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Essays on Russian Labour Market Issues

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Declaration of Own Work

I declare that this thesis was written and composed by myself and is the result of my own work unless clearly stated and referenced. This thesis has not been submitted for any other degrees or professional qualifications.

Sergei Plekhanov

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Abstract of Thesis

Being the largest transition economy Russia has interested economists since the collapse of the USSR. This thesis contributes to the literature on Russian labour market. In the first chapter I investigate cyclicality of real wages in Russia, the second chapter looks into consequences of wage arrears for workers' future and the third chapter develops a model of wage arrears that arise as a result of firms' opportunistic behaviour. The principal source of data used in this thesis is the Russia Longitudinal Monitoring Survey (the RLMS).

The first chapter investigates cyclicality of real wages in Russia. The analysis is carried out both at the country as well as regional levels and the influence of wage arrears on the cyclicality is examined. The estimated cyclicality coefficient is three to four times larger in magnitude than those observed for Germany, the UK, the USA and other developed countries. An increase in unemployment rate by one percentage point leads to an average reduction in real wages of four percent. The results are robust to changes in sample period and estimation technique. Wage arrears do not prove to be the driving force of this strong procyclicality.

The second chapter investigates influence of wage arrears on the future of affected workers. Limited dependent variable models are used to analyse the effects of wage arrears on the probability of future wage arrears and frequent separation from employers. Difference-in-difference approach is used to analyse effects on earnings. The

results suggest that affected workers are twice as likely to experience wage arrears again within next three years. Job-movers are able to decrease the probability of repeated wage arrears by nine percentage points. The effect on separations is more modest: affected workers are approximately forty percent more likely to change jobs the following year and eleven percent more likely to experience frequent separations within five years after wage arrears. The effect on future earnings is relatively small and short-lived. Take-home wages decrease by 1 000 RUB compared to unaffected workers and recover within the following year. Analysis of stocks and flows of wage arrears indicates that in the period from 1998 to 2012 on average three quarters of wage debts were repaid.

The third chapter picks up the discussion of the nature of wage arrears in Russia. An indirect evidence suggests that sometimes the firms choose to withhold wages despite having the resources to pay and in certain circumstances the employees accept it. The chapter presents a model of wage arrears that is based on worker-firm interactions. Calibration to the Russian data indicates that the parameter values observed in the RLMS dataset are consistent with a stable equilibrium in which an approximately half of the labour force experience late payments. The model predicts average duration of wage arrears of four months. This prediction is consistent with the Russian reality in the late 1990s.

Lay Summary

Being the largest transition economy Russia has interested economists since the collapse of the USSR. This thesis contributes to the literature on Russian labour market. In the first chapter I investigate cyclicality of real wages in Russia, the second chapter looks into consequences of wage arrears for workers' future and the third chapter develops a model of wage arrears that arise as a result of firms' desire to increase the profits. The principal source of data used in this thesis is the Russia Longitudinal Monitoring Survey (the RLMS).

The first chapter investigates whether real wages in Russia decrease in recessions and grow during expansions. The analysis is carried out both at the country as well as regional levels. The results suggest that an increase in unemployment rate by one percentage point leads to an average reduction in real wages of four percent. This estimate is approximately three to four times larger in magnitude than observed in such countries as the USA, the UK and Germany.

The second chapter investigates influence of wage arrears on the future of affected workers. The results suggest that affected workers are twice as likely to experience wage arrears again within next three years. Individuals who change jobs are able to decrease the probability of repeated wage arrears by nine percentage points. The effect on separations is more modest: affected workers are approximately forty percent more likely to change jobs the following year and eleven percent more likely

to experience frequent separations within five years after wage arrears. The effect on future earnings is relatively small and short-lived. Take-home wages decrease by 1000 RUB compared to unaffected workers and recover within the following year.

The third chapter picks up the discussion of the nature of wage arrears in Russia. An indirect evidence suggests that sometimes the firms choose to withhold wages despite having the resources to pay and in certain circumstances the employees accept it. The chapter presents a model of wage arrears that is based on worker-firm interactions. When the model is calibrated to the Russian data it predicts average duration of wage arrears of four months. This prediction is consistent with the Russian reality in the late 1990s.

To my incredible wife Yulia for her endless love, support and understanding, and to my parents Anatoliy and Galina, and my brother Alexander for their immeasurable contribution to who I am.

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Chapter 1. Real Wage Cyclicality in Russia. Evidence from the RLMS

The chapter investigates cyclicality of real wages in Russia. The analysis is carried out both at the country as well as regional levels and the influence of wage arrears on the cyclicality is examined. The estimated cyclicality coefficient is three to four times larger in magnitude than those observed for Germany, the UK, the USA and other developed countries. The results are robust to changes in sample period and estimation technique. Wage arrears do not prove to be the driving force of this strong procyclicality.

1.1 Introduction

The question of whether real wages are procyclical has been in focus of the literature for more than 20 years. A few decades ago wage stickiness was considered by vast majority of researchers to be a key feature of many business cycles models. However empirical evidence supporting rigidity came from time-series analysis of countries' aggregate data (Solon et al., 1994). Since the early 1990s research in this area has

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shifted towards the analysis of micro-panel datasets that contain information about jobs and wages of individual people. Results of such studies have found evidence of procyclicality. One of the reasons why the results from aggregated data differ from the ones obtained from micro-panel studies is aggregation bias described in details by Solon et al. (1994). The basic idea is that weights of different groups of people (high- and low-skilled workers) in country-level indices vary between recessions and expansions. This creates a countercyclical bias.

A great amount of empirical work that sheds light on behaviour of real wages of different types of workers over business cycles has been done in the last 15 years. Devereux (2001) focuses on workers who change employers but retain the same job using the Panel Study of Income Dynamics dataset. He estimates cyclicality parameters separately for workers who are paid hourly and salaried workers and distinguishes between cyclicality of base wage and that of income from bonuses or overtime work. The results are mixed. Full sample estimation provides a significant coefficient of -0.012[1], however the result is mainly driven by wages of hourly paid individuals and earnings of salaried people who have additional income sources such as bonuses. Devereux concludes that increasing popularity of incentive-based pay induces procyclicality of wages.

Shin and Solon (2007) attempt to replicate the result using a different dataset (National Longitudinal Survey of Youth). Although they agree that a substantial proportion of procyclicality comes from compensation that exist in addition to wages, they also find significant a coefficient of -0.015 for the average hourly earnings of salaried job-stayers. In contrast, the coefficient obtained by Devereux (2001) is -

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[1]Interpretation of this coefficient is "semi-elasticity of real wages with respect to the chosen cyclical indicator is equal to -1.2%". Negative sign indicates that wages move in the opposite direction to the indicator used. The standard choice for the indicator in the literature is unemployment rate. Therefore the negative sign is interpreted as procyclicality: when unemployment rate decreases by 1 percentage point real wages grow by 1.2%.

0.0008.

Devereux and Hart (2006) estimate wage cyclicality distinguishing between job-stayers (individuals who keep the same jobs within the same firms), within-company job-movers and cross-company job-movers. They use the New Earnings Survey Panel Data (NESPD) dataset that contains 1% of British workers in employment. Its structure enables them to carry out complex analysis by distinguishing between the public and the private sector and between workers who are covered and not covered by collective bargaining agreements. According to their results procyclicality of real wages of job-stayers (estimated cyclicality coefficient of -0.017) is lower compared to that of job-movers. Wages of cross-company job-movers (increment in cyclicality of -0.012 compared to job-stayers) are more procyclical than wages of within-company movers (increment of -0.002 compared to job-stayers). Based on the results the authors conclude that rigid wage models are not relevant for the modern UK labour market.

Similar results are obtained by Hart and Roberts (2011). They use more recent version of the same dataset which includes observations up to 2010 and follow the estimation approach of Devereux and Hart (2006). The results support previous findings and suggest that spot market conditions are the main power that affects wages in the UK.

Another aspect covered in recent literature is a comparison of wage cyclicality of full- and part-time workers. Hart (2006) shows that though part-time jobs are a quantitatively important part of total employment adding it to the analysis does not change the overall picture.

Though studies exploring datasets from the USA and the UK prevail in the literature, several papers provide evidence from other countries. Peng and Siebert (2007) compare wage cyclicality in Germany and Great Britain following the methodology

of Devereux and Hart (2006). Their study shows that real wages in West Germany exhibit procyclical behaviour similar to that of wages in Great Britain (estimated coefficients for job-stayers in private sector are around -0.01 for both countries). Wages in East Germany are less proycliclical, the estimated semi-elasticity is about half the size of the one obtained for West Germany. Using administrative data from Germany, Stuber and Snell (2014) establish large asymmetries in wage adjustments. They find highly significant semi-elasticity equal to -1.75% when unemployment is low and insignificant response of wages to changes in unemployment when the latter is high. Such results provide support to theoretical models of downward real wage rigidity.

Peng and Siebert (2008) investigate wage cyclicality in Italy and find a substantial flexibility of wages. They also point out large variation in results between regions. Insignificant results for Central and Southern Italy are contrasted to a very large in magnitude coefficient of -0.09 for the Northern regions.

Carneiro et al. (2012) and Martins et al. (2010) analyse cyclicality of wages of newly hired workers using Portuguese matched employer-employee dataset. Carneiro et al. (2012) define newly hired workers as those whose tenure is less than 1 year and differentiate them in estimation using dummy variable. The authors find an increment of -0.006 for new hires compared to job-stayers' result of -0.018. Martins et al. (2010) discuss weaknesses in this identification strategy and propose to determine entry level positions within each firm and track wages paid to newly hired workers in those jobs. They find a slightly lower degree of cyclicality. Entry level wages tend to be 1.8 % higher when unemployment is 1 percentage point lower. Authors also obtain a cyclicality coefficient equal to -0.026 for job-movers. That is in line with earlier findings in the literature that suggest that wages of job-movers are particularly procyclical.

A number of studies also investigate wage cyclicality with the view to determe the appropriate wage setting models for various countries. See for example Kilponen and Santavirta (2010) for Finland and Messina et al. (2009) for aggregate country-level data analysis for 18 OECD countries.

Very little research in the area has been carried out for developing countries, especially the ones in transition. Accurate estimates of wage cyclicality coefficients are crucial for correctly calibrating macro models for those countries and making policy recommendations. On top of that, the results could aid further understanding of whether labour markets in transition countries differ significantly from those of developed economies. That in turn would help to modify existing or develop new, more appropriate models, tailored for developing and transition world.

This paper contributes to the literature by analysing real wage cyclicality in Russia. The principal source of data is the RLMS (1994 - 2011 sample)[2]. The results suggest that real wages in Russia have been highly procyclical over the last decades. The estimated cyclicality coefficient is approximately -0.04. That is significantly larger than the estimates obtained previously for the USA, the UK and other countries.

Influence of wage arrears on wage cyclicality is investigated. Wages of workers affected by irregular pay are more procyclical compared to wages of unaffected workers. The difference between the estimates is approximately 1 percentage point. However, accounting for wage arrears does not change the overall picture, workers who have never been affected by payment delays experience a 4% decrease in real wages in response to 1 percentage point increase in unemployment. Therefore I conclude that wage arrears are not the driving force behind strong procyclicality.

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[2]"Russia Longitudinal Monitoring survey, RLMS-HSE", conducted by the National Research University Higher School of Economics and ZAO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS.

Regional decomposition reveals that the Far-Eastern federal district is charac-terised by the most flexible wages with the estimated coefficient of -0.07. On the other side of the spectrum is North-Western district – the only one with an insignif-icant estimate. The results are robust to various changes in the sample period and estimation technique.

The rest of the paper is organised as follows: Section 1.2 describes the data, Section 1.3 presents the specification used for the empirical analysis, the main results are presented in section 1.4, followed by robustness checks in Section 1.5. Section 1.6 concludes.

1.2   Data

1.2.1   Sources

The main source of the data are waves 5 (1994) to 20 (2011) of the "Russia Lon-gitudinal Monitoring survey, RLMS-HSE" (hereafter the RLMS) which is an open access panel of around 10 000 individuals. The survey is dwelling based. When occupiers move home interviewers attempt to follow them up in addition to includ-ing new respondents into the dataset. The survey has a detailed job related section that contains information about up to three jobs that individuals keep. Questions in that section could in principle allow to distinguish between job-stayers, cross- and within-firm job-movers as well as differentiate firms by size, ownership structure and the sector of the economy. However infrequent and inconsistent answers to those questions, combined with the absence of firm identifiers and several updates to the survey structure, make this task complicated. Other sections of the dataset provide general information on responders' background such as education, ethnicity, place of birth etc. Unfortunately the survey was not conducted in 1997 and 1999.

Other sources include the World Economic Outlook database of the IMF[3], statistical bulletins "Economic activity of Russian population" and the "Annual statistics bulletin" published by the Russian Federal Statistics Office[4], and current labour market statistics published on the the official web page of the Russian statistics office.

1.2.2 Features of the dataset

As a business cycle indicator I choose unemployment rate. It is a standard approach in the literature as unemployment rate is believed to reflect outside options available to workers when they start employment or consider changing their job.

To account for procyclicality of working hours, real hourly wage is used in estimations. It is constructed as a ratio of real monthly labour income to the number of hours spent on jobs. The respondents are explicitly asked to report the actual number of hours spent on each job. It decreases the probability of procyclical bias that arises when contract hours are used (Shin and Solon, 2007). Indeed, if fixed contract hours were used, a decrease in reported take-home monthly wage would result in a greater drop in observed hourly wages compared to the measure that accounts for potentially shorter working hours during recessions.

As mentioned above the RLMS provides information on up to three jobs per individual. Only data from the primary and secondary jobs is used in estimations because information about the third job is rare and most of the time incomplete[5]. Likewise information about the second job is taken into account only if it is complete

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[3]Can be accessed with following URL:
http://www.imf.org/external/pubs/ft/weo/2013/01/weodata/weoselgr.aspx.
Information about Russia is mainly provided by by the Russian Federal Statistics Office
[4]Can be accessed through official Federal Statistics Office web page: http://www.gks.ru/.
[5]"Incomplete" in this context means that either the number of hours spent on a job during last month or income are missing.

and only if information about the main job is also present.

In the period from 1994 to 2011 the RLMS contains 73 672 real wage observations constructed as described above. This is a relatively small number compared to datasets used in other studies, especially considering missing observations from 1997 and 1999. That means that estimation techniques that employ first-differencing will not use information from 1998 and 2000 as well, reducing the number of observations even further. Table 1.2.1 presents summary statistics for the key variables. As discussed further in the text, wage arrears play an important role in the analysis of wage cyclicality in Russia therefore the data decomposition by arrears is presented.

The fact that the sample is relatively small across both time and individuals dimensions raises two questions important for any cyclicality study: is the sample representative and is there enough variation in the business cycle indicator i.e. were there enough cycles? To check representativeness of the sample I conduct a simple test: I compare unemployment rate that I calculate based on the RLMS data[6] and the official unemployment rate published by the national statistics office. The latter is based on a survey of more than 69 000 people each year, which is approximately 7 times larger sample than the RLMS[7]. As can be seen on figure 1.2.1a the unemployment rate obtained from the RLMS is generally slightly lower than the official one. However the trends are the same and the average difference is only 0.8 of a percentage point. One can thus conclude that the RLMS is at least as representative as the larger samples used by the Federal Statistics Office.

As for the existence of cycles, the variation in both measures seems sufficient. Hard post-USSR times that culminated in the financial crisis and the default on government bonds in 1998, followed by the stabilisation of the 2000s and the impact

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[6]Respondents' availability to start work within the next fortnight required by the ILO to be classified as unemployed is not taken into account before 1998. The corresponding question was not part of the survey in early years.

[7]Federal Statistics Office methodological guidelines can be accessed at http://www.gks.ru/

Table 1.2.1: Means (standard deviations in parentheses) of main variables

	Years	Affected by arrears*	Not Affected**	Full Sample
Number of observations				
	1994-2011	35637	38035	73672
	1996-2011	30212	37163	67375
Mean log real wage lnW				
CPI based	1994-2011	3.59	3.95	3.77
		(0.94)	(0.82)	(0.90)
	1996-2011	3.58	3.94	3.78
		(0.93)	(0.82)	(0.89)
GDP deflator based	1994-2011	3.72	4.03	3.88
		(0.91)	(0.80)	(0.87)
	1996-2011	3.72	4.03	3.89
		(0.90)	(0.79)	(0.86)
Log real wage changes (ΔlnW)				
CPI based	1994-2011	0.06	0.07	0.07
		(0.75)	(0.61)	(0.69)
	1996-2011	0.11	0.08	0.1
		(0.71)	(0.60)	(0.65)
GDP deflator based	1994-2011	0.05	0.05	0.05
		(0.74)	(0.61)	(0.68)
	1996-2011	0.08	0.05	0.07
		(0.71)	(0.60)	(0.65)
Average unemployment rate (%)				
	1994-2011		8.62	
			(1.91)	
	1996-2011		8.72	
			(2.00)	
Av. change in unemployment rate				
	1994-2011		-0.04	
			(1.23)	
	1996-2011		-0.2	
			(1.21)	

Notes: *people who have reported being affected by arrears at least once during the sample period
**people who have not reported being affected by arrears even once during the sample period

(a) Unemployment rates   (b) Inflation (based on CPI)
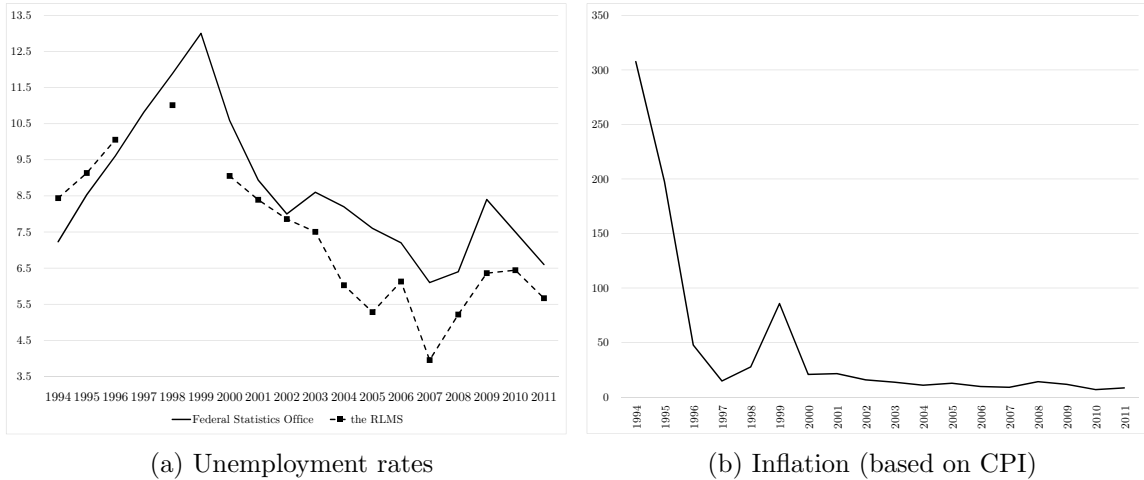
Figure 1.2.1: Unemployment and inflation rates in Russia

of the global economic crisis on unemployment in 2009 – all can be clearly identified on the graph. These events definitely should have affected real earnings of the population, however only estimation will show whether such variation is sufficient to estimate cyclicality coefficient with sufficient precision.

Trends and turning points coincide for both versions of the unemployment rate, therefore there is little difference which one to use. In all estimations presented below I use the official unemployment rate. The choice is explained by the low number of observations per region in the RLMS. It makes official figures more reliable for the analysis at the regional level thus, to be consistent, I use them throughout the paper.

Workers' experience which is used as one of the controls in estimations is calculated as respondents' age minus years they spent in education minus 7. If the result happens to be negative, a zero value is assigned. 7 stands for the age at which children go to school in Russia. Years of education are assigned based on the information on completed and incomplete degrees held by respondents. Lengths of education programmes are standardised in Russia. This allows for mapping degrees into years required to obtain them. There was a change from 8 to 9 years of com-

pulsory schooling in the late 2000s. However, responders affected by that change are too young to appear in the sample.

1.3   Specification

The great advantage of a micro-panel approach over time-series analysis of country-level data for estimation of wage cyclicality is the ability to get around the composition bias problem discussed in details in Solon et al. (1994). Country level wage statistics is essentially an average of wages of different groups of people weighted by the number of hours worked. Low-skilled workers tend to have more procyclical working hours and therefore they are assigned less weight in aggregate statistics during recessions compared to expansions. This in turn creates a countercyclical bias.

The most straightforward way to address the composition bias is to estimate a balanced panel. However, this approach would result in a very low number of observations. Thus to use maximum of information the RLMS provides I employ a widely-used methodology suggested by Solon et al. (1994). The regression is specified in the following way:

$$lnW_{it} = \alpha_1 + \alpha_2 t + \alpha_3 t^2 + \alpha_4 (u_t - \delta_1 - \delta_2 t - \delta_3 t^2) + \alpha_5' Z_i + \alpha_6' X_{it} + \alpha_7' X_{it}^2 + \alpha_8' Z_i X_{it} + \epsilon_{it}$$

(1.1)

where W_{it} is the real wage of individual i, u_t is the unemployment rate, t is a time trend, Z_i is a vector of time invariant worker characteristics[8], X_{it} is a worker's

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[8]Standard practice in the literature is to control for education and race. I do not use race information. This issue is of much less importance for the Russian labour market than, for example, in the case of the USA. Even if I wanted to control for it, the closest information to race the RLMS contains is self-perceived ethnicity. However, it is reported only in 70% of the cases and 85% of the answers indicate that the person is Russian. The second chapter expands the argument for omitting the ethnicity variable.

experience, ϵ_{it} is a random error term. A quadratic trend included in the equation allows for cyclical deviations of the variables from their trends. The estimated sign of α_4 indicates whether the real wages exhibit procyclical (< 0), countercyclical(> 0) or noncyclical $(= 0)$ behaviour. Hereafter I refer to equation (1.1) as "the model in levels". First-differencing gives:

$$\Delta lnW_{it} = \beta_1 + \beta_2 t + \beta_3 \Delta u_t + \beta_4 X_{it} + e_{it} \tag{1.2}$$

where $\beta_2 = 2(\alpha_3 - \alpha_4\delta_3)$, $\beta_1 = \alpha_2 - \alpha_3 + \alpha_4(\delta_3 - \delta_2) + \alpha_6 - \alpha_7$, $\beta_4 = 2\alpha_7$. The coefficient $\beta_3 = \alpha_4$ is the one of interest. In addition to taking into account the effect of work experience on wage (it directly enters the relationship) equation (1.2) controls for time-invariant worker characteristics as they are differenced out.

Under the assumption that error term e_{it} in equation (1.2) does not depend on business cycle conditions[9], first differencing successfully addresses the composition bias. Estimation focuses on changes in individuals' wages rather than on their levels. Hereafter I refer to equation (1.2) as the "first-differenced model".

The first-differenced model can be estimated by OLS. However, as shown by Moulton (1986), the estimates of standard errors are likely to be biased due to cross-sectional dependence in e_{it}. All individuals in the sample share the same country environment. That might come with many unmeasurable common effects but on top of that all individuals face the same unemployment rate in any given year and therefore have the same value used in estimations. Following a common approach, to deal with this problem, the estimation is carried out in two stages. First OLS is

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[9]An example of a situation when the error term is not independent of the busyness cycle is when a large proportion of respondents leave the sample because of current economic conditions. In this case the estimates would be biased. For a detailed discussion see e.g. Solon et al. (1994). This problem is less likely when the survey has a follow up practice. It is the case with the RLMS.

applied to the following micro-level equation:

$$\Delta ln W_{it} = \gamma_1 + \gamma_2 X_{it} + \gamma_3' D, \tag{1.3}$$

where D is a vector of year dummies. Estimates of components of γ_3 comprise time series of real wages. Essentially each dummy's coefficient is equal to the average change in real wages that year in comparison to the base year taking into account workers' characteristics. At the second stage OLS is applied to

$$\gamma_{3,t} = \eta_1 + \eta_2 t + \eta_3 \Delta u_t, \tag{1.4}$$

where η_3 is an estimate of β_3.

An alternative approach (results of which are presented in Section 1.5) is a direct estimation of equation (1.1) with worker fixed effects included. The fixed effects estimation deals with the composition bias in a way similar to first differencing. The estimation focuses on deviations of individuals' wages from their means rather than on the levels. I use this approach as a robustness check.

1.4   Results

The results presented in this section are obtained by estimation of equation (1.2) using 2-stage technique described in the previous section. CPI is used to calculate real wages, the base year is 2008. Years 1994 and 1995 are omitted from the sample. In those times Russia suffered from severe hyperinflation (as illustrated by Figure 1.2.1b). It is open for a debate whether it makes sense to analyse real wages during periods of hyper inflation. I believe that those years will obscure true degree of cyclicality as wages are likely to appear more procyclical than they really are.

During hyperinflation real wages must have been decreasing incredibly fast. The specification used would attribute most of that decrease to unemployment which was constantly on the rise. That would result in a very large cyclicality coefficient. However, growth of unemployment in the 1990s was no more significant than its decline in the 2000s. Therefore the result would be an overestimation of the actual cyclicality observed during normal times.

1.4.1 Main findings

The results in Table 1.4.1 indicate that when the unemployment rate increases by one percentage point real wage declines on average by more than 4 percent. This coefficient is quite large in absolute terms and reflects strong cyclicalyty that real wages in Russia have been exhibiting over the last decades. Absolute value of the coefficient is approximately 3 times larger that the one Solon et al. (1994) find for men in similar unbalanced estimation using the PSID dataset (-0.014). The estimates close to their are obtained by Shin and Solon (2007) for the USA using the NLSY dataset (-0.015 for salaried job-stayers, -0.01 for hourly paid job-stayers and -0.014 for the full sample). For the UK Devereux and Hart (2006) find that a one unit increase in unemployment results in a 1.7 percent decrease in real wages of male job stayers. Results of Peng and Siebert (2007) suggest that real wages in West Germany are also procyclical with a cyclicality coefficient around -0.01. Thus wages in Russia are found to be significantly more flexible than in many developed economies.

Table 1.4.1: Estimated real wage cyclicality in 1996 - 2011

	Coef.		[95% Conf.	Interval]
Δu_t	-0.043	***	-0.0691	-0.0168
	(0.011)			

significance levels: *10%, **5%, ***1%

The 95% confidence interval for the estimated coefficient is quite large (from -0.017 to -0.07) which is likely to be a result of a small number of observations available for the estimation. The final sample size that is actually used to produce table 1.4.1 is only 36 882 at the first stage. This number of observations seems small for a time period of more that 10 years so in Section 1.5 I attempt to address this issue and show that the results do not change dramatically. However even taking it into account large confidence interval the estimation result suggests that real wages have been strongly procyclical over the last 15 years.

1.4.2 Wage arrears: obscuring the reality?

Wage arrears is a situation when firms delay wage payments or simply do not pay. Wage arrears have received attention in the literature and the majority of research in the area has been done using the RLMS. Earle and Sabirianova (2002) provide a detailed discussion on possible rationale behind the arrears. They discuss both the reasons why certain firms have to and certain firm choose to withhold wages as well as the motives for workers to stay and keep working despite irregular pay. In their later work Earle and Peter (2009) develop a model of managerial decision to use arrears and argue that practice of violating employment contracts may be seen as an institution. Lehmann and Wadsworth (2007) show that wage arrears dramatically increase inequality. Skoufias (2003) and Guariglia and Kim (2003) study the effects of wage arrears on formation of precautionary savings, investigate which types of consumption are most protected, and how likely affected workers are to take up a second job. Lehmann et al. (1999) find that wage arrears are the dominant factor of job insecurity in Russia where, unlike in other transition economies, the absolute majority of workers have permanent full-time contracts. Wage arrears are interesting on their own and I will consider them in greater detail in the following chapters of

this thesis.

What is more important wage arrears might play an important role in a cyclicality study. If economic environment is in a bad state and workers are affected by arrears they are likely to report no income from their jobs. Next period, when economic situation becomes better firms are more likely to repay debts in full or at least partially. Workers in turn are likely to report higher income – several months worth of monthly wages. So one can clearly see that the arrears might create a procyclical bias.

The question that naturally follows is how common wage arrears are in Russia. They reached their peak in the late 1990s. 58% of workers in the RLMS indicated that firms owed them money in 1998. Thereafter the share of affected workers was constantly declining but never reached zero. Unfortunately even nowadays wage arrears are a problem, though a much less serious one than before[10].

A significant part of the sample that I use in the study overlaps with years when the arrears were common. As can be seen from table 1.2.1 half of the respondents in the sample have been affected by irregular pay at least once. Therefore it is a valid hypothesis that unusually strong procyclicality of real wages might be a result of strong presence of wage arrears in the sample.

On the other hand, procyclicality induced by wage arrears might seem to be similar in nature – in recessions, when wage arrears are likely, wages fall and during expansions they grow. Therefore it might not be necessary to draw a distinction. However even if one sticks to this interpretation it is interesting to understand whether the Russian case is of the specific nature.

In most cases people affected by arrears do not report their wages in that period.

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[10]The official data on wage arrears is vague and does not allow direct comparison between different periods of time. The way the data is presented changed several times: "total sum of withheld wages in the country" vs "number of firms that are currently in debt to their workers" etc. In this case the RLMS is the more reliable source.

As a result those observations are not taken into account (both income and hours should be reported for an observation to be used in estimations). Thus only around 6.3% of observations used are "affected" by arrears. Ignoring those observations practically doesn't change the result: point estimate goes slightly down to -0.041 (the first row in table 1.4.2).

However, omitting such observations doesn't solve the problem completely. Reappearance of "automatically dropped" individuals in the sample when they have been repaid and might report larger income could still create a bias. Moreover the fact that some observations are automatically dropped from the sample is actually an indication of a potential composition bias. If wage arrears are indeed caused by economic conditions, the fact that affected people leave the sample is not independent of the business cycle. The unlikely problem discussed in section 1.3 might be present. Therefore I separately run regressions for people who have never been affected by arrears and for those who have been affected at least once (the second and the third rows in table 1.4.2 respectively).

Table 1.4.2: Real wage cyclicality (1996 - 2011), decomposition by wage arrears

Specification	Coef.		[95% Conf.	Interval]
No "arreared" observations	-0.041 (0.011)	***	-0.068	-0.015
Not a single arrear	-0.040 (0.015)	**	-0.075	-0.004
Wage arrears at least once	-0.049 (0.009)	***	-0.070	-0.028

significance levels: *10%, **5%, ***1%
Note: "no "arreared" observations": observation is dropped if a person currently suffers from arrears; "Not a single arrear": only observations on individuals who have never been affected by wage arrears are used; "Wage arrears at least once": observations on individuals who have reported wage arrears at least once are used

As can be seen the results are close to the original ones and suggest strong

procyclicality of real wages.

Wages of individuals affected by arrears are more procyclical. That is expected as they are more likely to miss wages in recessions and receive wages in better periods. However true degree of procyclicality of their wages might be underestimated due to specific characteristics of the questions in the survey. Individuals are asked whether their firm owes them *any money for missed wages* and what was their *income in the last month* before the interview. Given such questions infrequent data is likely to smooth registered income fluctuations of affected workers.

The estimation also mixes people who have been affected only once with those who have suffered in several years. This also contributes to the cyclicality of wages of affected workers being underestimated. Information on the size of arrears and in-kind payments could yield a more accurate estimate. Relevant questions exist in the RLMS though suffer from lower response rate and inconsistency of provided information.

However, the main point of this exercise was to show that the procyclicality of wages is not driven by the arrears and possible composition bias is not a concern. The results strongly support this view. Alternative explanations for strong procyclicality should be looked for.

One could argue that workers in transition economies are often forced to take unpaid leave but don't formally become unemployed and thus the changes in unemployment rate could be understated compared to developed economies. That in turn would lead to a higher estimate of the cyclicality coefficient. However, while unpaid leaves existed, even in the 1990s (at their strongest) only a small percentage of the workforce were affected (less than 7.5% in 1996 (Lehmann et al., 1999)). In addition to that, due to first-differencing and missing observations from 1997 and 1999 my baseline estimation uses observations only from 2001 and later, when phenomena

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such as unpaid leave were of even smaller concern.

Potentially the answer lies in the low power of trade unions. According to OECD (2011), despite high unionisation numbers collective bargaining over wages in Russia is weak compared to the majority of OECD economies. The authors believe that, in combination with weak enforcement of regulations, it contributes to a very flexible labour market that was able to sustain low unemployment throughout the crises. This view is consistent with flexibility of real wages I find in the data.

The results can also be partly explained by the expansion nature of the time period. Lehmann et al. (2013) find that in the period from 2003 to 2008 Russian labour market was very dynamic and could easily absorb people who lost their jobs. Downward wage rigidity has been in focus of contract theory for a long lime and asymmetric responses of wages to positive and negative shocks are well documented for developed countries (see fore example Stuber and Snell (2014) for evidence from Germany and review of evidence from other countries.) Therefore, the large gap in cyclicality of wages between Russia and developed economies could be a result of the latter having gone through a larger number of cycles in estimation periods.

1.5   Robustness of the results

To check that the results described above are not spurious, a number of robustness checks are presented in this section. Small time dimension, relatively small initial number of observations topped up by significant losses due to first-differencing are among key potential concerns. Results could also be sensitive to choice of the deflator used to calculate real wages.

1.5.1 Estimation in levels

First differencing nearly halves the number of available observations. An alternative approach is to estimate equation (1.1) introducing fixed effects. To overcome cross-sectional dependence in error terms the same 2-step procedure as in the case of first-difference estimator can be used. The results are presented in Table 1.5.1[11]. This approach increases number of observations to 67 375.

Table 1.5.1: Real wage cyclicality (1996 - 2011) : model in levels, decomposition by wage arrears

Specification	Coef.		[95% Conf.	Interval]
Full Sample	-0.086	**	-0.1526	-0.0185
	(0.030)			
Not a single arrear	-0.077	**	-0.1469	-0.0074
	(0.031)			
At east one arrear	-0.091	**	-0.1569	-0.0248
	(0.030)			

significance levels: *10%, **5%, ***1%
Note: "no "arreared" observations": observation is dropped if a person currently suffers from arrears; "Not a single arrear": only observations on individuals who have never been affected by wage arrears are used; "Wage arrears at least once": observations on individuals who have reported wage arrears at least once are used

The obtained coefficient is now larger and suggests a decrease in real wages of 8.6 percent when unemployment increases by 1 percentage point[12]. This procyclicality is much higher than the one observed in the UK, the USA or Germany. However

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[11]When estimation in levels is performed one might be concerned about stationarity issues at the second stage. It is not obvious whether year dummies and unemployment series are stationary around a trend. Results of the Dickey and Fuller (1979, 1981) tests give mixed results depending on the specification (including indications that one or both series are non-stationary). However, the small number of data points makes use of procedures designed to detect the correct specification of the test (e.g. ones discussed in Dolado et al. (1990)) difficult. Moreover the estimated autocorrelation coefficients in Dickey-Fuller equations are far from unity. Therefore I carry out estimation acknowledging that this approach might be less reliable than the one used earlier.

[12]Standard errors in the table are likely to be underestimated due to positive low lag autocorrelation. The use of the standard methods of correction would assume that the observations are regularly spaced, which is not true in the sample

it is close to the result for northern Italy obtained by Peng and Siebert (2008) who estimate the coefficient of -0.091 for job-stayers in that region in contrast to noncyclical wages in centre-south. They conclude that the markets in the North seem to be efficient and focus on the difference in results between regions that can be partially explained by collective bargaining that takes into account current situation in the North only and passes on resulting wages to the South. This insight once again emphasizes the role of the unions. Unfortunately the RLMS does not distinguish between workers covered by collective bargaining from the rest[13].

Estimations controlling for wage arrears support earlier findings: real wages of affected workers are more flexible but wage arrears do not drive the overall procyclicality.

1.5.2 Estimation by regions

One of the concerns is the fact that the sample period covers only 16 years and in two of them survey was not conducted. To deal with this issue I carry out separate estimation for different regions in Russia. Under the assumption that regional labour markets are independent (this assumption is relaxed later) I obtain $14 \times$ number of regions independent time observations. Moreover estimation by regions might shed light on crucial differences between the regional labour markets.

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[13]The data distinguish between the private and the public sector, but the private sector does not mean the absence of collective bargaining.

Table 1.5.2: Regional level estimation (separate and Seemingly Unrelated Equations Estimator)

Region	first-differenced model			model in levels		
	coef.	[95% Conf.	Interval]	coef.	[95% Conf.	Interval]
1. Central Federal District	-0.037 (0.020)	* -0.083	0.009	-0.079 (0.032)	** -0.151	-0.007
2. Southern Federal District	-0.022 (0.012)	* -0.049	0.005	-0.041 (0.027)	-0.102	0.020
3. Northwestern Federal District	-0.017 (0.013)	-0.048	0.013	-0.039 (0.020)	* -0.084	0.006
4. Far Eastern Federal District	-0.076 (0.032)	** -0.149	-0.004	-0.072 (0.030)	** -0.139	-0.005
5. Siberian Federal District	-0.044 (0.010)	*** -0.067	-0.021	-0.053 (0.018)	** -0.093	-0.014
6. Urals Federal District	-0.055 (0.030)	* -0.124	0.013	-0.082 (0.023)	*** -0.134	-0.030
7. Volga Federal District	-0.035 (0.012)	** -0.063	-0.007	-0.059 (0.027)	* -0.120	0.002

SURE

Region	first-differenced model			model in levels		
	coef.	[95% Conf.	Interval]	coef.	[95% Conf.	Interval]
1. Central Federal District	-0.048 (0.009)	*** -0.067	-0.030	-0.043 (0.012)	*** -0.068	-0.019
2. Southern Federal District	-0.023 (0.004)	*** -0.030	-0.016	-0.021 (0.008)	*** -0.037	-0.005
3. Northwestern Federal District	-0.011 (0.007)	-0.025	0.003	-0.030 (0.006)	*** -0.041	-0.018
4. Far Eastern Federal District	-0.073 (0.020)	*** -0.112	-0.035	-0.044 (0.011)	*** -0.066	-0.022
5. Siberian Federal District	-0.044 (0.005)	*** -0.055	-0.034	-0.037 (0.007)	*** -0.052	-0.023
6. Urals Federal District	-0.056 (0.016)	*** -0.086	-0.025	-0.056 (0.009)	*** -0.075	-0.037
7. Volga Federal District	-0.026 (0.007)	*** -0.040	-0.011	-0.034 (0.009)	*** -0.051	-0.016

significance levels: *10%, **5%, ***1%

(a) Federal districts   (b) Regional unemployment rates
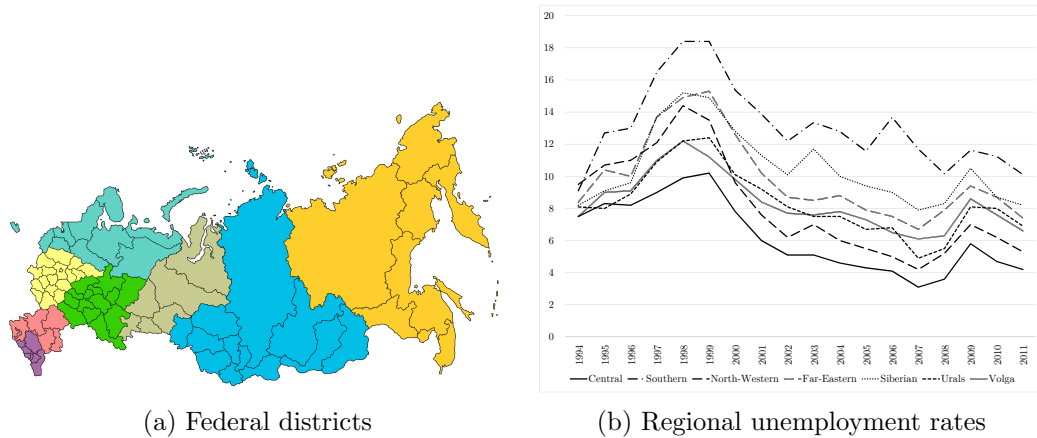
Figure 1.5.1: Federal districts and corresponding unemployment rates

I look at the seven federal districts introduced in 2000. The reason I prefer this subdivision is that it maintains a sufficiently large number of observations per region. In my estimation I use the original 7 districts and ignore the separation of the North-Caucasian district from the Southern district in 2010. Such approach gives me an average of 4 610 observation per region.

One other potentially interesting subdivision of those regions is a separate estimation for large metropolitan areas such as Moscow and Saint-Petersburg. However, Lehmann and Wadsworth (2000) find no evidence of hiring rates being different in the capital compared to other regions. Therefore, a given unemployment level does not reflect a drastically different set of outside options available to workers. Thus, in my eyes the benefits of such analysis would not outweigh the costs of having fewer observations.

Figure 1.5.1b demonstrates that clear ranking of the districts in terms of unemployment level exists with some regions swapping positions at the turn of the century. At the same time all regions share same trends and similar variation in unemployment. It suggests that differences in how local labour markets operate might not be large.

The results of region-by-region estimation of both the model in first-differences and the model in levels are shown in table 1.5.2. These results are obtained under the assumption of independence of regional labour markets. Such assumption might be plausible for some regions, mainly eastern, where the density of population is significantly lower and costs of moving to another city for a job are high. However a person from, for example, the North-western district can more easily move to the Central district or the other way around. Saint-Petersburg and Moscow are an example of two cities in different districts with noticeable labour flows between them. To relax the assumption of regional independence I estimate both the "first-differenced model" and the "model in levels" using Zellner (1962) Seemingly unrelated equations estimator. The results are also presented in table 1.5.2[14].

The coefficients estimated using a simple region-by-region approach vary. However, all of them are large (vary from -0.022 to -0.076)[15]. As in section 1.4.1, the first-differenced model suggests slightly weaker procyclicality compared to the estimates obtained from the model in levels. The largest difference, is in the case of Central Federal district, although even then the two estimates lie within the respective 95% confidence intervals.

The estimates suggest that real wages are more procyclical in the Asian part of Russia compared to the regions in the European part. In addition, real wages show weak procyclical behaviour in the North-Western and Southern districts. The estimates for both are on the border of being significant at the 10% level in one of the specifications and insignificant in the other one.

When SURE estimation is used the differences in estimates between the models

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[14]A two-step SURE estimation is used to produce the result in table 1.5.2. Estimates can be shown to be consistent after two steps. Iteration does not give significant efficiency gain, some estimates the "model in levels" spuriously diverge. Iterated estimates are available on request.

[15]Estimation in levels suffers from a slight low lag autocorrelation in residuals which is treated in the same way as in section 1.5.1

become much smaller and the coefficient for the Southern district becomes significant. This result supports the cross-regional dependence hypothesis. The findings on the relative degree of procyclicality between regions are unchanged, and the only region with noncyclical real wages is the North-Western federal district.

Alternative approach that takes into account interaction between regional labour markets and at the same time yields a single coefficient (and is thus likely to produce a more precise country-level estimate) is pooling of regional equations with cluster-robust standard errors[16].

Table 1.5.3: Estimation with cluster robust s.e. and restricted SURE

Cluster Robust s.e.							
first-differenced model				model in levels			
coef.		[95% Conf.	Interval]	coef.		[95% Conf.	Interval]
-0.039	***	-0.061	-0.017	-0.042	*	-0.093	0.008
(0.010)				(0.023)			
Restricted SURE							
first-differenced model				model in levels			
coef.		[95% Conf.	Interval]	coef.		[95% Conf.	Interval]
-0.036	***	-0.042	-0.030	-0.040	***	-0.052	-0.029
(0.003)				(0.006)			

significance levels: *10%, **5%, ***1%

The results are presented in table 1.5.3. In the estimation of the specification in levels additional dummies were used to account for differences in wage levels across regions. Restricted SURE estimates (where all regional coefficients are forced to be the same) are presented in the same table for comparison. The estimates are similar but not identical. Clustering allows for arbitrary correlation within groups and does not affect point estimates, whereas SURE uses covariances of the residuals from all equations to create a new coefficient estimate.

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[16]Generalisation of Huber (1967) and White (1982) sandwich-type estimator of variance-covariance matrix suggested by Rogers (1994) is used. Regional level data is clustered by years allowing for interaction between regions in any given year.

Irrespective of the approach regional estimations also provide evidence of strong procyclicality of real wages. Semi-elasticity is estimated to be around -4% for the whole sample. Separate regional coefficients vary but show clear procyclical behaviour in all regions except the North-western.

A possible explanation for the relatively weak cyclicality of wages in the Southern Federal District is constantly high unemployment. In such an environment workers' outside options are poor. This may force them to stay in firms and have fewer renegotiations of their contracts irrespective of cyclical changes. Noncyclical behaviour of wages in the North-western federal district is harder to explain. It might be related to stricter regulations and better enforcement in individual states within that region. That could create much stronger downward wage rigidity and contribute to weaker cyclicality. However, further research is needed to understand reasons behind such result.

1.5.3   1-step estimation

As mentioned above, a common 2-stage estimation procedure is used to overcome cross-sectional dependence in the error terms. It is not the only possible approach. In this subsection I present the results obtained by direct estimation of equation (1.2) with corrected standard errors.

I use the standard error correction introduced by Driscoll and Kraay (1998) and generalised for unbalanced panels by Hoechle (2007). They show that the non-parametric estimator of variance-covariance matrix is robust to a very general form of cross-sectional dependence. Moreover, a large N dimension is not a constraint so the approach is suitable for micro-panel studies[17]. The main drawback is the

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[17]Usual worry with parametric estimators is that as the number of observations N grows, the number of spatial correlations increases at the rate of N^2.

reliance of this approach on large-T asymptotic. Furthermore although such correction helps with the issue of unobserved effects that influence all individuals, it is powerless against the lack of unemployment information. There are only 16 different unemployment values at the country level and 112 at the regional level. I expect the confidence intervals to be much narrower because of considerably larger number of observations used to determine the coefficient. However I admit that the standard errors are still likely to be slightly underestimated as shown by Monte-Carlo simulations in Hoechle (2007). Hence I use this estimator as a robustness check.

For comparison I also present the results of a 1-step fixed-effects estimation of the model in levels (equation 1.1 with added worker fixed effects). To account for both cross-sectional dependence and potential serial correlation I use two-way clustering of standard errors developed in Cameron et al. (2006) and implemented in statistical software by Correia (2014).

Table 1.5.4: 1-step estimation results, first-differenced model, corrected standard errors Driscoll and Kraay (1998); Hoechle (2007)

Specification	coef.		[95% Conf.	Interval]
Full sample	-0.043 (0.004)	***	-0.052	-0.034
Not a single arrear	-0.038 (0.006)	***	-0.050	-0.026
At least one arrear	-0.049 (0.004)	***	-0.057	-0.041

significance levels: *10%, **5%, ***1%
Note: "no "arreared" observations": observation is dropped if a person currently suffers from arrears; "Not a single arrear": only observations on individuals who have never been affected by wage arrears are used; "Wage arrears at least once": observations on individuals who have reported wage arrears at least once are used

The 1-step estimation of the model in first differences provides similar results. As in the case of the 2-step approach, specification in levels provides less conservative estimates. However, estimation in levels uses a larger number of years. When the

Table 1.5.5: 1-step estimation results, model in levels, two-way clustered standard errors Cameron et al. (2006); Carneiro et al. (2012)

Specification	coef.		[95% Conf.	Interval]
Full sample	-0.073 (0.026)	**	-0.128	-0.017
Not a single arrear	-0.053 (0.025)	*	-0.107	0.001
At least one arrear	-0.088 (0.025)	***	-0.142	-0.033

significance levels: *10%, **5%, ***1% Note: "no "arreared" observations": observation is dropped if a person currently suffers from arrears; "Not a single arrear": only observations on individuals who have never been affected by wage arrears are used; "Wage arrears at least once": observations on individuals who have reported wage arrears at least once are used

sample is restricted to the observations used by first-difference estimator the coefficients are even slightly lower than the baseline ones (see table 1.5.6). Thus the strong procyclicality result is broadly robust to the choice of estimation technique.

Table 1.5.6: 1-step estimation results, model in levels, two-way clustered standard errors Cameron et al. (2006); Carneiro et al. (2012). The same sample as in the first-differenced model

Specification	coef.		[95% Conf.	Interval]
Full sample	-0.036 (0.012)	***	-0.064	-0.009
Not a single arrear	-0.028 (0.014)	*	-0.059	0.002
At least one arrear	-0.046 (0.012)	***	-0.073	-0.019

significance levels: *10%, **5%, ***1% Note: "no "arreared" observations": observation is dropped if a person currently suffers from arrears; "Not a single arrear": only observations on individuals who have never been affected by wage arrears are used; "Wage arrears at least once": observations on individuals who have reported wage arrears at least once are used

1.5.4 Inclusion of hyperinflation years and other minor checks

I previously argued that the inclusion of 1994 and 1995 in the sample period might be misleading because of hyperinflation in those years. Below I present the results that are obtained when those years are added to the sample (Table 1.6.1). As expected, the coefficients have larger absolute values. Estimates for equation (1.2) suggest that a 1 percentage point increase in unemployment rate leads roughly to a 10% decrease in real wages. Estimates in levels suggest an even higher degree of procyclicality. Region-by-region SURE estimation produces the most conservative results but the estimates are still approximately double the baseline ones. The results echo findings on the relative magnitudes of the coefficients in different regions. Overall such estimates seem to be a bit extreme and are influenced by hyperinflation in the early years. Estimates presented in Section 1.4 better reflect the cyclicality of real wages in the absence of hyperinflation.

To test robustness of the results to the deflator choice, I conducted all estimations using real wages based on the GDP deflator (the base year is 2008). The main results are shown in table 1.5.7. Overall, the use of GDP deflator does not change the results significantly. The estimated semi-elasticities appear to be lower but real wages still exhibit procyclical behaviour. However, a larger number of coefficients are statistically insignificant.

Though it is a valid robustness check, GDP deflator is less relevant for a wage study than CPI. The Russian economy is heavily dependent on minerals and oil extraction, processing and export. Those sectors make a significant contribution to the country's GDP and consequently have large weight in GDP deflator. At the same time they are heavily influenced by the changes in world oil prices. However those changes do not have direct influence on consumers. CPI, on the other hand, captures changes in prices that are directly relevant for household consumption. Therefore

the results obtained with CPI-based real wages are preferable.

Table 1.5.7: Estimation results with GDP deflator-based real wage

Specification	coef.		[95% Conf.	Interval]
		1996-2011		
First-differenced	-0.012		-0.053	0.029
	(0.018)			
In levels	-0.058	*	-0.12464	0.009239
	(0.030)			
		1994-2011		
First-differenced	-0.065	*	-0.133	0.003
	(0.031)			
In levels	-0.090	***	-0.140	-0.040
	(0.023)			

significance levels: *10%, **5%, ***1%

I also estimated the first-differenced model treating 2-year gaps in the data as if they were consecutive observations. The results mainly supported earlier findings, however coefficient for the workers unaffected by wage arrears becomes marginally insignificant. I believe that it is a result of the treatment of the gaps which happened in very specific years around the 1998 financial crisis.

In addition I estimated time series regression of the following form:

$$lnW_t = \alpha_1 + \alpha_2 t + \alpha_3 t^2 + \alpha_4 U_t + \epsilon_t. \qquad (1.5)$$

Before the analysis of micro-panel data became popular the studies that used estimations of this type could not support cyclicality of real wages. Maybe surprisingly, the result is almost identical to the one obtained from panel estimations. Real wages are procyclical with an estimated coefficient of around -0.05. As an aggregate wage statistics I used "*average monthly nominal gross payroll (for working people)*" published by the Russian Federation Statistics Service in the "Socio-economic indicators

of standard of living" section of the "Annual statistics bulletin".

This result also supports procyclicality of real wages and is remarkable given evidence the literature that this type of estimation may dramatically underestimate the actual procyclicality. The composition bias appears to be lower in Russia than, for example, in the USA.

1.6   Conclusion

This paper fills the gap in the literature by investigating cyclicality of real wages in Russia. The principal data source for the study is the RLMS dataset (1994 - 2011). Following the methodology suggested by Solon et al. (1994) and widely used in recent cyclicality studies, I find that real wages in Russia to be highly procyclical.

Depending on the sample period, real wages are 4 to 9 percent higher when unemployment rate decreases by 1 percentage point. Real wages tend to be more flexible to the East of the Ural mountains.

Wages in the Southern federal district are less procyclical. They increase by 2.2% in reaction to a 1 percentage point decrease in unemployment. This can be partially explained by the permanently higher unemployment level in the region. Workers have poorer outside options and fewer opportunities to renegotiate their contracts during expansions.

The North-western federal district is the only one with noncyclical wages. Potentially this could be related to local regulations and better enforcement that create strong downward wage rigidity. Further research is needed to identify the underlying differences between this region and the rest of the country.

The estimated degree of procyclicality is higher than those obtained by other researches for the USA, the UK, Germany or Portugal. This may be due to weakness of

collective bargaining in Russia. OECD studies found that despite high unionisation numbers, the unions in Russia are weak. As a result the labour market is flexible and is able to maintain low unemployment during crises. The results may also be partly driven by the the expansion nature of the majority of years used in baseline estimations.

Wage arrears do not prove to be the driving force for strong procyclicality of real wages. However, semi-elasticity of wages of people facing arrears tends to be approximately 1 percentage point higher that of the unaffected workers.

The results of this paper raise several questions that could be addressed in future research. First, a separate investigation of downward and upward adjustments in wages as well as an analysis of the role of collective bargaining could aid better understanding of the reasons behind wage flexibility. Unfortunately the RLMS does not contain information on trade unions and therefore different data sources need to identified.

Furthermore one could use additional questions from the survey related to firm size, ownership structure and workers' careers to obtain more precise estimates for specific groups of individuals. For example for job-stayers and job-movers or people employed in the private and the public sectors. However, small sample size for each category combined with data quality issues make estimation difficult.

Finally, wage arrears have little impact on the results of the study. This indirectly supports the view that wage arrears are not always related to financial difficulties during recessions (see Earle and Sabirianova (2002) for a discussion). This points in the direction of additional research on the nature of wage arrears.

Table 1.6.1: Real wage cyclicality (1994 - 2011). Results from various specifications

Specification	coef.		[95% Conf.	Interval]
First-differenced	-0.099	**	-0.174	-0.023
	(0.034)			
First-differenced, 1-step	-0.080	***	-0.131	-0.030
	(0.026)			
In levels, 2-steps	-0.125	***	-0.180	-0.070
	(0.025)			
Regions clustered, first-differenced	-0.086	***	-0.136	-0.037
	(0.023)			
Restricted SURE, first-differenced	-0.069	***	-0.083	-0.055
	(0.007)			

	Region-by-region (independence assumed)				SURE estimation			
Region	coef		[95% Conf.	Interval]	coef		[95% Conf.	Interval]
1. Central Federal District	-0.090	**	-0.164	-0.015	-0.064	***	-0.092	-0.035
	(0.034)				(0.014)			
2. Southern Federal District	-0.063	**	-0.120	-0.007	-0.042	***	-0.057	-0.027
	(0.025)				(0.008)			
3. Northwestern Federal District	-0.088	*	-0.178	0.002	-0.039	***	-0.069	-0.010
	(0.041)				(0.015)			
4. Far Eastern Federal District	-0.138	***	-0.210	-0.067	-0.115	***	-0.147	-0.083
	(0.032)				(0.016)			
5. Siberian Federal District	-0.081	**	-0.161	-0.001	-0.053	***	-0.080	-0.027
	(0.036)				(0.016)			
6. Urals Federal District	-0.085	*	-0.175	0.005	-0.081	***	-0.115	-0.048
	(0.040)				(0.017)			
7. Volga Federal District	-0.098	**	-0.181	-0.015	-0.053	***	-0.087	-0.018
	(0.037)				(0.018)			

significance levels: *10%, **5%, ***1%

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Chapter 2: Scarring effect of wage arrears

This investigates influence of wage arrears on the future of affected workers in Russia. The principal source of data is the RLMS (1994 - 2012). Limited dependent variable models are used to analyse the effects of wage arrears on the probability of future wage arrears and frequent separations from employers. Difference-in-difference approach is used to analyse effects on earnings. The results suggest that affected workers are twice as likely to experience wage arrears again within next 3 years. Job-movers are able to decrease probability of repeated wage arrears by 9 percentage points. The effect on separations is more modest: affected workers are approximately 40% more likely to change jobs the next year and 11% more likely to experience frequent separations within 5 years after wage arrears. The effect on future earnings is relatively small and short-lived. Take-home wages decrease by 1 000 RUB compared to unaffected workers and recover within next year. Analysis of stocks and flows of wage arrears indicates that in the period from 1998 to 2012 on average $\frac{3}{4}$ of wage debts were repaid.

2.1 Introduction

Wage arrears proved to be an extremely serious problem in the Russian economy. According to the RLMS dataset around 60% of workers were affected by delays in wage payments in 1998. Though wage arrears have become less common in the 2000s they have not disappeared completely. In fact when the great recession started wage arrears made a noticeable comeback (Walker, 2008). Though they never reached dramatic levels of the late 1990s wage arrears made international news when Fabio Capello, former Russia international team manager, was not paid for 6 months in a row after the World Cup in 2014. If even high paid public figures experience such problems (Fabio's salary was rumoured to be €12 000 000 per annum), one can only guess what the true situation for ordinary working class citizens is.

Wage arrears are not purely Russian phenomenon. Examples from China, India, Romania, the Kyrgyz Republic, Greece, Portugal, Bosnia and Herzegovina, Albania, Serbia and the Ukraine can be found in academic literature(Demirguc-Kunt et al., 2011, 2013; Cheng et al., 2013; Tiongson and Yemtsov, 2008). Cases from countries such as the UAE, Brazil and even the UK surface the news (Hadid, 2006; Liddington, 2016; Cockburn, 2016; Calnan, 2016; HRW, 2006).

Reasons behind wage arrears vary between countries and even within a country. Often arrears are thought to be caused by an aggregate negative shock (Boyarchuk et al., 2005) , but sometimes they are a result of opportunistic behaviour of entrepreneurs and even may be considered as part of local custom (Earle and Sabirianova, 2002; Earle and Peter, 2009). Naturally workers of different age, education levels and gender have different chances of avoiding wage arrears. Majority of papers including Earle and Sabirianova (2002), Earle and Peter (2009), Richter (2006), Cheng et al. (2013) and Guariglia and Kim (2003) find that men are more likely to suffer from wage arrears than women. Low skilled jobs are characterised by

higher risk of wage arrears. Incidence of arrears is usually much lower in metropolitan areas than in rural regions. "Newer" sectors of transition economies, such as banking and services in general, are less affected than production sector (Earle and Sabirianova, 2002; Fankhauser et al., 2008). Not only are unaffected workers characterised by higher levels of education, but recent graduates are under-represented among affected workers (Lehmann and Wadsworth, 2007). This increases returns to education in times of wage arrears.

The existence of wage arrears imposes both private and public costs. One of the obvious public consequences of wage arrears is increased income inequality. Results of counterfactual wage distribution modelling by Lehmann and Wadsworth (2007) suggest that wage arrears were responsible for as much as 30 % of inequality in Russia in the late 1990s. This is a serious problem given all the evidence on how inequality negatively affects growth and its sustainability (for a discussion of the literature on that topic see for example Ostry et al. (2014)). When talking about the effects of wage arrears for individuals the literature focuses on how people respond to the situation. The results of Skoufias (2003) and Guariglia and Kim (2003) indicate that affected workers and members of their families make more precautionary savings and are more likely to moonlight. Food consumption is shown to be characterised by the smallest reductions in response to wage arrears. textcolorredSimilar results are found by Desai (2001) who also investigates in more detail various survival strategies used by affected workers including barter trade.

This paper contributes to the literature on private costs of wage arrears and investigates whether arrears leave a "scar" that affects workers' future and whether the effects are short- of long-term. The literature does not come to definitive conclusion about whether the companies target specific workers for arrears. Earle and Sabirianova (2002) and Earle and Peter (2009) discuss of various reasons why it might be

the case[18]. At the same time Lehmann and Wadsworth (2007) note that the parameters of the counterfactual distribution in the absence of wage arrears are very close to the parameters of the actual one. That suggests that "victims" are drawn from throughout the underlying distribution, and can be seen as an argument against targeting. However, given all the evidence on characteristics of affected workers it is clear that wage arrears are not a random event irrespective of whether firms target specific employees on purpose or not.

Famous results of Davis and Wachter (2011) and Couch and Placzek (2010) show that wages of workers who have been displaced during mass layoffs do not recover in 20 years after the event. Lehmann et al. (2013) find that though in Russia the costs of job displacement are mainly associated with foregone earnings due to unemployment rather than with lower wages upon re-employment, monthly income losses are still statistically significant for 3 years after the displacement.

Just as mass layoffs wage arrears often affect a large share of firm's workers and happen against workers' will. This raises a question whether the consequences of the events are similar.

It has been more than 15 years since the first incidences of wage arrears in Russia and the sample of affected people is large relative to other countries[19]. The RLMS dataset contains several questions related to wage arrears that allow me to analyse the "scarring" effect. Lehmann et al. (1999) use the early years of the RLMS and find a positive effect of wage arrears on the probability of quitting a job and discuss characteristics of workers affected multiple times. However, the data available at the time did not allow to study mid- or long-term effects.

In this paper I focus on three different repercussions of wage arrears. First of

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[18]We discuss those reasons in more details in the following chapter.

[19]For comparison the highest proportion of affected workers Cheng et al. (2013) find in their sample is 9% compared to 58% in the RLMS.

all such experience may mean that the worker is more likely to be affected by wage arrears again in the future. This may be due to some observed or unobserved characteristics that make them more vulnerable. For example, certain levels of education and ability, or loyalty that stops them from leaving the company. The probability of future arrears may be increased even if the worker changes jobs. New firm may be able to extract a negative signal from the mere fact that the worker had such experience in the past. Firms might look more closely for flaws or just decide that in case of difficulties that worker is a good candidate to be among the first ones not to be paid. A presumption that a person, who has suffered from wage arrears before, might have resignation to such experience, can also make the difference.

The second hypothesis considered in this paper is that affected workers are more likely to experience separations from their current and future employers. The main reasons for separation from the current employer would be either dissatisfaction with the ongoing situation (failure to get repaid, recurring arrears etc.) or a desire to avoid such episodes in the future. Reasons for why they might change jobs more often in the future include potential difficulties with adapting to new environments and building up trust with a new employer. The adaptation argument is mainly relevant for high tenure workers that have not been on the labour marker for a long time. The trust argument is valid for all age and tenure groups. Having experienced wage arrears once, workers may be much less forgiving in the future, especially if the debt has not been repaid. Therefore they might be much quicker to leave new firms than their colleagues without arrears experience. On top of that, every separation leads to a loss of firm specific human capital and in many cases an additional unemployment spell. Unemployment spells contribute to lower wages at new jobs and new firm-specific human capital takes time to accumulate. This also makes it easier to leave if workers are not completely satisfied at their new job.

The discussion of firm-specific human capital and additional unemployment spells makes a bridge to the discussion of the third adverse effect of wage arrears considered in this paper. Just as with job displacement one could expect wages of affected workers to drop. When workers change jobs they might get lower pay associated with a probation period or lack of firm specific knowledge. During recessions they might experience higher competition for jobs or have to change their profession. Both could force them to accept entry level wages. Given the evidence in the job displacement literature it is not unreasonable to suspect that recovery of wages to the pre-arrears trajectory may take a significant amount of time.

The list of potential effects of wage arrears on workers' future is far from being inclusive. One can easily imagine many more effects related to stress and health, forced relocation to another region, lack of motivation and the resulting underdevelopment of personal skills. If wage arrears are widespread enough they affect the overall productivity in the economy, slow down growth and impose large social costs. However, many of the effects from this potentially endless list are hard to measure. The first three, on the other hand, can be identified directly from the questions in the RLMS.

This paper considers a longer times pan than previous studies on wage arrears in Russia: 1994 to 2012. To analyse the influence of wage arrears on the future wage arrears and future separations I use limited dependent variable models. Wage effects are investigated with a difference-in-difference approach following Davis and Wachter (2011). The results indicate that workers that experience wage arrears are on average twice as likely to face the same problem within the following 5 years as unaffected workers (30 percentage points increase in probability). They are also 40% more likely to change jobs within a year after wage arrears (4.5 percentage points increase in probability) and 11% more likely to experience two or more separations

within next 5 years. The effect of wage arrears on the level of wages is less significant. On average in the year of the event affected workers experience a 1 000 RUB drop in take-home wages compared to unaffected ones. The wage recovers already in the following year. The results are consistent with earlier findings of Lehmann et al. (1999) about wage arrears and separations in period from 1994 to 1996 and Lehmann et al. (2013) about minimal wage losses upon re-employment.

Another interesting question important for understanding the costs of wage arrears is whether the arrears are repaid. In an attempt to give an answer to this question I perform a stocks-and-flows analysis of wage arrears. The results should be taken with care due to data issues, however they suggest that approximately 70% of wage arrears are paid back. This conclusion is consistent with previous findings of Lehmann and Wadsworth (2007) for the 1994 - 1998 sample.

The rest of the paper is organised as follows: section 2.2 contains description of the data, section 2.3 presents the results and robustness checks for the recurring wage arrears effect, section 2.4 analyses the effects of wage arrears on future separations, section 2.5 investigates the response of wages to wage arrears, section 2.6 analyses stocks and flows of wage arrears and section 2.7 concludes.

2.2 Data

The principal source of data used in this paper are waves 5 (1994) to 21 (2012) of the RLMS ("Russia Longitudinal Monitoring survey, RLMS-HSE"[20]). The survey was not conducted in 1997 and 1999 therefore there are no observations from those years.

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[20]"Russia Longitudinal Monitoring survey, RLMS-HSE", conducted by the National Research University Higher School of Economics and ZAO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS.

To identify affected workers I use respondents' answers to the following question *"are you currently owed any money that your firm failed to pay you on time?"*. To construct measures of stocks and flows of arrears answers to the to the following two questions are used: *"how much money do they owe you?"* and *"how many months do they owe you the money for?"*. The last question is related to the Russian custom of using monthly wages as numeraire for wage arrears. Further in the text I refer to the information based on the former question as "self-reported" stock of arrears. Information from the latter question is used to construct measures of both stocks and flows "based on duration of wage arrears" by multiplying by *average monthly wage*.

The dataset also contains other questions related to the debt size, information from which I do not use. For example in some years respondents were also asked whether they had received any production output instead of money and whether they had been able to sell it. In case they were successful in selling they were also asked how much money they had been able to get that way. However these questions were dropped from the data set in 2008 and were rarely answered in the earlier waves.

Other variables used in this study include real wages, occupation, geographical region and personal characteristics such as gender, age, level of education and marital status. The RLMS has two separate questions related to wages. The first one asks for the *take-home* wage the worker received within 30 days before the interview. The second one asks for the *average monthly wage* irrespective of whether it is paid on time or not. Such distinction allows to analyse the difference in effects of wage arrears on the take-home wage and contract wage. Real wages are calculated using CPI with the 2008 base year. The dataset contains information on up to three jobs per individual. However information on the third one is rare and often incomplete so combined wages from 2 main jobs are used in the analysis.

The *level* of education reported by respondents is transformed into *years of education*.[21] The RLMS contains information on the highest complete and incomplete degrees held by the respondents. Years of education are assigned based on the length of the educational programmes that lead to those degrees in Russia[22].

The tenure variable is generated based on the question *"What year did you start your employment at current firm, at current job. If you have had multiple employment periods at this firm name the most recent start date"*. The question is interpreted differently by different respondents and even by the same individuals in different years. This leads to a rather noisy measure of tenure.

The RLMS does not contain race questions and instead asks for self-perceived ethnicity which is historically considered more important in former soviet republics. The response to the ethnicity question is registered only 70% of the time and 85% of those observation indicate that the respondent is Russian. This is of little surprise. Ethnicity information was excluded from the Russian IDs after collapse of the USSR to fight discrimination. Since then there has been a tendency among citizens not to answer the ethnicity questions to emphasise its irrelevance. For obvious reasons one could expect such behaviour from minorities. All this contributes to little variance in the variable and very few observations for ethnicities other than Russian. For this reason the results presented in this paper are obtained without ethnicity as a control variable. However the results hold when such a variable is included and can be provided on request.

The main issue with the data on wage arrears in the RLMS is its frequency. The questions do not provide information about the date when wage arrears happen.

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[21]The lengths of education programmes are standardised in Russia. This allows for mapping degrees into years required to obtain them.

[22]Lengths of all educational programmes in Russia are stantardised. There was a change from 8 to 9 years of compulsory schooling in late 2000s, however people affected by that change are too young to appear in the survey

Neither does the survey specify how exactly the questions should be answered. For example, consider a worker who does not get paid anything one month and another worker who gets half of the wage two months in a row. They both might say that they are owed 1 month of wages, however the second worker can indicate that they are owed "for two months". There is no way of distinguishing between cases when wages are partially paid and when a payment is missed completely. The number of individual occurrences of wage arrears within a year also can not be observed. All this has an effect on types of analysis that are feasible. General drawback of the dataset is the high attrition rate. The average number of observations per individual in the 1994 - 2012 sample is only 4. It substantially limits the extent to which long-term effects can be analysed.

Table 2.7.1 in the appendix presents summary statistics for the main variables over several years for comparison. Gender composition as well as the average tenure, age and education are stable throughout the sample.

2.3 Current and Future Wage Arrears

2.3.1 Baseline estimation approach and results

There are different views in the literature on whether firms target specific employees when they do not pay wages on time. The results of a multinominal logit analysis of Earle and Sabirianova (2002) provide some evidence that firms do differentiate among employees when it comes to wage arrears, especially based on tenure and shareholdings. Counterfactual wage distribution modelling by Lehmann and Wadsworth (2007) on the other hand suggests that affected workers are drawn from across the distribution of wages. That can be seen as an argument against targeting. Irrespective of whether firms use any targeting techniques when they don't pay

wages, workers affected by wage arrears might indeed posses certain observable or unobservable characteristics that made them victims. For example they might have low level of qualification or education. Firms that experiences financial difficulties but for various reasons do not want to lay off any workers would naturally delay wages of the least productive employees. The same firms may want to violate employment contract of a higher tenure or of an older employee as those are usually less mobile and therefore are less likely to leave. Affected workers might be employed in certain sectors of the economy or geographical regions where incidence of wage arrears is very high because all firms have financial difficulties and have to delay wages to survive. In that case even if there is no targeting the workers are likely to suffer from wage arrears several times during their careers.

Not only might workers posses certain characteristics prior to their first wage arrears experience, they may also acquire them after the first instance. People tend to be more disturbed and react more aggressively when something unpleasant happens to them for the first time. You can compare it to owning a brand new car: the first stone chip on the bumper is quite upsetting, the five hundred and thirty first may go unnoticed. By the same token, workers might become accustomed to wage arrears. One could have an endless discussion of numerous examples from an infinite list of observed and unobserved, possibly acquired qualities related to wage arrears.

The point is that once workers have experienced delays in wage payments they can expect to suffer again in the future. This is one of the "scars" left by wage arrears and to investigate how strong this effect is I run a series of cross sectional estimations of the following probit model:

$$P(\omega_i^t = 1 | \omega, X) = \Phi(\alpha \omega_i + X_i'\beta), \tag{2.1}$$

where Φ is the cumulative distribution function of a standard normal distribution, ω_i is equal to 1 if a worker is affected by wage arrears in a given year and 0 otherwise, X_i is a vector of controls, α and β are coefficients. The dependant variable ω_i^t is a boolean variable that is equal to 1 for the workers that experience wage arrears within next t years (hereafter I refer to t as an *event window*). I refer to w_i as *current* wage arrears. This is the event the scarring effect of which is analysed. I refer to ω_i^t as *future* wage arrears. Those are hypothesised to be partly caused by the *current* arrears.

The main advantage of the year-by-year estimation is the ease of analysis of the differences in the effect of wage arrears that happened in different time periods, for example before Russia's default on its bonds in 1998 and after. The desire to make such distinction is explained by the potentially different nature of wage arrears in the 1990s and the 2000s. Wage arrears in the 2000s are likely to be more "normal" in the sense that they are likely to be a result of firms' financial problems. Wage arrears in the 1990s were likely to be at least partially caused by a short-term government bonds bubble. Returns on those bonds exceeded 200 % (Richter, 2006). Firms had a lot of temptation to invest workers' money to make extra profit. Earle and Sabirianova (2002) discuss other incentives not to pay wages for firms in the 1990s Russia[23].

Fewer and fewer years are left in the dataset after each year considered in the estimation. Therefore there are less future time periods for workers to be affected by wage arrears. If not taken into account, that would create decreasing time trend in the estimates and obscure the results when coefficients are compared across years. The event window of t years is introduced to overcome this problem.

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[23]Third chapter of the thesis contains more elaborate discussion of this matter and develops a model to investigate whether proposed differences in nature of wage arrears could be responsible for high incidence of them at the turn of the century

The set of controls includes age, gender, marital status, current tenure and years of education for each individual.

As demonstrated by (Brown and Light, 1992) using the the Panel Study of Income Dynamics, tenure variables in survey based datasets are prone to measurement error – respondents may misreport their tenure due to changing nature of questions or simply memory issues. This may lead to inconsistencies of tenure within observations for each particular individual. That in turn can lead to biased estimates. The bias may be quite severe when tenure effects are large, especially in limited dependent variable models. Brown and Light suggest several ways of correcting the internal inconsistencies in the sample. The results are strongly affected by the choice of the correction procedure. To determine the best tenure partition for the PSID they use employer codes in the National Longitudinal Survey (NLS) to determine the true partition and pick the correction procedure that works best.

In this paper I do not to use any correction procedures for the following reasons: First of all, only 4.7% of observations are plagued by unambiguously inconsistent tenure. Moreover, as demonstrated further in the text, the effects of tenure are small compared to the effects of the main explanatory variable (wage arrears). In several estimations tenure is insignificant for the majority of years in the sample[24]. On top of that, the results I obtain for the early years of the sample are consistent with results in Lehmann et al. (1999) and Lehmann and Wadsworth (2000) where a correction in line with one of the procedures described in Brown and Light (1992) was performed.

I do not include ethnicity as the explanatory variable due to concerns discussed in section 2.2. Unlike in the US ethnicity and race are not, or at least significantly less, important for the Russian labour market[25]. This is partially explained by the

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[24]Estimations without tenure have been performed and the coefficients of interest are not affected in any significant way. Those results are available on request.

[25]For literature on racial wage and unemployment gaps see for example Couch (2002) and Ritter and Taylor (2011).

common cultural background with the former USSR republics where the majority of migrants working in Russia come from[26]. One could mistake lower wages of workers from central Asia for an example of a racial wage gap. However, migrants from those regions are usually low-skilled and employed at jobs that require little qualification. Therefore such "race effect" should be captured by the education level and tenure variables. Section 2.3.5 discusses alternative approaches to estimation and compares the results.
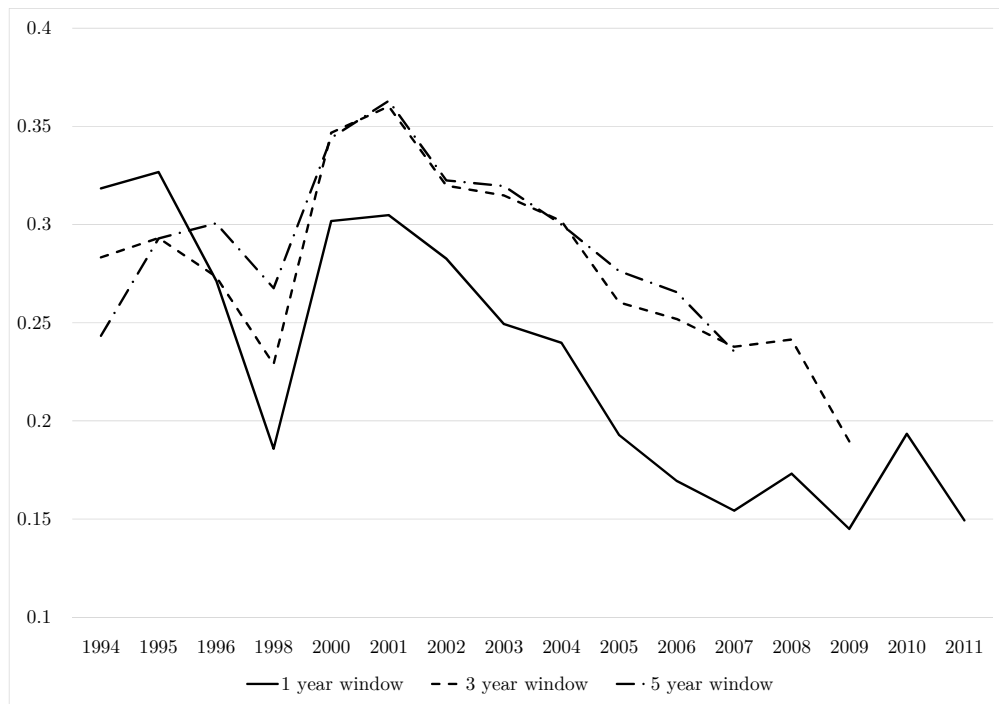
Figure 2.3.1: Marginal effects of current wage arrears on future wage arrears within the next 1, 3 and 5 years

The estimations were carried out for 1, 3 and 5-year event windows. Full estimation results can be found in tables 2.7.2 - 2.7.7 in the appendix. The coefficient on current arrears is highly statistically significant in all the years. Here, we are

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[26]Recent statistics can be found for example in (Scherbakova, 2012)

truly interested in the corresponding marginal effects. All marginal effects presented below were calculated at sample means of other variables. For instance the marginal marginal effect of the current wage arrears ω is given by $\Phi(\hat{\alpha} + \bar{X}_i'\hat{\beta}) - \Phi(\bar{X}_i'\hat{\beta})$, where "hats" represent estimates. Figure 2.3.1 plots the estimated marginal effects of current wage arrears on probability of future wage arrears.

The marginal effects in all years are large. People who were affected by wage arrears in the early 2000s were 35 percentage points more likely to be affected again within the next 3 years. The effect is smaller for the late 2000s. However, it exceeds 15 percentage points. To put it into context, for a 3 year event window, the predicted probability of future arrears for unaffected workers is 17.5 % in 2001 and 5 % in 2009. On average, affected workers are estimated to be more than twice as likely to suffer from wage arrears again compared to the unaffected counterparts.

There is a noticeable downward trend in the marginal effect. This is likely to be related to the fact that the incidence of wage arrears has been consistently declining from almost 60% in 1998 to 3.5% in 2012 according to the RLMS[27]. As wage arrears were less and less common, it is natural that the marginal effect of wage arrears on future wage arrears was declining as well.

The drop in the marginal effect in 1998 is most likely explained by the absence of observations in 1997 and 1999. In estimations for 1996, and 1998 the next year observation is missing. In these cases the event window was extended from 1 year to 2 years, so the estimate for those years shows effect of current wage arrears on probability of wage arrears at the time of next interview rather than next year. However, the event windows were not extended for the 3 and 5- year cases. It means that people affected by wage arrears in 1998 had fewer future observations. These effects are compounded by Russia's default on short-terms bonds in August 1998.

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[27]Figure 2.7.1 in the appendix presents proportion of affected workers in all the years

As extreme rate of returns on those bonds was one of the reasons why firms did not pay wages on time[28], many firms lost incentives to use wage arrears and reverted to normal practices.

The fact that the influence of the current wage arrears on the future ones was the strongest in 2000 and 2001, in my opinion, is also related to the default of 1998. Firms that kept violating employment contracts after the 1998 financial crisis were much more likely to experience genuine financial difficulties. Employees of such firms would be more likely to continue experiencing delays in payments. If the problems were industry- or regionwide even change of employer would not help to avoid future problems. Section 2.3.2 investigates differences in consequences of wage arrears for job-stayers and job-movers.

Interestingly the marginal effects for 3 and 5-year windows are practically identical. On the one hand it suggests that new instances of wage arrears tend to occur within 3 years after previous ones. On the other hand, this result could be driven by the low number of consecutive observations for each worker in the dataset.

During 1994-1995 the trend in marginal effects of current wage arrears is increasing and the largest impact on probability of future wage arrears is estimated for the 1 year event window. This suggests that a person affected by wage arrears was more and more likely to be affected the following year. The economy entered a spiral where wage arrears were creating even more wage arrears. This is consistent with the view that short-term bonds and other "opportunities" and grey schemes in the mid-1990s played a significant role in the rise of wage arrears in Russia.

Remarkably, the harmful effect of current arrears on the future has remained strong even when the economy converged back to its normal state.

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[28]For more detailed discussion see Earle and Sabirianova (2002), Earle and Peter (2009), Richter (2006) and the third chapter of this thesis)

2.3.2 Job-stayers and Job-movers

Different workers react differently to complications that arise in their relationships with employers. Some are more willing to compromise, others are ready to leave the company at the first opportunity. When it comes to wage arrears the optimal behaviour is far from obvious at all. On the one hand, if workers leave the firm they are very unlikely to be able to collect the arrears. Especially in Russia where up until recently employees had no right to initiate bankruptcy hearings on the grounds of wage arrears. And even if the company is declared bankrupt former employees are one of the very last in repayment order[29]. On the other hand, by staying in the company workers encourage the firm to keep violating the contract, and there may be limit after which nobody would be willing to work for free.

As one would expect with such a complicated matter, respondents in the RLMS dataset do not behave according to any distinct pattern. However the fact that some of them stay in firms longer than others shed light on the extent to which changing jobs can help to avoid wage arrears in the future.

To find an answer to that question I estimated model 2.1 separately for between-company job-movers and job-stayers. In this exercise I do not distinguish between job-stayers and within-company job-movers. There are two reasons for that. First of all the dataset does not contain firm identifiers. This makes identification of within-company job-movers very complicated even if a 4 digit ISCO08 occupation code is used. The second reason is that *between-company* moves are the important ones for the analysis. The hypothesis is that moving to a different firm rather than changing the role within a firm can help to reduce the future impact of wage arrears. To a new employer an affected worker could seem no different from any other new hire

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[29]For further discussion of the reasons why workers might want to stay despite not being paid see Earle and Sabirianova (2002) , Earle and Peter (2009) and the third chapter of this thesis.

who have not experienced wage arrears.

In the absence of firm identifiers in the dataset I use tenure to identify between-company job-movers. Due to the nature of the data workers who return to one of their previous employers and choose to report the original (previous) job start date are not identified as job-movers. However, employers are likely to have records about any returning employees and therefore to have more information about those workers than a new employer would. Thus, we do not necessarily want to distinguish such cases when testing the theory and this identification problem is of small concern.

The estimation is carried out for the same event windows as in previous section. Figure 2.3.2 compares marginal effects for job-stayers and job-movers.

(a) event window: 1 year   (b) event window: 3 years   (c) event window: 5 years
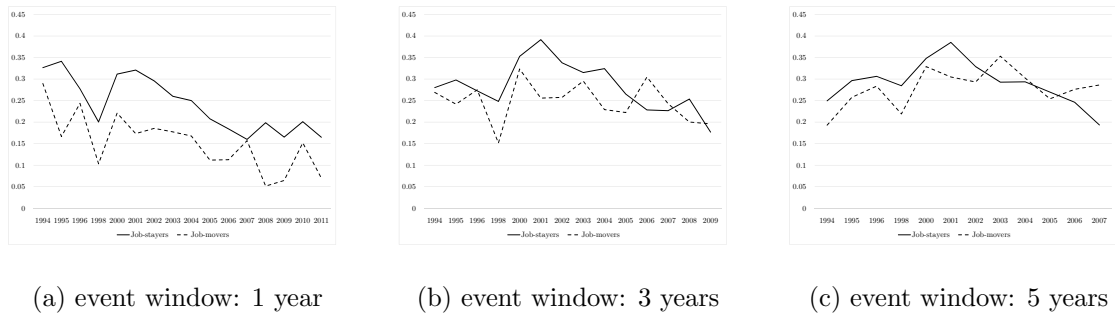
Figure 2.3.2: Marginal effects of current wage arrears on future wage arrears: job-stayers vs job-movers

On average current wage arrears have an 8 percentage points stronger effect on probability of wage arrears in the next year for job-stayers. The impact of current arrears is statistically insignificant for job-movers in 2008 and significant only at the 10% level thereafter. Job-stayers experience a highly significant and large effect throughout the sample – a more than 15 percentage points increase in probability of wage arrears next year compared to unaffected workers. The conclusion is that moving jobs is indeed a remedy, at least to some extent.

The difference between the two groups over 3 years following the event is con-

sistently smaller throughout the sample. In the case of a 5-year event window, the lines representing marginal effects practically merge. By switching jobs workers may not be able to get rid of both observable and unobservable characteristics that make them victims in the first place. Over several years new firms are able to learn about qualities of the workers and as a result moving job has a smaller effect on probability of future arrears over a longer period.

In these estimations, however, job-stayers are defined as workers who have not changed their employer a single time during the event window. Everyone else is considered a job-mover. In other words, a worker could stay at his original firm for two or three years, experience recurring wage arrears and then leave the firm. Such a person would also be considered a job-mover. This can obscure the true effect of changing firms.

To investigate this issue further I define job-movers as workers who change jobs in the year following the event. The results of such estimations for 3 and 5-year windows are presented in figure 2.3.3.
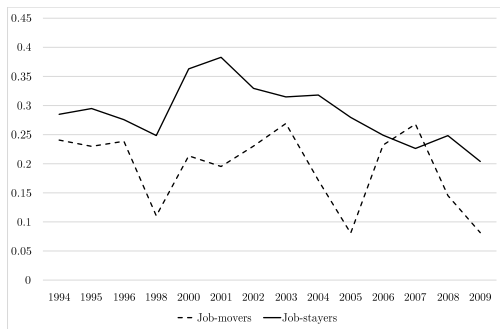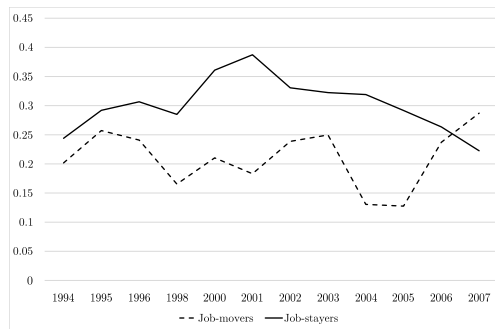
(a) event window: 3 years   (b) event window: 5 years

Figure 2.3.3: Marginal effects of current wage arrears on future wage arrears: job-stayers vs job-movers under alternative (strict) definition on job-stayers

The results suggest that the average difference in marginal effects of current

wage arrears for workers who change employers immediately after bad experience and those who do not is 9 percentage points. It is twice the difference obtained with a less strict definition of job-stayers. The difference between the groups is larger in the mid-2000s with moving jobs having less of a positive effect in the 1990s and the late 2000s. Such result indicates that people who stay with their employer despite irregular pay do experience wage arrears regularly. And though the impact of wage arrears on the future likelihood of wage arrears is very large either way, changing jobs does help to reduce it.

2.3.3 Occupational and Regional Effects

There is a significant amount of evidence in the literature that the incidence of wage arrears depends on the occupation and region, see for example Earle and Sabirianova (2002), Lehmann and Wadsworth (2007). Several channels contribute to this result. If wage arrears are prevalent in the region or among firms of the same sector of the economy, outside options available to workers are poor. This allows firms to exploit wage arrears more. This situation is likely to occur in the so-called mono-towns, where majority of workers are employed by a single big factory, and quite unlikely in large megalopolises like Moscow and Saint-Petersburg.

Younger workforce and lower importance of firm-specific knowledge contribute to more mobile labour. In an industry characterised by these factors wage arrears are unlikely to become widespread.

In this subsection I investigate whether occupational and regional differences not only affect probability of wage arrears but also the "depth of the scar" left by them.

To distinguish between occupations I use highest level, single digit, classification according to the International Standard Classification of Occupations (ISCO08)[30].

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[30]The codes can be found here: http://www.ilo.org/public/english/bureau/stat/isco/isco08/

The RLMS contains lower level 4-digit occupation codes as well, but the distinction at a finer level does not leave enough observations per group. Even with single digit codes some groups proved to be too small to be included in estimation, for example "armed forces occupations" after 2004 and "skilled agricultural, forestry and fishery workers" after 1996.

The regional differentiation is based on the Federal Districts of Russia rather than on smaller regional divisions. Even with this approach, the number of observations for the Far-Eastern federal district drops to around of 260, but I am able to maintain an average of 830 observation per region.

The results from section 2.3.1 suggest that there is little difference in the effect over 3 and 5 years and both are substantially larger than the effect on the next year only. Therefore in this section I focus on the analysis of the 3-year event window.

Figure 2.3.4a presents marginal effects of wage arrears on future wage arrears across regions. The effects seems to be very similar for the majority of regions. Interestingly, the North-Western and Far-Eastern regions are characterised by the strongest and the weakest impact of current wage arrears throughout the sample. However their respective position changed after 1998. From 1994 to 1998 workers in the North-Western district experienced the largest increase in probability of future problems when affected by wage arrears. At the same time employees in the Far-Eastern district enjoyed the lowest effect. From 2000 onwards the regions swapped their positions. Figure 2.3.4b illustrates this point and compares the extreme regions to full sample result.

This result is most likely related to the amount of effort individual regions put into fighting wage arrears. The arrears, at least in the late 1990s - early 2000s, were a state wide problem that was getting a lot of attention from the national news and federal government. However Russia is a federative state where regions have considerable

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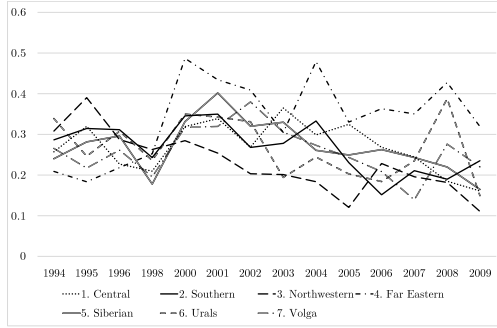
(a) All federal districts
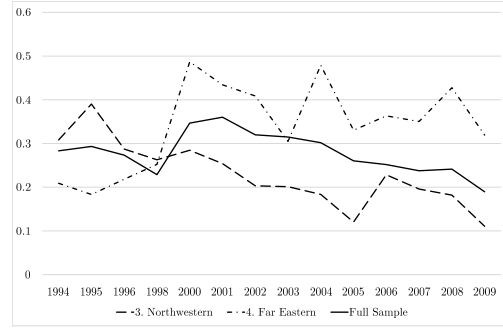
(b) North-Western and Far-Eastern federal districts

Figure 2.3.4: Marginal effects of current wage arrears on future wage arrears: cross-region comparison

power over local regulations and policies. For example Saint-Petersburg, the largest city of the North-Western federal district, had special programmes designed to ensure that losses of population during the crisis of 1998 were minimal and to boost economic growth of the region way above the country average (ETLA, 2000). Maybe as a result of these policies, the levels of wage arrears in the region were one of the lowest in the country[31].

Unfortunately official information on regional policies from that time is very scarce. However if during the times of widespread use of wage arrears regions in the North-Western district were putting significant effort to prosecute companies exploiting the practice and help the firms experiencing genuine difficulties. That would suggest that workers affected by wage arrears were employed by the companies who were not able to pay on time despite the intervention from regional authorities. It means that such firms were experiencing deep problems and would be unlikely to pay their employees on time in the near future.

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[31]According to the RLMS, "only" 34% were affected in 1998 with average delay in payments under 2.5 months compared to 5.5 country average.

Now consider a region with fewer government interventions. Wage arrears would carry no extra signal about the true financial state of the enterprise and thus the impact of arrears on the future would be smaller.

In times when wage arrears were not as widespread competition between firms on the labour market would become an important factor. In a region with good outside options, workers would leave the company that pays irregularly. Such experience would have relatively small impact on their future. In contrast, in a region characterised by large share of remote mono-towns, for example mining towns in the Far East, many workers would be trapped in their firms. As firms would have weaker incentives to pay on time, wage arrears would have stronger impact on probability of repeated wage arrears in the future. This theory helps to explain the results for North-Western and Far-Eastern federal districts. However it requires further investigation which in turn requires access to detailed archive information on regional policies.

Figure 2.3.5 presents marginal effects of current wage arrears by occupation groups. Differences across occupations are not obvious. The effect is consistent and strong for all of them and the groups change positions relative to other occupations every year. At the same time "Managerial" occupations were in the top 3 of the strongest effects in 9 years and "Services and Sales" were characterised by one of 3 weakest effects on 9 occasions. Figure 2.3.5b plots results of those groups against full sample results.

Relatively strong effect for managers is likely to be explained by the nature of their jobs. Many of them are either partially responsible for payment decisions or are employed at positions critical for firms' survival. In both cases they would be one of the last to suffer from wage arrears. At the same time, again due to the nature of their jobs, they are less likely to abandon a "sinking ship" and are the ones to

navigate it through hard times. This suggests that if they experience wage arrears the situation is truly difficult and is not likely to change quickly.

Weaker effect for Sales and Services workers, in my opinion, is explained by the nature of the sector. As documented by Earle and Sabirianova (2002) wage arrears were less common in "newer" sectors of economy, such as sales and banking. Lower incidence of wage arrears in a sector contributes to better outside options for workers and therefore reduces harmful effect of wage arrears.

(a) ISCO08 top level occupation groups   (b) Managers vs Service and Sales workers

Figure 2.3.5: Marginal effects of current wage arrears on future wage arrears: cross occupation comparison

2.3.4   Marginal Effects of Control Variables

Though the main focus of this paper is the impact of wage arrears on the future let us briefly talk about other explanatory variables[32]. All estimated coefficients have expected signs. However none of the controls proves to be consistently significant throughout the sample. Figure 2.3.6 presents the marginal effects of the control variables.

In the baseline estimations presented above "current" values of control variables

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[32]See tables 2.7.2 – 2.7.7 in the appendix for full estimation results

(a) event window: 1 year   (b) event window: 3 years   (c) event window: 5 years
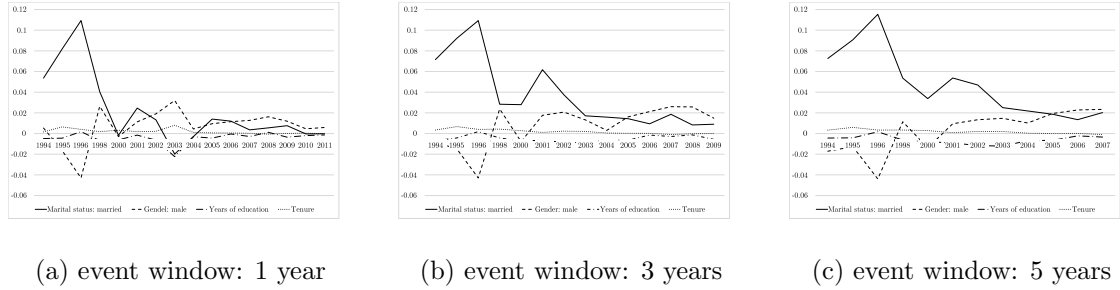
Figure 2.3.6: Marginal effects of control variables on future wage arrears

are used (as opposed to the values in the years when recurring wage arrears happen). For some variables, for example age, or gender it does not matter. Either those variables are invariant or firmly related to their later values. As predictors of future wage arrears they capture everything their future values would. For some variables, for example tenure, the argument does not hold. If a worker leaves their firm the tenure is reset. It is up for a debate which value is better and whether the choice affects the results. I argue that "current" tenure is more important.

Future wage arrears might depend on future tenure. However my goal is to study the scarring effect of *current* wage arrears and it is current tenure that affects the "depth" of the "scar". It defines how likely the worker is to change jobs, how much human capital she would lose by doing so, how outdated her knowledge is by the standards of the current labour market and many other things.

The estimated coefficient on tenure is positive – larger tenure contributes to larger probability of wage arrears in the future conditional on current problems. This is most likely explained by loyalty and lower mobility of high tenure workers. Interestingly, across all three estimation windows, tenure loses its significance around 2003 and does not gain it back. In my opinion it is another piece of evidence that supports the ideas of opportunistic nature of wage arrears in Russia and targeting of workers. If a firm experiences genuine problems they would be more likely to delay

payments to all employees. If they are trying to increase the profits they would target workers who are the least likely to leave.

When it comes to marginal effects they prove to be very small – tenths of a percentage point.

Years of education have the opposite effect compared to tenure. More education makes people less likely to suffer from wage arrears in the future. It is consistent with the belief that more educated and higher skilled people have better outside options available to them. In contrast to tenure education becomes significant in the 2000s and is not significant in the 1990s. Marginal effects also do not exceed 1 percentage point.

Age is insignificant in most estimations. Evidence on the effect of gender is mixed. Previous literature found that unskilled men suffer from wage arrears more often than other groups. My estimations suggest that after 2005 men were 2 percentage points more likely to experience future wage arrears across all 3 event windows. However, for the time period before 2005 gender proved to be largely irrelevant[33].

Marginal effects of marital status follow a time pattern similar to that of tenure – they are mainly insignificant starting from the early 2000s. On rare occasions certain types of relationships are significant in certain years. For example having a partner but not being married increased probability of wage arrears within next 3 years by 4 percentage points in comparison to single individuals in 2006. But it is not a consistent pattern. At the same time in the 1990s married respondents were on average 10 percentage points more likely to experience delays in payments than single individuals. This may be explained by lower mobility associated with having a family at the time of widespread wage arrears. In such conditions families were

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[33]The coefficient in 1996 is one of the few significant ones and suggests that men were 5 percentage points less likely to experience wage arrears in the future. However this result might be driven by irregularly spaced data (missing observations in 1997 and 1999).

more likely to have to move further away to escape the "arreared region" compared to later days when it would be enough to find a job on the other side of the city.

The results in this section illustrate how significant the role of wage arrears has been throughout the whole sample period in predicting recurring wage arrears. In addition the analysis of other explanatory variables highlights the difference in nature of wage arrears of different eras. The next section checks how robust the results are.

2.3.5 Robustness: Alternative Specifications

Two common alternatives to (2.1) are logit

$$P(\omega_i^t = 1|\omega, X) = \Lambda(\alpha\omega_i + X_i'\beta), \tag{2.2}$$

and linear probability model (LPM)

$$P(\omega_i^t = 1|\omega, X) = \alpha\omega_i + X_i'\beta, \tag{2.3}$$

where Λ is the c.d.f. of a logistic function. Full estimation results for the 1, 3 and 5-year event windows can be found in Tables 2.7.8 - 2.7.19 in the appendix. Figure 2.3.7 presents estimated marginal effects.

The results are very similar to those of probit estimation. The difference is most noticeable in the effect on probability of wage arrears one year later. From 1998 onwards LPM produces larger and logit smaller marginal effects than Probit, but the largest difference does not exceed 0.8 of a percentage point.

Fitting a correct panel model is quite challenging as within the panel framework the model in question is dynamic. For the event window of length 1 the LPM looks
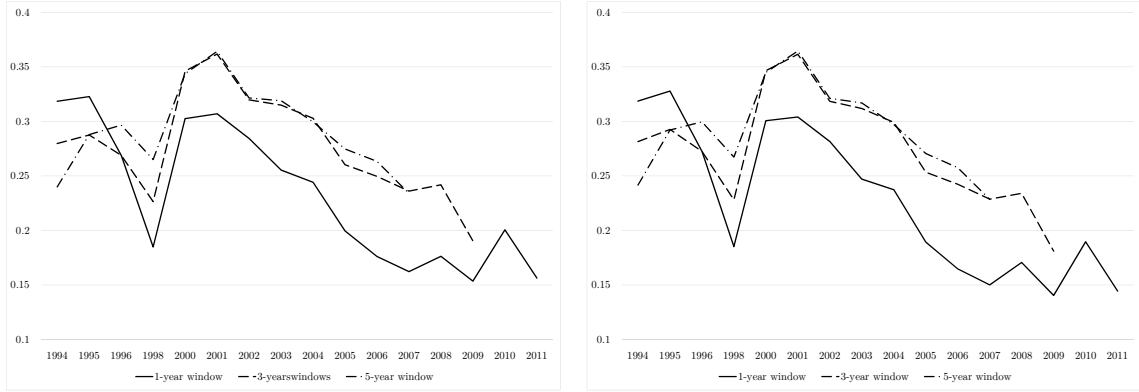
(a) LPM   (b) Logit

Figure 2.3.7: Marginal effects of current wage arrears on future wage arrears: LPM and Logit models

as follows:

$$P(\omega_{it} = 1|\omega, X) = \alpha\omega_{i,t-1} + X'_{i,t-1}\beta. \tag{2.4}$$

In case of a wider event window as many lags of ω should be included as the width of the window. Inclusion of the lags of other explanatory variables would give rise to collinearity problems. At this point we can also revisit earlier discussion about which values of explanatory variables should be included – from the years when the "event" happens or from when recurring wage arrears occur. Looking slightly ahead I can confirm that marginal effects of wage arrears on probability of future wage arrears are insensitive to the choice of the values of other explanatory variables. That is expected given that majority of them have a clear time trend[34].

The main advantage of the panel framework is its ability to deal with individual level unobserved effects as well as a significant increase in the number of observations. However the non-linear limited dependent models suffer from a well-known

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[34]As the results are virtually identical I do not report tables for different specifications. In the panel estimations presented below values at the time of future wage arrears are used by default. The reason for that is to demonstrate that the results are robust to such manipulations with specification. The results of estimations with "current" values of controls are available on request.

incidental parameters problem. Unlike in the linear case estimation of individual unobserved effects leads to inconsistent estimates of the parameters of interest. For a detailed discussion see for example Wooldridge (2010). Simulations by (Heckman, 1981) show that the incidental parameters problem is even more severe in a dynamic setting. Moreover, an additional problem arises known as the initial conditions problem. Lagged dependent variables violate strict exogeneity. The initial value of the dependent variable is likely to be correlated with the unobserved individual effect. That effect in turn affects future realisations of the dependent variable. Several approaches to treatment of the initial observation have been introduced in the literature, including (Heckman, 1981) and (Wooldridge, 2005). However as mentioned in the latter, the log-likelihoods are derived for balanced panels. Carro et al. (2015) show that ignoring unbalancedness of the panel results in inconsistent estimates when either the unbalancedness is correlated with individual effects or the process underlying the dependent variable is not in the steady state. Given evidence on the changing nature of wage arrears over time, the assumption that the underlying process is in steady state is unreasonable. According to the same authors maximisation of log-likelihood that does not rely on those assumptions in unbalanced panels is impossible with standard commands in econometrics software. Alternative approach would be to estimate a balanced sub-panel. However the average number observations per individual in the dataset is only 4, which makes this approach unattractive.

The dynamic LPM does not suffer from the mentioned problems as the individual unobserved effect can be differenced out. Pua (2015) shows that IV based estimators of dynamic LPM such as Anderson and Hsiao (1981) provide inconsistent estimates of average marginal effects. Thus I favour GMM estimator of Arellano and Bond (1991) for which such analytical result does not hold[35]. Table 2.3.1 presents the

---

[35]Though Pua (2015) provides an example where the obtained estimates lie outside nonparametric bounds derived by Chernozhukov et al. (2013) under the assumption of monotonicity

results.[36]

Table 2.3.1: Panel LPM. Arelano-Bond estimator.

	coef.	p-value	[95% conf. int.]	
ω_{t-1}	0.193	0.000	0.153	0.234
ω_{t-2}	0.086	0.000	0.057	0.115
ω_{t-3}	0.068	0.000	0.045	0.091
ω_{t-4}	0.020	0.033	0.002	0.039
ω_{t-5}	0.010	0.230	-0.006	0.027

The effect of wage arrears in the previous period is approximately 4 percentage points lower than the average marginal effect over the years obtained from cross-sectional probit (22.8) and LPM (23.2) estimations. The cumulative effect of 3 lags of wage arrears is 34.7 percentage points. It exceeds the average marginal effect obtained from cross-sectional estimations by approximately 6.5 percentage points. The same holds for the cumulative marginal effect over 5 years. Panel estimation results also indicate insignificance of wage arrears that happened 5 years ago. This is consistent with very similar results for 3 and 5-years event windows reported in section 2.3.1.

Overall, the results obtained from a dynamic LPM are similar to the baseline results. Some of the difference can be attributed to different set of explanatory variables. The Arelano-Bond estimator is a first-difference type estimator therefore all time invariant variables were dropped from the estimation. Also such estimation uses a significantly lower number of observations (18770) compared to the series of cross sectional estimations (total of 62101 for the 5-year event window). This is due to first differencing, use of past values as instruments and missing observations in

of marginal effects

[36]Specification checks indicate no autocorrelation of order higher than 1. The Sargan test rejects the validity of instruments, however I attribute this result to heteroscedasticity implied by LPM. The Sargan test has asymptotic χ^2 distribution only under homoscedasticity and over-rejects validity of instruments when this assumption is violated (Arellano and Bond, 1991).

1997 and 1999.

As time-invariant unobserved individual effects are differenced out in this estimation. The fact that the results are similar to the ones in section 2.3.1 further supports validity of cross-sectional approach.

2.3.6 Robustness: Heteroscedastic Probit

Probit model that accounts for potential heteroscedstisity

Heteroscedasticity has very different consequences in probit and logit models compared to linear models. We can rewrite (2.1) in its equivalent latent form:

$$
\begin{aligned}
\omega_i^{t*} &= \alpha\omega_i + X_i'\beta + \epsilon_i, \\
\omega_i^t &= 1 \quad if \quad \omega_i^{t*} > 0.
\end{aligned}
\tag{2.5}
$$

Then $P(\omega_i^t = 1|\omega, X_i) = P(\omega_i^{t*} > 0) = P(\epsilon_i < \alpha\omega_i + X_i'\beta) = \Phi(\alpha\omega_i + X_i'\beta)$. However, the last equality uses assumptions about the distribution of ϵ. More precisely in probit model this distribution is assumed to be standard normal. However, if the variance of the error term in (2.5) is not constant the correct representation is

$$
P(\omega_i^t = 1|\omega, X) = P\left(\frac{\epsilon_i}{\sigma_i} < \frac{\alpha\omega_i + X_i'\beta}{\sigma_i}\right) \neq \Phi(\alpha\omega_i + X_i'\beta),
\tag{2.6}
$$

where σ is the standard deviation of ϵ. For detailed derivations and discussion see for example Keele and Park (2006) or Williams (2009). Quite often this problem is described in the literature as inconsistency of probit estimates under heteroscedasticity that comes from the fact that model is wrongly specified (Wooldridge, 2010).

Solution to this problem was suggested by Harvey (1976) and later generalised to arbitrary c.d.f.[37] The idea is to allow the variance of the error term to depend

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[37]Williams (2010) discusses the general case and its implementation in statistical packages.

on a set of covariates z in a multiplicative way:

$$\sigma^2 = exp(z_i\gamma)^2. \tag{2.7}$$

Under this assumption the probability function becomes

$$P(\omega_i^t = 1|\omega, X_i) = \Phi\left(\frac{\alpha\omega_i + X_i'\beta}{exp(z_i\gamma)}\right) \tag{2.8}$$

and the log-likelihood is given by

$$lnL = \sum_{\omega_i^t=1}^{N}\left[\omega_i^t ln\Phi\left(\frac{\alpha\omega_i + X_i'\beta}{exp(z_i\gamma)}\right) + (1 - \omega_i^t)ln\left(1 - \Phi\left(\frac{\alpha\omega_i + X_i'\beta}{exp(z_i\gamma)}\right)\right)\right]. \tag{2.9}$$

A simple LR-test of $\gamma = 0$ indicates whether heteroscedasticity in the form specified by (2.7) is a concern. The proposed model has number of shortcomings. Very different interpretations of the results are possible especially if the results are significantly different from those of the usual probit estimation. This is due to the fact that it is hard to separate the effects of explanatory variables themselves from the effects of variances of residuals associated with those variables. But more importantly researchers have to guess the variables to be included into the variance equation (2.7). Keele and Park (2006) study performance of the model using Monte Carlo simulations. Their results suggest that over fitting (2.7) causes some distortions but worryingly omitting important variables causes bias stronger than in a model that ignores the issue altogether. Williams (2010) suggests that despite these results and efficiency losses it is a good practice to estimate heterogeneous choice model for diagnostics purposes.

Results under multiplicative heteroscedasticity

Given theories of potential targeting of employees by firms and the changing nature of wage arrears, heteroscedasticity can be a concern in this study[38]. Below I present the results of estimation of equation (2.8). Variables chosen for the variance equation (2.7) include age, tenure, years of education and gender[39].

Table 2.3.2 represents p-values for the LR-test for heteroscedasticity ($H_0 : \gamma = 0$).

Table 2.3.2: Heteroscedastic probit. Test results for significance of the heteroscedastic element of the model

| | $H_0 : \gamma = 0$. p-values | | | | $H_0 : \gamma = 0$. p-values | | |
	1 year	3 years	5 years		1 year	3 years	5 years
1994	0.929	0.200	0.329	2004	0.077	0.044	0.024
1995	0.150	0.073	0.133	2005	0.188	**0.021**	**0.027**
1996	0.060	0.060	0.092	2006	**0.010**	0.224	0.504
1998	0.851	0.818	0.529	2007	**0.021**	**0.004**	**0.012**
2000	0.907	0.652	0.537	2008	0.355	0.637	
2001	0.553	0.180	0.408	2009	0.076	0.577	
2002	**0.001**	**0.013**	**0.006**	2010	0.276	0.181	
2003	0.126	**0.039**	**0.010**	2011	**0.013**		

I reject the null of homoscedasticity in 28% of cases (12 out of 43). In all those cases tenure component of variance equations (2.7) is significant at the 5% level. Gender is significant part of that equation in estimation of 5-year event window for 2007.

Figure 2.3.8 plots the marginal effects. They are generally slightly lower. The largest differences are of 2.3 and 1.6 percentage points in estimations of 1 year event window for 2006 and 2007, respectively. Those are also the years where I reject homoscedasticity at the 5% level of confidence. These results suggest that the genuine

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[38]Variances of the error terms might very between, for example, different age and tenure groups.

[39]Estimations with self-perceived ethnicity and marital status have also been conducted. The results were similar and those variables were dropped to achieve higher efficiency in estimation avoiding over fitting the variance equation.

downward trend in marginal effects can be actually steeper than the one presented in section 2.3.1, albeit by a tiny margin. Overall, the results of heteroscedastic estimation support the findings from the baseline estimation.

Figure 2.3.8: Marginal effects of current wage arrears on future wage arrears within the next 1, 3 and 5 years. Probit corrected for heteroscedasticity

2.4 Wage Arrears and Future Separations

In this section I explore the effects of wage arrears on future separations. At least two interesting questions arise. First of all, do wage arrears make workers more likely to leave the firm that pays irregularly despite of all the unpleasant consequences of separations? The second question is whether wage arrears make workers more likely to experience frequent separations in the future, not only from their current employer

but from future employers as well. Higher tenure workers might have difficulties adopting to new environments. That can cause them to be less productive and fail to make it past employment trial period. Or they might switch firms more often in an attempt to find the one that resembles their original place of employment in as many aspects as possible. Even such non-quantifiable aspects as working atmosphere might become very important for somebody who had spend a long time at one firm and was forced to leave. Lack of trust with the new employer may also play a role. If wage arrears happen at the new job the worker might react faster than previously and leave the firm quicker. On the other side of the spectrum very low-tenure workers also might be affected. It is easier for them to move jobs, but if they start changing firms too often, even if wage arrears are the reason, it may raise suspicions of their future employers about their qualities.

The second question, in my opinion, is about a persistent effect caused by the arrears. In contrast, the first question might seem to be only indirectly related to "scarring". It is about how people react to wage arrears rather than the impact of arrears on the future. At the same time if a separation is indeed caused by wage arrears, it qualifies if not as a scar then at least as a wound. Besides, these results can be of great help to researches developing models of wage arrears[40].

Lehmann et al. (1999) find a significant effect of wage arrears on probability of quitting a job in period from 1994 to 1996. A much longer time span of the dataset available today allows to see if their findings hold in more recent years and whether there are any long-term effects.

To answer both questions I employ the same technique as in section 2.3.

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[40]The third chapter of this thesis presents a model that is built on assumptions partially motivated by the results of this chapter.

2.4.1 Effect of wage arrears on the probability of at least one separation in the future

To answer the first question I run a series of cross-sectional estimations of the following model:

$$P(s_i^t = 1|\omega, X) = \Phi(\alpha\omega_i + X_i'\beta), \qquad (2.10)$$

where $s_i^t = 1$ if a worker experiences at least one separation within next t years and all the other notation is the same as before. As before, to eliminate the downward trend associated with a decreasing number of future observations, I estimate the effect over 1, 3, and 5-year long event windows. The separation is identified by observing either unemployment after employment or a tenure of zero years. The fact that the data is yearly can create distortions in the measurement of the number of separations but should not affect the ability to detect at least one separation.

Full estimation results can be found in tables 2.7.20-2.7.25 in the appendix. The coefficient on current wage arrears proves to be significant in all years except the ones near the turn of the century and 2007. Insignificant coefficients in 1996 and 1998 can be once again explained by the gaps in the data and the fact that the dependent variable is forward looking. Insignificance in 2000 and 2007 are more likely to be genuine results. One possible explanation is that those years can be seen as post- and pre-crisis ones. Suppose that the Russian economy has been transitioning between 2 equilibria over last 20 years – one with no wage arrears and one with high arrears. After the default in 1998 the economy started its movement towards the steady state with few arrears. Workers were seeing improvement and did not see any reason to react to wage arrears, believing they might disappear in very near future. On the other hand, if the situation still was not normal 3 years after the default, workers could reassess the situation. This would explain why the

coefficient becomes significant again.

In my opinion the reason for 2007 result is very different. The dependent variable is forward looking. The financial crisis reached Russia in 2008 and had severe consequences for the economy in upcoming years. Wage arrears increased once again. Many people would experience a separation in 2008 and 2009 irrespective of whether they were affected by wage arrears in 2007 or not, thus the insignificant coefficient.

Figure 2.4.1a plots marginal effects from a probit estimation. An upward trend is observed. This is hardly surprising given that incidence of wage arrears has been steadily declining after 2000. The less common the arrears were, the easier it was to find a firm that would pay on time. Therefore workers would be more likely to leave firms in response to wage arrears.

Another observation that differs from the findings about the probability of future arrears is the fact that the marginal effect is always larger for longer event windows. This is consistent with workers not always reacting to wage arrears immediately. Such behaviour may be driven by loyalty and desire to give the employer a second chance or by the desire to collect arrears first and only then leave.
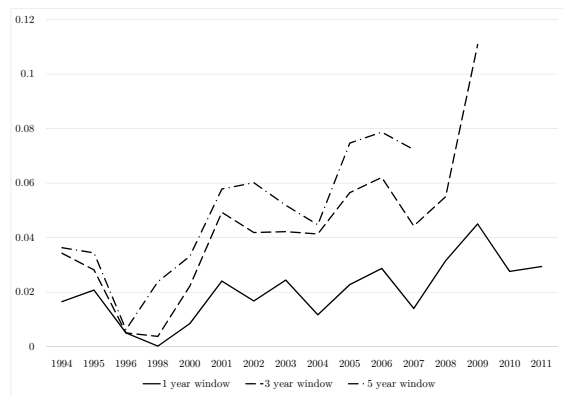
(a) Probit   (b) Heteroscedastic Probit

Figure 2.4.1: Marginal effects of current wage arrears on the probability of experiencing a separation within next the 1, 3 and 5 years. Probit model

Finally the magnitude of marginal effects is way lower compared to the ones seen in section 2.3. A worker affected by wage arrears after 2000 was on average 4.5 percentage points more likely to experience a separation within a year. Based on the estimates, the predicted probability of a separation within 1 year for an unaffected worker with mean characteristics is on average 10.5%[41]. A worker affected by wage arrears was thus on average 44% more likely to leave their current employer. This is a large effect.

As for the effects of other control variables, all of them except marital status are consistently significant throughout the sample period. All the signs are as expected and can be explained by differences in mobility between groups of people. Older respondents are less likely to experience separations, as are higher tenure workers. Better educated workers are also less likely to separate, potentially due to being more important for firms and therefore having better employment conditions. Unsurprisingly men are also more likely to change jobs than women, these patters are well established in the literature for various countries (see for example Fuller (2008) and Alison L. Booth (1999)).

The marginal effects of control variables are not particularly large. The effects of tenure are below half a percentage point and the effects of age are about 1 percentage point when 5 future years are considered. Education has a larger effect of 2 percentage points in magnitude over the same period. However, in case of future separations these small magnitudes make up a much larger share of the total probability. Moreover, the gender effect is as large as the effect of wage arrears. The results are broadly consistent with findings of Lehmann et al. (1999) and Lehmann and Wadsworth (2000) for the early years of the dataset.

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[41]Based on the estimates in years after 2000
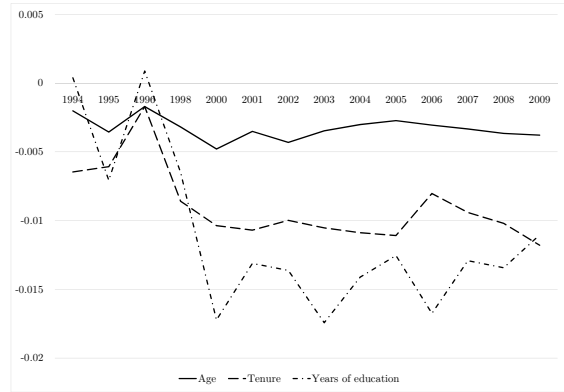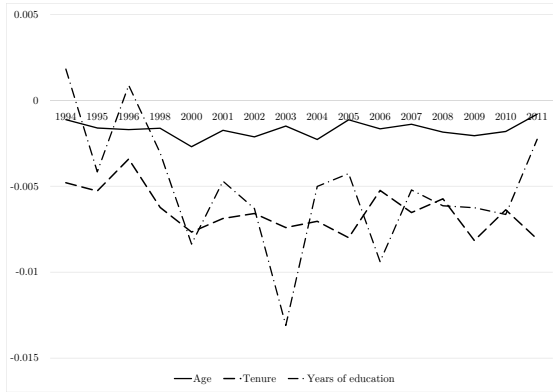
(a) Age, tenure and education: 1 year event window

(b) Age, tenure and education: 3 year event window
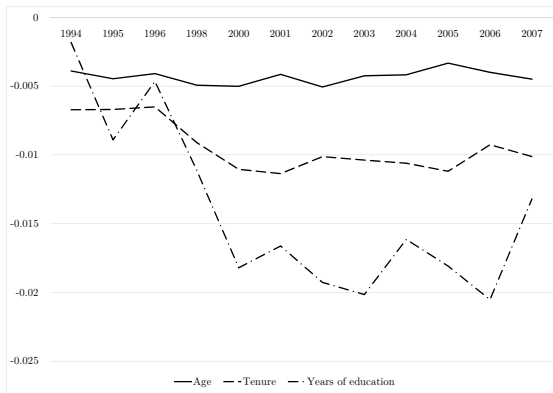
(c) Age, tenure and education: 5 year event window
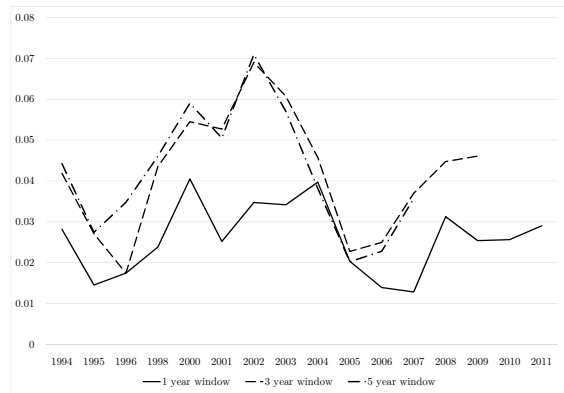
(d) Gender

Figure 2.4.2: Marginal effects of control variables on probability of experiencing at least 1 separation within 1, 3 and 5 years

For diagnostic purposes, I also estimate probit model with multiplicative error term variance (equation (2.7)). As in section 2.3.6, the variables included in the variance equation are age, tenure, years of education and gender.

The results of the test for heteroscedasticity are much stronger, and the null of homoscedasticity is rejected in all years. Tenure once again is suggested as the main

source of heteroscedasticity with age and education having significant coefficients from time to time. As can be seen from Figure 2.4.1b, the marginal effects suggested by heteroscedastic model are slightly lower in magnitude. The gap in the estimates is larger for 3 and 5-year event windows. There is a slight decrease in percentage effect as well. To be precise, workers affected by wage arrears are 36% more likely to experience a separation within a year compared to 44% when heteroscedasticity is ignored. This is still a large effect. Despite strong results of the heteroscedasticity test I cannot be sure that I have included *all* potential variables that cause unequal variance of the error term in the variance equation. Therefore, given the results of Keele and Park (2006) discussed above I would not trust them more than the standard probit results. The true effect is likely to lie in the range between the estimates and is approximately 40%.

The estimates of the Logit and LPM specifications further support the results with marginal effects presented in figure 2.4.3.

(a) LPM   (b) Logit
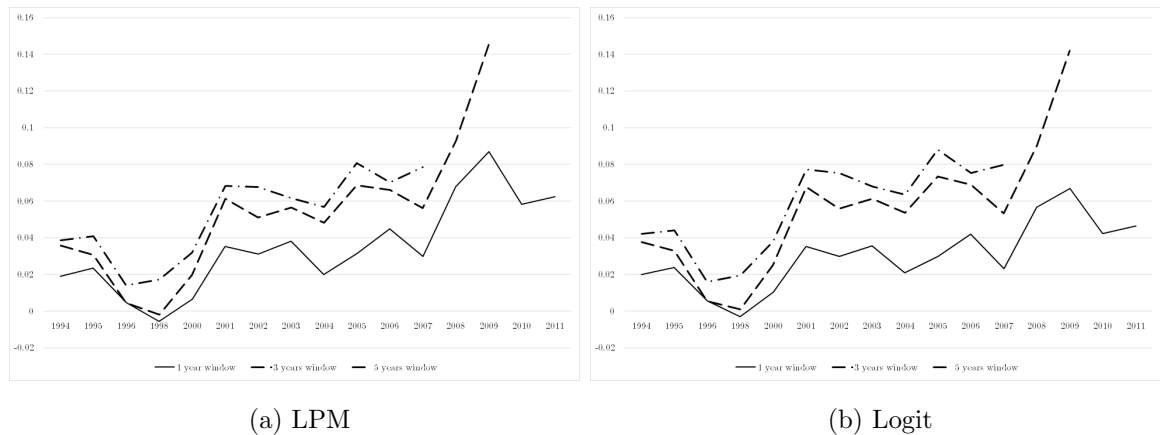
Figure 2.4.3: Marginal effects of current wage arrears on probability of experiencing at least 1 separation within next 1, 3 and 5 years. LPM and Logit models

The panel framework approach to this estimation is slightly simpler than in the case of future wage arrears. The model is not dynamic – lagged dependent vari-

able does not appear on the right-hand side. A pooled LPM with fixed effects is a straightforward approach that takes care of individual time-invariant unobserved effects. Non-linear estimations of the models with unobserved effect are still going to suffer from the incidental parameters problem. The assumptions required for estimations of the models with unobserved effects are strict and unrealistic in the set-up considered, even if independence between unobserved effect and the regressors holds, we would also have to assume that outcomes of the dependent variable (separations from employers) are not correlated over time. But such an approach contradicts the idea of scarring. Wooldridge (2010) suggests estimation of pooled probit model that does not rely on this assumption. It allows the effects of interest at an average value of the unobserved effect across individuals to be estimated. If unobserved effects are truly present the error terms will be serially correlated thus requiring clustering by individuals. Table 2.4.1 contains the results for a 1 year event window.

The coefficients are close to the average effect suggested by the series of cross sectional heteroscedastic probit estimations (of 2 percentage points)[42].

2.4.2 The effect of wage arrears on probability of frequent separations

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To answer the second question asked in the beginning of this section I run a series of similar estimations. The dependent variable in (2.11), s^f, is a boolean which turns 1 when a person experiences frequent separations within next 5 years. This estimation captures not only the initial departure but also subsequent separations from new employers. Significance of the coefficient on wage arrears tells whether the affected workers do indeed leave their new firms more often than their peers

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[42]Including the years in which the influence of wage arrears is insignificant.

Table 2.4.1: Panel framework approach: fixed effects LPM and Pooled Probit estimations

	LPM				
	Coef.		[95% Conf.	Interval]	
ω_i	0.017	***	0.009	0.024	
	(0.004)				
Age	-0.007	***	-0.007	-0.006	
	(0.000)				
Tenure	0.005	***	0.005	0.006	
	(0.000)				
Years of education	-0.002		-0.005	0.001	
	(0.002)				
Const.	0.363	***	0.315	0.412	
	(0.025)				
Observations	95720				

	Pooled Probit				
	Coef.		[95% Conf.	Interval]	Marginal effect
ω_i	0.137	***	0.108	0.165	0.027
	(0.014)				(0.003)
Age	-0.009	***	-0.011	-0.008	-0.002
	(0.001)				(0.000)
Tenure	-0.035	***	-0.038	-0.033	-0.007
	(0.001)				(0.000)
Years of education	-0.027	***	-0.033	-0.022	-0.005
	(0.003)				(0.001)
Gender: man	0.145	***	0.120	0.171	0.027
	(0.013)				(0.002)
Marital status:					
married	-0.096	***	-0.132	-0.059	-0.018
	(0.018)				(0.004)
partner	0.010		-0.034	0.054	0.002
	(0.022)				(0.004)
divorced	0.082	***	0.029	0.136	0.017
	(0.027)				(0.006)
widow(er)	0.010		-0.072	0.092	0.002
	(0.042)				(0.008)
married but separated	0.099		-0.070	0.267	0.020
	(0.086)				(0.019)
Const.	-0.332	***	-0.419	-0.246	
	(0.044)				
Observations:	95466				

Note: robust standard errors in parentheses

*** (LR) p-value≤0.01, ** (LR) p-value≤0.05, * (LR) p-value ≤0.1.

$$P(s_i^f = 1|\omega, X) = \Phi(\alpha\omega_i + X_i'\beta), \tag{2.11}$$

The results of such estimation can vary depending on the definition of "frequent". I decided to use all multiple separations. If a person experiences at least 2 separations $s_i^f = 1$. One of the reasons behind this approach is the relatively low number observations per person in the dataset (4 on average). Thus after each "current" year, on average, there are only 3 more observations to consider. Besides, even the second separation is already an indicator that a person did not settle at a new place. Thus I argue that the variable defined this way is a valid proxy to study the adverse effects of wage arrears. Figure 2.4.4 presents the obtained marginal effects.

The test once again reveal the presence of heteroscedasticity in every estimation and the tenure is its likely source. As in the case of at least 1 separation, the effect of wage arrears is not significant at the turn of the century. As before the estimates of marginal effects obtained under the specified variance equation are slightly lower in magnitude. According to the probit model, on average, people affected by wage arrears are 36% more likely to experience frequent separations over the next 5 years. The result obtained from the heteroscedastic model is 32%.

Full estimation results can be found in tables 2.7.26 and 2.7.27 in the appendix.

The analysis of a dynamic panel specification would shift the focus away from the coefficients of interest. If past realisations of separations were partly explained by wage arrears then the lagged dependent variable and wage arrears would be strongly correlated. Such an estimation would suffer from wide confidence intervals and obscure the true effect. A non-dynamic specification does not take into account the fact that the dependent variable contains information about 5 upcoming years and all possible combinations of multiple separations are allowed (i.e. in years 2 and 3 after wage arrears as well as in years 1 and 5).
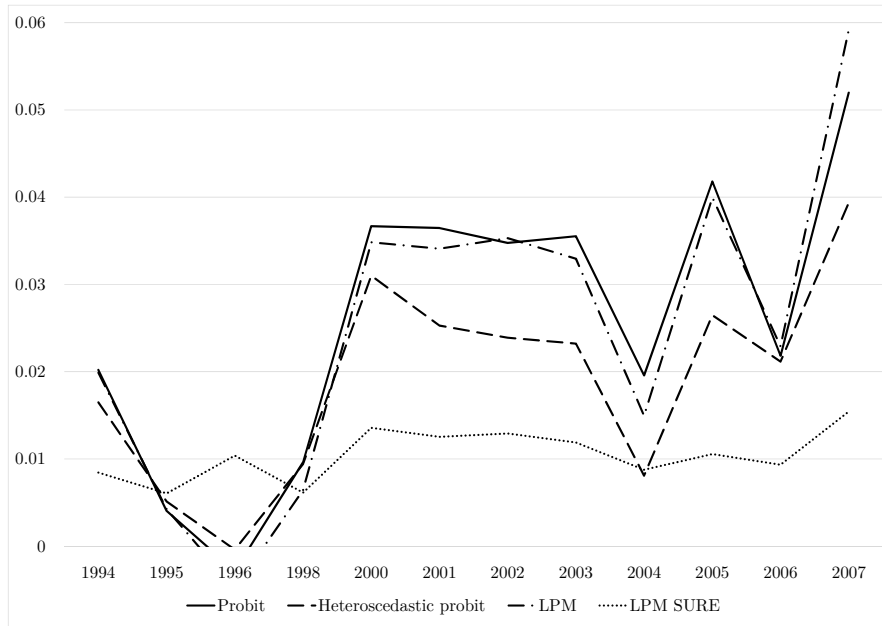
Figure 2.4.4: Marginal effects of current wage arrears on probability frequent separations over next 5 years

I obtain Zellner (1962) SURE estimator of linear probability model to take into account the fact that year-by-year estimations may not be independent of each other. The dotted line on Figure 2.4.4 indicates lower and flatter profile of the effect of wage arrears when this approach is used. The effect is estimated to be consistently around 1 percentage point. It translates, on average, into an 11% increase in the probability of frequent separations for workers affected by wage arrears.

The results in this section demonstrate that wage arrears have an impact on probability of workers leaving firms that pay irregularly as well as on the probability of subsequent separations. The effect is weaker than in the case of recurring wage arrears but is not negligible.

2.5 Wage Arrears and Future Wages

In this section I consider the effect of wage arrears on future wages. It has been well established in the literature on displaced workers that job loss is very costly – resulting in a wage loss that is substantial and persistent. Wages fall by approximately 30% and do not recover to their counterfactual path over the next 20 years (Davis and Wachter, 2011; Couch and Placzek, 2010; Carrington and Fallick, 2015). Results of Lehmann et al. (2013) suggest that wage losses from displacement in Russia as well as other European countries are much less severe but nevertheless statistically significant for 3 years after the displacement.

Wage arrears are similar to job displacement in many ways – they often affect majority of firms' workers, they are outside of workers' control, they are to some extent unexpected and they affect earnings. As we saw in the previous section wage arrears do make workers more likely to leave their employer and contribute to more frequent separations in the future. Those in turn potentially contribute to the number of unemployment spells and their duration. As shown in Cooper (2013) and Flaaen et al. (2015), these in turn affect the path of future wages. All these effects in theory have a negative influence on future earnings. So it is logical to ask whether wage arrears and job displacement have similar effects on future wages.

To answer this question I employ a difference-in-difference technique similar to Davis and Wachter (2011). For each displacement year (the event year) they estimate a model in which the difference in paths of earnings between displaced and non-displaced workers is captured by dummy variables. Each dummy variable represents the deviation from a counterfactual path of earnings in a given year after the event. One of the important underlying assumptions needed to obtain average deviation from the control group in n^{th} year since the event is that of events being independent across years.

As demonstrated above the incidents of wage arrears in different years cannot be treated as independent. An affected worker is more likely to be affected again. This is an important feature of the wage arrears framework. Thus in my model I take into account the fact that each individual at any moment of time can be under the influence of multiple "events". To understand it better consider a worker, let's call her Anna, who experienced wage arrears only in 1998. Her earnings are likely to differ from the earnings of the luckier workers who were not affected in 1998, lets call those people "the original control group". A dummy variable that is equal to 1 for Anna in 2002 tells how her earnings in 2002 differ from those of the original control group 4 years after the event. Now consider a worker who was affected in 1998 and 2001, let's call him Ivan. His earnings in 2002 also differ from those of the original control group. However, this is not only because he was affected by wage arrears in 1998 but also because of wage arrears in 2001. To estimate the effect of each year after an event correctly I need to take into account the fact that the same person can be under the influence of several instances of wage arrear events at the same time. The estimation of the impact of each event year separately and averaging the results for dummies that correspond to the number of years after an event would be misleading.

I specify the regression in the following way:

$$w_{it} = \alpha_i + \gamma_t + \beta_1 \cdot age + \beta_2 \cdot age^2 + \sum_{k=-3}^{10} \delta^k D_{it}^k + u_{it}, \qquad (2.12)$$

where w_{it} is real wage, α_i and γ_t are individual and time fixed effects, k is the "distance" from an event, D_{it}^k is a dummy that is equal to 1 if worker i in year t is k years away from an event. δ^k is a coefficient that captures the effect of being k years away from wage arrears on the current wage. So each individual in each year has 13 dummies representing the distance from the past or future wage arrears. Coming

back to Ivan who was affected in 1998 and 2001, in year 2000 2 dummies for him will be equal to 1, $D_{i,2000}^{-1}$ and $D_{i,2000}^{2}$, indicating that he was affected by wage arrears 2 years ago and will be affected next year.

Each δ^k compares affected individuals to the control group who are not at the same distance from wage arrears i.e. do not experience wage arrears in the same years. Note that the control groups are not the people who have never experienced wage arrears. Given how widespread wage arrears were, such a control group would consist of workers with very specific characteristics e.g. top managers or extremely skilled and productive workers. Also note that dummies for several years before each event are included to capture pre-existing differences in paths of earnings between the groups. Lastly the time span of the effect is limited to 10 years rather than 15 or 20 years common in literature on job displacement. This is done purely because of data limitations.

If equation (2.12) was specified in logarithms it would be possible to interpret the coefficients of interest as percentage deviations of the wages of affected workers from the ones of the control group. However affected individuals quite often do not report their wage from the main job. In order not to lose those observations I use specification in levels. The measure of the wage is constructed using information about 2 occupations[43].

The RLMS has 2 separate wage variables. The first contains information about take-home wage, the second one is a proxy for contract wage. The estimation is performed for both measures, however, the sample period for contract wage estimation is shorter. The question was added to the RLMS in 1998. Multi-way clustering of the error terms (Cameron et al., 2006) by individual and year is used. It allows for common effects in each year that affect all workers and for potential correlation of

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[43]The RLMS holds information on up to 3 jobs per individual, however, information about the third job is rarely complete and is unreliable.

residuals between years for each individual. The graphs below (figure 2.5.1) depict the coefficients and confidence intervals.

(a) Take-home wages

(b) Contract wages
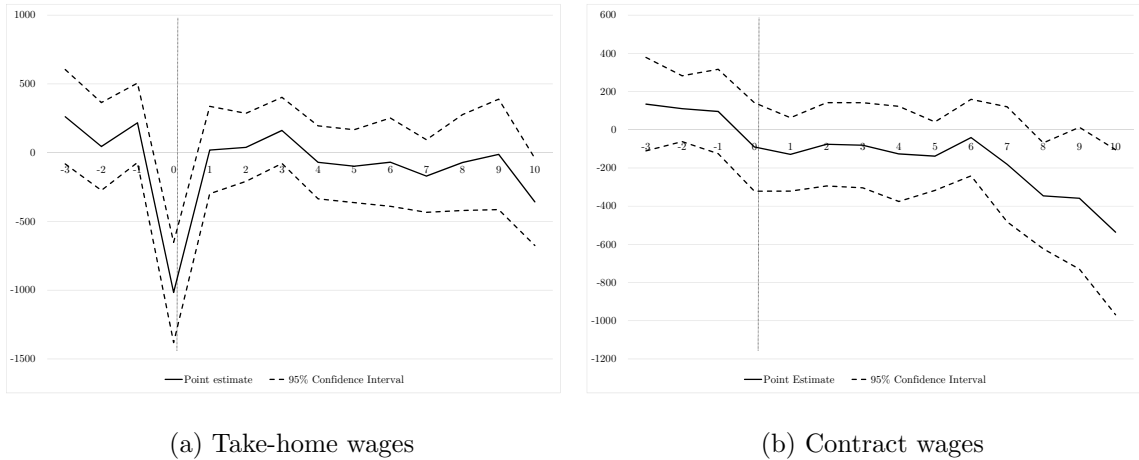
Figure 2.5.1: Absolute effect of wage arrears on the earnings of affected workers compared to the earnings their unaffected peers. The years before and after the wage arrears

The coefficients are mainly insignificant. 95% confidence interval almost always contains 0 in its middle. Take-home wages drop by 1 000 RUB in the year when wage arrears happen and recover the next year. To put this number into context, the average real wage of unaffected workers in 1998 was 8 454.

The contract wages do not react to wage arrears. The only significant coefficients suggest that contract wages of affected workers are four and five hundred rubles lower than of the control group in the 8th and 10th years after the event respectively. The 10th year coefficient is also the only significant post-event coefficient in the estimation of the effect on take-home wages. Most likely these results are driven by a set of unrelated to wage arrears events that happened to the very few respondents who remain in the sample for 10 years after the wage arrears.

Two of the findings are interesting. First of all a relatively small decrease in take home wages compared to control group. One could expect almost a 100% decrease if

wages are not being paid[44]. I see 2 possible explanations for this effect. The first one is moonlighting. People are looking for additional part-time jobs to compensate the decrease in earnings. This behaviour of affected workers is documented by Skoufias (2003). The second explanation lies in the features of the data. It is annual and the question in the survey asks whether the worker is owed any missed wages. It does not specify when those wages were supposed to be paid. However the take-home wage question asks for the amount of money the worker received in the last month before the interview. Therefore when the wages are paid partially and when the debt is being repaid the reported take home wage of affected workers is not necessary significantly lower than of their unaffected peers.

If one was to improve the survey for the purposes of studying wage arrears, a question that explicitly asks for the dates when the payments were missed is an obvious step. As well as a question that asks whether the wage was partially paid or missed completely.

The second surprise is that the effect is short-lived. In my opinion an explanation to this lies in the relationship between a take-home and a contract wage. The insignificance of the dummies corresponding to the years after the arrears suggests that the contract negotiation that leads to a lower wage does not take place. During wage arrears a part of the contract wage is withheld but its level stays the same. And this is potentially the key to understanding why take-home wages revert back so fast.

Unlike in case of job displacement, workers who face wage arrears are not forced into unemployment. If they wish they may never leave the firm or they can engage in on-the-job search. As already mentioned, duration of unemployment is important

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[44]My results are broadly consistent with results of Lehmann and Wadsworth (2007). According to them, in the years when wage arrears were widespread, the average earnings in the absence of wage arrears would have been 20% to 50% higher. It is more than is implied by the estimation in this section, but also suggests that the earnings do not decrease to zero during wage arrears.

for future wages (Cooper, 2013) and in this case we would observe direct job-to-job transitions. In addition, employers often use information about previous wages when negotiating a starting wage. But in the case of wage arrears the previous contract wage is not affected and workers may not reveal the true reason why they decided to change jobs. All this contributes to the new wage being not lower than the previous one.

2.6 Stocks and Flows of Wage Arrears

So far I have established that wage arrears do have an effect on workers' future. Most noticeably it is expressed in a much higher probability of recurring arrears. To a less extent workers become more prone to job transitions. Effects on wages seem relatively low and short-lived.

However, given this information it is still hard to estimate monetary value of future losses induced by the current wage arrears. If workers experienced persistent wage effects then the cost could be approximated by lifetime present value of wage loss multiplied by expected extra number of occurrences of wage arrears.

In an attempt to shed some light on the true costs of wage arrears I undertake a stocks and flows analysis of wage arrears in the RLMS [45]. This analysis can help to understand whether wage arrears are being eventually cleared or written off. In addition to an extra insight about the costs of wage arrears, this analysis will also aid better understanding of assumptions that can be used in modelling.

To analyse stocks of wage arrears I construct two measures. The first one is the sum of money owed to workers reported by respondents themselves. The second one is obtained by multiplying the average monthly wage by the answer to the question

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[45] A similar exercise was performed by (Lehmann and Wadsworth, 2007), however a much longer time span of the data available today will hopefully provide an even better insight

"how many months are you owed money for". I refer to the first measure as "self-reported" and to the second as one being "based on the duration of arrears".

Approximately 85% of "arreared" observations include information about how much the individuals are owed. Unfortunately people do not report this consistently.They often report the amount owed one year but do not the year after. A measure based on the duration of arrears is used in an attempt to overcome this problem. However, it is not better in terms of the response rate and it is unclear what people report when wages are partially paid several months in a row[46]. Given these problems and the annual frequency of the data, all the measures are rather noisy and require several strong assumptions.

The sample I use for this analysis is 1998 to 2012. This is due to the fact that the average monthly wage variable was added to the dataset in 1998. Given the quality of the data, inference based on a single measure would not qualify as robust. The assumptions I employ are:

- Non-monetary payments, i.e. chairs, nails and other types of output are not taken into account

- Yearly flows are calculated: current stock of arrears minus stock from previous year

- If a worker appears in the sample with a positive stock of arrears it is assumed to be formed during the previous year

- In cases when the stock of the previous year is known but the current observation is missing (not reported) the flow is assumed to be 0

- A person who changes jobs is assumed to give up on arrears

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[46]As discussed in the data section, a worker who was getting half of their wage 4 months in a row could report that the delay in payments is 4 months. They could also report it as only 2 months worth of wages

The correlation between the two measures of flows is 0.55 which is not bad considering data quality issues. The values of stocks and flows of the arrears themselves are of no particular interest. What is interesting is the relationship between them. It allows to understand how much is eventually paid back. For each year I consider the average stock of wage arrears corresponding to those who are affected in year t but not in the year $t + 1$. Then I compare this stock to the average flow of wage arrears accrued by people who are not affected in year $t + 1$ but were affected in the year t.

To put it differently, I consider people who stopped reporting that their firm owes anything to them between years t and $t + 1$. Based on the assumptions I made, if such a person stayed in the same firm, they must have been repaid. If they left the firm, the arrears have been written off. This approach is simplistic in the way that it ignores the possibility that a worker stopped reporting arrears. It also ignores the possibility that workers might report lower wage instead of continuing to report arrears as they may have become used to them and consider them to be a downward adjustment of their wage. Additional analysis found a close to 0 correlation between the negative flows of arrears constructed based on my assumptions and the reductions in reported contract wages. Therefore the second situation is of little concern. The first possibility unfortunately cannot be ruled out with the available data.

As can be seen from Figure 2.6.1 the average stock of wage arrears corresponding to individuals that stopped being affected by wage arrears is always smaller than the average flow they receive before leaving the "arreared" category. This suggests that not all wage arrears are repaid. Somewhat surprisingly, the share of repaid wage arrears is relatively large: 75% based on the self-reported measure and 71% based on the duration of arrears. The time profile seems relatively flat with a slight downward trend from almost 80% in early 2000s to 67% in 2012. This suggests that
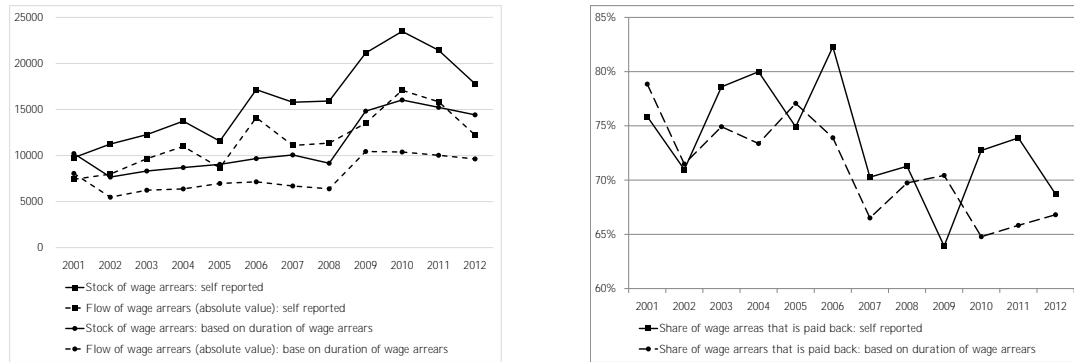
(a) Real stocks and flows of arrears (in rubles) based on 2 different measures

(b) Share of wage arrears that is paid back

Figure 2.6.1: Comparison of stocks and flows of wage arrears for people who stop reporting wage arrears between 2 consecutive years. Absolute value of flows is shown

in most of the cases workers stay in firms waiting for repayment. Combined with the results from section 2.4, a common behavioural pattern for workers facing wage arrears emerges: they stay in the firm to get paid and then change the job. Of course this is not the only scenario and individual experiences differ. However it can be a good starting building block of a model that in contrast to Earle and Peter (2009) incorporates workers' decisions.

As for the original question raised in this subsection, wage arrears seem to be repaid in majority of the cases. Therefore I agree with the view of Lehmann and Wadsworth (2007) that wage arrears in Russia is the problem of irregular pay rather than completely missing payments. Which is arguably a better scenario. Though of course the utility loss from half a year delay of payments (the average duration of wage arrears according to the RLMS in 1998 was 5.5 months) is significant.

2.7 Conclusion

This paper investigates the influence of wage arrears on the future of affected workers. The hypothesis is that wage arrears can leave severe "scars" and result in recurring wage arrears in the future, significant loss in earnings relative to unaffected people and more frequent separations from firms. The 1994 to 2012 sample of the RLMS dataset is used for the analysis. The results are consistent with previous studies that used only the early years of the dataset such as Lehmann et al. (1999) Lehmann and Wadsworth (2000) and with recent work by Lehmann et al. (2013) who focused on displaced workers.

The cross sectional and panel analysis of limited dependent variable models suggests that wage arrears have the most significant effect on probability of recurring wage arrears. Affected workers are approximately 30 percentage points more likely to experience wage arrears again within the next 3 years. The marginal effect of wage arrears has a distinctive downward trend which can be explained by decreasing use of wage arrears and improving outside options. On average, job-movers are able to decrease the probability of repeated wage arrears by 9 percentage points. Early years of the sample are characterised by increasing marginal effect of current wage arrears on probability of future wage arrears. Moreover, the largest marginal effect is estimated for a 1-year event window. This result is consistent with the economy entering into an uncontrolled spin towards an equilibrium, in which very few firms pay on time. That era ended with the Russian default of 1998.

The effect on separations is more modest: the affected workers are approximately 30% more likely to change jobs at least once within 3 years after wage arrears and 10% more likely to experience frequent separations within 5 years after wage arrears.

The difference-in-difference analysis in line with that used in the job displacement literature reveals that the influence of wage arrears on future earnings is relatively

small and short-lived. Take-home wages drop by 1 000 RUB compared to unaffected workers in the year of wage arrears and recover within the next year. Contract wages do not react to wage arrears.

Analysis of stocks and flows of wage arrears indicates that in the period from 1998 to 2012 on average $\frac{3}{4}$ of wage debts were repaid. This suggests that wage arrears in Russia are a phenomenon of irregular pay rather than that of missing payments. Therefore in money terms losses of workers are mainly associated with the net present value of earnings.

A combination of the stocks-flows analysis with the results on future separations suggests that the most common reaction to wage arrears was to wait for repayment and look for another job afterwards.

All control variables such as age, tenure, years of education, marital status and gender have expected effects on separations and recurring wage arrears. However, their influence is weak compared to the effect of wage arrears. It leads to the conclusion that wage arrears indeed have very unpleasant consequences for the future.

In the struggling Russian economy wage arrears have once again become more common in recent years. A promising direction of future research could be an attempt to quantify the scarring effect. Certain simple modifications to the RLMS questionnaire could greatly improve the quality of the data, enabling researchers to obtain cleaner measures of the share of paid back wage arrears and to estimate the monetary value of future losses. The results presented in this paper also lay the foundation for a model that takes into account workers' reaction to wage arrears.

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Appendix

A. Current and future wage arrears

Table 2.7.1: Means and standard deviations (in parentheses) of main variables

	1994			1998		
Wage arrears	39.04%	affected	unaffected	58.83%	affected	unaffected
Age	43.414	39.085	44.598	43.078	39.864	44.374
	(18.140)	(11.123)	(19.460)	(18.689)	(11.552)	(20.749)
Tenure	8.241	9.332	7.539	7.492	8.421	6.174
	(9.090)	(9.356)	(8.845)	(8.966)	(9.392)	(8.146)
Years of education	10.550	11.488	10.289	10.815	11.907	10.368
	(3.220)	(2.455)	(3.357)	(2.992)	(2.226)	(3.147)
Take-home real wage	10 640	9 338	8.907	5 926	4 827	8.454
	(13 780)	(13 976)	(0.923)	(8 648)	(9 160)	(0.918)
Contract real wage				5 310	4 656	6 463
				(5 513)	(4 745)	(6 499)
Gender (proportion of men)	43.85%	53.80%	41.14%	43.28%	49.14%	40.92%
	2002			2011		
Wage arrears	20.26%	affected	unaffected	3.91%	affected	unaffected
Age	42.739	41.488	42.881	43.774	39.347	43.874
	(18.902)	(11.095)	(19.588)	(18.474)	(12.288)	(18.577)
Tenure	7.081	9.486	6.596	7.115	7.233	7.110
	(9.067)	(9.811)	(8.831)	(8.645)	(9.724)	(8.598)
Years of education	11.111	11.862	11.025	11.545	11.873	11.537
	(2.857)	(2.069)	(2.921)	(2.631)	(2.152)	(2.640)
Take-home real wage	7 546	5 830	7 832	13 027	11 097	13 059
	(9 247)	(8 040)	(9 404)	(11 097)	(11 042)	(11 097)
Contract real wage	6 659	5 144	7 075	12 194	11 553	12 223
	(7 790)	(4 565)	(8 417)	(9 590)	(9 412)	(9 597)
Gender (proportion of men)	42.91%	52.75%	41.79%	42.48%	55.09%	42.20%
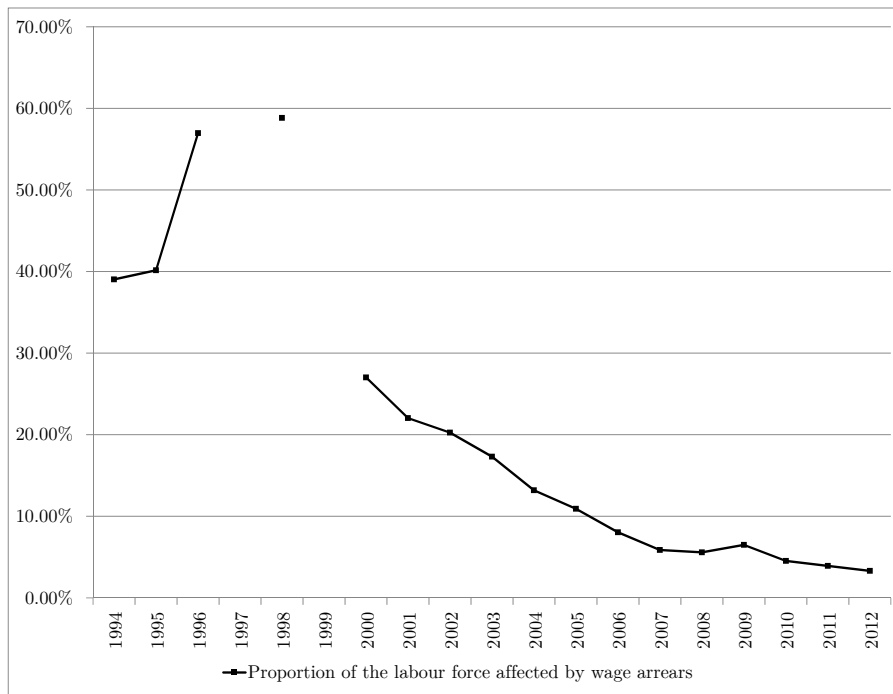
Figure 2.7.1: Proportion of labour force affected by wage arrears

Table 2.7.2: Baseline results 1994-2003. Probit model. Event window: 1 year

Variable	1994 coef.	1995 coef.	1996 coef.	1998 coef.	2000 coef.	2001 coef.	2002 coef.	2003 coef.
ω_i	0.913 ***	0.846 ***	0.728 ***	0.738 ***	1.015 ***	1.064 ***	1.049 ***	1.066 ***
	(0.040)	(0.040)	(0.042)	(0.051)	(0.047)	(0.048)	(0.049)	(0.052)
Age	-0.001	-0.002	-0.001	-0.006 ***	-0.004 *	-0.001	-0.003	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Tenure	0.004 *	0.016 ***	0.010 ***	0.007 **	0.013 ***	0.006 **	0.009 ***	0.014 ***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Years of education	-0.014 *	-0.011	0.005	-0.025 **	-0.025 **	-0.029 ***	-0.008	-0.042 ***
	(0.008)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Gender: male	0.016	-0.042	-0.111 ***	0.098 **	-0.012	0.008	0.057	0.123 **
	(0.041)	(0.040)	(0.041)	(0.047)	(0.048)	(0.047)	(0.048)	(0.051)
Marital status:								
married	0.163 **	0.212 ***	0.292 ***	0.155 *	-0.007	0.060	0.126	0.093
	(0.071)	(0.068)	(0.070)	(0.083)	(0.079)	(0.077)	(0.077)	(0.088)
partner	0.107 *	0.154 *	0.145	-0.032	0.001	0.015	-0.026	0.207 **
	(0.098)	(0.094)	(0.096)	(0.116)	(0.103)	(0.099)	(0.098)	(0.103)
divorced	0.159	0.064	0.077	-0.074	-0.209 *	0.097	0.007	0.238 **
	(0.126)	(0.125)	(0.125)	(0.120)	(0.116)	(0.107)	(0.109)	(0.115)
widow(er)				0.103	-0.116	0.002	-0.029	0.157
				(0.147)	(0.146)	(0.140)	(0.149)	(0.140)
married but separated							-0.153	
							(0.412)	
Const.	-0.903 ***	-0.587 ***	-0.940 ***	-0.979 ***	-0.845 ***	-1.035 ***	-1.342 ***	-1.326 ***
	(0.136)	(0.135)	(0.143)	(0.169)	(0.168)	(0.165)	(0.169)	(0.183)
Log likelihood	-2665.784	-2756.246	-2651.368	-1962.392	-1904.583	-1933.142	-1864.963	-1584.076
LR χ^2	577.72	559.82	399.88	276.17	521.35	538.51	503.76	493.19
% correctly predicted (cut-off=0.5)	71.1%	67.2%	64.7%	79.6%	81.0%	83.7%	86.0%	89.5%
Observations:	4809	4427	4219	4152	4454	4976	5225	5415

Note: standard errors in parentheses. *** LR p-value $\leq$ 0.01, ** LR p-value $\leq$ 0.05, * LR p-value $\leq$ 0.1.
Marital status base category: single

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Table 2.7.3: Baseline results 2004-2011. Probit model. Event window: 1 year

Variable	2004 coef.	2005 coef.	2006 coef.	2007 coef.	2008 coef.	2009 coef.	2010 coef.	2011 coef.
ω_i	1.062 ***	0.997 ***	1.047 ***	0.950 ***	0.970 ***	1.028 ***	1.258 ***	1.179 ***
	(0.058)	(0.066)	(0.070)	(0.079)	(0.079)	(0.079)	(0.073)	(0.081)
Age	-0.001	-0.001	-0.007 **	0.001	0.001	-0.004	-0.002	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure	0.008 **	0.005	0.007 *	0.004	-0.006 *	0.002	0.008 **	-0.005
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Years of education	-0.022 *	-0.041 ***	-0.006	-0.035 **	0.013	-0.056 ***	-0.037 ***	-0.032 **
	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)	(0.016)	(0.013)	(0.014)
Gender: male	0.032	0.087	0.146 **	0.154 ***	0.175 ***	0.186 ***	0.084	0.133 **
	(0.053)	(0.059)	(0.060)	(0.058)	(0.057)	(0.066)	(0.057)	(0.062)
Marital status:								
married	-0.020	0.136	0.189 *	0.044	0.063	0.136	-0.007	-0.005
	(0.083)	(0.095)	(0.098)	(0.093)	(0.086)	(0.105)	(0.087)	(0.099)
partner	-0.143	0.132	0.432 ***	0.127	0.030	0.152	-0.119	0.038
	(0.104)	(0.116)	(0.111)	(0.109)	(0.108)	(0.123)	(0.108)	(0.115)
divorced	-0.185	0.116	0.307 **	0.092	0.137	0.244 *	0.145	0.196
	(0.120)	(0.132)	(0.131)	(0.128)	(0.120)	(0.144)	(0.120)	(0.132)
widow(er)	-0.259	-0.051	0.230	-0.308	0.130	0.220	-0.114	-0.243
	(0.166)	(0.184)	(0.187)	(0.206)	(0.164)	(0.190)	(0.172)	(0.207)
married but separated				0.085	0.145		-0.084	
				(0.330)	(0.281)		(0.312)	
Const.	-1.314 ***	-1.380 ***	-1.854 ***	-1.576 ***	-2.048 ***	-1.382 ***	-1.609 ***	-1.981 ***
	(0.189)	(0.210)	(0.204)	(0.199)	(0.198)	(0.231)	(0.194)	(0.213)
Log likelihood	-1454.539	-1177.423	-1098.723	-1138.274	-1228.004	-893.608	-1196.723	-983.476
LR χ^2	365.19	255.50	251.19	168.17	156.48	189.89	303.59	212.03
% correctly predicted (cut-off=0.5)	91.2%	93.4%	95.5%	95.6%	95.1%	96.5%	97.0%	97.7%
Observations:	5512	5377	6685	6777	6697	6521	10036	10089

Note: standard errors in parentheses. *** LR p-value≤0.01, ** LR p-value≤0.05, * LR p-value ≤0.1.

Marital status base category: single

Table 2.7.4: Baseline results 1994-2002. Probit model. Event window: 3 years

Variable	1994 coef.		1995 coef.		1996 coef.		1998 coef.		2000 coef.		2001 coef.		2002 coef.	
ω_i	0.720	***	0.768	***	0.728	***	0.746	***	0.949	***	1.028	***	0.959	***
	(0.038)		(0.041)		(0.042)		(0.046)		(0.044)		(0.045)		(0.046)	
Age	-0.002		-0.002		-0.001		-0.010	***	-0.005	**	-0.004	*	-0.005	**
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Tenure	0.009	***	0.017	***	0.010	***	0.013	***	0.008	***	0.004	***	0.008	***
	(0.002)		(0.002)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Years of education	-0.017	**	-0.011		0.005		-0.013		-0.022	**	-0.020	**	-0.031	***
	(0.008)		(0.008)		(0.009)		(0.010)		(0.010)		(0.010)		(0.010)	
Gender: man	-0.021		-0.038	***	-0.111	***	0.074	*	-0.023		0.057		0.074	*
	(0.038)		(0.040)		(0.041)		(0.044)		(0.043)		(0.042)		(0.042)	
Marital status:														
married	0.182	***	0.232	***	0.292	***	0.088		0.082		0.209	***	0.137	***
	(0.065)		(0.066)		(0.070)		(0.077)		(0.071)		(0.069)		(0.068)	
partner	0.136		0.143		0.145		0.005		0.037		0.105		0.039	
	(0.090)		(0.092)		(0.096)		(0.105)		(0.093)		(0.088)		(0.085)	
divorced	0.057		-0.053		0.077		-0.116		-0.024		0.216	**	0.103	
	(0.117)		(0.123)		(0.125)		(0.110)		(0.100)		(0.096)		(0.094)	
widow(er)							-0.002		0.024		0.128		-0.064	
							(0.138)		(0.129)		(0.126)		(0.133)	
married but separated													-0.182	
													(0.362)	
Const.	-0.321	***	-0.258	*	-0.940	***	-0.719	***	-0.466	***	-0.771	***	-0.668	***
	(0.125)		(0.133)		(0.143)		(0.157)		(0.149)		(0.146)		(0.149)	
Log likelihood	-3113.037		-2804.176		-2651.368		-2272.201		-2484.622		-2543.350		-2478.259	
LR χ^2	418.36		478.57		399.88		338.20		503.82		568.21		499.88	
% correctly predicted (cut-off=0.5)	64.4%		63.9%		64.7%		72.6%		72.8%		76.4%		79.3%	
Observations:	4809		4427		4219		4152		4454		4976		5225	

Note: standard errors in parentheses. *** LR p-value≤0.01, ** LR p-value≤0.05, * LR p-value ≤0.1.
Marital status base category: single

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Table 2.7.5: Baseline results 2003-2009. Probit model. Event window: 3 years

Variable	2003 coef.		2004 coef.		2005 coef.		2006 coef.		2007 coef.		2008 coef.		2009 coef.	
ω_i	1.012	***	1.016	***	0.973	***	0.953	***	0.909	***	0.974	***	0.917	***
	(0.048)		(0.054)		(0.060)		(0.061)		(0.070)		(0.072)		(0.072)	
Age	0.000		-0.002		-0.003		-0.003		0.001		-0.002		-0.001	
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Tenure	0.008	***	0.002		0.002		0.001		-0.006	**	-0.002		0.001	
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Years of education	-0.036	***	-0.028	**	-0.037	***	-0.009		-0.018	*	-0.009		-0.049	***
	(0.010)		(0.011)		(0.012)		(0.011)		(0.011)		(0.011)		(0.013)	
Gender: man	0.055		0.014		0.092	*	0.128	***	0.160	***	0.177	***	0.128	**
	(0.044)		(0.045)		(0.049)		(0.045)		(0.045)		(0.048)		(0.052)	
Marital status:														
married	0.073		0.075		0.084		0.061		0.122	*	0.060		0.084	
	(0.072)		(0.072)		(0.077)		(0.070)		(0.072)		(0.072)		(0.082)	
partner	0.079		0.039		0.124		0.230	***	0.124		0.028		0.027	
	(0.086)		(0.088)		(0.094)		(0.083)		(0.087)		(0.090)		(0.100)	
divorced	0.092		-0.049		0.022		0.079		0.140	*	0.173	*	0.291	***
	(0.097)		(0.101)		(0.110)		(0.098)		(0.099)		(0.100)		(0.111)	
widow(er)	-0.273	*	-0.177		-0.044		0.060		0.005		0.118		0.050	
	(0.141)		(0.141)		(0.152)		(0.135)		(0.139)		(0.138)		(0.154)	
married but separated							-0.253		0.040		0.004		0.225	
							(0.272)		(0.265)		(0.255)		(0.406)	
Const.	-0.878	***	-0.884	***	-0.943	***	-1.314	***	-1.373	***	-1.433	***	-1.120	***
	(0.155)		(0.161)		(0.176)		(0.152)		(0.154)		(0.165)		(0.184)	
Log likelihood	-2253.651		-2094.573		-1741.308		-2068.888		-2043.075		-1823.293		-1471.791	
LR χ^2	503.60		387.42		291.77		274.47		201.51		199.69		191.47	
% correctly predicted (cut-off=0.5)	82.8%		85.4%		88.8%		89.9%		90.4%		91.7%		93.5%	
Observations:	5415		5512		5377		6758		6777		6697		6543	

Note: standard errors in parentheses. *** LR p-value≤0.01, ** LR p-value≤0.05, * LR p-value ≤0.1.
Marital status base category: single

Table 2.7.6: Baseline results 1994-2001. Probit model. Event window: 5 years

Variable	1994 coef.	1995 coef.	1996 coef.	1998 coef.	2000 coef.	2001 coef.
ω_i	0.623 ***	0.775 ***	0.773 ***	0.774 ***	0.913 ***	0.991 ***
	(0.039)	(0.041)	(0.041)	(0.044)	(0.044)	(0.045)
Age	-0.001	-0.002 **	-0.005 **	-0.010 ***	-0.007 ***	-0.004 **
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure	0.008 ***	0.015 ***	0.008 ***	0.009 ***	0.008 ***	0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Years of education	-0.011	-0.011	0.004	-0.017 *	-0.022 **	-0.027 ***
	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)
Gender: man	-0.043	-0.032	-0.110 ***	0.031	-0.038	0.028
	(0.038)	(0.040)	(0.041)	(0.043)	(0.042)	(0.040)
Marital status:						
married	0.182 ***	0.229 ***	0.294 ***	0.150 **	0.094	0.163 **
	(0.064)	(0.066)	(0.068)	(0.074)	(0.069)	(0.066)
partner	0.096	0.135	0.130	-0.049	0.032	0.061
	(0.089)	(0.092)	(0.094)	(0.102)	(0.090)	(0.085)
divorced	0.020	-0.065	0.117	-0.019	0.026	0.160 *
	(0.116)	(0.122)	(0.123)	(0.105)	(0.097)	(0.092)
widow(er)				-0.021	0.029	0.020
				(0.133)	(0.126)	(0.122)
married but separated						
Const.	-0.160	-0.187	-0.611 ***	-0.468 ***	-0.244 *	-0.453 ***
	(0.124)	(0.133)	(0.141)	(0.151)	(0.145)	(0.141)
Log likelihood	-3160.955	-2793.718	-2702.270	-2480.540	-2636.169	-2750.533
LR χ^2	318.55	466.75	434.08	384.73	475.18	542.59
% correctly predicted (cut-off=0.5)	60.7%	63.9%	64.6%	66.1%	70.8%	74.0%
Observations:	4809	4427	4219	4152	4454	4976

Note: standard errors in parentheses. *** LR p-value$\leq$0.01, ** LR p-value$\leq$0.05, * LR p-value $\leq$0.1.
Marital status base category: single

Table 2.7.7: Baseline results 2002-2007. Probit model. Event window: 5 years

Variable	2002 coef.		2003 coef.		2004 coef.		2005 coef.		2006 coef.		2007 coef.	
ω_i	0.921	***	0.968	***	0.929	***	0.919	***	0.915	***	0.840	***
	(0.045)		(0.047)		(0.052)		(0.058)		(0.059)		(0.069)	
Age	-0.005	**	-0.002		-0.003		-0.003		-0.004	*	0.001	
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Tenure	0.007	***	0.007	***	0.001		0.000		0.001		-0.005	**
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Years of education	-0.038	***	-0.046	***	-0.027	***	-0.031	***	-0.012		-0.018	*
	(0.010)		(0.010)		(0.010)		(0.011)		(0.010)		(0.010)	
Gender: man	0.044		0.055		0.041		0.090	**	0.116	***	0.124	***
	(0.041)		(0.042)		(0.042)		(0.046)		(0.042)		(0.043)	
Marital status:												
married	0.158	**	0.096		0.088		0.089		0.073		0.112	
	(0.065)		(0.069)		(0.067)		(0.071)		(0.065)		(0.067)	
partner	0.063		0.148	*	0.060		0.078		0.206	***	0.100	
	(0.082)		(0.082)		(0.082)		(0.088)		(0.079)		(0.082)	
divorced	0.079		0.089		-0.051		0.071		0.142		0.128	
	(0.092)		(0.094)		(0.095)		(0.100)		(0.090)		(0.093)	
widow(er)	-0.074		-0.228	*	-0.109		-0.056		0.087		-0.011	
	(0.128)		(0.134)		(0.131)		(0.141)		(0.125)		(0.130)	
married but separated	0.290								-0.381		-0.092	
	(0.307)								(0.271)		(0.263)	
Const.	-0.446	***	-0.570	***	-0.700	***	-0.825	***	-1.117	***	-1.197	***
	(0.144)		(0.149)		(0.152)		(0.163)		(0.143)		(0.145)	
Log likelihood	-2669.673		-2474.956		-2413.081		-2079.668		-2406.376		-2339.143	
LR χ^2	478.67		486.04		345.65		275.56		268.96		177.29	
% correctly predicted (cut-off=0.5)	76.9%		80.4%		82.2%		85.6%		87.5%		88.4%	
Observations:	5225		5415		5512		5377		6758		6777	

Note: standard errors in parentheses. *** LR p-value$\leq$0.01, ** LR p-value$\leq$0.05, * LR p-value $\leq$0.1.
Marital status base category: single

Table 2.7.8: Robustness checks 1994-2003. Linear probability model. Event window: 1 year

Variable	1994 coef.		1995 coef.		1996 coef.		1998 coef.		2000 coef.		2001 coef.		2002 coef.		2003 coef.	
ω_i	0.318	***	0.323	***	0.269	***	0.185	***	0.303	***	0.307	***	0.284	***	0.255	***
	(0.014)		(0.015)		(0.015)		(0.012)		(0.015)		(0.016)		(0.015)		(0.015)	
Age	0.000	*	-0.001		-0.001		-0.002	***	-0.001	*	0.000		-0.001		0.000	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.000)		(0.000)	
Tenure	0.001	*	0.006	***	0.004	***	0.002	***	0.003	***	0.001	**	0.002	***	0.003	***
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Years of education	-0.005		-0.004		0.002		-0.007	**	-0.006	**	-0.006	**	-0.002		-0.007	***
	(0.002)		(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.002)		(0.002)	
Gender: man	0.005		-0.015		-0.040	***	0.027	**	-0.001		0.003		0.011		0.018	**
	(0.013)		(0.014)		(0.015)		(0.013)		(0.011)		(0.010)		(0.009)		(0.008)	
Marital status:																
married	0.050	**	0.074	***	0.101	***	0.042	*	0.000		0.013		0.024		0.011	
	(0.021)		(0.023)		(0.024)		(0.022)		(0.019)		(0.016)		(0.015)		(0.012)	
partner	0.033		0.054		0.049		-0.004		0.002		0.002		-0.004		0.030	*
	(0.029)		(0.033)		(0.033)		(0.028)		(0.025)		(0.021)		(0.018)		(0.015)	
divorced	0.049		0.022		0.025		-0.015		-0.043	*	0.020		-0.001		0.035	**
	(0.039)		(0.043)		(0.044)		(0.029)		(0.025)		(0.023)		(0.020)		(0.017)	
widow(er)							0.028		-0.032		-0.005		-0.009		-0.004	
							(0.038)		(0.035)		(0.031)		(0.027)		(0.024)	
married but separated													-0.034			
													(0.073)			
Const.	0.186	***	0.280	***	0.162	***	0.183	***	0.199	***	0.150	***	0.098	***	0.107	***
	(0.040)		(0.047)		(0.049)		(0.041)		(0.039)		(0.035)		(0.031)		(0.028)	
F-statistics	74.29		81.96		56.79		34.22		50.14		46.78		37.31		37.16	
Observations:	4809		4427		4219		4152		4454		4976		5225		5415	

Note: standard errors in parentheses. *** p-value≤0.01, ** p-value≤0.05, * p-value ≤0.1.
Marital status base category: single

Table 2.7.9: Robustness checks 2004-2011. Linear probability model. Event window: 1 year

Variable	2004 coef.		2005 coef.		2006 coef.		2007 coef.		2008 coef.		2009 coef.		2010 coef.		2011 coef.	
ω_i	0.244	***	0.200	***	0.176	***	0.162	***	0.176	***	0.154	***	0.201	***	0.156	***
	(0.017)		(0.018)		(0.017)		(0.020)		(0.021)		(0.019)		(0.019)		(0.019)	
Age	0.000		0.000		-0.001	**	0.000		0.000		0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Tenure	0.001	***	0.001	*	0.001	**	0.000		-0.001	*	0.000		0.001	***	0.000	
	(0.001)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Years of education	-0.004	**	-0.005	***	-0.001		-0.003	***	0.001		-0.004	***	-0.002	***	-0.002	**
	(0.002)		(0.002)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Gender: man	0.007		0.012	*	0.014	***	0.014	***	0.017	***	0.013	***	0.006	*	0.007	**
	(0.007)		(0.007)		(0.005)		(0.005)		(0.005)		(0.005)		(0.003)		(0.003)	
Marital status:																
married	-0.001		0.015		0.014	*	0.004		0.007		0.009		0.000		-0.001	
	(0.012)		(0.010)		(0.007)		(0.008)		(0.008)		(0.007)		(0.005)		(0.004)	
partner	-0.021		0.014		0.040	**	0.012		0.002		0.012		-0.007		0.001	
	(0.015)		(0.013)		(0.011)		(0.010)		(0.010)		(0.009)		(0.006)		(0.006)	
divorced	-0.025		0.011		0.024		0.009		0.013		0.017	*	0.009		0.010	
	(0.016)		(0.014)		(0.010)		(0.011)		(0.012)		(0.010)		(0.008)		(0.007)	
widow(er)	-0.027		-0.004		0.020		-0.019		0.013		0.015		-0.004		-0.010	
	(0.020)		(0.019)		(0.013)		(0.012)		(0.015)		(0.012)		(0.009)		(0.007)	
married but separated							0.006		0.013				-0.003			
							(0.027)		(0.027)				(0.015)			
Const.	0.096	***	0.082	***	0.035	***	0.058	***	0.014		0.069	***	0.049	***	0.024	**
	(0.026)		(0.024)		(0.017)		(0.017)		(0.018)		(0.016)		(0.013)		(0.011)	
F-statistics	24.600		15.790		21.030		8.820		8.190		9.650		12.190		8.660	
Observations:	5512		5377		6685		6777		6697		6521		10036		10089	

Note: standard errors in parentheses. *** p-value$\leq$0.01, ** p-value$\leq$0.05, * p-value $\leq$0.1.
Marital status base category: single

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Table 2.7.10: Robustness checks 1994-2002. Linear probability model. Event window: 3 years

Variable	1994 coef.		1995 coef.		1996 coef.		1998 coef.		2000 coef.		2001 coef.		2002 coef.	
ω_i	0.280	***	0.287	***	0.269	***	0.226	***	0.346	***	0.362	***	0.320	***
	(0.014)		(0.014)		(0.015)		(0.013)		(0.016)		(0.016)		(0.016)	
Age	-0.001		-0.001		-0.001		-0.003	***	-0.001	**	-0.001		-0.001	**
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Tenure	0.003	***	0.006	***	0.004	***	0.004	***	0.003	***	0.001		0.002	***
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Years of education	-0.006	**	-0.004		0.002		-0.004		-0.007	**	-0.006	**	-0.008	***
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Gender: man	-0.008		-0.015		-0.040	***	0.023	*	-0.007		0.017		0.021	*
	(0.014)		(0.015)		(0.015)		(0.014)		(0.013)		(0.012)		(0.011)	
Marital status:														
married	0.067	***	0.086	***	0.101	***	0.028		0.027		0.058	***	0.036	**
	(0.024)		(0.025)		(0.024)		(0.024)		(0.023)		(0.019)		(0.017)	
partner	0.050		0.054		0.049		0.003		0.013		0.028		0.010	
	(0.033)		(0.034)		(0.033)		(0.032)		(0.029)		(0.024)		(0.022)	
divorced	0.021		-0.018		0.025		-0.034		-0.007		0.059	**	0.023	
	(0.043)		(0.045)		(0.044)		(0.033)		(0.031)		(0.027)		(0.025)	
widow(er)							-0.003		0.006		0.033		-0.015	
							(0.042)		(0.042)		(0.035)		(0.032)	
married but separated													-0.050	
													(0.089)	
Const.	0.374	***	0.402	***	0.162	***	0.248	***	0.314	***	0.218	***	0.249	***
	(0.046)		(0.049)		(0.049)		(0.046)		(0.046)		(0.042)		(0.038)	
F-statistics	57.61		71.12		56.79		42.36		56.43		60.04		44.81	
Observations:	4809		4427		4219		4152		4454		4976		5225	

Note: standard errors in parentheses. *** p-value≤0.01, ** p-value≤0.05, * p-value ≤0.1.
Marital status base category: single

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Table 2.7.11: Robustness checks 2003-2009. Linear probability model. Event window: 3 years

Variable	2003	2004	2005	2006	2007	2008	2009
	coef.	coef.	coef.	coef.	coef.	coef.	coef.
ω_i	0.315 ***	0.303 ***	0.260 ***	0.250 ***	0.236 ***	0.242 ***	0.190 ***
	(0.017)	(0.019)	(0.020)	(0.020)	(0.023)	(0.024)	(0.021)
Age	0.000	0.000	0.000	-0.001	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.002 ***	0.001	0.000	0.000	-0.001 *	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Years of education	-0.008 ***	-0.006 ***	-0.006 ***	-0.002	-0.003 *	-0.002	-0.006 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Gender: man	0.013	0.005	0.018 **	0.022 ***	0.028 ***	0.026 ***	0.015 **
	(0.010)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)
Marital status:							
married	0.016	0.016	0.015	0.010	0.019 *	0.010	0.010
	(0.016)	(0.013)	(0.013)	(0.011)	(0.011)	(0.010)	(0.009)
partner	0.017	0.007	0.022	0.042 ***	0.020	0.004	0.005
	(0.019)	(0.019)	(0.017)	(0.015)	(0.014)	(0.013)	(0.011)
divorced	0.020	-0.011	0.005	0.013	0.023	0.026	0.036 **
	(0.022)	(0.020)	(0.018)	(0.015)	(0.015)	(0.015)	(0.014)
widow(er)	-0.057 **	-0.027	-0.005	0.011	0.002	0.017	0.008
	(0.028)	(0.025)	(0.024)	(0.020)	(0.020)	(0.019)	(0.016)
married but separated				-0.027	0.007	0.001	0.034
				(0.026)	(0.037)	(0.032)	(0.058)
Const.	0.188 ***	0.181 ***	0.157 ***	0.096 ***	0.086 ***	0.079 ***	0.114 ***
	(0.035)	(0.033)	(0.031)	(0.024)	(0.024)	(0.023)	(0.022)
F-statistics	45.95	31.840	21.860	17.830	13.420	12.070	11.500
Observations:	5415	5512	5377	6758	6777	6697	6543

Note: standard errors in parentheses. *** p-value$\leq$0.01, ** p-value$\leq$0.05, * p-value $\leq$0.1.
Marital status base category: single

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Table 2.7.12: Robustness checks 1994-2001. Linear probability model. Event window: 5 years

Variable	1994 coef.		1995 coef.		1996 coef.		1998 coef.		2000 coef.		2001 coef.	
ω_i	0.240	***	0.288	***	0.297	***	0.265	***	0.344	***	0.364	***
	(0.014)		(0.014)		(0.015)		(0.014)		(0.016)		(0.016)	
Age	0.000		-0.001		-0.002	**	-0.003	***	-0.002	***	-0.001	**
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Tenure	0.003	***	0.005	***	0.003	***	0.003	***	0.003	***	0.001	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Years of education	-0.004		-0.004		0.002		-0.006	*	-0.007	**	-0.008	***
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Gender: man	-0.016		-0.013		-0.041	***	0.010		-0.012		0.009	
	(0.014)		(0.015)		(0.015)		(0.015)		(0.014)		(0.013)	
Marital status:												
married	0.069	***	0.085	***	0.107	***	0.051	**	0.032		0.050	**
	(0.024)		(0.025)		(0.025)		(0.026)		(0.024)		(0.020)	
partner	0.037		0.050		0.048		-0.015		0.011		0.018	
	(0.034)		(0.034)		(0.034)		(0.034)		(0.030)		(0.026)	
divorced	0.008		-0.022		0.044		-0.007		0.008		0.048	*
	(0.044)		(0.045)		(0.045)		(0.035)		(0.033)		(0.029)	
widow(er)							-0.008		0.009		0.005	
							(0.044)		(0.043)		(0.037)	
married but separated												
Const.	0.437	***	0.429	***	0.272	***	0.330	***	0.391	***	0.318	***
	(0.047)		(0.049)		(0.051)		(0.050)		(0.048)		(0.044)	
F-statistics	43.74		68.97		61.57		48.83		55.65		60.83	
Observations:	4809		4427		4219		4152		4454		4976	

Note: standard errors in parentheses. *** p-value$\leq$0.01, ** p-value$\leq$0.05, * p-value $\leq$0.1.
Marital status base category: single

Table 2.7.13: Robustness checks 2002-2007. Linear probability model. Event window: 5 years

Variable	2002 coef.		2003 coef.		2004 coef.		2005 coef.		2006 coef.		2007 coef.	
ω_i	0.321	***	0.319	***	0.300	***	0.275	***	0.263	***	0.234	***
	(0.016)		(0.017)		(0.019)		(0.021)		(0.021)		(0.024)	
Age	-0.001	**	-0.001		-0.001		-0.001		-0.001	*	0.000	
	(0.001)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)	
Tenure	0.002	***	0.002	***	0.000		0.000		0.000		-0.001	*
	(0.001)		(0.001)		(0.001)		(0.001)		(0.000)		(0.000)	
Years of education	-0.011	***	-0.011	***	-0.007	***	-0.006	***	-0.002		-0.003	*
	(0.003)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Gender: man	0.014		0.014		0.011		0.021	**	0.023	***	0.025	***
	(0.012)		(0.011)		(0.010)		(0.010)		(0.008)		(0.008)	
Marital status:												
married	0.045	**	0.023		0.021		0.018		0.014		0.021	*
	(0.018)		(0.017)		(0.015)		(0.015)		(0.012)		(0.012)	
partner	0.018		0.036	*	0.016		0.015		0.043	***	0.018	
	(0.023)		(0.021)		(0.020)		(0.019)		(0.016)		(0.015)	
divorced	0.021		0.021		-0.013		0.014		0.026		0.024	
	(0.026)		(0.023)		(0.022)		(0.020)		(0.017)		(0.017)	
widow(er)	-0.017		-0.052	*	-0.019		-0.010		0.018		-0.001	
	(0.033)		(0.029)		(0.028)		(0.026)		(0.022)		(0.022)	
married but separated	0.084								-0.045	*	-0.012	
	(0.117)								(0.026)		(0.037)	
Const.	0.316	***	0.269	***	0.231	***	0.191	***	0.132	***	0.115	***
	(0.041)		(0.037)		(0.036)		(0.034)		(0.027)		(0.027)	
F-statistics	45.03		47.38		30.910		22.790		19.310		12.580	
Observations:	5225		5415		5512		5377		6758		6777	

Note: standard errors in parentheses. *** p-value$\leq$0.01, ** p-value$\leq$0.05, * p-value $\leq$0.1.
Marital status base category: single

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Table 2.7.14: Robustness checks 1994-2003. Logit model. Event window: 1 year

Variable	1994 coef.		1995 coef.		1996 coef.		1998 coef.		2000 coef.		2001 coef.		2002 coef.		2003 coef.	
ω_i	1.515	***	1.367	***	1.189	***	1.330	***	1.756	***	1.862	***	1.866	***	1.963	***
	(0.067)		(0.066)		(0.069)		(0.096)		(0.082)		(0.083)		(0.086)		(0.095)	
Age	-0.001		-0.003		-0.002		-0.011	***	-0.007	*	-0.001		-0.006		0.000	
	(0.004)		(0.003)		(0.003)		(0.004)		(0.004)		(0.005)		(0.005)		(0.005)	
Tenure	0.007	*	0.027	***	0.017	***	0.013	***	0.022	***	0.011	**	0.019	***	0.027	***
	(0.004)		(0.004)		(0.004)		(0.005)		(0.005)		(0.005)		(0.005)		(0.005)	
Years of education	-0.024	*	-0.018	*	0.008		-0.043	**	-0.045	**	-0.051	**	-0.017		-0.080	***
	(0.014)		(0.014)		(0.015)		(0.018)		(0.020)		(0.020)		(0.021)		(0.023)	
Gender: man	0.024		-0.071		-0.185	***	0.172	**	-0.016		0.017		0.104		0.214	**
	(0.069)		(0.067)		(0.068)		(0.082)		(0.085)		(0.086)		(0.088)		(0.098)	
Marital status:																
married	0.286	**	0.354	***	0.487	***	0.280	*	-0.007		0.112		0.229		0.170	
	(0.121)		(0.114)		(0.117)		(0.148)		(0.141)		(0.141)		(0.144)		(0.171)	
partner	0.196		0.260	*	0.247		-0.026		0.000		0.020		-0.039		0.397	**
	(0.168)		(0.155)		(0.159)		(0.205)		(0.183)		(0.180)		(0.183)		(0.199)	
divorced	0.280		0.112		0.136		-0.140	*	-0.364	*	0.167		-0.004		0.450	**
	(0.213)		(0.205)		(0.207)		(0.217)		(0.211)		(0.196)		(0.205)		(0.220)	
widow(er)							0.197		-0.262		-0.039		-0.097		0.000	
							(0.258)		(0.268)		(0.259)		(0.283)		(0.308)	
married but separated													-0.337			
													(0.795)			
Const.	-1.509	***	-0.96313	***	-1.537	***	-1.705	***	-1.415	***	-1.800	***	-2.304	***	-2.308	***
	(0.231)		(0.222419)		(0.236)		(0.296)		(0.300)		(0.303)		(0.313)		(0.352)	
Log likelihood	-2665.560		-2756.269		-2651.077		-1962.352		-1904.841		-1933.178		-1863.208		-1582.858	
LR χ^2	578.17		(559.770)		400.46		276.25		520.84		538.44		507.27		495.62	
% correctly predicted (cut-off=0.5)	71.1%		67.2%		64.5%		79.6%		81.1%		83.74%		86.0%		89.4%	
Observations:	4809		4427		4219		4152		4454		4976		5225		5415	

Note: standard errors in parentheses. *** p-value$\leq$0.01, ** p-value$\leq$0.05, * p-value $\leq$0.1.
Marital status base category: single

Table 2.7.15: Robustness checks 2004-2011. Logit model. Event window: 1 year

Variable	2004 coef.	2005 coef.	2006 coef.	2007 coef.	2008 coef.	2009 coef.	2010 coef.	2011 coef.
ω_i	1.971 ***	1.911 ***	2.083 ***	1.885 ***	1.895 ***	2.106 ***	2.565 ***	2.482 ***
	(0.104)	(0.121)	(0.131)	(0.145)	(0.143)	(0.152)	(0.136)	(0.156)
Age	-0.001	-0.002	-0.016 **	0.001	0.001	-0.009	-0.005	0.011 *
	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Tenure	0.016 ***	0.013 *	0.017 **	0.011	-0.013	0.007	0.019 ***	-0.006
	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)	(0.009)	(0.007)	(0.009)
Years of education	-0.046 *	-0.080 ***	-0.014	-0.077 ***	0.021	-0.128 ***	-0.086 ***	-0.077 **
	(0.025)	(0.029)	(0.030)	(0.030)	(0.028)	(0.035)	(0.030)	(0.033)
Gender: man	0.088	0.198 *	0.335 ***	0.345 ***	0.384 ***	0.407 ***	0.207	0.319 **
	(0.104)	(0.121)	(0.130)	(0.128)	(0.123)	(0.149)	(0.130)	(0.147)
Marital status:								
married	-0.017	0.283	0.379 *	0.104	0.165	0.301	-0.008	-0.021
	(0.165)	(0.199)	(0.217)	(0.206)	(0.188)	(0.238)	(0.199)	(0.235)
partner	-0.294	0.271	0.888 ***	0.286	0.063	0.379	-0.241	0.070
	(0.211)	(0.241)	(0.239)	(0.237)	(0.234)	(0.273)	(0.244)	(0.271)
divorced	-0.355	0.223	0.639 **	0.242	0.063	0.549 *	0.338	0.455
	(0.240)	(0.279)	(0.286)	(0.277)	(0.234)	(0.323)	(0.271)	(0.307)
widow(er)	-0.407	-0.083	0.486	-0.710	0.313	0.505	-0.141	-0.531
	(0.328)	(0.392)	(0.410)	(0.481)	(0.355)	(0.431)	(0.388)	(0.497)
married but separated				0.179	0.310		-0.151	
				(0.750)	(0.621)		(0.746)	
Const.	-2.311 ***	-2.464 ***	-3.401 ***	-2.810 ***	-3.767 ***	-2.330 ***	-2.852 ***	-3.734 ***
	(0.368)	(0.433)	(0.444)	(0.431)	(0.423)	(0.516)	(0.441)	(0.500)
Log likelihood	-1453.511	-1176.854	-1098.298	-1137.614	-1228.039	-893.277	-1195.773	-983.877
LR χ^2	367.25	256.63	252.04	169.49	156.41	190.55	305.49	211.23
% correctly predicted (cut-off=0.5)	91.2%	93.4%	95.5%	95.6%	95.1%	96.5%	97.0%	97.7%
Observations:	5512	5377	6685	6777	6697	6521	10036	10089

Note: standard errors in parentheses. *** p-value$\leq$0.01, ** p-value$\leq$0.05, * p-value $\leq$0.1.
Marital status base category: single

Table 2.7.16: Robustness checks 1994-2002. Logit model. Event window: 3 years

Variable	1994 coef.		1995 coef.		1996 coef.		1998 coef.		2000 coef.		2001 coef.		2002 coef.	
ω_i	1.157	***	1.246	***	1.189	***	1.284	***	1.553	***	1.700	***	1.611	***
	(0.062)		(0.067)		(0.069)		(0.083)		(0.073)		(0.075)		(0.076)	
Age	-0.002		-0.003		-0.002		-0.017	***	-0.008	**	-0.006		-0.008	**
	(0.003)		(0.003)		(0.003)		(0.004)		(0.004)		(0.004)		(0.004)	
Tenure	0.014	***	0.028	***	0.017	***	0.022	***	0.013	***	0.006		0.015	***
	(0.004)		(0.004)		(0.004)		(0.004)		(0.005)		(0.004)		(0.004)	
Years of education	-0.028	**	-0.019		0.008		-0.022		-0.036		-0.034	**	-0.054	***
	(0.012)		(0.014)		(0.015)		(0.017)		(0.017)		(0.017)		(0.018)	
Gender: man	-0.035		-0.062		-0.185	***	0.120		-0.038		0.098		0.131	*
	(0.062)		(0.066)		(0.068)		(0.075)		(0.072)		(0.072)		(0.074)	
Marital status:														
married	0.297	***	0.376	***	0.487	***	0.153		0.143		0.358	***	0.244	
	(0.107)		(0.108)		(0.117)		(0.130)		(0.121)		(0.121)		(0.120)	
partner	0.223		0.231		0.247		0.023		0.067		0.180		0.070	
	(0.147)		(0.150)		(0.159)		(0.179)		(0.157)		(0.154)		(0.151)	
divorced	0.093		-0.093		0.136		-0.217		-0.044		0.366	**	0.163	
	(0.192)		(0.200)		(0.207)		(0.191)		(0.172)		(0.167)		(0.168)	
widow(er)							-0.015		0.028		0.203		-0.116	
							(0.236)		(0.222)		(0.221)		(0.238)	
married but separated													-0.370	
													(0.671)	
Const.	-0.518	**	-0.409	*	-1.537	***	-1.223	***	-0.761	***	-1.299	***	-1.100	***
	(0.204)		(0.217)		(0.236)		(0.266)		(0.252)		(0.254)		(0.261)	
Log likelihood	-3113.040		-2804.239		-2651.077		-2271.828		-2484.709		-2543.462		-2477.437	
LR χ^2	418.36		478.44		400.46		338.95		503.64		567.98		501.53	
% correctly predicted (cut-off=0.5)	64.4%		64.0%		64.5%		72.6%		72.8%		76.4%		79.2%	
Observations:	4809		4427		4219		4152		4454		4976		5225	

Note: standard errors in parentheses. *** p-value≤0.01, ** p-value≤0.05, * p-value ≤0.1.
Marital status base category: single

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Table 2.7.17: Robustness checks 2003-2009. Logit model. Event window: 3 years

Variable	2003 coef.		2004 coef.		2005 coef.		2006 coef.		2007 coef.		2008 coef.		2009 coef.	
ω_i	1.735	***	1.756	***	1.728	***	1.707	***	1.633	***	1.771	***	1.736	***
	(0.081)		(0.090)		(0.102)		(0.103)		(0.118)		(0.123)		(0.127)	
Age	0.000		-0.004		-0.006		-0.006		0.002		-0.003		-0.003	
	(0.004)		(0.004)		(0.005)		(0.004)		(0.004)		(0.005)		(0.005)	
Tenure	0.016	***	0.005		0.004		0.003		-0.010	*	-0.004		0.002	
	(0.005)		(0.005)		(0.006)		(0.005)		(0.006)		(0.006)		(0.007)	
Years of education	-0.063	***	-0.052	**	-0.069	***	-0.018		-0.034	*	-0.021		-0.100	***
	(0.019)		(0.020)		(0.023)		(0.020)		(0.021)		(0.022)		(0.026)	
Gender: man	0.096		0.039		0.192	**	0.251	***	0.332	***	0.360	***	0.264	**
	(0.079)		(0.083)		(0.094)		(0.088)		(0.088)		(0.096)		(0.109)	
Marital status:														
married	0.130		0.142		0.171		0.113		0.254	*	0.141		0.171	
	(0.131)		(0.134)		(0.149)		(0.137)		(0.144)		(0.146)		(0.172)	
partner	0.148		0.067		0.232		0.438	***	0.249		0.065		0.080	
	(0.157)		(0.164)		(0.181)		(0.159)		(0.171)		(0.181)		(0.206)	
divorced	0.160		-0.098		0.046		0.146		0.297		0.361	*	0.590	***
	(0.177)		(0.190)		(0.216)		(0.192)		(0.196)		(0.200)		(0.227)	
widow(er)	-0.521	**	-0.287		-0.084		0.107		0.011		0.250		0.129	
	(0.266)		(0.267)		(0.302)		(0.268)		(0.284)		(0.280)		(0.324)	
married but separated							-0.574		0.090		0.006		0.490	
							(0.605)		(0.540)		(0.536)		(0.792)	
Const.	-1.492	***	-1.484	***	-1.602	***	-2.267	***	-2.402	***	-2.484	***	-1.868	***
	(0.280)		(0.297)		(0.337)		(0.295)		(0.300)		(0.328)		(0.379)	
Log likelihood	-2253.331		-2094.674		-1741.177		-2068.736		-2042.544		-1822.822		-1472.099	
LR χ^2	504.24		387.22		292.03		274.78		202.57		200.63		190.85	
% correctly predicted (cut-off=0.5)	83.0%		85.4%		88.8%		89.9%		90.4%		91.7%		93.5%	
Observations:	5415		5512		5377		6758		6777		6697		6543	

Note: standard errors in parentheses. *** p-value $\leq$ 0.01, ** p-value $\leq$ 0.05, * p-value $\leq$ 0.1.
Marital status base category: single

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Table 2.7.18: Robustness checks 1994-2001. Logit model. Event window: 5 years

Variable	1994 coef.		1995 coef.		1996 coef.		1998 coef.		2000 coef.		2001 coef.	
ω_i	1.004	***	1.261	***	1.249	***	1.291	***	1.480	***	1.618	***
	(0.063)		(0.068)		(0.067)		(0.075)		(0.072)		(0.073)	
Age	-0.002		-0.004		-0.009	**	-0.017	***	-0.011	***	-0.007	**
	(0.003)		(0.003)		(0.003)		(0.004)		(0.004)		(0.004)	
Tenure	0.013	***	0.025	***	0.014	***	0.016	***	0.013	***	0.004	
	(0.004)		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)	
Years of education	-0.018		-0.018		0.007		-0.029	*	-0.036	**	-0.045	***
	(0.012)		(0.014)		(0.014)		(0.016)		(0.016)		(0.016)	
Gender: man	-0.070		-0.054		-0.180	***	0.046		-0.063		0.048	
	(0.061)		(0.066)		(0.067)		(0.071)		(0.069)		(0.069)	
Marital status:												
married	0.295	***	0.370	***	0.483	***	0.247	**	0.158		0.275	**
	(0.104)		(0.108)		(0.112)		(0.124)		(0.116)		(0.113)	
partner	0.157		0.216		0.218		-0.074		0.056		0.099	
	(0.144)		(0.150)		(0.154)		(0.171)		(0.151)		(0.145)	
divorced	0.033		-0.115		0.197		-0.045		0.039		0.265	*
	(0.188)		(0.200)		(0.202)		(0.176)		(0.163)		(0.157)	
widow(er)							-0.047		0.039		0.017	
							(0.223)		(0.213)		(0.212)	
married but separated												
Const.	-0.254		-0.293		-0.987	***	-0.773	***	-0.389		-0.735	***
	(0.200)		(0.217)		(0.230)		(0.250)		(0.242)		(0.240)	
Log likelihood	-3160.956		-2793.831		-2702.137		-2480.154		-2636.252		-2750.563	
LR χ^2	318.55		466.52		434.34		385.51		475.02		542.53	
% correctly predicted (cut-off=0.5)	60.7%		64.1%		64.6%		66.0%		70.8%		74.0%	
Observations:	4809		4427		4219		4152		4454		4976	

Note: standard errors in parentheses. *** p-value$\leq$0.01, ** p-value$\leq$0.05, * p-value $\leq$0.1.
Marital status base category: single

Table 2.7.19: Robustness checks 2001-2007. Logit model. Event window: 5 years

Variable	2002 coef.		2003 coef.		2004 coef.		2005 coef.		2006 coef.		2007 coef.	
ω_i	1.527	***	1.631	***	1.572	***	1.586	***	1.598	***	1.480	***
	(0.074)		(0.079)		(0.087)		(0.097)		(0.099)		(0.115)	
Age	-0.009	**	-0.004		-0.006		-0.005		-0.007	*	0.002	
	(0.004)		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)	
Tenure	0.012	***	0.014	***	0.003		0.001		0.002		-0.010	*
	(0.004)		(0.004)		(0.005)		(0.005)		(0.005)		(0.005)	
Years of education	-0.066	***	-0.079	***	-0.049	***	-0.055	***	-0.022		-0.034	*
	(0.017)		(0.018)		(0.019)		(0.020)		(0.018)		(0.019)	
Gender: man	0.077		0.094		0.080		0.175	**	0.221	***	0.251	***
	(0.070)		(0.074)		(0.076)		(0.084)		(0.079)		(0.081)	
Marital status:												
married	0.280	**	0.168		0.160		0.163		0.133		0.224	*
	(0.114)		(0.123)		(0.122)		(0.132)		(0.124)		(0.130)	
partner	0.113		0.259	*	0.102		0.136		0.380	***	0.195	
	(0.143)		(0.146)		(0.148)		(0.163)		(0.146)		(0.156)	
divorced	0.131		0.151		-0.098		0.128		0.259		0.260	
	(0.161)		(0.167)		(0.174)		(0.188)		(0.171)		(0.178)	
widow(er)	-0.123		-0.440	*	-0.181		-0.120		0.157		-0.020	
	(0.227)		(0.249)		(0.240)		(0.270)		(0.241)		(0.257)	
married but separated	0.482								-0.833		-0.180	
	(0.537)								(0.603)		(0.536)	
Const.	-0.715	***	-0.927	***	-1.152	***	-1.383	***	-1.894	***	-2.067	***
	(0.249)		(0.264)		(0.272)		(0.301)		(0.268)		(0.275)	
Log likelihood	-2669.135		-2474.644		-2413.259		-2079.773		-2406.378		-2338.776	
LR χ^2	479.75		486.66		345.29		275.35		268.96		178.03	
% correctly predicted (cut-off=0.5)	76.86%		80.37%		82.13%		85.59%		87.54%		88.43%	
Observations:	5225		5415		5512		5377		6758		6777	

Note: standard errors in parentheses. *** p-value≤0.01, ** p-value≤0.05, * p-value ≤0.1.
Marital status base category: single

B. Wage arrears and future separations

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Table 2.7.20: Baseline results: Probit 1994 - 2003. Number of future separations: at least 1. Event window: 1 year

Variable	1994 coef.	1995 coef.	1996 coef.	1998 coef.	2000 coef.	2001 coef.	2002 coef.	2003 coef.
ω_i	0.121** (0.051)	0.133** (0.052)	0.035 (0.053)	-0.018 (0.052)	0.054 (0.056)	0.188*** (0.055)	0.157*** (0.055)	0.191*** (0.057)
Age	-0.007** (0.003)	-0.009*** (0.003)	-0.009*** (0.003)	-0.008*** (0.003)	-0.015*** (0.003)	-0.009*** (0.003)	-0.011*** (0.002)	-0.008*** (0.002)
Tenure	-0.028*** (0.004)	-0.030*** (0.004)	-0.018*** (0.004)	-0.032*** (0.004)	-0.042*** (0.005)	-0.035*** (0.004)	-0.033*** (0.004)	-0.039*** (0.004)
Years of education	0.011 (0.011)	-0.024** (0.012)	0.005 (0.012)	-0.016 (0.012)	-0.045*** (0.013)	-0.024** (0.012)	-0.032*** (0.012)	-0.068*** (0.011)
Gender: man	0.166*** (0.051)	0.083 (0.052)	0.094* (0.053)	0.122** (0.053)	0.218*** (0.051)	0.129*** (0.048)	0.173*** (0.047)	0.176*** (0.046)
Marital status:								
married	-0.115 (0.079)	-0.086 (0.080)	0.126 (0.086)	-0.036 (0.086)	-0.081 (0.078)	0.003 (0.074)	-0.134** (0.069)	-0.090 (0.070)
partner	-0.013 (0.113)	0.002 (0.115)	0.227* (0.118)	0.135 (0.115)	-0.070 (0.102)	0.108 (0.092)	0.047 (0.085)	0.129 (0.082)
divorced	-0.152 (0.172)	-0.080 (0.174)	4.000 (0.133)	0.326*** (0.118)	-0.105 (0.118)	0.114 (0.106)	0.068 (0.099)	0.167* (0.097)
widow(er)				0.209 (0.162)	-0.024 (0.176)	-0.099 (0.165)	-0.065 (0.154)	0.097 (0.142)
married but separated							0.643** (0.307)	
Const.	-0.973*** (0.166)	-0.432** (0.177)	-0.976*** (0.184)	-0.510*** (0.184)	0.114 (0.181)	-0.414** (0.166)	-0.187 (0.164)	0.097 (0.164)
Log likelihood	-1563.530	-1481.740	-1466.003	-1521.202	-1598.293	-1841.856	-1961.982	-1989.043
LR χ^2	138.31	146.28	70.11	151.83	279.33	229.92	269.61	311.85
% correctly predicted (cut-off=0.5)	89.3%	88.8%	88.6%	87.1%	86.8%	86.6%	86.2%	86.5%
Observations:	4809	4427	4219	4152	4454	4976	5225	5415

Note: standard errors in parentheses. *** LR p-value$\leq$0.01, ** LR p-value$\leq$0.05, * LR p-value $\leq$0.1.

Table 2.7.21: Baseline results: Probit 2004 - 2011. Number of future separations: at least 1. Event window: 1 year

Variable	2004 coef.		2005 coef.		2006 coef.		2007 coef.		2008 coef.		2009 coef.		2010 coef.		2011 coef.	
ω_i	0.123	*	0.160	**	0.000	***	0.127		0.291	***	0.362	***	0.251		0.288	***
	(0.063)		(0.070)		(0.069)		(0.082)		(0.079)		(0.073)		(0.073)		(0.079)	
Age	-0.011	***	-0.006	***	-0.009	***	-0.008	***	-0.010	***	-0.011	***	-0.011		-0.005	***
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Tenure	-0.035	***	-0.041	***	-0.028	***	-0.036	***	-0.030	***	-0.045	***	-0.038		-0.050	***
	(0.004)		(0.004)		(0.003)		(0.004)		(0.003)		(0.004)		(0.003)		(0.004)	
Years of education	-0.025	**	-0.022	*	-0.050	***	-0.029	***	-0.032	***	-0.035	***	-0.040		-0.014	*
	(0.011)		(0.011)		(0.010)		(0.010)		(0.010)		(0.010)		(0.008)		(0.008)	
Gender: man	0.195	***	0.105	**	0.074	*	0.071		0.164	***	0.139	***	0.153		0.179	***
	(0.045)		(0.046)		(0.042)		(0.043)		(0.042)		(0.043)		(0.036)		(0.036)	
Marital status:																
married	-0.141	**	-0.144	**	-0.128	**	-0.067		-0.091		-0.134	**	-0.064		-0.152	***
	(0.066)		(0.067)		(0.061)		(0.062)		(0.060)		(0.061)		(0.052)		(0.051)	
partner	0.027		-0.123		-0.003		-0.066		0.013		-0.009		-0.018		-0.118	*
	(0.080)		(0.084)		(0.074)		(0.077)		(0.075)		(0.073)		(0.062)		(0.062)	
divorced	0.068		-0.012		0.017	**	0.142		0.066		0.044		0.150		-0.001	
	(0.095)		(0.097)		(0.087)		(0.088)		(0.088)		(0.092)		(0.076)		(0.078)	
widow(er)	0.081		-0.090		-0.288		0.020		0.143		0.121		-0.034		-0.160	
	(0.136)		(0.146)		(0.142)		(0.132)		(0.126)		(0.127)		(0.117)		(0.118)	
married but separated					0.209		0.261		-0.046		0.383		-0.276			
					(0.184)		(0.211)		(0.212)		(0.326)		(0.206)			
Const.	-0.214		-0.373	**	-0.046		-0.366	**	-0.279	*	-0.083		-0.170		-0.598	***
	(0.161)		(0.165)		(0.141)		(0.143)		(0.145)		(0.150)		(0.123)		(0.123)	
Log likelihood	-2099.537		-1980.713		-2393.464		-2347.628		-2396.498		-2315.431		-3284.883		-3259.523	
LR χ^2	288.13		246.65		275.25		249.12		276.28		404.10		473.02		490.53	
% correctly predicted (cut-off=0.5)	85.9%		86.7%		87.6%		88.1%		87.4%		87.1%		88.8%		89.0%	
Observations:	5512		5377		6758		6777		6697		6543		10036		10089	

Note: standard errors in parentheses. *** LR p-value≤0.01, ** LR p-value≤0.05, * LR p-value ≤0.1.

Table 2.7.22: Baseline results: Probit 1994 - 2002. Number of future separations: at least 1. Event window: 3 years

Variable	1994 coef.	1995 coef.	1996 coef.	1998 coef.	2000 coef.	2001 coef.	2002 coef.
ω_i	0.150***	0.118***	0.035	0.006	0.068	0.208***	0.166***
	(0.044)	(0.045)	(0.053)	(0.047)	(0.047)	(0.047)	(0.047)
Age	-0.008***	-0.013***	-0.009***	-0.012***	-0.015***	-0.011***	-0.013***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure	-0.026***	-0.023***	-0.018***	-0.033***	-0.032***	-0.033***	-0.030***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Years of education	0.002	-0.027***	0.005	-0.025**	-0.053***	-0.040***	-0.041***
	(0.009)	(0.010)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)
Gender: man	0.167***	0.103**	0.094*	0.165***	0.168***	0.162***	0.209***
	(0.044)	(0.045)	(0.053)	(0.047)	(0.043)	(0.040)	(0.039)
Marital status:							
married	-0.092	0.003	0.126	-0.117	-0.084	0.037	-0.084
	(0.071)	(0.072)	(0.086)	(0.077)	(0.068)	(0.064)	(0.060)
partner	0.010	0.065	0.227*	-0.102	-0.063	0.101	0.153**
	(0.100)	(0.101)	(0.118)	(0.106)	(0.089)	(0.081)	(0.075)
divorced	-0.191	-0.151	0.133	0.140	-0.087	0.219**	0.152*
	(0.149)	(0.156)	(0.171)	(0.109)	(0.099)	(0.090)	(0.085)
widow(er)				0.100	-0.064	0.020	-0.102
				(0.148)	(0.138)	(0.129)	(0.128)
married but separated							0.709**
							(0.309)
Const.	-0.517***	0.014	-0.976***	0.096	0.765***	0.334**	0.497***
	(0.145)	(0.153)	(0.184)	(0.166)	(0.151)	(0.142)	(0.140)
Log likelihood	-2173.033	-2082.823	-1466.003	-1951.292	-2457.315	-2749.823	-2910.469
LR χ^2	185.92	193.58	70.11	237.74	359.60	374.25	444.02
% correctly predicted (cut-off=0.5)	82.0%	80.6%	88.6%	80.1%	72.3%	72.6%	72.0%
Observations:	4809	4427	4427	4152	4454	4976	5225

Note: standard errors in parentheses. *** LR p-value≤0.01, ** LR p-value≤0.05, * LR p-value ≤0.1.

Table 2.7.23: Baseline results: Probit 2003 - 2009. Number of future separations: at least 1. Event window: 3 years

Variable	2003 coef.		2004 coef.		2005 coef.		2006 coef.		2007 coef.		2008 coef.		2009 coef.	
ω_i	0.192	***	0.165	***	0.225	***	0.214	***	0.164	**	0.277	***	0.427	***
	(0.049)		(0.054)		(0.060)		(0.060)		(0.070)		(0.071)		(0.066)	
Age	-0.011	***	-0.009	***	-0.009	***	-0.010	***	-0.011	***	-0.012	***	-0.012	***
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Tenure	-0.033	***	-0.034	***	-0.035	***	-0.026	***	-0.030	***	-0.033	***	-0.039	***
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Years of education	-0.054	***	-0.043	***	-0.040	***	-0.054	***	-0.041	***	-0.043	***	-0.036	***
	(0.010)		(0.010)		(0.010)		(0.008)		(0.008)		(0.009)		(0.009)	
Gender: man	0.187	***	0.141	***	0.072	*	0.080	**	0.118	***	0.143	***	0.150	***
	(0.039)		(0.038)		(0.040)		(0.035)		(0.035)		(0.036)		(0.036)	
Marital status:														
married	-0.145	**	-0.066		-0.045		-0.070		-0.083		-0.117	**	-0.180	***
	(0.060)		(0.059)		(0.059)		(0.053)		(0.053)		(0.052)		(0.053)	
partner	-0.064		0.059		-0.054		-0.010		-0.076		-0.070		-0.076	
	(0.073)		(0.071)		(0.074)		(0.065)		(0.065)		(0.065)		(0.064)	
divorced	0.048		0.067		0.104		0.096		0.062		0.103		0.037	
	(0.083)		(0.083)		(0.084)		(0.074)		(0.075)		(0.075)		(0.078)	
widow(er)	-0.117		-0.012		-0.053		-0.037		0.030		0.114		-0.037	
	(0.122)		(0.117)		(0.122)		(0.107)		(0.107)		(0.105)		(0.108)	
married but separated							0.078		-0.098		-0.273		-0.019	
							(0.167)		(0.197)		(0.186)		(0.309)	
Const.	0.628	***	0.426	***	0.352	**	0.491	***	0.415	***	0.500	***	0.493	
	(0.138)		(0.139)		(0.142)		(0.119)		(0.120)		(0.124)		(0.129)	
Log likelihood	-2980.064		-3062.871		-2911.848		-3628.471		-3649.497		-3582.786		-3415.219	
LR χ^2	430.72		383.67		351.43		373.10		421.78		496.91		602.58	
% correctly predicted (cut-off=0.5)	72.4%		72.2%		73.9%		74.8%		74.4%		74.4%		75.2%	
Observations:	5415		5512		5377		6758		6777		6697		6543	

Note: standard errors in parentheses. *** LR p-value$\leq$0.01, ** LR p-value$\leq$0.05, * LR p-value $\leq$0.1.

Table 2.7.24: Baseline results: Probit 1994 - 2001. Number of future separations: at least 1. Event window: 5 years

Variable	1994 coef.		1995 coef.		1996 coef.		1998 coef.		2000 coef.		2001 coef.	
ω_i	0.138	***	0.135	***	0.053		0.060		0.095	**	0.206	***
	(0.042)		(0.043)		(0.044)		(0.043)		(0.045)		(0.045)	
Age	-0.013	***	-0.014	***	-0.013	***	-0.015	***	-0.014	***	-0.011	***
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Tenure	-0.022	***	-0.022	***	-0.021	***	-0.027	***	-0.030	***	-0.031	***
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Years of education	-0.006		-0.029	***	-0.015		-0.033	***	-0.049	***	-0.045	***
	(0.009)		(0.010)		(0.010)		(0.010)		(0.010)		(0.009)	
Gender: man	0.146	***	0.089	**	0.113	***	0.137	***	0.160	***	0.137	***
	(0.041)		(0.043)		(0.044)		(0.044)		(0.041)		(0.039)	
Marital status:												
married	-0.039		-0.044		0.060		-0.060		-0.140	**	-0.012	
	(0.067)		(0.068)		(0.071)		(0.073)		(0.067)		(0.062)	
partner	0.043		0.067		0.193	**	-0.109		-0.117		0.111	
	(0.095)		(0.096)		(0.099)		(0.100)		(0.087)		(0.079)	
divorced	-0.194		-0.190		0.049		0.066		-0.111		0.142	
	(0.140)		(0.144)		(0.140)		(0.103)		(0.095)		(0.087)	
widow(er)							0.202		-0.171		-0.066	
							(0.134)		(0.131)		(0.121)	
married but separated												
Const.	-0.079		0.297	**	-0.010		0.523	***	0.952	***	0.690	***
	(0.137)		(0.145)		(0.153)		(0.154)		(0.145)		(0.136)	
Log likelihood	-2541.141		-2378.699		-2261.690		-2371.910		-2718.999		-3040.664	
LR χ^2	229.14		228.64		170.96		259.88		377.52		415.30	
% correctly predicted (cut-off=0.5)	75.9%		74.9%		75.5%		71.2%		66.4%		65.9%	
Observations:	4809		4427		4219		4152		4454		4976	

Note: standard errors in parentheses. *** LR p-value $\leq$ 0.01, ** LR p-value $\leq$ 0.05, * LR p-value $\leq$ 0.1.

Table 2.7.25: Baseline results: Probit 2002 - 2007. Number of future separations: at least 1. Event window: 5 years

Variable	2002 coef.		2003 coef.		2004 coef.		2005 coef.		2006 coef.		2007 coef.	
ω_i	0.199	***	0.183	***	0.171	***	0.234	***	0.202	***	0.213	***
	(0.045)		(0.047)		(0.052)		(0.058)		(0.059)		(0.067)	
Age	-0.014	***	-0.012	***	-0.011	***	-0.009	***	-0.011	***	-0.013	***
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Tenure	-0.028	***	-0.028	***	-0.029	***	-0.031	***	-0.026	***	-0.029	***
	(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.002)	
Years of education	-0.052	***	-0.055	***	-0.044	***	-0.051	***	-0.058	***	-0.037	***
	(0.009)		(0.009)		(0.009)		(0.009)		(0.008)		(0.008)	
Gender: man	0.193	***	0.156	***	0.104	***	0.057		0.064	*	0.101	***
	(0.038)		(0.037)		(0.037)		(0.038)		(0.034)		(0.034)	
Marital status:												
married	-0.065		-0.079		-0.028		-0.049		-0.026		-0.060	
	(0.059)		(0.059)		(0.057)		(0.057)		(0.051)		(0.051)	
partner	0.141	*	-0.024		-0.030		-0.099		0.008		-0.062	
	(0.074)		(0.071)		(0.070)		(0.072)		(0.063)		(0.063)	
divorced	0.123		0.123		0.106		0.055		0.089		0.059	
	(0.083)		(0.081)		(0.080)		(0.081)		(0.071)		(0.073)	
widow(er)	-0.051		-0.036		0.062		-0.132		0.005		0.009	
	(0.120)		(0.114)		(0.110)		(0.116)		(0.101)		(0.102)	
married but separated	0.655								0.087		-0.119	
	(0.309)								(0.161)		(0.190)	
Const.	0.844	***	0.836	***	0.707	***	0.723	***	0.799	***	0.636	***
	(0.135)		(0.133)		(0.134)		(0.136)		(0.115)		(0.115)	
Log likelihood	-3172.856		-3290.285		-3381.141		-3230.015		-4045.841		-4022.138	
LR χ^2	466.23		418.50		376.16		373.43		438.03		479.83	
% correctly predicted (cut-off=0.5)	66.4%		66.2%		65.5%		67.7%		68.2%		68.6%	
Observations:	5225		5415		5512		5377		6758		6759	

Note: standard errors in parentheses. *** LR p-value$\leq$0.01, ** LR p-value$\leq$0.05, * LR p-value $\leq$0.1.

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Table 2.7.26: Wage arrears and frequent separations in the future. Probit 1994 - 2001

Variable	1994 coef.	1995 coef.	1996 coef.	1998 coef.	2000 coef.	2001 coef.
ω_i	0.191 ***	0.039	-0.024	0.058	0.246 ***	0.166 ***
	(0.061)	(0.064)	(0.063)	(0.055)	(0.078)	(0.054)
Age	-0.010 ***	-0.014 ***	-0.013 ***	-0.013 ***	-0.010 ***	-0.013 ***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Tenure	-0.026 ***	-0.022 ***	-0.021 ***	-0.040 ***	-0.043 ***	-0.038 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Years of education	-0.024 *	-0.040 ***	-0.023	-0.035 ***	-0.047 ***	-0.049 ***
	(0.013)	(0.015)	(0.015)	(0.013)	(0.010)	(0.012)
Gender: man	0.164 ***	0.192 ***	0.091	0.107 *	0.177 ***	0.202 ***
	(0.062)	(0.064)	(0.063)	(0.055)	(0.042)	(0.047)
Marital status:						
married	-0.188 **	-0.002	0.015	-0.008	-0.064	-0.015
	(0.090)	(0.097)	(0.096)	(0.087)	(0.061)	(0.071)
partner	-0.031	0.149	0.240 ***	-0.052	-0.025	0.101
	(0.132)	(0.137)	(0.133)	(0.122)	(0.074)	(0.090)
divorced	-0.229	0.111	0.034 *	0.101	0.135	0.282 ***
	(0.215)	(0.213)	(0.210)	(0.127)	(0.088)	(0.101)
widow(er)				0.157	0.079	0.064
				(0.175)	(0.132)	(0.154)
married but separated					0.026	
					(0.232)	
Const.	-0.758 ***	-0.577 ***	-0.677 ***	-0.180	-0.054	0.090
	(0.201)	(0.215)	(0.218)	(0.194)	(0.141)	(0.164)
Log likelihood	-1019.528	-945.809	-981.916	-1363.120	-1739.824	-1956.073
LR χ^2	113.32	92.44	80.30	181.53	302.80	334.69
% correctly predicted (cut-off=0.5)	94.1%	94.1%	93.4%	88.8%	84.9%	84.8%
Observations:	4809	4427	4219	4152	4454	4976

Note: standard errors in parentheses. *** LR p-value$\leq$0.01, ** LR p-value$\leq$0.05, * LR p-value $\leq$0.1.

Table 2.7.27: Wage arrears and frequent separations in the future. Probit 2002 - 2007

Variable	2002 coef.		2003 coef.		2004 coef.		2005 coef.		2006 coef.		2007 coef.	
ω_i	0.158	***	0.160	***	0.094		0.202	***	0.110		0.246	***
	(0.054)		(0.056)		(0.064)		(0.069)		(0.072)		(0.078)	
Age	-0.013	***	-0.011	***	-0.011	***	-0.011	***	-0.012	***	-0.010	***
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Tenure	-0.035	***	-0.029	***	-0.035	***	-0.043	***	-0.032	***	-0.043	***
	(0.004)		(0.004)		(0.004)		(0.004)		(0.003)		(0.004)	
Years of education	-0.060	***	-0.071	***	-0.048	***	-0.052	***	-0.064	***	-0.047	***
	(0.012)		(0.011)		(0.011)		(0.012)		(0.010)		(0.010)	
Gender: man	0.227	***	0.116	***	0.109	**	0.055		0.135	***	0.177	***
	(0.046)		(0.045)		(0.045)		(0.047)		(0.042)		(0.042)	
Marital status:												
married	-0.074		-0.067		-0.050		-0.043		0.018		-0.064	
	(0.069)		(0.069)		(0.067)		(0.067)		(0.061)		(0.061)	
partner	0.160	*	0.066		0.017		-0.152	*	0.046		-0.025	
	(0.083)		(0.081)		(0.082)		(0.086)		(0.075)		(0.074)	
divorced	0.209	**	0.155		0.204	**	0.110		0.150	*	0.135	
	(0.097)		(0.095)		(0.094)		(0.097)		(0.088)		(0.088)	
widow(er)	-0.022		0.146		0.080		-0.136		-0.003		0.079	
	(0.154)		(0.136)		(0.138)		(0.155)		(0.136)		(0.132)	
married but separated	0.944	***							0.003		0.026	
	(0.309)								(0.208)		(0.232)	
Const.	0.211		0.299	*	0.035		0.130		0.140		-0.054	
	(0.163)		(0.160)		(0.162)		(0.167)		(0.141)		(0.141)	
Log likelihood	-2039.598		-2111.281		-2091.174		-1964.115		-2418.614		-2445.007	
LR χ^2	359.74		270.39		268.59		298.58		318.09		377.37	
% correctly predicted (cut-off=0.5)	85.0%		85.5%		86.1%		86.7%		87.3%		86.9%	
Observations:	5225		5415		5512		5377		6758		6777	

Note: standard errors in parentheses. *** LR p-value$\leq$0.01, ** LR p-value$\leq$0.05, * LR p-value $\leq$0.1.

Chapter 3: Wage arrears as a result of worker-firm interactions

Financial difficulties faced by firms are not the only reason for wage arrears. An indirect evidence suggests that sometimes the firms have resources to pay their employees but choose not to do so to achieve various goals. In certain circumstances the employees accept it. This paper presents a model of wage arrears that is based on worker-firm interactions. Calibration to the Russian data indicates that the parameter values observed in the RLMS dataset are consistent with a stable equilibrium in which an approximately half of the labour force experience wage arrears. The model predicts the average duration of the arrears spell of 4 months. This prediction is consistent with the Russian reality in the late 1990s.

3.1   Introduction

From time to time workers all over the world experience irregular wage payments. The list of countries where this problem was widespread enough to be noticed by academic literature includes China, India, Romania, the Kyrgyz Republic, Greece, Portugal, Bosnia and Herzegovina, Albania, Serbia and the Ukraine (Demirguc-Kunt et al., 2011, 2013; Cheng et al., 2013; Tiongson and Yemtsov, 2008). Cases from more

countries including the UAE, Brazil and even the UK surface the news (Hadid, 2006; Liddington, 2016; HRW, 2006; Cockburn, 2016; Calnan, 2016).

The extent of the problem varies. In some countries the arrears are mainly isolated incidents, in others, for example China, almost 10% of the labour force are affected (Cheng et al., 2013). That is a substantial proportion, but sometimes the incidence of wage arrears becomes extreme. Almost 60% of workers in Russia were not getting paid on time in the late 1990s (according to the data from the RLMS[47]).

Given how common wage arrears were in Russia and that the RLMS survey contains a number of questions that were specifically designed to study the phenomenon, it is not surprising that the majority of research in the area has focused on the Russian case.

The results of a large number of studies suggest that men are more likely to suffer from wage arrears than women, low skilled jobs are characterised by a higher risk of wage arrears and the incidence of the arrears is usually much lower in metropolitan areas compared to rural regions. "Newer" sectors of transition economies, such as banking and services in general, tend to be less affected by the arrears than production sector (Earle and Sabirianova, 2002; Fankhauser et al., 2008; Richter, 2006; Guariglia and Kim, 2003; Lehmann et al., 1999).

Another aspect covered in the literature is the consequences of wage arrears for both the affected individuals and the society. By constructing a counterfactual wage distribution Lehmann and Wadsworth (2007) show that the wage arrears were responsible for approximately 30% of the inequality in Russia in the late 1990s. Skoufias (2003) and Guariglia and Kim (2003) find that people who experience irregular payments make more precautionary savings, moonlight and use self-production.

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[47]"Russia Longitudinal Monitoring survey, RLMS-HSE", conducted by the National Research University Higher School of Economics and ZAO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS

Food proves to be the most protected part of their consumption. Similar results can be found in Desai (2001) who also investigates in more detail various survival strategies used by affected workers including barter trade. The results of the previous chapter of this thesis indicate that the affected workers are twice as likely to experience recurring wage arrears and 10% more likely to frequently change employers within the following 5 years.

The unprecedented incidence of wage arrears is not the only reason why the Russian case is of particular interest. There is no doubt that wage arrears can be caused by a negative aggregate productivity shock or by idiosyncratic shocks experienced by individual firms. However, they may also be a result of an opportunistic behaviour of the firms.

Earle and Sabirianova (2002) discuss numerous reasons for the Russian firms to *want* to use wage arrears in the 1990s and explain why the workers would accept the situation. The main official reason for the missed payments was the lack of cash due to the clients failing to pay on time. It explains some proportion of the delayed payments and the cuts in government spending account for a certain share of the arrears in the public sector. However, the reasons that were never publicly announced were much deeper and significantly more diverse.

According to Earle and Sabirianova (2002), it was possible to use wage arrears to get a tax exemption and government subsidies. In the times of limited external finance options the arrears could act as an interest free loan from the workers. Moreover, some firms were simply too reluctant to lay off unproductive workers as the "USSR mindset" was giving them a false hope for an extensive help from the government. In those cases irregular payments to the unproductive workers were a natural solution.

In addition, a poor monitoring of managerial decisions allowed managers to use

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workers' wages to participate in various get-rich-quick schemes without risking their own money. The short-term government bonds with an annual rate of return that exceeded 160% are an example of such opportunity. To cap it all, wage arrears were used to imitate financial difficulties and force the minor shareholders to sell their stakes in the company. The arrears were a tool that was used to acquire full control over the enterprises during the times of "privatisation" (the post-USSR period when many state-owned companies became private).

Among the main reasons for the employees to keep working despite not being paid on time Earle and Sabirianova (2002) mention poor outside options and good non-wage compensations. The latter includes both the standard benefits, such as an additional medical insurance and lower prices for certain services, as well as the possibilities for theft of output and equipment. The authors also mention that in some cases the workers, especially who were minor shareholders, were willing to lend their wages to the firms to help them through the hard times. It is an interesting scenario in which the workers insure their firms against unforeseen difficulties. Essentially it is the reverse of the standard view that firms insure the workers formalised in implicit contract models of, for example, Baily (1974) and Azariadis (1975). Using the RLMS data from 1994 to 1996 Lehmann et al. (1999) find that being a minor shareholder (owning less than 5% of the firm) was indeed significantly increasing the probability of experiencing wage arrears, whereas ownership of the firm had similar in magnitude negative effect on the probability of arrears.

An alternative behavioural explanation of the workers' actions (or lack of those) is suggested by Javeline (2003). She argues that one of the reasons why only less than 1% of the labour force protested against the arrears in Russia was a simple lack of information. The reasons behind the arrears were complex and specifying the blame required too much time and energy.

Russia is not the only country where wage arrears are used by firms to achieve their goals. Wage arrears in the construction sector in the United Arab Emirates in the mid-2000s is another example (HRW, 2006). The corporations new they would have less problems avoiding the payments to migrant workers and hired them to reduce the costs of building the skyscrapers.

These examples lead to the question of modelling of wage arrears. An accurate model could help to evaluate the validity of the discussed reasons behind wage arrears. That would help to avoid an escalation of the problem in any country to the levels observed in Russia in the 1990s and avoid the huge costs associated with them. It is especially relevant given that such events as the recent financial crisis provide a strong ground for wage arrears in countries with a weaker enforcement of labour regulations.

Probably one of the main reasons why wage arrears have not received much attention in theoretical literature is the belief that the arrears cannot be a part of an equilibrium. If a firm does not pay, the workers are free to leave. In addition to that the reputation of the firm is ruined and it struggles to replace the workers. When the workers have nowhere to go, for example there are no firms that pay wages, there is no incentive to exert any effort. This situation results in zero output and the economy collapses. That cannot be an equilibrium.

However, wage arrears do exist and sometimes are sustained for a long enough period of time to raise a question whether it is an equilibrium rather than a transitory phenomenon. The two most sophisticated models of wage arrears are the ones of Earle and Peter (2009) and Boyarchuk et al. (2005).

Earle and Peter (2009) develop a model of managerial decisions to use wage arrears and argue that the practice of violating employment contracts may be seen as an institution. In the model the manager chooses not to pay wages in hope to gain

private profits. By doing so she carries losses related to legal penalties, the workers' shirking behaviour, reduced productivity and increased probability of strikes. All the losses are assumed to be increasing in the incidence of arrears in the firm's region. The optimal amount of back-loaded wages is derived as a reaction function of the incidence of wage arrears in the region and of the manager's and workers' individual characteristics. The reaction function is assumed to be either linear or cubic. In the latter case multiple equilibria are possible, two of which are stable: "everyone pays on time", "no one pays on time". A transition between the stable equilibria may happen under an influence of an exogenous shock. The authors argue that the short-term government bonds in Russia provided the shock required for the transition to the "no one pays on time" equilibrium.

Boyarchuk et al. (2005) is an example of a different approach to wage arrears modelling. The authors use a neoclassical growth model to study the welfare consequences. In their model, firms are hit by negative idiosyncratic shocks and use wage arrears to minimise the losses they incur. Workers acknowledge the possibility of wage arrears and their effective wage consists of a fraction of the contractual wage that is paid in a given period plus the debt carried over from the previous period. The wages are assumed to be eventually repaid. The depreciation of the debt accounts for the real-life cases when the debt is not repaid and for the fact that the unpaid wages lose value due to inflation. The steady state with a constant density of wage arrears is considered and calibrated to the Ukrainian data.

These two models are interesting in many ways but suffer from several significant shortcomings. The main one is a very limited role of workers. In the former model their behaviour is narrowed down to exogenously defined functions. This approach does not allow to predict such important figures as additional unemployment that arises because of the irregular pay and the proportion of affected workers. In the

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latter model, all the reasons for the rise of wage arrears other than financial difficulties are left out of the consideration. Wage arrears are seen as random idiosyncratic shocks and workers just accept that from time to time they may receive only a fraction of the wage. They can not quit the job. Such approach allows to analyse the formation of precautionary savings but once again does not allow to make any predictions about the labour market dynamics.

In real life avoiding strikes and preventing the economy from collapsing involves interaction between the employers and employees. If wages are missed or paid irregularly the workers' reaction can lead to a significant drop in output. The firms have to anticipate it and weigh the loss against potential gains from using the arrears. At the same time the workers have to evaluate whether it is worth keeping the job or it is better to quit and search for a different one. Obviously it depends on whether they expect the firm to keep reneging on the contract or to pay them back soon enough. This interaction is often ignored in existing models.

Another important aspect, that has not yet been covered in existing models, is wage determination. A fixed wage is standard in the literature in this area. However, instead of using wage arrears the firms could cut the existing wages and such option should arguably be allowed in the models. On the other hand, there are many plausible arguments against this view. Wage cuts might have an even worse psychological effect than the arrears. If workers believe that the arrears is a one time event then suffering for a month is better that agreeing to a permanently lower pay. In addition to that an official wage cut makes it significantly harder for the managers to use extra money in their disposal in get-rich-quick schemes. Therefore wage cuts and wage arrears pursue different goals for the firms and thus an addition of a possibility to cut wages to the model would not provide a better understanding of wage arrears. An alternative view is that wage arrears are *the* way to cut real

wages (Bewley, 2007) and therefore there is no need to give the firms two options that are supposed to achieve the same goal.

At the same time, a wage determination does not need to be considered as a substitute for wage arrears in a model. It could be the case that firms and workers negotiate a higher wage but agree that it would be paid irregularly. In this case a built-in wage determination mechanism would potentially create additional incentives for the firms to use wage arrears.

Earle and Peter (2009) argue against such idea. According to them it does not make sense for the parties to simultaneously negotiate a wage contract and a contract to violate the former one. Moreover, if wages are negotiated with the unions they are outside of firms' everyday control. Thus depending on the particular labour market in focus an exogenous wage might be the better option.

I do not agree with "a contract to violate another contract" argument. In my view wage arrears do not require such thing. An acknowledgement from both parties that either of them may renege on the agreement could be enough for consistent delays in payments. However any protocol that allows both the wage renegotiation and irregular payments raises a rather complicated time inconsistency issue. In order to keep the workers, the firm has to promise to pay them later all the wages that are not paid on time. The workers have to believe the firm. But when the time to repay the debt comes, the firm has very few incentives to pay *all* the delayed wages. From the workers' point of view the wages that were not received in previous periods are *sunk cost*. It may be enough for the firm to pay one regular wage or a sum of wages that exceeds the workers' outside option to keep them on the jobs.

Of course one could introduce a more complicated mechanisms that would ensure full repayment (e.g. a court or a loss of reputation). However, not only it would complicate the model, but it would also distance the model further from the real-

ity. The countries where wage arrears affect a large number of workers are usually characterized by less established institutions and weaker employee protection laws. Given this argument, it seems beneficial to leave an endogenous wage determination for future research and focus on a model that tackles the worker-firm interaction issue[48].

To my knowledge the model developed in this paper is the first one to generate wage arrears as an outcome of worker-firm interactions. In the model firms choose whether to pay on time or not and workers can make a decision to leave the firm that pays irregularly. In the stable equilibrium case, the firms that delay payments make that strategy more attractive for the other firms. This feedback loop is obtained by addition of a simple job market to the model rather than assumed, as it has been done in the previous literature.

The majority of assumptions used in the model, especially the ones related to behaviour of workers, are based on the analysis of the RLMS dataset for the period from 1994 to 2012. The parameter values for the calibrations of the model are also based on the values observed in the dataset.

The baseline monthly calibration predicts that an affected respondent would indicate that they haven't been paid wages in approximately 4 months. More than half of the working population is predicted to be affected by the arrears in equilibrium. Both of these predictions match the values observed in Russia in the late 1990s. The return on investment that has to be available to firms in order for the economy to converge to the equilibrium with the characteristics mentioned above is extremely high – between 44% and 55%. However that parameter in the model compounds *all* the positive effects of wage arrears for the firms discussed in Earle and Sabirianova

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[48]The model with asymmetric information on worker-firm match quality and non enforceable bonus payment developed by Halac (2012) could be a good starting point for a combined "wage negotiation - wage arrears" model.

(2002).

The paper proceeds as follows: in section 3.2 I build up the model, discuss possible equilibria and consider the comparative statics, section 3.3 contains a calibration to the Russian data and discusses the implications, section 3.4 concludes.

3.2   Model

3.2.1   Setup

The model presented in this section rests on the assumption that the firms that pay wages irregularly do so not because of the genuine difficulties they experience but to achieve certain goals, namely to increase their profits. In this sense the model is tailored towards the economies where such interpretation of wage arrears is possible. However, in concluding remarks (section 3.4) I point towards another possible application of this model.

The model is set up in discrete time. The economy is populated by a mass of risk-neutral workers[49] equal to M and a mass of risk-neutral firms equal to N. Both workers and firms discount future by a common factor β per period. In every period a fraction of workers u are unemployed and with probability f each of them is matched to a firm. Employed workers can decide to leave the firm in any period or keep the job until it is exogenously destroyed. When a worker becomes unemployed she spends at least one period without a job and receives a benefit b every period until she gets matched to a firm.

There are two types of firms: *Good* and *Bad*. Good firms always pay a fixed wage w on time whereas Bad firms delay the payments to all their employees for n

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[49]It is common in the literature to assume that workers are risk-averse. However, the considered model is deterministic and therefore this assumption is not crucial.

periods. Bad firms can invest the unpaid wages for the whole n periods and earn compound interest r per period. In the end of the nth period the firms pay all the delayed wages but keep the interest earned[50]. Each firm can choose its type and is considered to be Bad as soon as the payments are delayed for one period. The proportion of Good firms is denoted p_g. Each firm can have any number of workers and each employed worker produces y units of output per period. The value of y is constant over time and known by both workers and firms.

When workers are matched to their new employers they have no information about the firm's type. It takes one period to find it out. When a payment is missed the worker knows that the firm is Bad but it is too late to join the unemployment pool in the same period.

It is natural to assume that workers hate being employed by Bad firms. This preference is reflected in the model by different separation rates for Bad and Good firms – λ_b and $\lambda_g(p_g)$ respectively. $\lambda_g(p_g)$ is assumed to be an increasing function of the proportion of Good firms. The range of $\lambda_g(p_g)$ is assumed to have a lower bound of zero and an upper bound equal to the separation rate for Bad firms ($\lambda_g(0) = 0$ and $\lambda_g(1) = \lambda_b$).

The intuition behind such assumption is as follows: if a worker knows that she is employed by a Good firm she tries harder to keep the job when unforeseen exogenous events happen. For example, if some distant relative from another city unexpectedly becomes sick she is less likely to move because if she quits the job her next employer might be of the Bad type. The lower the proportion of Good firms is the higher

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[50]This assumption is based on the results of Lehmann and Wadsworth (2007) who suggests that wage arrears in Russia are a result of irregular pay rather than missing payments. My own analysis of stocks and flows of the arrears in the RLMS dataset supports these finding. The results suggest that approximately 70% of wage arrears in Russia are paid back. Given that the data is infrequent (annual observations) such analysis requires a set of rather strong assumptions. All of those assumptions as well as the details about specific information from the dataset that was used to calculate the flows are presented in section 6 of the second chapter of this thesis.

the chances to be matched with a Bad firm after an unemployment spell are. This causes stronger concerns among Good firms' employees and lowers the separation rate applicable to Good firms compared to the one for Bad firms. On the other hand, when the number of Bad firms is negligible ($p_g \to 1$), the worker does not exert any extra effort to keep any job for longer than the other ones. After a period of unemployment she will be almost certainly matched with a Good firm. Thus the separation rates are the same for both types of firms in that case.

If a worker decides to leave a Bad firm in-between the payments that take place every n periods she does not get paid for the time she has worked since the last payment. This assumption, as well as the assumption that Bad firms do not share with the workers the profits they receive from the investment of unpaid wages, is based on the reality of the countries where such opportunistic behaviour of the firms is possible[51].

Though the workers know only the type of their firm, the values of all exogenous parameters are common knowledge.

The described setup allows both workers and firms to use numerous different strategies. A large, potentially infinite, number of equilibria with and without wage arrears are possible depending on the strategies each party chooses. Additional assumptions are required to narrow down the set of possible strategies and to guarantee a finite number of equilibria.

The results of the analysis of separations in the RLMS dataset using limited dependent variable models suggest that the workers affected by wage arrears are

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[51] For example, according to the Russian law a worker affected by wage arrears is entitled to a very small compensation from the firm. It is set at the level of $\frac{1}{300}$ of the central bank's key interest rate per day. Such compensations is very close to nothing even in the level of enforcement was high.

Before the recent changes in the Russian employment laws, that took place after 2010, the workers were unable to initiate bankruptcy hearings on the grounds of wage arrears. However even now, when it is possible, the former employees are close the bottom of the bankruptcy repayment queue. Thus the workers who decide to quit before collecting the arrears effectively write off the debt.

more than 40% more likely to quit their job[52]. At the same time my analysis of stocks and flows of the arrears suggests that more than 70% of them are repaid. Taking into account that in countries with weak labour protection it is difficult for the workers to claim the debt from the firms once they have quit, a common behavioural pattern emerges: The workers affected by wage arrears tend to change jobs after they have been repaid. This pattern is the basis for an additional assumption discussed below that is used to limit the options available to workers in the model.

3.2.2 Workers

Assumption 1. *The workers affected by wage arrears **do not** stay in the firm after they have collected the arrears.*

A worker can be unemployed or employed in either a Good or a Bad firm. The values of those states (W^u, W^g and W^b respectively) can be represented as follows:

$$
\begin{aligned}
W_t^u &= b + \beta(1-f)W_{t+1}^u + \beta f\left(p_g W_{t+1}^g + (1-p_g)W_{t+1}^b\right), \\
\\
W_t^g &= w + \beta\left(1 - \lambda_g(p_g)\right)W_{t+1}^g + \beta\lambda_g(p_g)W_{t+1}^u, \\
\\
W_t^b &= \beta\lambda_b W_{t+1}^u + \beta^2\lambda_b(1-\lambda_b)W_{t+2}^u + \ldots + \beta^n\lambda_b(1-\lambda_b)^{n-1}W_{t+n}^u + \\
&\quad + \left(\beta(1-\lambda_b)\right)^n w(n+1) + \beta^{n+1}(1-\lambda_b)^n W_{t+n+1}^u,
\end{aligned}
\tag{3.1}
$$

In each period an unemployed worker receives an unemployment benefit and in the following period either stays unemployed or is matched to a firm that can be of either type. A worker who is employed in a Good firm receives a wage and in the following period either stays with the same firm or loses the job. A Bad firm's employee does

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[52]The detailed description of the methodology as well as the extensive discussion of the results can be found in section 4 of the second chapter of this thesis.

not get paid anything for n consecutive periods but may become unemployed due to exogenous reasons. n periods after the first missed payment she collects all the arrears and receives an on-time payment for the work in that period. Therefore her total earnings in the period when the debt is repaid are equal to $n+1$ monthly wages. By assumption 1 she then leaves the firm.

The value of being employed in a Bad firm depends on the amount of time the worker has spent in the match. The more periods the worker spends in the Bad firm the fewer periods are left until the repayment. The value of being employed in a Bad firm after having spent one period in the match is given by:

$$W_{t+1}^b = \beta\lambda_b W_{t+2}^u + \beta^2\lambda_b(1-\lambda_b)W_{t+3}^u + \ldots + \beta^{n-1}\lambda_b(1-\lambda_b)^{n-2}W_{t+n}^u +$$

$$+ \left(\beta(1-\lambda_b)\right)^{n-1}w(n+1) + \beta^n(1-\lambda_b)^{n-1}W_{t+n+1}^u. \quad (3.2)$$

Using the properties of geometric progressions the following steady state version of (3.1) and (3.2) can be obtained:

$$
\begin{aligned}
W^u &= b + \beta(1-f)W^u + \beta f\left(p_g W^g + (1-p_g)W_m^b\right), \\
W^g &= w + \beta\left(1-\lambda_g(p_g)\right)W^g + \beta\lambda_g(p_g)W^u, \\
W_m^b &= \frac{\beta\lambda_b W^u\left(1-\left(\beta(1-\lambda_b)\right)^n\right)}{1-\beta(1-\lambda_b)} + \left(\beta(1-\lambda_b)\right)^n w(n+1) + \beta^{n+1}(1-\lambda_b)^n W^u, \\
W_{m+1}^b &= \frac{\beta\lambda_b W^u\left(1-\left(\beta(1-\lambda_b)\right)^{n-1}\right)}{1-\beta(1-\lambda_b)} + \left(\beta(1-\lambda_b)\right)^{n-1} w(n+1) + \beta^n(1-\lambda_b)^{n-1} W^u,
\end{aligned}
$$

$$(3.3)$$

where W_m^b and W_{m+1}^b denote the values of being employed in a Bad firm when the match is formed and one period later respectively.

The values of W_m^b and W_{m+1}^b are crucial for the analysis. The former is a part of the value of unemployment and thus determines its attractiveness. The latter is directly compared to the value of being unemployed by the workers experiencing

wage arrears when they decide whether to quit or to stay.

In steady state it is never optimal for a worker affected by wage arrears to wait a few periods after the Bad firm's type has been revealed and then leave without collecting the arrears. The intuition for this statement is as follows: if a worker decides that it is better to wait n periods to be paid than to become unemployed then they should also prefer to keep waiting in the following period as the waiting time is shorter. Mathematically it can be shown that steady state value of being employed in a Bad firm is decreasing in number of periods that are left until the payment. The derivation of this result can be found in the appendix.

The value of being being employed in a Bad firm, W_m^b and consequently W_{m+1}^b, are not guaranteed to be monotonic in duration of wage arrears n. However an increase in the value of being employed associated with a longer waiting times to receive wages contradicts the basic desire to be paid. Therefore I restrict the attention to the parametrisations under which the value of being employed in a Bad firm is monotonically decreasing in the length of the spell of wage arrears.

The workers matched to Bad firms quit if unemployment yields a higher value than waiting for the payments ($W^u > W_{m+1}^b$), and stay otherwise ($W^u \leq W_{m+1}^b$). The *workers' indifference condition*:

$$W^u = W_{m+1}^b, \tag{3.4}$$

in combination with system 3.3 provides the maximum duration of wage arrears that can be tolerated as a function of the proportion of Good firms ($n^*(p_g)$).

Both Good and Bad firms pay their workers the same wages. Because Good firms pay regularly their employees enjoy a higher present value of their earnings compared to the workers in Bad firms. In addition, the exogenous separation rate

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for Good firms is assumed to be less or equal to the one for Bad firms. Therefore the value of being employed in a Good firm always exceeds the one of being employed in a Bad one. The more Good firms there are on the market, the easier it is for the unemployed individuals to be matched with them. Therefore the value of being unemployed, W^u, is increasing in proportion of Good firms on the market, p_g.

By the workers' indifference condition (3.4), an increasing value of unemployment rises the minimum value of being employed in a Bad firm that is required by the workers to stay in the match. Therefore, given that W^b_m is decreasing in n, the maximum tolerated duration of wage arrears decreases when the value of being unemployed rises. Thus $n^*(p_g)$ is a decreasing function of p_g (Figure 3.2.1).
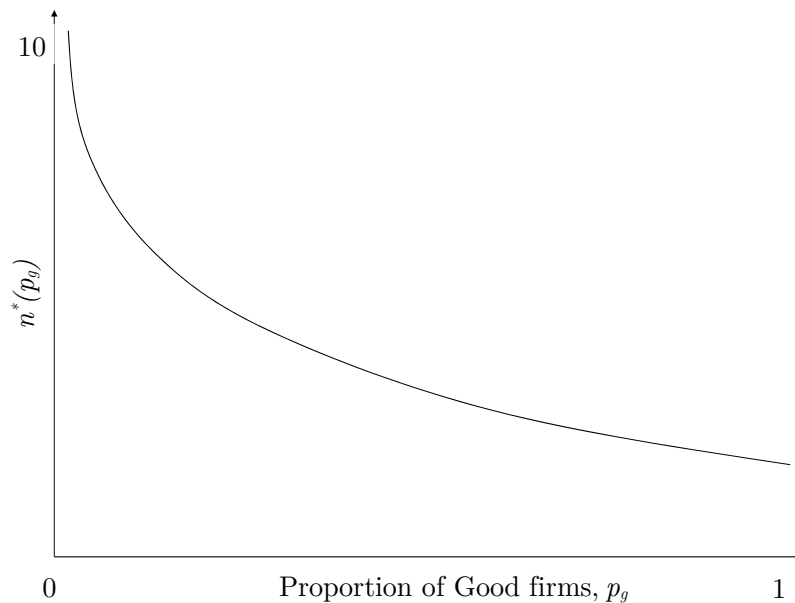
Figure 3.2.1: Solution to the workers problem: the maximum tolerated duration of a spell of wage arrears as a function of the proportion of Good firms

3.2.3 Labour Market

Denote the fractions of workers employed in Good and Bad firms by l_b and l_g respectively. Then

$$
\begin{aligned}
\triangle l_{g_t} M &= u_t M f p_g - \lambda_g(p_g) l_{g_t} M, \\
\triangle l_{b_t} M &= u_t M f (1 - p_g) - \lambda_b l_{b_t} M - (1 - \lambda_b)^n l_{b_{t-n}} M,
\end{aligned}
\tag{3.5}
$$

where the first line represents the law of motion of Good firms' employment and the second line represents the same for Bad firms. The former is standard – in every period a certain fraction of unemployed individuals find jobs in Good firms and a certain fraction of the jobs is exogenously destroyed. The latter is slightly different. In addition to the people whose jobs are destroyed due to exogenous reasons, the outflow from the Bad firms contains those workers who leave the firms after they have been paid. Before those workers can collect their wages they need to survive n potential job destructions in the firm. That is represented by the $(1 - \lambda_b)^n l_{b_{t-n}}$ term in the law of motion of employment in Bad firms.

From (3.5) it follows that in steady state:

$$
\begin{aligned}
l_g &= \frac{u f p_g}{\lambda_g(p_g)}, \\
l_b &= \frac{u f (1 - p_g)}{\lambda_b + (1 - \lambda_b)^n}.
\end{aligned}
$$

The relationship $u = 1 - l_g - l_b$ closes the description of the labour market and allows to obtain steady state values of unemployment and employment in both types of firms:

$$
\begin{aligned}
l_g &= \frac{f\left(\lambda_b + (1 - \lambda_b)^n\right) p_g}{f \lambda_g(p_g)\left(1 - p_g\right) + f p_g\left(\lambda_b + (1 - \lambda_b)^n\right) + \lambda_g(p_g)\left(\lambda_b + (1 - \lambda_b)^n\right)}, \\
l_b &= \frac{f \lambda_g\left(1 - p_g\right)}{f \lambda_g(p_g)\left(1 - p_g\right) + f p_g\left(\lambda_b + (1 - \lambda_b)^n\right) + \lambda_g(p_g)\left(\lambda_b + (1 - \lambda_b)^n\right)}, \\
u &= \frac{\lambda_g(p_g)\left(\lambda_b + (1 - \lambda_b)^n\right)}{f \lambda_g(p_g)\left(1 - p_g\right) + f p_g\left(\lambda_b + (1 - \lambda_b)^n\right) + \lambda_g(p_g)\left(\lambda_b + (1 - \lambda_b)^n\right)}.
\end{aligned}
\tag{3.6}
$$

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When a firm makes a decision to pay the wages on time or to withhold them, it takes into account the number of workers it has rather than the proportions of workers that are employed in *all the firms* of each type. Denote those numbers l_g^f and l_b^f for Good and Bad firms respectively. Because the firms of each type are identical, in steady state they employ the same number of workers given by:

$$
\begin{aligned}
l_g^f &= \frac{l_g M}{N p_g}, \\
l_b^f &= \frac{l_b M}{N(1-p_g)}.
\end{aligned}
\tag{3.7}
$$

Keeping everything else constant, the proportion of people employed in Bad firms is increasing in n and the proportion of workers in Good firms is decreasing in n.[53] Intuition behind this result is as follows: the workers get "hooked up" in Bad firms waiting to collect the arrears. As a consequence the number of people available to be matched with Good firms decreases.

3.2.4 Firms

When a firm decides to use wage arrears it commits to being Bad for the following n periods[54]. Firms do not discriminate between their employees and withhold the wages of all of them. In equilibrium, when firms have no incentives to change their type, the value (or profit) for a Bad firm can be expressed as follows:

$$
F_t^b = y l_{b_t}^f - w l_{b_{t-n}}^f (1-\lambda_b)^n (n+1) - w(l_{b_t}^f - (1-\lambda_b)^n l_{b_{t-n}}^f) +
$$
$$
+ (1+r)^n w(l_{b_{t-n}}^f - (1-\lambda_b)^n l_{b_{t-2n}}^f) + \beta F_{t+1}^b. \tag{3.8}
$$

---

[53]The partial first derivatives with respect to n are presented in the appendix.

[54]When the parameters of the model are constant, the case when a Bad firm wants to make payments before the n periods have elapsed is equivalent to choosing a smaller n in the first place.

In every period a Bad firm receives y units of output from all current employees, repays the debt to survived workers whose spell of arrears started n periods ago $[wl^f_{b_{t-n}}(1 - \lambda_b)^n(n+1)]$, invests wages of the rest of their current employees $[w(l^f_{b_t} - (1 - \lambda_b)^n l^f_{b_{t-n}})]$ and receives the return on investment made n periods ago $[(1 + r)^n w(l^f_{b_{t-n}} - (1 - \lambda_b)^n l^f_{b_{t-2n}})]$.

Equilibrium profit of a Good firm is represented by:

$$F^g_t = l^f_{g_t}(y - w) + \beta F^g_{t+1}. \tag{3.9}$$

In every period a Good firm receives the output from all employees and pays them the wages.

The properties of geometric progression yield the following steady state values:

$$F^g = \frac{l^f_g}{1 - \beta}\Big(y - w\Big), \tag{3.10}$$

$$F^b = \frac{l^f_b}{1 - \beta}\Big(\underbrace{y + (1 + r)^n w(1 - (1 - \lambda_b)^n)}_{A} \underbrace{-w\big((1 - \lambda_b)^n n + 1\big)}_{B}\Big). \tag{3.11}$$

Bad firms can choose the duration of the spell of wage arrears they use. Intuitively F^b should be increasing in n: By delaying the payments by one extra period the firms earn additional interest on their investment and have to repay to fewer workers as more of them lose their jobs due to exogenous reasons. From the mathematical point of view part A of equation (3.11) is strictly increasing in n. At the same time part B is hump-shaped: For low values of n, when $n < -\frac{1}{ln(1-\lambda_b)}$, it is decreasing and increasing otherwise. This is due to the fact that when the spell of arrears is short the workers are more likely to survive until repayment and therefore the firm will

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have to make more payments. However, if the expected increase in debt payments is not offset by the return on investment of wages Bad firms have no incentives to use wage arrears. In other words, as long as it is profitable to be a Bad firm the firm wants to delay wages for as long as possible.

This logic is valid only as long as the workers in Bad firms stay in the firm to collect the payments. Therefore Bad firms choose the maximum duration of the arrears that is tolerated by the workers given the market conditions. The maximum tolerated length of the arrears, $n^*(p_g)$ is decreasing in proportion of Good firms. It follows that the profits of Bad firms are decreasing in p_g.

The profits of Good firms are also affected by p_g as it affects the number of workers employed in the firms. Depending on the parametrisation it is possible for the number of workers in Good firms to be increasing in the proportion of Good firms on the market. However in the calibration section I check that the observed parameters are consistent with the number of employees in a Good firm decreasing in proportion of Good firms on the market[55]. Therefore I focus on this case. The intuition behind this result is that when the number of Good firms on the market is low their employees do not quit in fear to be matched to a Bad firm. Therefore the fewer Good firms there are on the market the larger in size they grow, absorbing the workers running from Bad firms. It results in the higher profits generated by Good firms when wage arrears are widespread. Mathematically the reason for such result is the assumption that the separation rate for Good firms is decreases when proportion of them on the market becomes lower.

Given that Bad firms are characterised by a larger outflow of workers in every period compared to Good firms, the model suggests that, in comparison to Good firms, Bad firms have a smaller steady state number of employees but generate more

---

[55]The mathematical condition that is required for such result to hold can be found in the appendix

profits from each of them. This prediction is consistent with the relative sizes of the firms reported by affected and unaffected respondents in the RLMS[56].

3.2.5 Equilibrium: existence and stability and comparative statics

For the observed value p_g workers determine the maximum tolerated length of arrears $n^*(p_g)$. Firms compare the profits generated by delaying the wages by $n^*(p_g)$ periods and by making regular payments and choose their type. Movements between the types affect p_g and workers update $n^*(p_g)$.

An equilibrium is reached when both types generate the same profit. Thus it is a solution to the system of equations (3.3) augmented with workers' indifference condition (3.4), expressions for the profits of both types of Firms (equations (3.10) and (3.11)) and the profit equivalence condition $F^b = F^g$:

$$
\begin{aligned}
W^u &= b + \beta(1-f)W^u + \beta f\left(p_g W^g + (1-p_g)W^b\right), \\
W^g &= w + \beta\left(1 - \lambda_g(p_g)\right)W^g + \beta\lambda_g(p_g)W^u, \\
W^b_m &= \frac{\beta\lambda_b W^u\left(1 - \left(\beta(1-\lambda_b)\right)^n\right)}{1-\beta(1-\lambda_b)} + \left(\beta(1-\lambda_b)\right)^n w(n+1) + \beta^{n+1}(1-\lambda_b)^n W^u, \\
W^b_{m+1} &= \frac{\beta\lambda_b W^u\left(1 - \left(\beta(1-\lambda_b)\right)^{n-1}\right)}{1-\beta(1-\lambda_b)} + \left(\beta(1-\lambda_b)\right)^{n-1} w(n+1) + \beta^n(1-\lambda_b)^{n-1} W^u, \\
W^u &= W^b_{m+1}, \\
F^g &= \frac{l^f_g}{1-\beta}(y-w), \\
F^b &= \frac{l^f_b}{1-\beta}\left(y + (1+r)^n w(1 - (1-\lambda_b)^n) - w((1-\lambda_b)^n n + 1)\right), \\
F^b &= F^g.
\end{aligned}
$$

$$(3.12)$$

---

[56]In the RLMS the average firm's size reported by affected by wage arrears respondents is 852 employees compared to 1041 reported by unaffected individuals

In this setup an equilibrium always exists. Either all firms are of the same type (whichever guarantees the higher profit) or some of the firms are Good and some are Bad with equal profits. Hereafter I refer to the former situation as pooling equilibria and to the latter as separating equilibrium.

The pooling equilibria are of little interest in the scope of this paper. The equilibrium in which all firms pay on time represents the normal situation in the majority of countries. The equilibrium when none of the firms pay on time represents a hypothetical country where it is the local custom to pay wages once in several months, and therefore the late payments are not perceived as arrears.

A graph that depicts the profits of both firms' types can shed light on existence of a separating equilibrium. Both F^g and F^b are decreasing in p_g, therefore various outcomes are possible depending on the relative slopes and curvature. Figure 3.2.2 depicts potential outcomes. Note that this graph already takes into account the fact that Bad firms pick the maximum possible duration of arrears, $n^*(p_g)$, determined by the workers for every proportion of Good firms on the market.

The profit equivalence determines a stable equilibrium if the profits of Bad firms exceed the profits of Good firms when p_g is high and fall short of the Good firms' profits when p_g is low (Figure 3.2.2a). This is the most interesting equilibrium that can arise because of the investment opportunities and "get-rich-quick" schemes available to Firms. When the opportunities to create extra profits by investing the wages do not exist or are small ($r \approx 0$) the profits of Good firms exceed the profits of Bad firms. In this scenario Bad firms are unable to get any return from using the arrears and lose the workers who quit after collecting the debt. This corresponds to the normal state of the world in the majority of countries – all firms choose regular on-time payments. As an increase in r boosts the profits of Bad firms the F^b curve shifts up and may intersect the F^b curve once or several times. If the curves intersect

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in the way as presented on figure 3.2.2a a part of Good firms change their type to Bad and a stable equilibrium with wage arrears arises.
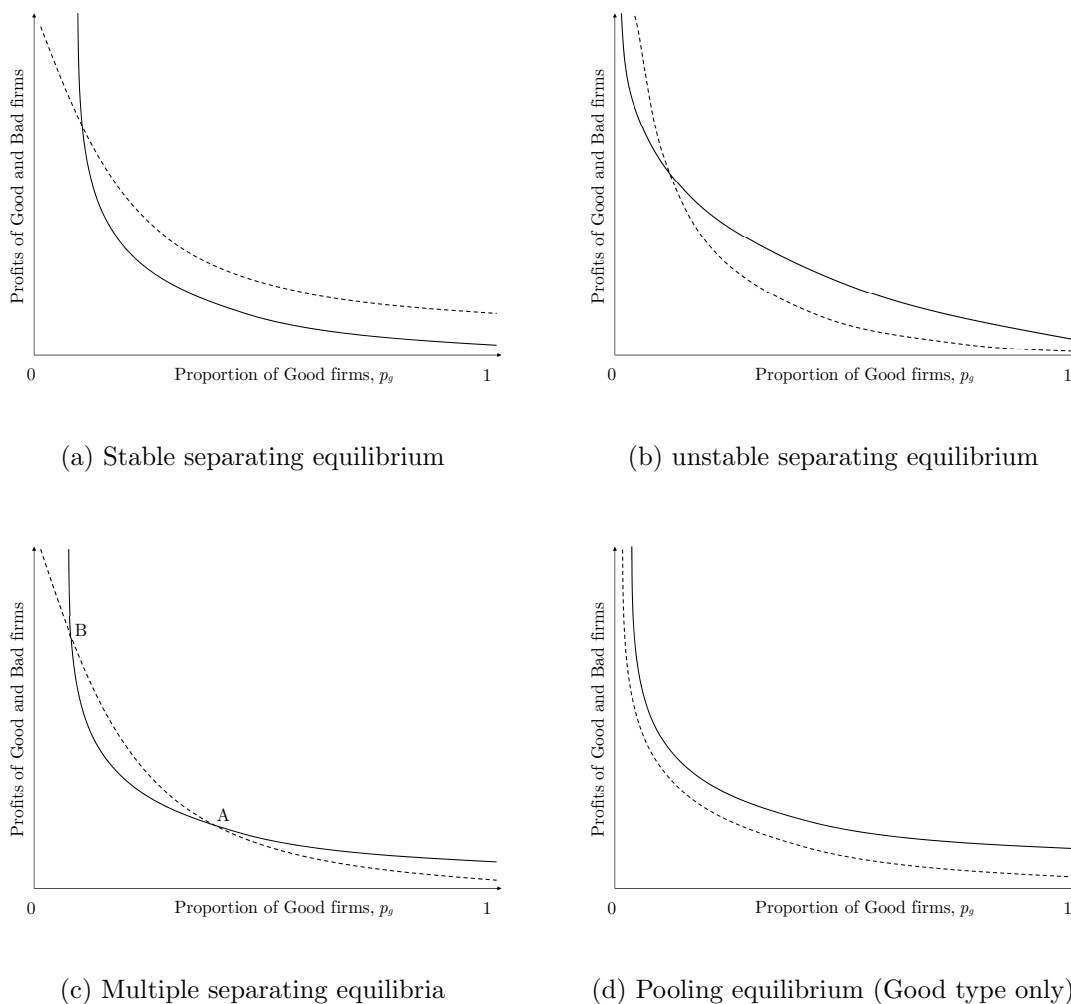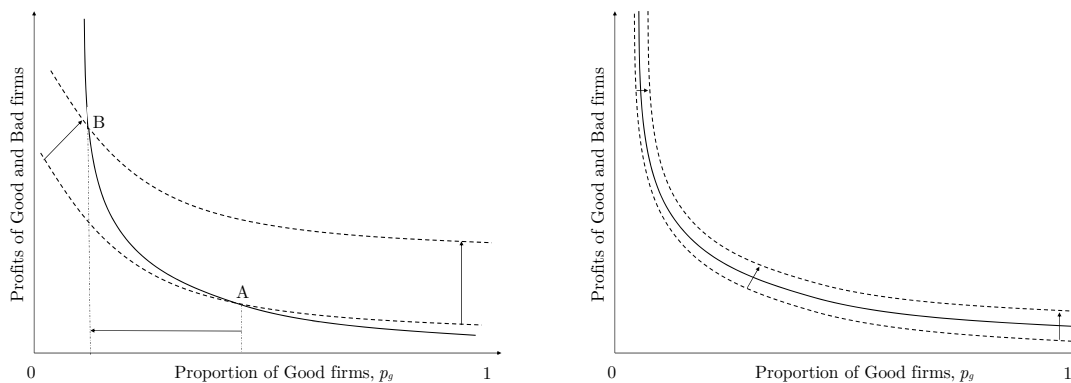

(a) Stable separating equilibrium

(b) unstable separating equilibrium

(c) Multiple separating equilibria

(d) Pooling equilibrium (Good type only)

Figure 3.2.2: Stability of Equilibrium. F^g —— , F^b - - -

The existence of a stable equilibrium depends on the relative slopes and convexity of F_g and F_b. If those curves are parallel to each other, then an increase in r to a certain number $\tilde{r}$ makes all the firms indifferent between the types. A further increase to an $r > \tilde{r}$ makes delays in payments the optimal strategy for all firms. The economy flips between the two pooling equilibria (figure 3.2.3b).

If F^g is consistently less steep than F^b the separating equilibrium is unstable. It is better for the firms to choose the type that is dominant on the market (Figure 3.2.2b). If one of the functions is considerably more convex then multiple equilibria may arise with at least one of them being stable (equilibrium B presented on Figure 3.2.2c is the stable one of the two).

(a) The economy moves between two stable sepa-
rating equilibria

(b) The economy moves between the pooling equi-
libria

Figure 3.2.3: Comparative statics. F^g — , F^b - - -

The complexity of the functions does not allow me to obtain an interpretable condition for the parameter values that would ensure existence of a stable equilibrium. The numerical simulations reveal that the main parameters that affect the stability are the separation rates, and the job-finding rate.

A larger value of λ_b contributes to a greater difference in convexity of the profit functions. This is due to the fact that the separation rate for Good firms is bounded by the separation rate for Bad firms ($0 < \lambda_g(p_g) < \lambda_b$). Thus a larger value of λ_b allows a larger variation between the rates. On the contrary, a low value of λ_b implies a smaller relative gain for Good firms when p_g is low. The workers quit Good jobs because of exogenous almost as often as the Bad ones. Thus there are less incentives for the firms to stick to the Good type.

A concave functional form of $\lambda_g(p_g)$ helps to achieve a stable equilibrium. This is because when the number of Good firms is small the value of $\lambda_g(p_g)$ falls rapidly. It gives a boost to the Good firms' profits and makes the type attractive. At the same time when p_g is high the value of the Good firms' separation rate decreases slower. This means that the workers do not quit Bad jobs much more often than the Good ones because of exogenous reasons. This reduces the costs of becoming a Bad firm and makes that type more attractive.

In the case of job-finding rate, its value relative to the values of the separation rate from Bad firms is important. If the job-finding rate is substantially larger, the unemployment is attractive for the Bad firms' employees. Therefore, the maximum duration of arrears tolerated by the workers and consequently the profits of Bad firms are relatively low. Thus wage arrears are unattractive especially when Good firms prevail on the market. It contributes to realisations of unstable separating and pooling equilibria.

The comparative statics for an unstable separating equilibrium is of little interest. If the equilibrium is unstable then any change in the values of the parameters will push the economy into one of the pooling equilibria.

The comparative statics for a stable equilibrium in this model is intuitive. A decrease in both the unemployment benefits and the job-finding rate make unemployment less attractive for the workers affected by wage arrears. That releases pressure from the maximum tolerated duration of arrears and consequently boosts the Bad firm's profits. As the result the proportion of Good firms in equilibrium is smaller. Figure 3.2.3 illustrates this scenario, the economy moves from equilibrium A to equilibrium B.

An increase in the discount factor (more patient workers) and in the rate of return on investments r have the same effect. The former allows to delay the payments for

longer and the latter increases the return received by Bad firms in every period. Both factors contribute to an increase in the Bad firms' profits.

Higher wages lead to a reduction of the profits of Good firms. They become tempted to compensate these losses by using wage arrears and therefore new equilibrium is characterised by a lower number of Good firms.

Finally, if the labour productivity, y, increases the number of Bad firms in equilibrium falls. This is because the reduction in steady state number of employees that is associated with the Bad type becomes more costly.

The duration of wage arrears is longer in all equilibria that are characterised by a lower proportion of Good firms. This follows from the workers indifference condition 3.4 and profit maximising behaviour of Bad firms.

The comparative statics in pooling equilibria mimics the one of the stable separating equilibrium in the sense that the changes in all parameters have the same effects of the profits of Good and Bad firms. As a result of those changes the economy may either make a transition to the other pooling equilibria (figure 3.2.3b) or to a separating equilibrium as described above.

In this section I established that a stable equilibrium in which some firms pay wages every period and some delay the payments is possible. In the following section I perform a calibration and check whether the observed parameters are consistent with an equilibrium of this type.

3.3   Calibration

In this section I perform a calibration of the model to the Russian data. The data source is the RLMS[57]) for the years from 1994 to 2012. The dataset is based on an

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[57]"Russia Longitudinal Monitoring survey, RLMS-HSE", conducted by the National Research University Higher School of Economics and ZAO "Demoscope" together with Carolina Population

annual dwelling based survey that contains a detailed job related section that allows to distinguish the workers affected by wage arrears.

Figure 3.3.1 presents the proportion of the labour force affected by irregular wage payments according to the RLMS. The wage arrears were becoming more and more widespread in the 1990s. The incidence reached its peak in the 1998, the same year Russia defaulted on its short-term bonds. Since then the arrears have been steadily declining.

The hump-shaped graph of the incidence of the arrears supports the view about their unusual nature in Russia discussed in the literature and the previous chapters of this thesis (see, for example, Earle and Sabirianova (2002)). Many new opportunities for the managers appeared with the collapse of the USSR. They were involved in the get-rich-quick schemes and wars for the control over the former state-owned enterprises. To minimise their risks they were using the money of their employees. The wage arrears were becoming more and more widespread and the economy was transitioning toward the equilibrium in which many firms would pay irregularly.

When the bubble burst, the access to the abnormal returns on the government bonds was terminated and the process of privatisation of state-owned companies came to its end, the economy started its movement towards the "normal" equilibrium. That equilibrium also features some persistent, but low, level of wage arrears due to the fact that from time to time firms experience financial difficulties.

The proportion of the labour force affected by wage arrears grew by 41% (17 percentage points) between 1995 and 1996 but only by 3% (2 percentage points) between 1996 and 1998. It may be an indication that the economy reached the steady state around 1998. Therefore I mainly use the data from that year in the calibration.

Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS.
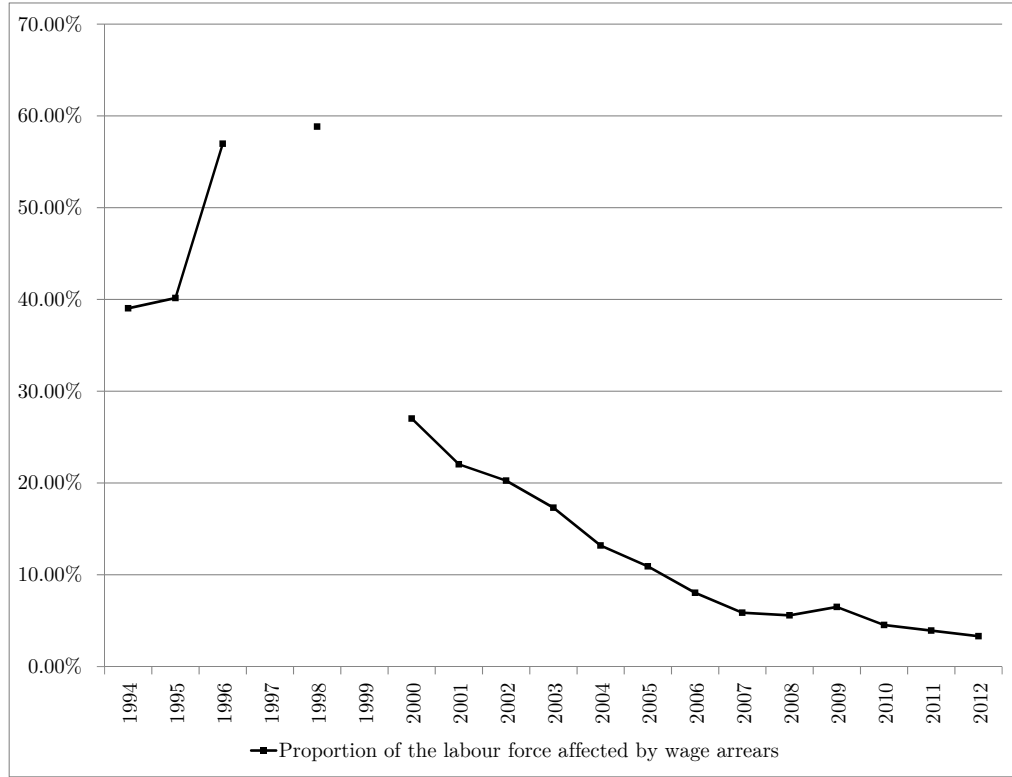
Figure 3.3.1: Proportion of the labour force affected by wage arrears according to the RLMS

The time period in the calibration is taken to be one month. The two endogenous outcomes of the model that could be directly compared to the data are the duration of the arrears and the proportion of Good firms in the equilibrium.

To identify the duration of wage arrears, the respondents in the RLMS are asked *"How many months do they owe you the money for?"*. However, when they answer that question they may be in the middle of their ongoing wage arrears spell. The following mapping makes the prediction of the model comparable with the survey:

$$n^{survey}(n^*) = \sum_{m=1}^{n^*_{(p_g)}} \frac{\lambda_b}{1 - (1 - \lambda_b)^n} m(1 - \lambda_b)^{m-1}. \tag{3.13}$$

The expression (3.13) is the expected value of an answer to the survey question which is given by a Bad firm's employee.

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Unfortunately the RLMS does not contain firms' identifiers. Therefore instead of comparing the predicted proportion of Good firms to the data, I compare the predicted fraction of affected workers. The value implied by the model is given by $\tilde{l} = \frac{l_b}{(l_b+l_g)}$.

Without loss of generality the output produced by each worker is normalised to 1. Following Hall and Milgrom (2008) the unemployment benefit is set to 70% of the average productivity. The wage is fixed halfway between the average productivity and the unemployment benefit.

Because of the gaps in the survey in 1997 and 1998 it is impossible to calculate the transition probabilities between employment and unemployment in the late 1990s. Over the last 15 years the annual job-finding rate has been fluctuating between 30% and 40% without a trend and averaged at 35%. The annual separation rate reported by workers unaffected by arrears averaged around 17% .The separation rate for workers affected by irregular pay has been consistently higher – 23.5% on average[58]. This evidence supports the assumption of the different separation rates used in the model.

Within a year a worker may change jobs several times which is not reflected in the survey. To take that into account when calculating the monthly transition rates I use the Markov chain time aggregation approach discussed in Elsby et al. (2015).[59] The results are 3.06% and 4.29% for the monthly separation rates from Bad firms and the job-finding rate respectively. The separation rate for Good firms is assumed to be a concave function of the proportion of Good firms.

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[58]The separation is identified by observing either unemployment after employment or a tenure of zero years. The tenure is calculated as the difference between the start date on the job and the date of the RLMS survey.

[59]I consider two separate 2-state Markov chains. The first one considers transitions between unemployment and a job in a Bad firm. The second one considers transitions between unemployment and employment in a Good firm. I use this approach rather than a 3-state Markov chain because neither the proportion of Good firms is observed in the data nor it is fixed in the model. Therefore I cannot identify the annual transition probability between the two types of firms.

It is not surprising that there is no official time series for r. The returns on the government bonds prior to 2000 are no longer reported. Drobishevskiy (1999) indicates that the annual returns to investment in government bonds in 1998 were in the region of 140% – 160%. It corresponds to approximately 8% per month. Richter (2006) reports the annual rate of 200% prior to the presidential elections in 1996. Unreliable sources such as tabloids and Wikipedia articles mention returns of up to 300% in the last month before the default in 1998. The same sources claim that other grey schemes in Russia were providing monthly returns of up to 20% in 1997 and 1998. In absence of a reliable time series I do not stick to any specific value of r and rather analyse the value that is required for the existence of a stable steady state.[60].

Table 3.3.1: Parameter values based on the RLMS and the results of steady state result

Parameter	Value	Steady State		Target	
β	0.996	Stable			
y	1				
w	0.85				
b	0.7	n^{survey}	8	n^{survey}_{RLMS98}	5.5
f	0.043	$\tilde{l}$	0.56	$\tilde{l}_{RLMS98}$	0.58
λ_b	0.03				
$\lambda_g(p_g)$	$\lambda_b p_g^{0.8}$				
r	0.48				

The numerical simulations suggest that to achieve a stable steady state the value of r has to exceed 35%. The value of is 48% per month is required to obtain the ratio of the workers in Bad and Good firms of 0.56 which is close to the value observed in the data. The predicted response to the survey question about the ongoing spell of arrears is 8 months compared to the average of 5.5 months reported

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[60]All calibrations discussed below are performed in MatLab. The source code is available on request

by the respondents in 1998. The shocking result is the predicted unemployment of 64% that is drastically different from the observed in the RLMS values of 11% - 12%.

This outcome may be a result of the measurement error in the estimations of job-finding and separation rates. The separation rate for Bad firms is crucial for the model and at the same time is the one of the least reliable parameters when it comes to any survey based data. The tenure data in the dataset is sometimes inconsistent and the disaggregation technique used to obtain the monthly values may also be a source of the measurement error because it imposes certain assumptions that may not be valid[61].

Interestingly the job-finding and separation rates that are observed in the RLMS are significantly lower than the ones that are observed in developed economies. Partially it could be explained by a lower mobility of the labour force and existence of the "mono-towns"[62] which are characterised by fewer outside options available to the workers. However, what is surprising is the relative magnitude of the job-finding and separation rates.

Consider the steady state value of unemployment implied by the model in absence of wage arrears:

$$u^* = \frac{\lambda_b}{\lambda_b + f} = \frac{0.03}{0.03 + 0.043} = 0.41 \tag{3.14}$$

The considered labour market is very basic – it lacks the search frictions, all parameters are exogenous and on-the-job search is not permitted. That could explain part of the gap between the predicted value of unemployment and the data (unemployment of 11% in 1998). However the gap seems to be too large to be fully accounted for by the simplicity of the labour market in the model. It raises some concerns about the reliability of the data.

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[61]For instance, two separate Markov chains for affected and unaffected workers assume that workers do not move between the firms of different types within a given year

[62]A town that has grown around a single enterprise

Given the argument above I suspect that the transition rates observed in the RLMS may reflect the reality inaccurately. Therefore I allow them to vary in addition to r and target 3 data moments: $u = 0.1$, $\tilde{l} = 0.5$, $n^{survey} = 4$[63]. Minimisation of a quadratic loss function reveals two competing parametrisations presented in Table 3.3.2.

Table 3.3.2: The parameters obtained by minimisation of a quadratic loss function

Specification 1		Specification 2		Target	
β	0.996	β	0.996		
y	1	y	1		
w	0.85	w	0.85		
b	0.7	b	0.7	n^{survey}	4
f	0.11	f	0.41	$\tilde{l}$	0.5
λ_b	0.075	λ_b	0.115	u	0.1
$\lambda_g(p_g)$	$\lambda_b p_g^{0.8}$	$\lambda_g(p_g)$	$\lambda_b p_g^{0.8}$		
r	0.52	r	0.55		
		Steady State			
Stable		Stable of multiple			
n^{survey}	4	n^{survey}	4		
$\tilde{l}$	0.4	$\tilde{l}$	0.58		
u	0.44	u	0.24		

3.3.1 Discussion

Both specifications from the table 3.3.2 achieve an accurate prediction of the reported length of wage arrears at the cost of a higher separation and job-finding rates. Specification 1 manages to preserve the ratio of the rates. The separation rate is predicted to be approximately equal to two thirds of the job-finding rate whereas the ratio observed in the data is equal to 0.7. This result suggests that the

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[63] We do not know whether the economy in 1998 was actually in the steady state. To account for the fact that the economy could potentially "overshoot" its steady state, I choose slightly less extreme values for the targets than the ones that were observed in the 1998.

model implies a slightly more mobile labour force but the fundamental nature of the matching in the labour market may be reflected correctly in the dataset.

If that is the case, then the difference between the predicted and the observed unemployment rate indicates an extreme popularity of on-the-job search. Yakubovich (2006) and Smirnova (2004) find that the most common job search strategy in Russia in the 1990s and the early 2000s was to look for a job leads through personal social networks. At the same time, firms were mainly using passive recruitment strategies, the majority of vacancies were never advertised. The recruitment managers would call the people they had in mind for the interviews and the candidates would contact the firms with the recommendations from their current employers. It is not surprising that in this conditions the workers preferred to keep their current jobs, no matter how bad they were, until they could find a new one.

Specification 1 predicts a smaller share of the labour force to be affected by wage arrears. The model can be reconciled with the data in this dimension if a looser interpretation of unemployment is allowed. In reality people do not necessarily leave the firms after they have collected the arrears. Some of them start a new cycle of arrears, others go on strike or stop working without official termination of employment ("you pretend to pay, we pretend to work"). In the survey all these people would indicate that they were affected by wage arrears. However in the model they would appear unemployed.

The second specification accurately predicts the share of affected workers. The separation and job-finding rates that provide this result are very close to the ones observed in literature for the USA. For example Shimer (2005) sets monthly separation rate to 10% and job-finding rate to 43%[64].

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[64]It might seem strange that the separation rate in Shimer's work is compared to the separation rate for Bad firms. However λ_b is the separation rate that prevails in the economy in absence of wage arrears and thus is a comparable parameter.

A graph similar to Figure 3.2.2c represents the solution of the model under parametrisation 2. The economy is characterised by 2 separating equilibria, and the one with larger number of Good firms is unstable. It means that if the economy starts from the equilibrium in which all firms pay on time and get-rich-quick schemes are not available to the managers, an increase in r from 0 to a positive number is not enough on to make the wage arrears attractive for the firms.

This is an illustration of the problem of relative convexity of F^b and F^g. Such difference between the separation and the job-finding rates is large enough to create multiple equilibria. A value of $\lambda_b > 0.1$ generates a very convex F^g. When the number of Good firms on the market is small, they are able to benefit more from their reputation compared to the parametrisations with lower levels of λ_b. At the same time a large f means that unemployment is an attractive option for Bad firms' employees. Thus it is very costly to for the firms to use wage arrears when the majority do not do use them. The result is a double crossing of the profit functions of Good and Bad firms. The equilibrium with the smaller number of Good firms is stable. However to converge to that equilibrium, the firms would have to collude. For this particular parameter values the profits of Good firms only marginally exceed the profits of Bad firms when p_g is close to 1. Therefore in this particular case the collusion may happen, especially within a small region or a sector of the economy which consists of a few large firms (e.g. heavy manufacturing or defence industry).

Both specifications require the return on the firms' investments to be in excess of 50% per month. It is unrealistically high even for the returns to the short-term government bonds in Russia in the 1990s. However, though I call this parameter the "return on investment" throughout the paper, it captures *all* the benefits of wage arrears for the firms firms. The combined effect of all the channels discussed by Earle and Sabirianova (2002), including tax exemptions, potential subsidies and obtaining

full control over an enterprise could be in the region of 50%.

The model tends to generate a high unemployment rate. This is due to the fact that the workers are assumed to leave Bad firms as soon as they have collected the arrears. At the same time the data and the literature suggest the popularity of on-the-job search. In this circumstances, within the framework of this model, it makes sense to target a higher unemployment and a lower share of affected workers[65]. I am targeting both equal to 30%.

Table 3.3.3: The calibration with a higher target for unemployment and a lower target for the proportion of affected workers

Parameter Values		Steady State	
β	0.996		
y	1	Stable	
w	0.85	n^{survey}	3
b	0.7	$\tilde{l}$	0.39
f	0.43	u	0.26
λ_b	0.14		
$\lambda_g(p_g)$	$\lambda_b p_g^{0.8}$		
r	0.44		

The results of loss minimisation (table 3.3.3) suggest the parameters that are closer to the specification 2 from Table 3.3.2. A higher separation rate closes the gap to the job-finding rate, which solves the double-crossing of the firms' profit functions problem. The resulting equilibrium is stable and colluding is not necessary to achieve it. A lower target for the proportion of affected workers releases the pressure from the required r which is now below 45%.

The last parameter that has not yet been discussed is the functional form of $\lambda_g(p_g)$. Though it could greatly affect the transition towards a steady state (mainly the speed of convergence) it does not matter much for the steady state analysis.

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[65]The workers who are forced into unemployment in the model may stay on their job and keep reporting the arrears. Therefore a part of the affected workers in the data should be accounted for by unemployment in the model.

Consider the ratio of the fractions of workers employed in Good and Bad sectors:

$$\frac{l_b}{l_g} = \frac{(1 - p_g)\lambda_g(p_g)}{\left(\lambda_b + (1 - \lambda_b)^n\right)p_g}.$$

The calibrations require this ratio to be quite large in steady state. To achieve it, either the duration of wage arrears, n, has to be very large or the number of Good firms has to be very small. However, the duration is also a target in calibrations. Thus it is the p_g that determines the ratio of the workers in two types of firms. Given that the value of p_g has to be close to zero in steady state, the value of $\lambda_g(p_g)$ is also close to zero irrespective of the functional form. Thus the functional form of the separation rate for Good firms is largely irrelevant for the steady state analysis.

3.4   Conclusion

This paper presents a model in which wage arrears arise in equilibrium as a result of the worker-firm interaction. Firms can choose to pay wages on time or delay them. In the latter case they use the workers' wages to create an extra profit by investing into outside projects. Workers make a decision whether to keep the job or to quit by comparing the value of employment in the firm with the value of unemployment. The ability of workers to walk away limits the duration of wage arrears used by the firms. A larger number of the firms that delay payments worsens the workers' outside options. They have to tolerate a longer spells of arrears. That, in turn, makes the practice of postponing the payments attractive for the other firms. This feedback effect is achieved endogenously in contrast to being assumed in the previous literature. In equilibrium the firms that pay on time attract more workers. The firms that use wage arrears are smaller but enjoy a higher profit per worker. This prediction of the relative size of the firms is consistent with the Russian data.

The existence of a stable equilibrium with wage arrears depends on the parametrisation of the model. To be more precise on the relationship between the separation and job-finding rates. The parameter values observed in RLMS dataset are consistent with a stable equilibrium. However an unrealistically high unemployment level is implied by the transition probabilities observed in the data. It raises a suspicion that the rates are misreported. To my knowledge it is the first work that mentions this concern despite the fact that many papers use this dataset and report the same numbers including Smirnova (2004), Furmanov and Shelkovnikova (2014), Earle and Sabirianova (2002), Foley (1997), Lofmark (2008) and others. An alternative explanation is an extreme popularity of on-the-job search. A further investigation in this direction would be useful for any work that deals with the labour section of the RLMS dataset.

When calibrated to the Russian data from 1998, the model accurately predicts the duration of wage arrears and the proportion of the labour force affected by irregular pay. However to generate those results it requires the return to the firms' investments to be very high – between 44% to 55% per month. The short-term government bonds are unable to fully account for such returns. However that parameter compounds *all* the types of benefits that the firms are able to receive by using wage arrears. Among the others those include tax exemptions and gain of control over the enterprise. The combined monetary value of those benefits is hard to estimate, however if the understanding of the nature of wage arrears presented in this paper is correct, the obtained numbers can be considered as an estimate of the outside returns the managers had access to.

The model has a number of shortcomings that can be addressed in future research. First of all, it tends to generate a higher unemployment than the one observed in the data. The main reason for that is the combination of an exogenously fixed

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job-finding rate and a constant large outflow of workers from the firms that delay payments. The latter is a result of the assumption that the workers never stay in the firm after they have collected the arrears. A certain share of affected workers who keep the job in real life are forced into unemployed in the model. An addition of an endogenous job-finding rate as well as introduction of on-the-job search could help to reconcile the model with the data.

A concave production could be introduced to the model. It could potentially make sure that the uniqueness of the steady state to a less extent depends on the relationship between the job-finding and job-destruction rates. Some sort of a wage determination mechanism is necessary in this case to ensure that Good firms never have negative profits, for example a standard assumption that the wage is equal to the marginal product of labour. However, the simulations suggest that such modification contributes to an unstable equilibria. When the number of Bad firms is large it is profitable to join them. They have small number of workers and therefore promise high wages which in turn mean large extra profits from investing them. When the number of Bad firms is small it is very costly to join the practice of wage arrears. Bad firms have small steady state number of workers and a concave production function implies a larger reduction in the firm's output associated with the change of the type compared to the linear case.

Potentially a very interesting modification is the one where the workers and the firms would agree on a new wage every single time a new match is formed. In such setup the firms would have very few incentives to keep their promises. However if this time inconsistency problem is solved a modified model could provide a useful tool for the analysis of the joint behaviour of wages and arrears. For example, workers may negotiate a higher wage when they think the wage arrears are likely. The data does not support this behaviour in Russia but it could prove useful for the analysis

of other countries.

The multi-armed bandit theory is an alternative approach that could yield a stable equilibria with wage arrears and several types of firms. Its main advantage is that it would not require a stable wage arrears cycle. The different types of firms would pay wages with different probabilities and it would take time for a worker to learn the type of the firm. The optimal stopping strategy would identify the moment when the worker leaves the firm. The weak spot of this approach is the proof of the optimal stopping strategy in style of Rothschild (1974). According to the stocks and flows analysis of wage arrears presented in the previous chapter, in the majority of cases in Russia the wage arrears are eventually paid back. If the repayment is assumed the value functions of the "hands" are no longer monotonic, which is a requirement for the proof of the optimal stopping strategy. However this brunch of the literature could provide a model suitable for the countries where the arrears are usually not paid back.

The model presented in this paper is tailored for the countries where wage arrears are a result of opportunistic behaviour of the firms and at the same time are eventually paid back. Not all the countries satisfy these criteria and the applications of this model may seem limited. However a straightforward change in terminology would allow an application of the model to the analysis of trade credit arrears. In many developed countries wages are honoured but 30% to 60% of the payments on trade credit are overdue (Alfandari and Schaffer (1996), Ghee (2010)). The efforts in this direction seem promising.

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Appendix

Proposition 1. *Steady state value of being employed in a Bad firm is decreasing in number of periods that are left until the payment.*

Proof

Consider the difference between the steady state values of being employed in a Bad firm in 2 consecutive periods, when the worker has to wait n and $n-1$ periods for the payment respectively. The subscripts denote the number of periods until the payment:

$$W_n^b = \frac{\beta \lambda_b W^u \left(1 - \left(\beta(1-\lambda_b)\right)^n\right)}{1 - \beta(1-\lambda_b)} + \left(\beta(1-\lambda_b)\right)^n w(n+1) + \beta^{n+1}(1-\lambda_b)^n W^u,$$

$$W_{n-1}^b = \frac{\beta \lambda_b W^u \left(1 - \left(\beta(1-\lambda_b)\right)^{n-1}\right)}{1 - \beta(1-\lambda_b)} + \left(\beta(1-\lambda_b)\right)^{n-1} w(n+1) + \beta^n(1-\lambda_b)^{n-1} W^u,$$

$$W_{n-1}^b - W_n^b = w(n+1)\left(\beta(1-\lambda_b)\right)^{n-1}\left((1-\beta(1-\lambda_b)) + \frac{\beta W^u}{1-\beta(1-\lambda_b)}\left(\beta(1-\lambda_b)\right)^{n-1} \cdot \right.$$
$$\left. \cdot \left[(1-\beta(1-\lambda_b))^2 + (1-\beta-\lambda_b(1-\beta))\right]\right.$$

Given that λ_b and β are positive and less than 1, all elements of this expression are positive. Therefore the fewer period the worker has to wait for the repayment the larger the value of the employment in the firm is. Thus if $W_n^b > W^u$ it must be the case that $W_{n-1}^b > W^u$. Therefore if a worker prefers employment in a Bad firm to unemployment at the moment when the type is revealed, she will also prefer it in all the following periods before she collects the arrears.

Proposition 2. *Keeping everything else constant, the proportion of people employed*

in Bad firms is increasing in n and the proportion of workers in Good firms is de-creasing in n.

Proof

Consider the proportions of the workers employed in each type of the Firm:

$$l_g = \frac{f\big(\lambda_b + (1-\lambda_b)^n\big)p_g}{f\lambda_g(p_g)\big(1-p_g\big) + fp_g\big(\lambda_b + (1-\lambda_b)^n\big) + \lambda_g(p_g)\big(\lambda_b + (1-\lambda_b)^n\big)},$$

$$l_b = \frac{f\lambda_g\big(1-p_g\big)}{f\lambda_g(p_g)\big(1-p_g\big) + fp_g\big(\lambda_b + (1-\lambda_b)^n\big) + \lambda_g(p_g)\big(\lambda_b + (1-\lambda_b)^n\big)}.$$

All the parameters are positive and less than 1. Taking the derivative with respect to n I obtain

$$l_g' = \frac{f^2\lambda_g p_g(1-p_g)(1-\lambda_b)^n ln(1-\lambda_b)}{\big[f\lambda_g(p_g)\big(1-p_g\big) + fp_g\big(\lambda_b + (1-\lambda_b)^n\big) + \lambda_g(p_g)\big(\lambda_b + (1-\lambda_b)^n\big)\big]^2} < 0,$$

$$l_b' = -\frac{f(1-\lambda_b)\lambda_g(p_g)(1-p_g)\big(\lambda_g(p_g) + fp_g\big)ln(1-\lambda_b)}{\big[f\lambda_g(p_g)\big(1-p_g\big) + fp_g\big(\lambda_b + (1-\lambda_b)^n\big) + \lambda_g(p_g)\big(\lambda_b + (1-\lambda_b)^n\big)\big]^2} > 0.$$

Proposition 3. *The following should hold for the number of employees in each Good firm to be decreasing in proportion of good Firms:* $(\lambda_b + (1-\lambda_b)^n)(\lambda_g(p_g)' + f) + f((1-p_g)\lambda_g(p_g)' - \lambda_g(p_g)) > 0.$

Derivation

$$l_g^f = \frac{M}{N}\frac{f\big(\lambda_b + (1-\lambda_b)^n\big)}{f\lambda_g(p_g)\big(1-p_g\big) + fp_g\big(\lambda_b + (1-\lambda_b)^n\big) + \lambda_g(p_g)\big(\lambda_b + (1-\lambda_b)^n\big)}.$$

Consider the derivative with respect to p_g:

$$l_g^{f'} = -\frac{M}{N} f\big(\lambda_b + (1 - \lambda_b)^n\big) \cdot$$

$$\cdot \frac{\big(\lambda_b + (1 - \lambda_b)^n\big)\big(\lambda_g'(p_g) + f\big) + f\big((1 - p_g)\lambda_g'(p_g) - \lambda_g(p_g)\big)}{\big[f\lambda_g(p_g)(1 - p_g) + fp_g\big(\lambda_b + (1 - \lambda_b)^n\big) + \lambda_g(p_g)\big(\lambda_b + (1 - \lambda_b)^n\big)\big]^2}$$

For the whole expression to be negative the numerator of the fraction has to be positive.