained broadly stable since, although they suffered from dramatic increases in the level of wage dispersion, this suffering was offset by favourable changes in returns to human capital. Applying similar methodology, Glinskaya and Mroz (2000) find that the slight changes observed in the pay gap were attributable to the combination of large increases/decreases in wages for men at the $90^{th}/10^{th}$ percentile of the wage distribution alongside the relative stability of the female wage structure. Finally, Arabsheibani and Lau (1999) assess the gender pay gap in Russia, correcting for selectivity bias in the female wage equation. They suggest that although the degree of discrimination was still high it was lower than in studies not correcting for selectivity bias.

As a result of data limitations, the above studies derive their results from analysis of wages paid rather than wages due, yet it is not implausible that the incidence of payment arrears may have important gender implications. Indeed, Glinskaya and Mroz (2000) acknowledge that failure to account for the effect of non-payment of wages may seriously undermine any analysis of gender wage inequality. They approximate the contractual wage[4] from information on the incidence and extent of wage arrears

[3] Newell and Reilly (2001) provide decompositions for eleven transition countries, Paternostro and Sahn (2000) applied the Oaxaca-Ransom framework to Romanian data, Orazem and Vodopivec (1995, 2000) applied the Juhn et al. decomposition to Eastern Europe and Pailhe (2000) applies the Oaxaca decomposition to the countries of Central Europe.

[4] The construction of contractual wages using the RLMS is not straight forward since although the amount of arrears is recorded, the time of accrual is not and hence the real value of wage arrears cannot be determined.

and conclude that the effect of arrears on the gender pay gap is ambiguous but that the inclusion of occupational controls[5] may help in mitigating such effects.

Ogloblin (1999) also recognises the complications in estimating the wage gap arising from wage arrears and, correcting for (wage arrears) selectivity, assesses the wage gap for workers *not* in receipt of wage arrears. Implementing the selectivity correction Ogloblin finds that the gender earnings ratio increased from 68% to 72%. The majority of the remaining gender wage gap is explained by occupational and industrial affiliation with women being concentrated in industries and occupations which pay substantially less. Desai and Idson (2000) also emphasise the importance of occupation in finding that women were predominantly to be found in lower paying occupations – often employed as technicians, associated professionals or clerks. Notwithstanding this and the fact that low paid workers in general receive less arrears, Desai and Idson suggest that women with similar demographic and job market attributes as men were more likely to be in receipt of arrears. Furthermore, they find no strong evidence that payment in-kind was used to compensate workers denied their wages. This highlights an additional complication in such estimations. Namely, if there is occupational gender discrimination, then controls for occupation in wage equations cannot be considered as legitimate exogenous variables.

Lehman and Wadsworth (2001) pursue a different approach to overcoming the wage arrears problem. They construct various counterfactual estimates of the wage distribution and examine what the gender pay gap would have looked like had workers been paid in full and on time. They find that, were everyone paid in full, the level of wage dispersion between men and women would be substantially larger; indeed, the mean wage gap would have increased from 19% to 30%. This reflects the fact that women are prone to less severe wage arrears than men and provides support for the observation that women dominate in low paid occupations.

[5] In fact, given the policy driven spatial dimension to Russia's industrial landscape an equally important control variable might be industrial sector. However, the RLMS does not record this information. Hence, it is plausible that this effect is partially reflected in the regional coefficients.

What lessons can be culled from this literature to inform our analysis of Russia's gender pay gap? Firstly, the chosen measure of 'discrimination' is reliant on the robustness of the wage equations and hence, issues relating to selectivity, endogeneity and specification are particularly important. Secondly, there is a growing literature documenting the importance of occupational 'gender discrimination' in Russia and thus the role of occupation merits examination. Thirdly, and perhaps most importantly, the incidence of wage arrears, and to a lesser extent payment in-kind, have been widespread in transitional Russia to such an extent that focusing only on wages paid may produce erroneous results. Hence, the empirical results should reflect these peculiar features of the Russian labour market. Finally, analysis of discrimination based on average wage comparisons is of limited help if the discrimination experienced is not homogeneous. Therefore, analysis of the gender wage gap should take into account the complete distribution of discrimination experienced (Jenkins, 1994).

3. Estimation of the Wage Equations

This study is based on data procured from the second phase of the RLMS and consists of 8,954 individuals, on whom we have complete information, drawn from rounds 5 (1994), 6 (1995), 7 (1996) and 8 (1998). The RLMS is a nationally representative survey of the Russian Federation providing a range of demographic and settlement characteristics together with rich information on the labour market activities of its sample. Regarding wage arrears and payment in-kind, respondents are asked whether, conditional on having a 'main' job, they are owed money by the firm at that time and/or they have received goods in lieu of wages during the previous month.

We pool our data across waves and, in all of our estimations, account for the fact that we have repeated observations on individuals[6]. Our sample is restricted to those of

[6] In preliminary investigations, we tested our data using fixed effects and random effects models. The Breusch and Pagan LM test rejects the fixed effects model in favour of the random effects model, but the Hausman test rejects the random effects model. Hence, in this paper we use 'clustered' estimates. Although such estimates do not depend on the assumptions of the random effects model, the coefficient estimates were similar and, allowing for the residuals to be correlated within clusters whilst independent between clusters, provides us with consistent standard errors.

working age; that is, aged 18 to 60 for men and 18 to 55 for women. We measure real wages as the average real hourly wages received from the main job. This measure is obtained using the Goskomstat regional consumer price index, the total primary job hours reported for the month prior to the interview and the total net amount of money received from employers in the previous month. The survey does not ask whether the wage received is the contracted wage or not and, since we do not know the month in which wage arrears accrued *or* their real value, we have no way of establishing the contractual wage.

As mentioned, any gender wage decomposition is dependent on the specification of the underlying wage equations. Indeed, the legitimacy of the approach is contingent on a stable set of parameter estimates consistent with economic theory. This poses the problem of how best to capture the effect of premiums arising from an individual's particular occupational category or industrial sector when it could also be the case that their presence in that sector reflects the outcome of some discriminatory process. There is no accepted solution to this problem and so, in this paper, we provide estimates, separately for men and women[7], of basic human capital equations as well as estimates controlling for wage arrears, payment in-kind and occupation. This approach has two main appeals. First, it enables us to test for selectivity bias and omitted variable bias in our basic wage equations and second, it allows us to present a 'discrimination band'. For reasons detailed later in this section, we apply both OLS regressions and right-censored interval regression models to the different wage specifications.

In our basic human capital equations, we use five education categories[8] reflecting the highest qualification achieved by the respondent. We include controls for age and age squared, whether the respondent is married or not, the settlement type as well as

[7] For our full set of wage regression specifications, the Wald (chi-square) test of whether the male estimated coefficients of the data are equal to the female estimated coefficients is rejected at the one percent level. These results are available from the authors on request.

[8] This was preferred to 'years of education' because the effects of education on wages were found to be non-linear. See Newell and Reilly (1996) for details concerning the advantages of using a set of educational qualifications in place of years of education in transitional economies.

regional characteristics and dummy variables controlling for the round. Our augmented equations include additional controls for occupation[9], job tenure, wage arrears and payment in-kind.

Given data limitations and, as suggested by Earle and Sabirianova (1999), we include a qualitative variable which indicates if the interviewee is experiencing wage arrears in the main job at the time of the interview. This is, we know, a crude approximation of wage arrears, though no more so, given the available data, than attempts at constructing a 'contractual' wage[10]. As with wage arrears, we encounter data problems with payment in-kind and also included it as a qualitative dummy variable. Table 1 provides a full definition of the variables and summary statistics.

Moving on to the estimation, we first address the problem of selectivity bias and then discuss the problems of omitted variable bias and endogeneity bias. Following the work of Heckman (1979) it is well established that, if the error term from the selection rule (i.e. the work/not work probit equation) and the market wage are correlated, then standard OLS techniques applied to the wage equation will yield biased results[11]. In implementing this selectivity correction it is important to note that, for identification of the reservation wage function, at least one variable should be included in the selection equation which is not included in the wage equation. In addition, since the participation decision (based on the reservation wage) depends on the mean of the wage offer distribution, all of the variables included in the market wage equation must also be included in the probit equation[12].

In addition to the variables from our basic wage equation, the likelihood of working is assumed also to depend on the number of under 18 year olds in the household and a

[9] Classified according to the ISCO one digit classification scheme.
[10] For example, Glinskaya and Mroz (2000) constructed 'contractual' hourly wages using reported income in-kind paid in the last 30 days plus the total amount of arrears, divided by the number of months owed.
[11] For a clear exposition of selectivity issues see Maddala (1983).

dummy variable capturing the presence of elderly dependants. Dumwork is the binary variable that identifies the observations for which wages are observed (or selected). Given the growing informal sector in Russia, dumwork takes the value of 1 if the person is working in the formal sector, informal sector or both[13]. Here, the implicit assumption made is that the formal and informal sectors are both affected by the same reservation wage function. Whilst we recognise that this is far from realistic, modelling work choice applying conditional probit equations, which is more realistic, is complex and outside the scope of the present paper.

We do not incorporate job tenure, job occupation, wages arrears or payment in-kind in the wage or probit equation because they are meaningless for people not working. However, we examine the extent of the omitted variable bias in this 'restricted' wage equation by conducting a Lagrange Multiplier (LM) test for omitted variables[14].

Table A.1 (in the appendix) presents the results of the probit equation and the Heckman selectivity test. We found that neither the male wage equation nor the female wage equation exhibited sample selection bias at conventional five-percent levels[15]. Interestingly, the effect of marriage is statistically significant and increases the probability of being in work for males but decreases it for females. The number of children and the presence of elderly dependants in the household effect participation negatively and significantly for both males and females, although the magnitude of the effect of children is almost double for females. Note that, in the wage equations, these 'identifiers' are negative but not statistically significant[16].

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[12] Arabsheibani and Lau (1999) test for selection bias in the female wage equation and include more variables in the observed wage equation than in the selection equation. Pailhé (2000) includes occupational classification and firm ownership in the wage and selection equation.

[13] We also defined the dummy variable according to a specific number of hours e.g. we assigned 1 to people working in the informal sector at least 8 hours. The results do not differ substantially and are not reported.

[14] We thank an anonymous referee for this suggestion.

[15] The coefficient of the inverse mills ratio is negative for both males and females indicating a negative correlation between the error term in the wage and probit equations. That is, on average individuals we observe working earn less than an average non-worker would if drawn at random from the population. Despite being somewhat counter intuitive, this does concur with the findings of Arabsheibani and Lau (1999). A possible explanation for this negative truncation in Russia might lie in the dramatic fall in the participation rates (particularly amongst women) amongst a traditionally highly skilled labour force.

Overall, as in Newell and Reilly (1996) and Reilly (1999), our restricted human capital wage equation provides a satisfactory fit to the Russian data (see table A.2). In terms of returns to education, university qualifications and technical and medical training have a significant effect on both male and female wages. As expected, the female and male earnings pattern suggests that university graduates are the highest earners followed by technical and medical graduates, high school leavers and those with vocational training. However, females tended to be rewarded more for their qualifications than males.

Workers living in Central and Central-Black Earth, Volga-Vyatski and Volga-Basin, North Caucasus and the Urals fare worse, in terms of wages, than those living in other regions. The magnitude of the female disadvantage is larger than that for males. Living in Moscow and St. Petersburg does not significantly explain the male or female wage, although the sign, as expected, is positive. Not surprisingly, workers in towns and rural non-agricultural areas have a significant wage premium over workers living in rural agricultural areas.

One may ask how possible biases arising due to exclusion, from the wage equation, of potentially important variables such as wage arrears, payment in-kind, job tenure and occupational category will affect our analysis. To investigate this we implement LM tests for omitted variables. We first estimate the 'restricted' equation and obtain the estimated residuals. If the unrestricted regression is the true one, then the residuals from the restricted equation will be related to the omitted variables. Hence, we regress the estimated residuals from the restricted version on all of the regressors (i.e. those in the restricted version plus the additional variables from the unrestricted version) in an 'auxiliary' regression. The sample size (n) multiplied by the R^2 from this auxiliary regression follows a chi-square distribution with degrees of freedom equal to the number of added variables. For both males and females, our 'restricted' human capital regression is rejected in favour of the inclusion of wage arrears and payment in-kind, and this regression is, in turn, rejected in favour of a specification also

[16] The results of the regressions are not reported in the paper but are available upon request.

including job tenure and occupation type[17]. Since it is not possible to apply Heckman selectivity tests to the auxiliary regressions and the LM tests reflect the importance of the additional variables, in what follows, we present Oaxaca decompositions (without selectivity corrections) from each specification and hence 'bracket' the difference in the pay reward structure.

The estimation of our human capital model plus wage arrears and payment in-kind (Table A.3) show that, as expected, both additional variables have a significantly negative impact on the wage in both the male and female wage equations. Incorporating job specific variables, table A.4, reveals that job tenure has a positive and significant effect on wages for males, whilst managers, professionals and manual workers tend to earn significantly more than non-manuals, and unskilled males fare especially badly. The results from the basic human capital model remain robust to the inclusion of the extra labour market variables.

Besides the problem of measuring the 'contractual' wage when we do not have information about when and in what quantity each individual accrued wage arrears, another cause for concern is the potential endogeneity of these variables. A possible approach to surmounting these problems is to apply interval regression[18] - a generalisation of the tobit and censored regression models.

As a result of the inability to decipher the true contractual wage from the wage actually received in the previous month, we observe only the lower endpoints of individual wages whereas, in the presence of arrears or payment in-kind, the true contractual wage may be higher. Thus our data is 'right-censored'[19] and the unobserved wage is represented by a missing value. When the respondent has no arrears or payment in-kind, the wage at the upper and lower end points is identical.

[17] For ease of exposition, these results are not presented in the paper but available from the authors.
[18] See Stata Reference Manuals for more details.
[19] We make the implicit assumption that if a respondent has wage arrears then their wage this month is not their contractual wage but their contractual wage minus the arrears. In reality, the data does not allow us to identify the exact time at which the arrears accrued so our estimates may be viewed in some sense as representing the worst case scenario.

Note that we have two dependent variables defining the endpoints of the interval within which we know that the unobserved wage lies.

Thus, when it comes to estimation of the wage equations, we have male, female and pooled estimates incorporating two distinct methodologies and hence five separate specifications. That is, the standard OLS approach yields a basic human capital specification (Table A.2) plus two augmented estimates, (Tables A.3 and A.4) whilst the interval regression approach, incorporating the effects of wage arrears and payments in-kind as part of the dependent variable, yields a basic human capital estimation plus one including occupational characteristics (Tables A.5 and A.6).

The estimated coefficients of the interval regressions exhibit similar patterns to those found in the OLS regressions, except that the estimated coefficients of job tenure and round 7 are positive and statistically significant in both the female and male regressions. Nevertheless, the estimated coefficients might be biased because of possible selection problems and endogeneity. It may prove possible to implement a modified double (likelihood of working *and* the likelihood of wage arrears given that the individual works) Heckman selectivity test applying multivariate and conditional probabilities. However, for the purposes of this paper, we simply acknowledge this caveat and leave it on our agenda for further research.

4. Measuring the Gender Wage Gap

According to Oaxaca and Ransom (1989, 1994), the gross wage differential can be written as:

$$\ln \overline{W}_m - \ln \overline{W}_f = \overline{X}_m \hat{B}_m - \overline{X}_f \hat{B}_f$$

and can de decomposed as

$$\ln \overline{W}_m - \ln \overline{W}_f = (\overline{X}_m - \overline{X}_f)\hat{B}^* + [(\hat{B}_m - B^*)\overline{X}_m + (B^* - \hat{B}_f)\overline{X}_f]$$

where $\ln \overline{W}_m$ and $\ln \overline{W}_f$ are the average log wages of males and females, $\overline{X}_m$ and $\overline{X}_f$ are the average male and female characteristics or endowments, $\hat{B}_m$ and $\hat{B}_f$ are the estimated coefficients from the male and female regressions and B^* is the vector of

estimated coefficients from the non-discriminatory wage structure. We assume that B^* is an estimate of the common wage structure obtained from OLS estimation using a pooled sample of males and females. That is, the gender wage gap is explained by the differences in average endowments and by the differences in returns to those endowments. In the above equation, the first term on the right hand side represents the wage difference due to differential endowments, whilst the left-hand side of the term in brackets is interpreted as the 'male advantage' (MA) and the right hand side as the 'female disadvantage' (FD).

4.1. The size and composition of the gender wage gap

International comparisons show that the gross log gender wage differential in Russia, which stood at 0.26, according to our pooled data, is higher than that of the UK where it is approximately 0.20 (Wright and Ermish, 1991), the US where it is around 0.24 and the Scandanavian countries where it stands at approximately 0.15 (Gupta, Oaxaca and Smith, 2002). However, it is largely in line with the range of gross wage differentials in central and eastern European transition economies. According to Pailhé (2000), the raw wage gap between male and female employees in 1993 is the lowest in Hungary (0.23) and the highest in Poland (0.30).

However, once we consider the predicted wages from the interval regressions, the average gross log gender wage gap is much larger and stands 25 % higher than the mean actual log wage differential at 0.33. This is in line with the findings of Earle and Sabirianova (1999) that men are prone to experience greater incidence and depth of wage arrears, suggesting that failure to account for arrears results in underestimating the degree of wage discrimination.

Table 2 presents summary statistics of the log wage differential for each specification. In each case, the proportion of the gap explained by differences in returns overwhelms that explained by endowment differences although the addition of occupation controls redresses the balance slightly. The lower part of table 2 decomposes the return differentials into the MA and the FD and presents summary statistics for each specification. If the wage 'discrimination' experienced by women is confined simply

to differences in rewards accruing to human capital characteristics then it should be reflected in the human capital model. However, if discrimination also takes the form of occupational or workplace related discrimination then the FD and MA derived from the restricted human capital model should be interpreted as the maximum.

According to the different OLS wage estimations, the raw wage gap indicates that between 94% and 87% of the women in the sample receive lower wages than they would receive were they rewarded in accordance with the non-discriminatory pay structure. Similarly, the interval regression estimations indicate that at least 89% of women are at a disadvantage even when controlling for occupations. That is, however measured, the vast majority of women would have been better off had they received the non-discriminatory returns to characteristics. In percentage terms the mean of the FD goes from 4.9% to 3.4% as we progress from the most basic human capital model to those including all of the variables and from 5.4% to 3.5% in the interval regression estimations. Table 2 also reveals a clear pattern for the substantial MA: it ranges from 97% to 83% in the OLS estimations and from 98% to 82% in the interval regression estimations. In all cases the lower percentages occur once labour market controls are added.

Table 3 goes on to present detailed decompositions of the total log wage differential for each specification. The first point to note is that, in the basic human capital regressions, the more favourable endowments of females would actually serve to slightly decrease the wage gap if rewarded 'fairly'. This advantage is further enhanced by the inclusion of wage arrears and payment in-kind in the OLS regressions reflecting the fact that more men experience such measures. However, inclusion of job tenure and occupation, results in men having more favourable characteristics, suggesting a higher concentration of men in better paid occupations. The importance of occupation is further borne out through inspection of the decomposition of the MA and FD with returns to occupation explaining the entire MA. A further substantial part of the MA and FD, in all cases, is attributed to the male advantage in returns to equivalent characteristics and to variations in regional returns. Comparing the OLS based estimates with the interval regression estimates the *increase* in the wage gap would appear to be due to further male gains/female losses accruing from returns to

education and region. In other words, wage arrears and payments in-kind serve to distort the returns to human capital characteristics in a manner beneficial to women.

Comparing our two approaches, note that the relative size of the MA and FD, as well as their constituent elements, in the OLS model with arrears and payment in-kind are broadly in line with the results from the first interval regression model. By the same token, the OLS model with the full set of labour market variables mirrors the second interval regression. In the light of this observation and considering the advantages of the interval regression approach over OLS methods for our data, the remaining analysis will be drawn only from the interval regression estimates. As previously explained, the exclusion of job tenure and occupation type from the regression increases the MA and FD substantially. Therefore, we view the interval regression excluding (including) these variables as capturing the 'maximum' ('minimum') level of *wage* discrimination.

Accordingly, we take what we consider to be the most apposite approach to estimating a plausible 'wage discrimination band' and investigate the relationship between gender wage discrimination, the wage distribution, personal characteristics and the unique institutional features of the Russian labour market.

First, we examine to what extent wage discrimination varies through the wage distribution at each end of our discrimination band. Table 4 indicates that, although the differences are limited, men in the central percentiles of the wage distribution enjoyed the highest MA. Much more palpably, women in the lower percentiles of the wage distribution experienced by far the highest FD and this declines continuously as we move up the wage distribution. That is, we find that women in the high percentiles of the wage distribution suffer less from wage discrimination compared to women in the low and middle deciles of wages. This finding supports that of Lehman and Wadsworth (2001) who find that, in the absence of wage arrears, the largest wage gap is to be found at the 10^{th} percentile. The authors note that this contrasts with most Western economies where the widest divergence is more normally found towards the top of the distribution. The final two columns present the 'minimum' wage discrimination estimates, which incorporate controls for occupation and job tenure.

Comparing the maximum and the minimum, as expected, both MA and FD are lower but the decline is much steeper for FD. In other words, after controlling for differential endowments women are more likely to be employed in lower paid occupations.

To explore which individuals suffered in relation to the non-discriminatory wage structure, table 5 provides the FD and MA according to sub-groups delineated by education, age and region. The 'maximum' estimates show that, in terms of education, both the MA and FD are at their lowest amongst those with university level education indicating that wage discrimination is less prevalent amongst the highly trained. The highest MA occurs amongst those with technical and medical education, a category dominated by females. The highest FD was experienced by those with vocational training and incomplete high school. Intriguingly, once we control for labour market characteristics there is a re-ordering. First, the size of the MA for those with vocational or high school qualifications is now lower than that enjoyed by those with university qualifications. Second, females with technical and medical qualifications (34% of our sample) now experience the smallest FD. This, along with the observation that the highest MA occurs for this category, suggests that, although the largest proportion of women have this type of qualification, it is women/men who tend to fill the low/high paid occupations in medical and other technical professions. This concords with Desai and Idson's (2000) findings that women with technical education are often to be found employed in low paid occupations as clerks or associated professionals.

Inspecting the age sub-groups we see that the MA is similar across the different categories but that the FD is smallest for women aged 35 to 44. In general, the age categories reveal no particular pattern, so, bearing in mind Russia's regionally dictated industrial inheritance, a more interesting question relates to regional differences in wage discrimination. Indeed, the lowest FD and MA, occurs in the areas host to the heavy defence, mining and extraction industries – North and North Western, West Siberia and Eastern Russia. Women/men experience higher FD/MA in rural areas and less developed industrial areas – Central and Central Black Earth, the North Caucasus and the Urals. Moreover, once we control for labour market characteristics the FD is

more plainly lower for the defence, mining and extraction areas. As expected, the regional decompositions point out the potential importance of the industrial landscape.

4.2. The gender wage gap, wage arrears and income in-kind

We now turn to an analysis of whether, across gender and income percentiles, there is a positive or negative correlation between wage discrimination and wage arrears/payment in-kind. Since we have observed that wage discrimination is highest at the lower end of the wage distribution, a negative association would suggest that wage arrears were allocated amongst female employees according to the principle of equity, that is, those with the lowest wages were not also made to suffer by experiencing delays in wage payment. In contrast, a positive correlation will be found if an employer allocates wage arrears to women who are less educated or skilled and thus subject to higher levels of wage discrimination.

In our sample, only 58% of all workers are paid in full. That is, 43% of male workers and 40% of female workers experienced wage arrears or payment in-kind or both. The majority of these workers (76% of males and 79% of females) have wage arrears. Moreover, 63% (69%) of the males (females) that receive payment in-kind also suffer from wage arrears. That is to say, only a small percentage (9% of males and 3% of females) suffered from payment in-kind alone. Clearly, the more prevalent form of labour payment adjustment is wage arrears.

Tables 6 and 7 detail the extent of the MA and the FD for the different combinations of wage arrears and in-kind payments for each extremity of our discrimination band. The results reveal a very consistent and interesting pattern. Exploring the maximum MA, males experiencing any form of 'pay adjustment' enjoy a lower MA than those paid in full. For those experiencing only wage arrears the fall in MA is marginal compared to those with full pay.

In contrast, for the males with no wage arrears but in receipt of goods as payment the MA is substantially lower than for both males paid in full and males with only arrears. Indeed, for men in the bottom income decile, the magnitude of the MA is less than

half that encountered by either the reference group *or* those with arrears only. Once more, the decline in MA, associated with experiencing pay adjustment mechanisms is less severe at higher deciles. When we incorporate individuals with both arrears and payment in-kind we observe that, outside of the lowest 3 deciles in which those with in-kind payment enjoy the smallest advantage, the MA is at its lowest.

Turning our attention to the lower part of table 6 we appraise the role of labour market characteristics in influencing the MA. It is clear that the pattern mirrors that of the maximum discrimination case. Nevertheless there are several points worthy of note. First, limiting the sample to those with full pay, the size of the MA peaks much lower in the distribution than denoted in table 4 indicating that, for those spared from arrears and in-kind payment, (positive) discrimination really was higher at the lower end of the distribution. Second, the difference measured in MA, between those with full pay and those experiencing payment in-kind is even more tangible once occupational affiliation is controlled for. Indeed, for those experiencing payment in-kind, with *or* without arrears, the MA was no greater than 1% for the bottom two deciles and for those with both arrears and in-kind payments the MA never topped 2%.

That is, throughout the distribution, male workers in receipt of arrears, wages in-kind or both enjoy a lower MA. Specifically, amongst males in the lowest deciles, in particular those receiving payment in goods, we observe the sharpest fall in the magnitude of the MA. Controlling for occupation reduces the size of the MA across the income distribution but does so disproportionately at the lower deciles. It would appear that these methods of labour market adjustment are allocated in a manner which reduces the discriminatory wage advantage for males, but does so most noticeably at the lower end of the income distribution.

Table 7 advances the equivalent statistics for the female disadvantage. In contrast to male workers, women receiving full pay fare less well than all other groups in comparison with the non-discriminatory structure. Additionally, the differences are more clearly discernible than in the male case. Aside from the bottom income decile, female workers with both wage arrears and payment in-kind endure the lowest FD across the distribution. Interestingly, whilst FD decreases in severity as we move up

the wage distribution for women with wage arrears, females with payment in goods only, experience less FD in the bottom three deciles but thereafter the magnitude of the FD exceeds that experienced by women with full pay.

The estimates of the minimum FD, shown in the lower half of table 7, exhibit patterns broadly consistent with those described above. Once more, inclusion of the labour market controls, serves to reduce the degree of observed wage discrimination by more than half in all cases.

Tables 6 and 7 provide some evidence suggesting that workers who have experienced wage arrears and payment in-kind have been subjected to lower levels of wage discrimination, particularly amongst the 'poorest' workers. That is to say, females with wage arrears, payment in-kind or both tend to meet with lower FD, relative to their full paid counterparts, whilst equivalent males tend to experience lower MA. In general, the negative effects of payment in-kind on the MA and FD are more pronounced than those of wage arrears, particular at the 'minimum' band. When controlling for labour market characteristics the extent of discrimination is lower in all cases. To illustrate, consider workers, at the lower end of the distribution, in receipt of both wage arrears and payment in-kind. For such workers the discrimination band stretches from 3.18% to 10.61% compared to similar workers with full pay for whom the band runs from 9.08% to 13.43%. It would seem that wage arrears and payment in-kind were allocated in a manner that served to reduce the degree of wage discrimination in the labour market. A plausible interpretation of this finding is that enterprise managers were responding to equity considerations in their wage payment decisions.

In sum, wage arrears and payment in-kind act to reduce both the MA and the FD, and in so doing reduce the gender wage gap. That is, wage arrears and payment in-kind have transpired to act as 'compensating' mechanisms offsetting, at least partially, the gender wage differential. This result is in line with evidence provided by Earle and Sabirianova (1999) that the probability and magnitude of arrears depend positively on being a male. Furthermore, it lends support to Friebel and Guriev's (1999) association of in-kind payments with the 'attachment' strategies.

5. Conclusions

There has been a plethora of research relating separately to the Russian gender pay gap and to the emergence of wage arrears and payment in-kind in transitional Russia. Yet, in this paper, we put forward some evidence that these two important phenomena are in fact related in a manner that may shed light on both the 'real' composition and level of the aggregate gender pay gap and on the behavioural traits of Russia's enterprise managers.

Our basic and augmented OLS wage regressions provide a satisfactory fit to the Russian data. We find, significant premia for men and women holding higher levels of education, greater returns to living outside of rural areas, substantial inter-regional variation in wages, higher returns to skilled occupations and penalties for those with arrears and payment in-kind. Our interval regression wage estimates exhibit similar patterns to those found in the OLS. Also, the composition of the wage gap and the relative size of the MA and FD in the OLS estimates are in line with those from the interval regressions.

Accounting for the presence of wage arrears and payment in-kind we find a broader wage gap (33%) than relying simply on OLS (26%). The various wage estimations, show that between 87% and 97% (82% and 98%) of the women (men) in the sample receive lower (higher) wages than they would receive were they rewarded in accordance with the non-discriminatory pay structure. In all cases, the lower percentages refer to discrimination once additional labour market factors are controlled for, thus suggesting 'discrimination' in job occupations.

Looking at discrimination across the distribution we found evidence that, women (men) in the lower (central) percentiles of the wage distribution experienced the highest FD (MA). Examining our discrimination 'bands' it is apparent that the FD band is substantially wider than the MA band due to the differential affects of incorporating labour market characteristics. Notwithstanding obvious concerns

regarding endogeneity, this is commensurate with the observation that women are more likely to be employed in lower paid occupations.
Our sub-group analysis, based on interval regression estimates, provides evidence that discrimination tends to be the least among the best educated, is stable across the age spectrum for men but lower for middle aged women, and exhibits considerable regional diversity.

We scrutinised discrimination according to arrears and in-kind payment. We found that female workers at the lower end of the income distribution encountering wage arrears and/or payment in-kind faced lower discrimination bands than those on full pay. That is to say that both mechanisms acted as 'compensating levers' lowering both the MA and the FD and thus reducing the pay gap. Interestingly, at the 'minimum' discrimination, the negative effects of payment in-kind on discrimination dominate those of wage arrears. More generally, amongst women, arrears and payment in-kind appear to have been allocated to those in more favourable labour market situations. This would seem to suggest that equity considerations were important to those responsible for allocating arrears and payment in-kind.

Finally, some caveats regarding our conclusions. First, although we have bypassed the problem of endogeneity bias in our treatment of wage arrears and payment in-kind, our interval wage regression estimates make no distinction between them. Second, the lower bound of the discrimination band is drawn from wage estimates incorporating job tenure and occupation. The latter two variables are potentially endogenous.

A further problem that needs to be more systematically addressed is that of selectivity bias. On the one hand, we need to account for the decline in formal sector employment and the increase in informal sector employment. We partially address this problem when testing for selectivity bias in the OLS human capital model, although a proper account requires the application of conditional probit equations in either a sequential or a simultaneous framework. On the other hand, our interval wage regressions might suffer from selectivity bias and it would be desirable to design a modified Heckman selection test. Aside from the role of regional, industrial and occupational disparities, these issues offer up stimulating themes for future research.

Table 1

Definitions and Summary Statistics for Variables

Variable	Mean		Definition
	Male	**Female**	
Demographic Characteristics			
Age	38.5 (10.5)	38.2 (8.7)	Males: 18-59; Females: 18-54
Married	0.77 (.42)	0.65 (.48)	Whether respondent was married or not
Primary Employment			
Lnrwrlm	2.80 (1.03)	2.54 (.97)	Gross average real hourly wages in primary job
Job tenure	6.9 (8.3)	7.6 (7.8)	Job tenure in current primary job
Human Capital Controls			
University	0.22 (.42)	0.25 (.44)	Undergraduate university education or higher
Technical & medical	0.16 (.37)	0.34 (.47)	Technical and Medical School
Vocational training	0.27 (.45)	0.16 (.37)	Vocational Training (PTU, FZU, FZO)
High school	0.26 (.44)	0.19 (.40)	Complete high School education (11 years)
Incomplete high school	0.08 (.28)	0.05 (.21)	Incomplete high school education (8 years)
Occupation Type			
Manager	0.03 (.16)	0.02 (.13)	Legislators, senior managers & officials
Professional	0.21 (.41)	0.50 (.50)	Professionals, technicians & associated professionals
Non-manual	0.07 (.26)	0.23 (.42)	Clerks, service workers & market workers
Manual	0.58 (.49)	0.13 (.34)	Agriculture, fisheries, plant and machine operators, crafts and related trades
Unskill	0.09 (.29)	0.12 (.32)	Unskilled occupations
Region and Settlement Type			
Town	0.78 (.41)	0.77 (.42)	Urban areas
Rural non agricultural	0.05 (.22)	0.06 (.24)	Non-agricultural village
Rural agricultural	0.17 (.37)	0.16 (.37)	Agricultural village
Moscow, St. Petersburg	0.12 (.33)	0.11 (.32)	Moscow and St. Petersburg
North & North Western	0.08 (.27)	0.08 (.27)	North and North Western
Central&Central Black-Earth	0.19 (.39)	0.20 (.40)	Central and Central Black-Earth
Volga-Vyatski&Volga Basin	0.16 (.37)	0.17 (.38)	Volga-Vaytski and Volga Basin
North Caucasus	0.11 (.32)	0.09 (.29)	North Caucasus
Urals	0.17 (.38)	0.17 (.38)	Urals
Western Siberia	0.09 (.29)	0.09 (.28)	Western Siberia
Eastern Russia	0.08 (.27)	0.09 (.28)	Eastern Siberian and Far-Eastern
Selection Variables			
Dumpen	0.15 (.36)	0.16 (.36)	Household contains elderly dependants (dummy)
Children	1.01 (.92)	1.02 (.89)	Number of under 18's in the household
Other Variables			
Payment in-kind	0.10 (.30)	0.08 (.28)	Received goods in lieu of payment in last 30 days
Wage arrears	0.40 (.49)	0.38 (.49)	Owed money by enterprise at time of interview
Sample Size	**4,354**	**4,600**	

Standard deviations are reported in parenthesis.
Source: RLMS Rounds 5-8.

Table 2: Summary statistics of the log wage differential, male advantage (MA) and female disadvantage (FD)

	OLS human capital		OLS human capital, wage arrears, payment in-kind		OLS human capital, wage arrears, payment in-kind, occupation		Intreg human capital		Intreg human capital and occupation	
Differences										
Log wages	0.260		0.260		0.260		0.327		0.327	
Endowment	-0.007		-0.022		0.074		-0.014		0.107	
Returns	0.0268		0.0282		0.187		0.341		0.216	
	MA	FD	MA	FD	MA	FD	MA	FD	MA	FD
Mean	0.138	0.130	0.145	0.137	0.096	0.091	0.170	0.171	0.109	0.109
Median	0.141	0.127	0.150	0.134	0.086	0.095	0.174	0.166	0.101	0.112
Max	0.315	0.393	0.340	0.420	0.414	0.373	0.414	0.556	0.530	0.440
Min	-0.105	-0.145	-0.144	-0.200	-0.354	-0.265	-0.149	-0.204	-0.364	-0.221
Std deviation	0.066	0.083	0.073	0.089	0.111	0.081	0.084	0.103	0.129	0.087
% positive	97.4	94.1	96.5	93.7	82.5	87.0	97.5	96.5	81.7	89.3
Percentage Differentials with respect to the reference wage										
Mean	5.212	4.934	5.475	5.195	3.539	3.351	5.398	5.446	3.498	3.523
Median	5.141	4.643	5.495	4.924	3.154	3.545	5.457	5.128	3.081	3.620
Maximum	12.259	18.179	14.044	20.983	19.875	15.699	13.776	18.329	19.079	14.331
Minimum	-5.485	-7.573	-11.139	-12.67	-19.747	-18.438	-4.256	-5.958	-9.994	-6.991
Std deviation	2.574	3.275	2.889	3.618	4.498	3.342	2.675	3.414	4.255	2.858
Number Obs	**4,354**	**4,600**	**4,354**	**4,600**	**4,354**	**4,600**	**4,354**	**4,600**	**4,354**	**4,600**

Table 3

Summary statistics of the female disadvantage (FD) and male advantage (MA)

	OLS human capital	OLS human capital, wage arrears, payment in-kind	OLS human capital, wage arrears, payment in-kind, occupation	Intreg human capital	Intreg human capital and occupation
Total difference in log earnings	0.260	0.260	0.260	0.327	0.327
Endowment	-0.007	-0.022	0.074	-0.014	0.107
Age	-0.005	-0.007	-0.009	-0.011	-0.014
Married	0.011	0.013	0.011	0.018	0.015
Education	-0.003	-0.002	-0.002	0.000	0.000
Settlement	-0.026	-0.026	-0.035	-0.025	-0.038
Regions	0.006	0.005	0.005	0.002	0.003
Rounds	0.010	0.008	0.007	0.002	0.001
Arrears		-0.007	-0.007		
Pay in-kind		-0.006	-0.006		
Job tenure			-0.002		-0.006
Occupation			0.113		0.147
Returns	0.268	0.282	0.187	0.341	0.216
MA	0.138	0.145	0.096	0.170	0.109
Age	0.246	0.264	0.217	0.340	0.281
Married	0.010	0.004	0.010	-0.017	-0.007
Education	0.062	0.064	0.072	0.097	0.100
Settlement	-0.026	-0.031	-0.072	-0.054	-0.087
Regions	0.055	0.058	0.062	0.109	0.111
Rounds	-0.009	-0.010	-0.011	-0.018	-0.020
Arrears		-0.005	-0.001		
Pay in-kind		-0.009	-0.008		
Job tenure			0.007		0.021
Occupation			-0.127		-0.235
Constant	-0.201	-0.191	-0.053	-0.286	-0.055
FD	0.130	0.137	0.091	0.171	0.109
Age	-0.311	-0.388	-0.332	-0.614	-0.594
Married	0.057	0.058	0.046	0.059	0.046
Education	0.081	0.089	0.093	0.104	0.108
Settlement	-0.104	-0.123	-0.087	-0.172	-0.110
Regions	0.054	0.062	0.078	0.102	0.118
Rounds	-0.018	-0.022	-0.016	-0.029	-0.024
Arrears		0.007	0.005		
Pay in-kind		-0.007	-0.008		
Job tenure			-0.005		0.010
Occupation			0.014		-0.007
Constant	0.371	0.463	0.303	0.720	0.562

Note: Numbers do not exactly add up due to rounding.

Table 4

Female disadvantage (FD) and male advantage (MA) according to income percentiles based on interval regression estimates

Cum. Sample Share (%)	Maximum		Minimum	
	MA	FD	MA	FD
10	4.340	7.975	3.395	4.401
20	5.097	7.400	3.615	4.213
30	5.429	7.070	3.714	4.210
40	5.550	6.827	3.740	4.128
50	5.530	6.691	3.717	4.066
60	5.508	6.443	3.694	3.992
70	5.443	6.281	3.638	3.928
80	5.340	6.041	3.526	3.837
90	5.296	5.769	3.417	3.696
100	5.206	5.503	3.313	3.555

Table 5

Decomposition of female disadvantage (FD) and male advantage (MA) by endowment based on interval regression

	Maximum		Minimum	
	MA	FD	MA	FD
All	5.398	5.446	3.498	3.523
Education				
University	3.237	3.313	3.392	3.069
Technical & medical	8.421	4.219	6.064	2.848
Vocational training	4.923	9.284	2.889	5.167
High school	4.947	7.671	2.889	4.082
Incomplete high school	6.396	12.661	4.111	7.781
Age				
Age between 18 and 34	5.353	6.967	3.745	4.423
Age between 35 and 44	5.856	5.059	3.694	2.801
Age between 45 and 55	5.237	7.155	3.397	4.799
Region				
Moscow & St. Petersburg	4.384	5.762	3.340	4.168
Northern & North Western	1.756	2.180	-0.833	-0.791
Central & Central Black-Earth	5.491	5.739	3.312	3.385
Volga-Vyatski & Volga Basin	6.317	7.215	4.071	4.317
North Caucasian	4.462	7.102	2.834	3.940
Urals	6.394	7.980	4.752	5.203
Western Siberian	5.02	5.945	3.258	2.894
Eastern Siberian & Far-Eastern	5.863	5.926	3.383	3.246

Table 6

Maximum male advantage according to wage arrears and income in-kind (%)
based on interval regression

Cum. Sample share	No wage arrears, no payment in-kind	Wage arrears, payment in-kind	Wage arrears, no payment in-kind	Payment in-kind, no wage arrears
10	4.891	2.923	4.337	2.126
20	5.502	3.645	5.078	3.049
30	5.742	4.215	5.332	3.819
40	5.783	4.468	5.465	4.597
50	5.713	4.526	5.477	4.901
60	5.687	4.398	5.475	4.867
70	5.609	4.523	5.413	4.834
80	5.467	4.596	5.324	4.815
90	5.391	4.731	5.302	4.821
100	5.275	4.810	5.204	4.861

Minimum male advantage according to wage arrears and income in-kind (%)
based on interval regression

Cum. Sample share	No wage arrears, no payment in-kind	Wage arrears, payment in-kind	Wage arrears, no payment in-ki	Payment in-kind, no wage arrears
10	4.110	0.926	3.385	0.631
20	4.267	0.805	3.526	1.021
30	4.174	0.875	3.705	2.011
40	4.091	1.227	3.791	2.385
50	3.994	1.475	3.783	2.483
60	3.972	1.546	3.731	2.567
70	3.905	1.660	3.649	2.764
80	3.775	1.672	3.556	2.679
90	3.646	1.822	3.445	2.544
100	3.518	1.907	3.327	2.531

Table 7

Maximum female disadvantage according to wage arrears and income in-kind (%) based on interval regression

Cum. Sample share	No wage arrears, no payment in-kind	Wage arrears, payment in-kind	Wage arrears, no payment in-kind	Payment in-kind, no wage arrears
10	8.539	7.687	7.376	5.541
20	7.921	6.344	6.800	6.379
30	7.549	5.943	6.401	6.647
40	7.241	5.928	6.187	7.418
50	7.042	5.800	6.128	7.411
60	6.775	5.539	5.888	7.278
70	6.587	5.376	5.775	7.206
80	6.331	5.190	5.540	7.105
90	6.067	4.940	5.267	6.838
100	5.789	4.818	5.010	6.512

Minimum female disadvantage according to wage arrears and income in-kind (%) based on interval regression

Cum. Sample share	No wage arrears, no payment in-kind	Wage arrears, payment in-kind	Wage arrears, no payment in-kind	Payment in-kind, no wage arrears
10	4.973	2.255	3.920	1.207
20	4.716	2.647	3.644	3.012
30	4.608	2.895	3.692	3.556
40	4.524	2.834	3.616	3.756
50	4.432	2.877	3.587	3.780
60	4.351	2.680	3.526	3.999
70	4.273	2.500	3.490	4.015
80	4.178	2.463	3.398	4.034
90	4.045	2.354	3.249	4.084
100	3.900	2.399	3.100	3.918

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Appendix

Table A.1

Probit equation estimation results

	Male		Female	
	coefficient	t- value	Coefficient	t- value
Age	0.013	1.00	0.138	8.14
Age-squared	-0.2E-3	-1.53	-0.002	-7.20
Married	0.088	1.92	-0.183	-4.69
Town	0.450	9.60	0.237	5.10
Rural non-agricultural	0.084	1.05	0.086	1.06
Rural agricultural	Omitted		Omitted	
University	0.212	2.97	0.209	2.41
Technical & medical	0.131	1.79	0.203	2.44
Vocational training	0.050	0.75	0.017	0.19
Complete High school	0.021	0.32	0.104	1.22
Incomplete High school	Omitted		Omitted	
Moscow & St Petersburg	0.320	3.50	0.450	5.15
North & North Western	Omitted		Omitted	
Central&CentralBlack-Earth	-0.028	-0.35	0.209	2.78
Volga-Vyatski&Volga-Basin	-0.201	-2.56	-0.048	-0.65
North Caucasus	-0.104	-1.24	-0.094	-1.18
Urals	0.048	0.59	0.122	1.62
Western Siberia	-0.302	-3.43	-0.093	-1.14
Eastern Russia	-0.375	-4.31	-0.054	-0.67
Round 5	Omitted		Omitted	
Round 6	-0.174	-4.11	-0.137	-3.42
Round 7	-0.454	-10.75	-0.385	-9.00
Round 8	-0.269	-6.16	-0.255	-5.86
Children	-0.054	-2.53	-0.102	-4.72
Dumpen	-0.162	-3.41	-0.111	-2.26
Constant	-0.146	0.60	-2.251	-7.43
Lambda (inverse Mills ratio)	-0.115	-1.85	-0.153	1.30
N censored	2,626		2,589	
N uncensored	4,354		4,600	

t-values obtained from Huber/White/sandwich variance estimates

Table A.2

OLS wage equation estimation results: human capital
Dependent variable: ln hourly (gross) wage from main job

	Pooled		Male		Female	
	coefficient	t-value	coefficient	t-value	coefficient	t-value
Age	0.007	0.86	0.024	2.07	0.022	1.54
Age-squared	-0.1E-3	-1.09	-0.4E-3	-2.50	-0.3E-3	-1.47
Married	0.095	3.76	0.108	2.72	0.007	0.21
Town	0.672	18.59	0.747	14.30	0.571	11.64
Rural non-agricultural	0.579	9.15	0.647	6.69	0.523	6.25
Rural agricultural	Omitted		Omitted		Omitted	
University	0.451	8.86	0.408	5.95	0.587	8.17
Technical & medical	0.186	3.62	0.217	2.96	0.333	4.70
Vocational training	0.111	2.13	0.065	0.95	0.159	2.11
Complete High school	0.145	2.86	0.113	1.71	0.207	2.78
Incomplete high school	Omitted		Omitted		Omitted	
Moscow & St Petesburg	0.073	1.34	0.130	1.69	0.013	0.18
North & North Western	Omitted		Omitted		Omitted	
Central &CentralBlack-Earth	-0.400	-7.66	-0.373	-5.04	-0.424	-5.87
Volga-Vyatski&Volga-Basin	-0.661	-12.93	-0.597	-8.08	-0.716	-10.27
North Caucasus	-0.383	-6.84	-0.307	-3.83	-0.484	-6.43
Urals	-0.283	-5.52	-0.165	-2.30	-0.393	-5.56
Western Siberia	0.053	0.87	0.097	1.10	-0.005	-0.06
Eastern Russia	-0.014	-0.22	-0.005	-0.05	-0.013	-0.17
Round 5	Omitted		Omitted		Omitted	
Round 6	-0.235	-10.42	-0.235	-6.92	-0.221	-7.57
Round 7	-0.203	-8.05	-0.227	-6.10	-0.166	-4.96
Round 8	-0.622	-24.66	-0.642	-17.34	-0.594	-17.46
Constant	2.245	13.26	2.044	9.18	1.875	6.87
F	98.67		52.43		53.03	
R-squared	0.211		0.222		0.218	
N	8,954		4,354		4,600	

t-values obtained from Huber/White/sandwich variance estimates

Table A.3

OLS wage equation estimation results: human capital, wage arrears, payment in-kind
Dependent variable: ln hourly (gross) wage from main job

	Pooled		Male		Female	
	coefficient	t-value	coefficient	t-value	Coefficient	t-value
Age	0.0137	1.61	0.031	2.71	0.033	2.37
Age-squared	-0.2E-3	-1.77	-0.4E-3	-3.06	-0.4E-3	-2.28
Married	0.112	4.58	0.117	3.03	0.023	0.74
Town	0.572	16.51	0.649	13.10	0.462	9.83
Rural non-agricultural	0.458	7.33	0.542	5.68	0.388	4.82
Rural agricultural	Omitted		Omitted		Omitted	
University	0.431	8.61	0.369	5.50	0.598	8.49
Technical & medical	0.178	3.53	0.213	3.02	0.344	4.95
Vocational training	0.095	1.86	0.045	0.69	0.153	2.07
Complete High school	0.140	2.82	0.105	1.65	0.216	2.96
Incomplete high school	Omitted		Omitted		Omitted	
Moscow & St Petersburg	-0.031	-0.58	0.019	0.25	-0.091	-1.24
North & North Western	Omitted		Omitted		Omitted	
Central &CentralBlack-Earth	-0.477	-9.46	-0.450	-6.41	-0.509	-7.26
Volga-Vyatski&Volga-Basin	-0.694	-13.98	-0.626	-8.83	-0.753	-11.12
North Caucasus	-0.454	-8.35	-0.378	-4.99	-0.560	-7.58
Urals	-0.317	-6.40	-0.198	-2.90	-0.434	-6.29
Western Siberia	0.027	0.46	0.075	0.90	-0.044	-0.55
Eastern Russia	-0.001	-0.01	0.039	0.44	-0.028	-0.35
Round 5	Omitted		Omitted		Omitted	
Round 6	-0.241	-10.80	-0.249	-7.41	-0.220	-7.61
Round 7	-0.145	-5.85	-0.168	-4.59	-0.104	-3.14
Round 8	-0.521	-20.54	-0.536	-14.54	-0.487	-14.20
Wage arrears	-0.349	-15.71	-0.361	-11.38	-0.366	-12.27
Payment in-kind	-0.321	-8.09	-0.406	-7.24	-0.241	-4.36
Constant	2.379	14.38	2.188	10.19	1.917	7.13
F	116.52		63.53		62.01	
R-squared	0.2478		0.2662		0.2570	
N	8,954		4,354		4,600	

t-values obtained from Huber/White/sandwich variance estimates

Table A.4

OLS wage equation estimation results: human capital, wage arrears, payment in-kind and occupation
Dependent variable: ln hourly (gross) wage from main job

	Pooled		Male		Female	
	coefficient	t-value	coefficient	t-value	coefficient	t-value
Age	0.015	1.76	0.029	2.57	0.031	2.23
Age-squared	-0.2E-3	-2.23	-0.4E-3	-3.14	-0.4E-3	-2.33
Married	0.092	3.81	0.105	2.76	0.021	0.67
Town	0.549	16.27	0.637	13.10	0.434	9.28
Rural non-agricultural	0.455	7.56	0.525	5.58	0.384	4.89
Rural agricultural	Omitted		Omitted		Omitted	
University	0.457	8.63	0.273	3.66	0.554	7.69
Technical & medical	0.192	3.83	0.155	2.20	0.306	4.47
Vocational training	0.052	1.05	0.011	0.17	0.115	1.61
Complete High school	0.124	2.60	0.071	1.13	0.190	2.73
Incomplete high school	Omitted		Omitted		Omitted	
Moscow & St Petesburg	-0.007	-0.13	0.042	0.57	-0.096	-1.33
North & North Western	Omitted		Omitted		Omitted	
Central &CentralBlack-Earth	-0.466	-9.42	-0.426	-6.16	-0.522	-7.57
Volga-Vyatski&Volga-Basin	-0.689	-14.17	-0.611	-8.75	-0.767	-11.53
North Caucasus	-0.440	-8.28	-0.362	-4.85	-0.558	-7.66
Urals	-0.316	-6.50	-0.192	-2.86	-0.445	-6.55
Western Siberia	0.033	0.58	0.077	0.95	-0.040	-0.50
Eastern Russia	0.011	0.19	0.048	0.54	-0.025	-0.32
Round 5	Omitted		Omitted		Omitted	
Round 6	-0.230	-10.34	-0.241	-7.19	-0.210	-7.26
Round 7	-0.121	-4.89	-0.141	-3.86	-0.093	-2.80
Round 8	-0.496	-19.64	-0.513	-13.93	-0.477	-13.88
Wage arrears	-0.369	-16.80	-0.372	-11.74	-0.383	-12.72
Payment in-kind	-0.329	-8.27	-0.404	-7.21	-0.236	-4.26
Job tenure	0.003	1.99	0.004	1.95	0.004	1.74
Manager	0.415	5.58	0.391	4.08	0.253	1.94
Professional	0.116	3.65	0.154	2.62	0.104	2.79
Manual	0.316	10.47	0.104	2.10	0.273	5.45
Non-manual	Omitted		Omitted		Omitted	
Unskilled	-0.057	-1.41	-0.191	-3.00	0.052	-0.97
Constant	2.258	13.64	2.205	10.29	-1.955	7.26
F	105.69		54.98		52.87	
R-squared	0.2669		0.2771		0.2677	
N	8,954		4,354		4,600	

t-values obtained from Huber/White/sandwich variance estimates

Table A.5

Interval regression wage equation estimation results: human capital
Dependent variable: ln hourly (gross) wage from main job

	Pooled		Male		Female	
	coefficient	t-value	coefficient	t-value	coefficient	t-value
Age	0.027	2.79	0.046	3.57	0.061	3.93
Age-squared	-0.3E-3	-2.70	-0.6E-3	-3.60	-0.001	-3.80
Married	0.153	5.45	0.130	2.91	0.062	1.76
Town	0.283	6.46	0.398	6.43	0.156	2.64
Rural non-agricultural	0.131	1.76	0.270	2.41	0.040	0.42
Rural agricultural	Omitted		Omitted		Omitted	
University	0.430	7.07	0.310	3.94	0.666	7.69
Technical & medical	0.195	3.18	0.238	2.88	0.415	4.83
Vocational training	0.109	1.78	0.045	0.59	0.187	2.08
Complete High school	0.178	2.93	0.115	1.50	0.303	3.41
Incomplete high school	Omitted		Omitted		Omitted	
Moscow & St Petesburg	-0.304	-4.87	-0.213	-2.46	-0.389	-4.48
North & North Western	Omitted		Omitted		Omitted	
Central &CentralBlack-Earth	-0.668	-11.26	-0.578	-7.06	-0.750	-9.01
Volga-Vyatski&Volga-Basin	-0.829	-13.61	-0.712	-8.18	-0.928	-11.13
North Caucasus	-0.674	-10.12	-0.562	-6.21	-0.813	-8.78
Urals	-0.452	-7.45	-0.303	-3.66	-0.599	-7.05
Western Siberia	-0.001	-0.02	0.109	1.16	-0.122	-1.25
Eastern Russia	-0.026	-0.35	0.153	1.39	-0.154	-4.54
Round 5	Omitted		Omitted		Omitted	
Round 6	-0.232	-9.08	-0.251	-6.56	-0.191	-5.81
Round 7	0.030	1.03	0.009	0.21	0.071	1.88
Round 8	-0.226	-7.46	-0.267	-6.07	-0.185	-4.58
Constant	2.682	14.12	2.396	9.70	1.961	6.46
Chi-squared	982.33		502.59		620.94	
N	8,954		4,354		4,600	
Right-censored	3,768		1,896		1,872	

t-values obtained from Huber/White/sandwich variance estimates

Table A.6

Interval regression wage equation estimation results: human capital and occupation
Dependent variable: ln hourly (gross) wage from main job

	Pooled		Male		Female	
	coefficient	t-value	coefficient	t-value	coefficient	t-value
Age	0.025	2.65	0.041	3.19	0.058	3.74
Age-squared	-0.4E-3	-3.16	-0.6E-3	-3.66	-0.001	-3.95
Married	0.128	4.68	0.118	2.70	0.057	1.63
Town	0.271	6.46	0.392	6.50	0.138	2.39
Rural non-agricultural	0.151	2.13	0.264	2.39	0.060	0.65
Rural agricultural	Omitted		Omitted		Omitted	
University	0.473	7.48	0.255	2.90	0.591	6.88
Technical & medical	0.222	3.68	0.195	2.35	0.359	4.34
Vocational training	0.063	1.07	0.015	0.20	0.142	1.66
Complete High school	0.162	2.81	0.082	1.08	0.268	3.22
Incomplete high school	Omitted		Omitted		Omitted	
Moscow & St Petesburg	-0.269	-4.42	-0.188	-2.20	-0.389	-4.62
North & North Western	Omitted		Omitted		Omitted	
Central &CentralBlack-Earth	-0.652	-11.41	-0.553	-6.84	-0.759	-9.57
Volga-Vyatski&Volga-Basin	-0.828	-14.15	-0.704	-8.21	-0.945	-11.90
North Caucasus	-0.653	-10.14	-0.539	-6.03	-0.806	-9.03
Urals	-0.461	-7.91	-0.306	-3.76	-0.622	-7.67
Western Siberia	0.002	0.03	0.108	1.17	-0.109	-1.17
Eastern Russia	0.001	0.01	0.170	1.57	-0.132	-1.37
Round 5	Omitted		Omitted		Omitted	
Round 6	-0.213	-8.40	-0.241	-6.32	-0.173	-5.24
Round 7	0.062	2.19	0.044	1.05	0.095	2.51
Round 8	-0.200	-6.66	-0.239	-5.46	-0.170	-4.24
Job tenure	0.009	5.12	0.012	5.00	0.007	3.15
Manager	0.515	6.17	0.370	3.53	0.398	2.66
Professional	0.217	5.97	0.133	1.92	0.237	5.72
Manual	0.463	13.30	0.133	2.28	0.425	7.58
Non-manual	Omitted		Omitted		Omitted	
Unskilled	0.050	1.04	-0.198	-2.55	0.079	1.24
Constant	2.499	13.27	2.445	9.89	1.937	6.41
Chi-squared	1,303.25		594.73		725.87	
N	8,954		4,354		4,600	
Right Censored	3,768		1,896		1,872	

t-values obtained from Huber/White/sandwich variance estimates