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INFORMALITY AS A STEPPING STONE

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Неформальность является характерной чертой рынков труда многих стран. В этой работе анализируются типы мобильности формальных и неформальных работников в России. Наш анализ использует различные виды матриц переходов и динамическую мультиномиальную логит-модель. Мы не находим существенных свидетельств наличия жестких барьеров входа в формальный сектор. Исключением является нерегулярная трудовая деятельность, которая слабо связана с формальным сектором. Согласно нашим данным, неформальное и формальное предпринимательство связаны как сообщающиеся сосуды; при этом первое часто является прелюдией ко второму. С точки зрения шансов доступа к формальным рабочим местам неформально занятые по найму не отличаются от безработных. Анализ заработков и удовлетворенности жизнью подтверждает, что предпринимательство является самой желанной формой занятости, а те, кто занимается нерегулярной деятельностью, наименее счастливы.

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Informality is a deafining characteristic of labor markets in developing countries. This paper analyzes patterns of mobility across different forms of formal and informal employment in Russia. Using transition matrices and a dynamic multinomial logit model, we find little evidence of entry barriers to the formal sector. The main exception involves casual and irregular activities, which seem to be weakly integrated to the rest of the labor market. There is evidence that informal entrepreneurship acts as a stepping-stone toward formal entrepreneurship. Informal employees, on the contrary, are not more likely than unemployed individuals to get a formal position. An analysis of earnings and life satisfaction confirms that entrepreneurship is the most desirable position. Individual performing irregular activities are the least happy.

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1 Introduction

One of the defining characteristics of developing countries is a large informal sector. Informality characterizes a large set of economic activities, including the operations of the myriad small-scale enterprizes that are fully run by families or single individuals, but also informally hired employees working for otherwise formal firms.[1] Overall, in these countries a large share of the population is informally employed.[2]

There are multiple reasons why sprawling informality is seen as a negative phenomenon. First, the informal economy operates largely on the margins of State regulation and includes many outright illegal activities. Tax evasion is the norm rather than the exception. Second, in many cases the need to keep activities undetected leads to suboptimal scale and other inefficiencies. For the same reason, informality is typically associated with low investment rates and close to zero productive innovation. Informally hired workers rarely receive any formal training, so human capital accumulation is also low. Finally, earnings in some of these activities are low and irregular. Because informal workers are not covered by any kind of safety net (except maybe the one provided by family and friends), there is a link going from informality to poverty.

Theories that explain informality in the labor market can be divided into two opposing views. The early literature saw informality through the prism of duality and segmentation theories. In this view, rigidities in the urban labor market lead to an inefficient equilibrium

[1] While there is no agreement on a precise definition to be used in empirical studies, informal jobs comprise a wide range of activities, including small-scale home production for sale, petty trade and untaxed services, self-employment, and wage work that is not formally contracted and not covered by the social safety net (Perry et al., 2007).

[2] According to Gasparini and Tornarolli (2007), in many Latin American countries the share of informal employment exceeds 50% of the urban labor force. Existing estimates for Sub-Saharan Africa and Asia are even higher (Jütting, Parlevliet, and Xenogiani, 2008). For OECD countries, see Andrews, Sánchez, and Johansson (2011).

with perennial excess supply of workers who would want to take jobs at the going wage. For example, in the classical model by Harris and Todaro (1970) a minimum wage set above the market-clearing wage results in rationing of formal jobs. Since unemployment insurance benefits are low or nonexistent in developing countries, workers are left with informal activities as their only option.[3] An important point is that, in this view, wage differentials between formal and informal jobs are explained by institutional rigidities. Labor markets are segmented and informal workers, who are otherwise observationally identical to formal workers, must accept relatively lower wages simply because they were not lucky enough to get one of the scarce formal positions.[4]

An alternative perspective sees labor markets as integrated and competitive. Individuals are endowed with heterogenous skills, which are valued differently in the formal and informal sectors (Heckman and Sedlacek, 1985, Magnac, 1991). In addition, jobs in different sectors vary in non-pecuniary aspects such as amenities and hazards. Individuals choose among the existing employment opportunities according to their preferences and abilities. As a consequence, the integrated markets view implies that any comparison of earnings across sectors has to face the challenge of selection bias. Because individuals are not randomly assigned to sectors, correctly estimating wage differentials requires making assumptions about the counterfactual wages individuals would earn in alternative states.

A second important point of contrast between these views involves mobility across sectors. On one hand, while segmentation does not preclude the possibility of transitions between formal and informal jobs, higher wages in the formal sector should generally lead to re-

[3]Economic models rarely consider illegal or criminal activities are possible outcomes, although clearly this would be relevant. All available rankings show that the most dangerous/insecure cities in the world are in developing countries.

[4]In countries with important ethnic or racial divisions, it is rarely the case that formal and informal jobs are distributed "at random", so the segmentation literature closely associates informality and discrimination.

stricted employment opportunities there. Workers in the informal sector would in principle be willing to move to a formal position as soon as one is available. In contrast, transitions from formal to informal jobs should be infrequent and mostly related to involuntary displacements. On the other hand, if labor markets are integrated changing labor market conditions would result in flows of workers going in both directions.

Recent work by Maloney (1999, 2004) documents significant flows of workers moving between informal and formal jobs. Funkhouser (1997), Gong and Van Soest (2002), and Gong, Van Soest, and Villagomez (2004) look at patterns of mobility and the evolution of wages associated with different employment histories. These studies are inconclusive about which view is correct, although the integrated markets hypothesis has gained support.

An issue that has not received attention in the literature is whether informal employment functions as a "stepping stone" toward formal positions. There are several reasons to think that the probability of finding a formal job might be positively related to informal work experience. First, informal jobs might contribute to general human capital, increasing the worker's value in the market. Second, workers might gain in terms of an expanded social and professional network (compared to a non-employment alternative). This could result in better information on existing job vacancies and a relatively higher rate of arrival for offers from the formal sector. Third, some firms might use informal positions as a screening device and later offer regular positions to the best informal trainees. Finally, informal work might function as a signal of higher levels of ability or other unobservable traits relative to non-employed individuals. Thus, there are several channels though which informal employment may act as a "stepping stone".

In contrast to these arguments, it is not hard to think of scenarios in which informal employment experience has a negative effect on the prospects of finding a formal job. This could be the case if informality stigmatizes those affected or it carries with it some other kind

of "scarring" effect. Prolonged informal sojourns can be associated with losses of the human and social capital that could be required for re-employment in the formal sector (a "lock-in" effect). Finally, if informal work is the result of a voluntary choice (i.e. the best alternative in an expected utility sense) then transition rates to formal positions will be low. For this reason, whether informal jobs are "stepping stones" to a "better working life" or are instead "dead ends" remains an empirical question.

The paper addresses this issue using data from Russia, a middle-income country with moderate but rising levels of informality. According to various estimates, informal jobs can account for about 20–25% of employment (Gimpelson and Zudina, 2011, Slonimczyk, 2012). The Russian labor market is characterized by a series of non-standard institutions, coupled with selective state enforcement of regulations (Gimpelson and Kapeliushnikov, 2011). Employment protection legislation, as established by the Russian Labor Code, is quite strict by international standards. Russian employers have relied on informal employment as a way to bypass restrictive labor market regulations. As a result, informal employment has grown continuously in the last decade.

From the perspective of workers, informality involves both costs and benefits. On one hand, wages and benefits tend to be lower in informal jobs. In addition, informality involves a higher exposure to risk and little if any options to insure against it. On the other hand, informal employment is a relatively good alternative to unemployment in a context in which the replacement ratio is low. It provides a means of subsistence, while allowing a flexible work regime and accumulation of human capital. Most important for the focus of this paper, informal jobs might increase the probability of finding formal employment later on.

The paper is organized as follows. The next section discusses the data source, sample selection, and the definition of informality. Section three focuses on mobility across labor market states. We use transition matrices and a dynamic multinomial logit model to de-

termine which circuits are the most important for Russian workers. Section four looks at outcomes associated with the different employment categories. We examine earnings, hours and wages, as well as two different measures of life satisfaction. The final section discusses our finding and concludes.

2 Data

The source of the data for this study is the Russian Longitudinal Monitoring Survey (RLMS). The RLMS is a household panel survey based on the first national probability sample drawn in the Russian Federation.[5] I use data from rounds XI–XX covering the period 2002–2011. In a typical round, 10,000 individuals in 4,000 households are interviewed. These individuals reside in 32 oblasts (regions) and 7 federal districts of the Russian Federation. A series of questions about the household (referred to as the "family questionnaire") are answered by one household member selected as the reference person. In turn, each adult in the household is interviewed individually (the "adult questionnaire").

The structure of the employment module of the adult questionnaire is as follows. First, there are questions about a primary job. Next, individuals can provide information on a secondary job if they have one. Finally, individuals are also asked whether they perform what I will refer to as "irregular remunerated activities". The exact phrasing of this last questionnaire item is as follows: "Tell me, please: in the last 30 days did you engage in some additional kind of work for which you were paid or will be paid? Maybe you sewed someone a dress, gave someone a ride in a car, assisted someone with apartment or car repairs, purchased and delivered food, looked after a sick person, sold purchased food or goods in a market or on the street, or did

[5]The RLMS is conducted by the Higher School of Economics and the "Demoscope" team in Russia, together with Carolina Population Center, University of North Carolina at Chapel Hill.

something else that you were paid for?" The questionnaire structure is such that no one may answer questions on a secondary job unless they have a primary job. However, questions on the irregular activities are independent. In fact, in our sample 7.5% of those considered employed only work doing irregular activities.

The focus of this study is on the main job, defined as the primary job if the individual has one or irregular activities if that is the only source of labor income.

2.1 Sample Selection

The RLMS only started consistently asking questions on informality in 2002. The most recent data are from 2011. Our sample is composed of individuals between 15 and 65 years of age. Since the focus of the study is on mobility we only keep individuals who were observed in at least two consecutive rounds. After dropping a few individuals with missing information on employment status, we are left with an unbalanced panel of 18,818 individuals and 96,200 observations. Throughout, we analyze males and females separately.

2.2 Informality Definition

There are two most commonly used definitions of informality: the 'productive' definition and the 'legalistic' or social protection definition. The main difference between them is that while the 'productive' definition focuses on a number of characteristics of the production unit (e.g. the scale of production, whether it is a legal entity independent of the owners, etc.) the 'legalistic' definition focuses on to what extent workers are effectively protected by labor market institutions (e.g. whether social security payments are made). Slonimczyk (2012) discusses in detail the different definitions and how they can be applied using RLMS data. Here we provide only a brief description.

The classification in this paper starts by distinguishing between entrepreneurs and employees at a primary job. The former group

is composed of those doing entrepreneurial activities who are either owners of firms or self-employed individuals who work on their own account with or without employees but not at a firm or organization.[6] Next, we separate between formal and informal entrepreneurs and employees as follows. First, following the productive definition, entrepreneurs and employees not working at firms or organizations are considered informal. Second, for those working at firms or organizations the RLMS questionnaire includes an item that permits determining whether they are registered, i.e. working officially.[7] The Russian labor code mandates that all employees sign a written contract and deposit their 'labor book' with the employer. Therefore, following the social protection criterion, I classify unregistered entrepreneurs and employees as informal.

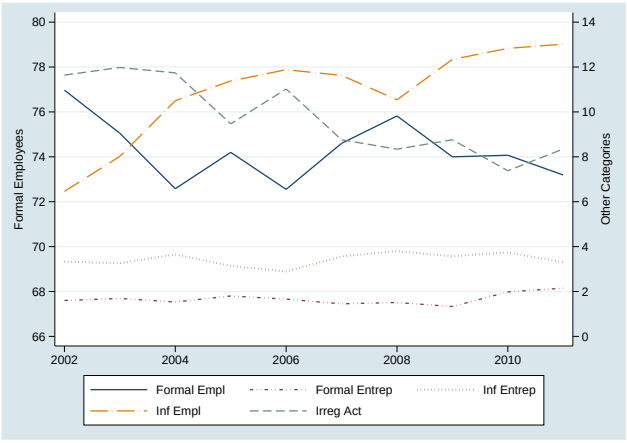
Applying these rules all individuals with a primary job can be classified into four groups: formal entrepreneurs, informal entrepreneurs, formal employees, and informal employees. A fifth and final group contains individuals without a primary job but who perform irregular activities for pay. Based on the productive definition, this category is considered informal.

Both for males and females, the category grouping the largest share of people is formal employees. Roughly 74% of males and 83% of fe-

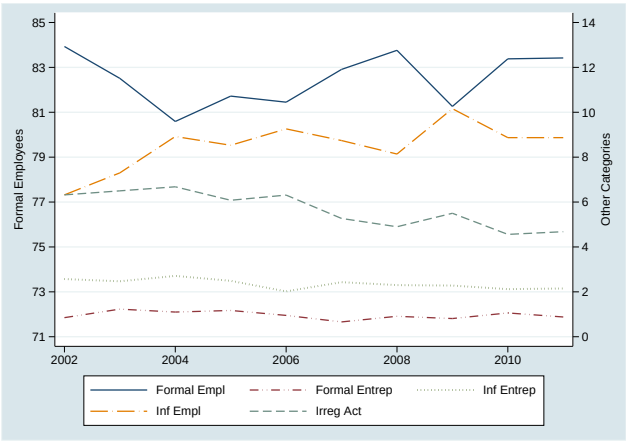
[6]This classification is based on four items of the adult questionnaire: 1) "do you work at an enterprize or organization? We mean any organization or enterprize where more than one person works, no matter if it is private or state-owned. For example, any establishment, factory, firm, collective farm, state farm, farming industry, store, army, government service, or other organization." Enterprize workers are considered entrepreneurs if they answer positively to both 2) "Are you personally an owner or co-owner of the enterprize where you work?" and 3) "In your opinion, are you doing entrepreneurial work at this job?". The distinction between entrepreneurs and employees for non-enterprize individuals is based on: 4) "At this job are you...(a) involved in an employer's or individual labor activity or (b) work for a private individual?"

[7]The question is: "Tell me, please: are you employed in this job officially, in other words, by labor book, labor agreement, or contract?" This item was not included in round X (2001).

Figure 1 – The Evolution of Informal Employment



(a) Males



(b) Females

Notes: The omitted residual category is formal employees.

males in the sample are in this category. Figure 1 shows the evolution

Table 1 – Distribution of Employment by Sub-groups: Males

	Formal Entrep.	Inf Entrep.	Formal Empl.	Inf Empl.	Irreg. Activ.
All Individuals	1.7	3.4	74.2	11.1	9.5
Age Group					
15–24	0.3	1.3	60.6	18.6	19.2
25–34	1.7	3.5	74.5	12.8	7.5
35–44	2.3	5.1	73.2	10.2	9.1
45–54	2.2	3.6	77.3	8.7	8.2
55–65	0.9	1.6	83.0	6.2	8.3
Education Comp.					
Less than Sec.	0.6	2.1	59.2	18.1	20.1
Secondary	1.1	3.7	67.9	12.6	14.6
Vocational	0.7	2.6	75.1	13.0	8.6
Technical	2.0	4.8	79.7	8.7	4.8
University+	4.1	4.0	82.8	5.2	4.0
Region					
Moscow & St Pete	1.8	2.2	80.2	9.9	5.9
North/North Western	1.4	3.2	80.5	9.3	5.6
Central	1.9	3.0	77.8	10.7	6.6
Volga	1.7	3.4	72.0	13.1	9.7
North Caucasian	1.4	5.1	61.9	11.8	19.8
Ural	2.0	3.1	78.0	9.7	7.2
Western Siberian	1.6	4.9	67.9	13.9	11.7
East Siberia	1.2	2.9	76.2	10.0	9.6
Other Charact.					
Russian National	1.6	3.1	76.5	11.1	7.8
Urban Location	2.0	3.7	76.3	10.9	7.0
Married	2.0	3.9	76.9	9.9	7.3
Pension	0.9	1.7	78.9	8.0	10.5
Good Health	1.7	3.7	73.1	11.5	10.1

Notes: Each line represents the distribution of employment for the corresponding sub-group.

of employment composition over time. First, formal employment has remained roughly constant over the period, although there seems to be a slight trend toward decreasing formal wage employment among males. Second, entrepreneurship is less frequent for females than for males. Third, both male and female informal entrepreneurs (self-employed individuals and unregistered entrepreneurs in organizations) represents a more of less constant fraction of employment over the period. Finally, the most dynamic categories are informal employees and irregular activities. While the former have increased in almost every period, the latter has had a decreasing trend.

Table 2 – Distribution of Employment by Sub-groups: Females

	Formal Entrep.	Inf Entrep.	Formal Empl.	Inf Empl.	Irreg. Activ.
All Individuals	1.0	2.3	82.6	8.6	5.6
Age Group					
15–24	0.2	0.8	70.1	17.1	11.8
25–34	0.8	1.9	83.6	9.6	4.1
35–44	1.2	2.9	83.9	7.5	4.5
45–54	1.3	3.0	85.0	6.3	4.5
55–65	0.7	2.1	83.3	6.3	7.7
Education Comp.					
Less than Sec.	0.4	1.9	66.8	15.8	15.1
Secondary	0.9	2.2	72.8	12.8	11.4
Vocational	0.7	2.6	78.6	12.5	5.6
Technical	1.1	2.9	84.9	7.2	3.9
University+	1.2	1.7	91.1	3.8	2.2
Region					
Moscow & St Pete	0.9	0.8	87.8	6.8	3.7
North/North Western	0.5	1.3	87.6	7.1	3.4
Central	1.3	2.7	85.4	7.9	2.8
Volga	0.7	2.4	83.6	8.1	5.2
North Caucasian	1.0	3.2	71.8	9.7	14.3
Ural	0.9	2.0	83.5	9.6	4.1
Western Siberian	1.2	3.2	78.4	10.6	6.6
East Siberia	1.2	2.8	79.6	9.9	6.5
Other Charact.					
Russian National	0.9	2.2	83.7	8.6	4.6
Urban Location	1.0	2.4	83.8	8.5	4.2
Married	1.1	2.6	84.0	7.6	4.6
Pension	0.7	1.7	84.1	6.5	7.0
Good Health	1.2	2.1	81.5	8.9	6.3

Notes: Each line represents the distribution of employment for the corresponding sub-group.

Table 3 – Proportion of New Jobs by Sector

	Males	Females
Formal Entrepreneur	14.07	10.29
Informal Entrepreneur	16.98	14.04
Formal Employee	21.22	16.19
Informal Employee	45.91	44.94

Notes: Proportion of jobs less than one year old. Based on 28,589 and 33,532 observations for males and females respectively.

2.3 Descriptive Statistics

Informal work is not evenly distributed across the population. Tables 1 and 2 look at the distribution of employment for different relevant subgroups. First, both for males and females, informal employees and irregular activities are very common employment types among the youngest individuals, those without higher education credentials, and in the North Caucasian region. Irregular activities are also frequent among individuals who receive a pension. Second, entrepreneurship is common among middle age workers and those with technical and university degrees. Third, other characteristics listed in the table have less power predicting the current state but might be more relevant in explaining movements across states.

3 Mobility Across Job Types

In this section we look at patterns of mobility across labor market states, including unemployment, non-participation, and the different employment categories. First, we use transition matrices and Kaplan-Meier survival curves to gain intuition regarding what circuits are most frequent. We then specify and estimate a dynamic multinomial logit model. Finally, the model is used to to produce simulated transition matrices that correct for possible selection on observables.

3.1 Job Duration

A well known fact about labor markets is that cross sectional pictures can be deceiving. The relatively stable employment composition shown in figure 1 is the result of large flows within and across states. Table 3 shows the fraction of new jobs (tenure less than one year) for each employment type. According to this metric, almost half of the jobs occupied by informal employees are new. This statistic partly reflects the fact that informal employment was increasing over the period. However, note that the fraction of new jobs among formal employees is also quite high despite the fact that this form of employment was stable or decreasing over the period.[8]

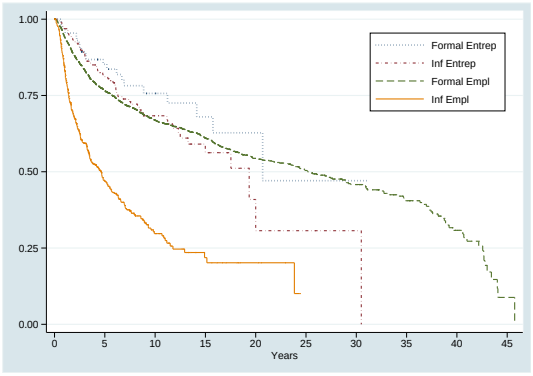
In order to get a more detailed look at employment duration, we use tenure data for the period 2008–2011 to estimate Kaplan-Meier (KM) survival curves for each employment type. We consider that an employment spell has ended when the individual is observed non-employed or when a positive response is provided for a special item asking whether the job has changed in the last year.[9] The spell is considered right-censored if the individual is lost to follow-up or if the end of the observation period is reached without a job termination. Figure 2 presents the KM curves.

The KM curves show that, both for males and females, 50% of jobs as an informal employee end before the fifth year. Employment spells for formal employees and entrepreneurs are longer but 10 to 20% are over before year five.

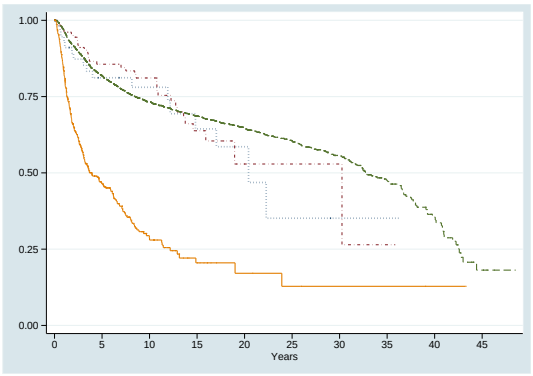
[8] We do not have tenure data for irregular activities. However, it is fair to assume that most jobs in this category are not very long-lasting. An item in the RLMS asking whether the irregular activities are incidental (as opposed to regular) receives positive answers in 68% of cases.

[9] Note that this method probably provides a over-estimate of survival times since it does not allow for formal jobs becoming informal or viceversa. An additional problem arises due to the large number of ongoing spells that started before the transition to the market economy.

Figure 2 – Kaplan-Meier Survival Curves



(a) Males



(b) Females

Notes: The curves are based on employment spells that were ongoing during the period 2008–2011. The number of observations are 4,996 and 5,772 for males and females respectively.

3.2 Transitions

The simplest way to describe mobility across states in the labor market is by a transition matrix. The top panels in tables 4 and 5 provide

Table 4 – Transition Matrices: Males

	NILF	Unemp.	Formal Entrep.	Inf Entrep.	Formal Empl.	Inf Empl.	Irreg. Activ.	$p_{i\cdot}$
				P-matrix				
NILF	70.7%	5.8%	0.1%	0.5%	9.6%	4.1%	9.2%	21.2%
Unemp.	26.4%	17.6%	0.3%	1.2%	31.3%	9.8%	13.4%	4.4%
Formal Entrep.	2.9%	0.5%	53.9%	19.0%	19.0%	2.7%	2.0%	1.2%
Inf Entrep.	2.5%	0.9%	11.8%	54.9%	10.1%	11.6%	8.2%	2.6%
Formal Empl.	3.2%	2.2%	0.4%	0.6%	86.7%	4.6%	2.3%	55.5%
Inf Employee	6.1%	4.6%	0.7%	4.0%	32.6%	44.5%	7.5%	7.9%
Irreg. Activ.	23.3%	7.9%	0.4%	2.7%	19.2%	11.8%	34.9%	7.2%
$p_{\cdot j}$	20.2%	4.2%	1.3%	2.6%	56.0%	8.6%	7.1%	
				V-matrix				
NILF		5.75	0.58	1.42	4.38	2.94	6.77	
Unemp.	5.41		0.56	1.57	5.11	2.50	3.51	
Formal Entrep.	1.07	0.31		44.45	5.54	1.22	0.91	
Inf Entrep.	0.93	0.58	44.38		3.01	5.40	3.91	
Formal Empl.	4.12	4.87	4.97	4.46		7.32	3.64	
Inf Employee	1.85	2.37	2.23	7.77	7.90		2.92	
Irreg. Activ.	6.04	3.49	0.94	4.53	3.95	3.79		
				T-matrix				
NILF		1.32	0.12	0.32	0.95	0.63	1.55	
Unemp.	1.51		0.12	0.30	1.19	0.58	0.87	
Formal Entrep.	0.33	0.08		9.39	1.44	0.32	0.25	
Inf Entrep.	0.28	0.16	10.97		0.77	1.36	1.06	
Formal Empl.	0.94	0.99	0.93	0.69		1.39	0.74	
Inf Employee	0.48	0.55	0.47	1.38	1.72		0.67	
Irreg. Activ.	1.60	0.82	0.20	0.82	0.88	0.84		

Notes: Calculations based on 34,405 transitions over the period 2002–2011. Elements in the P-matrix are $p_{ij} = \frac{N_{ij}}{N_{i\cdot}}$, where N_{ij} is the number of individuals in state i in $t-1$ and state j in t. Elements in the V-matrix are $v_{ij} = \frac{p_{ij}}{p_{\cdot j}(1-p_{ii})(1-p_{jj})}$. Elements in the T-matrix are $t_{ij} = \frac{N_{ij}/(N_{i\cdot}-N_{ii})}{(N_{\cdot j}-N_{jj})/\sum_{k\neq i}(N_{\cdot k}-N_{kk})}$.

Table 5 – Transition Matrices: Females

	NILF	Unemp.	Formal Entrep.	Inf Entrep.	Formal Empl.	Inf Empl.	Irreg. Activ.	$p_{i.}$
				P-matrix				
NILF	76.6%	5.2%	0.1%	0.3%	9.5%	3.3%	5.0%	28.3%
Unemp.	33.3%	18.2%	0.0%	0.7%	30.7%	9.7%	7.4%	4.0%
Formal Entrep.	2.5%	1.1%	51.6%	19.1%	19.9%	4.3%	1.4%	0.6%
Inf Entrep.	6.0%	0.4%	9.6%	65.0%	7.9%	7.8%	3.2%	1.6%
Formal Empl.	4.8%	1.9%	0.2%	0.3%	89.0%	2.9%	0.9%	56.0%
Inf Employee	11.1%	4.1%	0.6%	2.3%	32.8%	45.1%	4.2%	5.7%
Irreg. Activ.	34.3%	6.0%	0.1%	2.0%	15.7%	9.0%	33.0%	3.8%
$p_{.j}$	27.7%	3.7%	0.7%	1.6%	56.5%	6.0%	3.8%	
				V-matrix				
NILF		7.33	0.92	2.05	6.57	4.25	8.47	
Unemp.	6.27		0.00	1.50	6.06	3.61	3.59	
Formal Entrep.	0.81	0.73		70.17	6.63	2.71	1.17	
Inf Entrep.	2.66	0.41	84.27		3.67	6.74	3.65	
Formal Empl.	6.76	5.61	6.76	4.21		7.98	3.20	
Inf Employee	3.10	2.43	3.20	7.36	9.64		3.02	
Irreg. Activ.	7.88	2.95	0.28	5.16	3.78	4.08		
				T-matrix				
NILF		1.23	0.15	0.33	1.01	0.67	1.41	
Unemp.	1.31		0.00	0.29	1.11	0.68	0.71	
Formal Entrep.	0.19	0.17		15.26	1.38	0.58	0.26	
Inf Entrep.	0.62	0.09	17.71		0.75	1.43	0.81	
Formal Empl.	1.15	0.91	1.02	0.65		1.23	0.52	
Inf Employee	0.63	0.47	0.59	1.38	1.72		0.58	
Irreg. Activ.	1.69	0.60	0.05	1.01	0.71	0.79		

Notes: Calculations based on 42,975 transitions over the period 2002–2011. Definitions are as in table 4.

the conditional distribution of employment in year t given employment type in year $t-1$. First, the transition matrices provide additional evidence of significant turnover across states. One useful summary statistic is the average complement of the trace, which measures the average probability of making a transition.[10] This statistic is 56% for males and 54% for females.[11]

Second, the P-matrices document significant flows across formality lines. In particular, both for females and for males, there are non-negligible probabilities of flows from informal entrepreneurship into formal entrepreneurship and from informal employees into formal employees. Finally, prima facie it seems like irregular activities are segmented from the rest of the labor market. Indeed, almost one third of males and over 40% of females who performed irregular activities in $t-1$ end up non-employed in t.

As an indicator of mobility in the labor market, The P-matrix has some drawbacks. First, transition probabilities are not adjusted by the size of the destination state. Second, the P-matrix does not adjust for the fact that different sectors have different rates of turnover. In order to deal with these issues, Maloney (1999) suggested an alternative transition matrix (V-matrix). Formally, the elements of the matrix are

$$v_{ij} = \frac{p_{ij}}{p_{\cdot j}(1-p_{ii})(1-p_{jj})}$$

where p_{ij} are the P-matrix transition probabilities and $p_{\cdot j}$ is the relative size of the destination state. The V-matrix provides a correction for each of the two problems mentioned above. However, in practice

[10] Formally, this statistic is $\frac{1}{S-1}(S - \mathrm{tr}(P))$, where $\mathrm{tr}(P)$ stands for the trace of the P-matrix and S is the number of states considered.

[11] Note that the implied average durations are quite lower than those suggested by the KM curves. For example, the expected duration for a male informal employee is $\frac{1}{1-0.45} \approx 1.8$. In part, this divergence reflects the fact that the KM curves do not consider a job terminated when there is a change in employment type. It also results from the lack of correction for censored spells in the transition matrices.

the resulting coefficients are difficult to interpret. Duryea, Marquez, Pagés, and Scarpetta (2006) suggest a different correction (T-matrix). Formally,

$$t_{ij} = \frac{N_{ij}/(N_{i\cdot} - N_{ii})}{(N_{\cdot j} - N_{jj})/\sum_{k \neq i}(N_{\cdot k} - N_{kk})}$$

where N_{ij} refers to the number of transitions from sector i to sector j, $N_{i\cdot}$ is the total number of individuals in the origin state in $t-1$ and $N_{\cdot k}$ is the total number of individuals in the destination state at t. The numerator measures the transitions from i to j as a proportion of all individuals moving out of i. The denominator measures the number of individuals arriving to the destination state as a proportion of arrivals to all states other than the origin state. A t coefficient greater than one indicates transitions that are more frequent than what the size of the sectors and the overall levels of turnover would predict.

The middle and bottom panels of tables 4 and 5 present V and T-matrices for males and females respectively. The findings with both kinds of matrices are similar. The matrices confirm the existence of significant flows going from formal entrepreneurship into informal entrepreneurship and back. The flows between formal employees and informal employees are robust to the corrections but appear to be an order of magnitude weaker than the flow within entrepreneurship. There are also significant transitions from entrepreneur to employee and back, but only as long as the transition does not alter informality status. Finally, there is additional evidence that irregular activities are not integrated with the rest of the labor market.

3.3 Dynamic Multinomial Logit

As shown in tables 1 and 2, workers in different labor market states can be expected to be heterogenous. In this section we specify and estimate a dynamic multinomial logit model in order to determine whether the mobility patterns observed through transition matrices remain after controlling for observable characteristics.

Table 6 – Dynamic Multinomial Logit Estimates: Males

	(1) Unemp.	(2) Formal Entrep.	(3) Inf Entrep.	(4) Formal Empl.	(5) Inf Empl.	(6) Irreg. Activ.
Lagged State						
Unemp.	1.72***	1.05*	1.12***	1.65***	1.31***	0.93***
Formal Entrep.	-0.52	7.42***	5.26***	2.71***	1.85***	0.79
Inf Entrep.	1.12**	6.55***	6.73***	2.47***	3.67***	2.59***
Formal Empl.	1.83***	3.06***	2.10***	4.57***	2.62***	1.17***
Inf Employee	1.80***	3.33***	3.56***	2.98***	4.16***	1.70***
Irregular Activ.	1.06***	1.58***	2.03***	1.29***	1.69***	1.85***
Age Group						
25–34	0.60***	1.36***	1.29***	0.67***	0.68***	0.89***
35–44	0.18	0.88**	0.83***	0.07	-0.03	0.65***
45–54	0.17	0.77*	0.38	0.00	-0.36***	0.34***
55–65	-0.72***	-0.54	-0.50	-0.52***	-1.14***	-0.20
Education Comp.						
Secondary	0.33***	0.64**	0.51**	0.40***	0.06	0.12
Vocational	0.72***	0.92***	0.90***	1.01***	0.77***	0.45***
Technical	0.78***	1.87***	1.58***	1.37***	0.85***	0.31***
University+	1.24***	2.87***	1.87***	1.73***	0.71***	0.48***
Region						
North/North Western	-0.17	0.15	0.39	0.11	-0.08	-0.38**
Central	0.03	0.36	0.30	-0.05	0.09	0.02
Volga	-0.39***	-0.15	-0.01	-0.42***	-0.10	-0.03
North Caucasian	-0.22	-0.25	0.13	-0.61***	-0.40***	-0.03
Ural	-0.18	0.68**	0.36	0.04	-0.01	0.07
Western Siberian	0.01	-0.06	0.46*	-0.32***	-0.01	0.20
East Siberia	0.05	-0.14	0.25	-0.02	-0.03	0.28*
Year						
2004	0.07	-0.20	0.14	-0.02	0.32**	0.05
2005	-0.21	-0.33	-0.38*	-0.15	0.12	-0.36***
2006	-0.21	-0.11	0.06	0.07	0.41***	0.05
2007	-0.12	-0.03	0.20	0.17*	0.34***	-0.21*
2008	-0.12	0.05	0.40*	0.14	0.31**	-0.14
2009	0.05	-0.69**	-0.14	-0.18*	0.32**	-0.24**
2010	0.19	-0.00	0.24	-0.01	0.47***	-0.33***
2011	-0.09	0.01	-0.08	-0.07	0.40***	-0.26**
Household Size						
Two	-0.56***	-0.41	-1.21***	-0.48***	-0.59***	-0.82***
Three	-0.44**	-0.33	-1.20***	-0.51***	-0.60***	-0.88***
Four	-0.54***	-0.16	-1.39***	-0.72***	-0.84***	-1.02***
Five	-0.51**	-0.88*	-1.56***	-0.74***	-0.60***	-0.81***
Six	-0.31	-0.75	-1.52***	-0.57***	-0.53**	-0.77***
Seven	-0.72***	-0.50	-2.02***	-1.06***	-0.96***	-0.91***
Eight	-0.42	-0.57	-0.83*	-0.98***	-0.65**	-0.50**
Nine or more	-0.44*	-0.46	-2.89***	-1.30***	-1.21***	-0.78***
# of Children						
One	0.12	0.82***	0.63***	0.40***	0.30***	0.23*
Two	0.05	0.62**	0.87***	0.55***	0.42***	0.20
Three	0.06	1.42***	0.90***	0.29*	-0.17	0.26
Four or more	-0.16	1.07	0.61	-0.01	-0.35	-0.08
Other Charact.						
Married	0.16	0.98***	1.22***	0.86***	0.80***	0.54***
Russian National	-0.03	0.18	0.15	0.34***	0.23***	-0.01
Urban Location	0.33***	1.02***	0.58***	0.34***	0.32***	-0.17***
Pension	-1.16***	-1.90***	-2.04***	-1.80***	-1.75***	-1.42***
Good Health	-0.04	0.06	0.21**	0.18***	-0.04	0.05
Constant	-2.20***	-8.69***	-5.96***	-2.45***	-2.91***	-1.22***

Notes: Standard errors clustered at individual level are omitted. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Reference categories are: NILF, 15–24 years of age, Less than secondary education, Moscow and St.Petersburg, and Year 2003. Estimates based on 32,692 observations and 8,531 individuals. Log-likelihood= -26,692; Pseudo-R^2= 0.386; 74.10% correctly predicted.

We model individuals' choice of a labor market state as follows. Let S be the set of possible states.[12] Let j_{st} be an indicator of whether the individual chooses state s at time t ($\boldsymbol{J}_t$ designates the vector of indicators). Assume the utility associated with a state is given by

$$U_{st} = \alpha_s + X_t'\beta_s + \sum_{k \in S} \gamma_{k,s} j_{k,t-1} + \nu_{s,t}, \qquad s \in S$$

where X_t is a vector of observable individual characteristics at the time of the choice, and ν_{st} is a random component to the utility associated with the labor market state that reflects unobservable heterogeneity in individual preferences. In addition, utility depends on the previous period's state. The focus of our interest are the parameters $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$.

Individuals choose the alternative that maximizes their utility. For identification, we let nilf be the reference category and set the parameters associated with it to zero. Assuming the ν_{st} are i.i.d., independent of X_t and past choices, and extreme value (EV1) distributed, we can write[13]

$$\Pr(j_{s,t} = 1 \mid X_t, \boldsymbol{J}_{t-1}) = \frac{\exp(\alpha_s + X_t'\beta_s + \sum_{k \in S} \gamma_{k,s} j_{k,t-1})}{\sum_{h \in S} \exp(\alpha_h + X_t'\beta_h + \boldsymbol{J}_{t-1}'\boldsymbol{\gamma}_h)} \qquad (1)$$

Equation (1) can be used to obtain maximum likelihood estimates of the parameters. We present estimates, for males and females respectively, in tables 6 and 7. We control for the following characteristics: age group, education, region, year, household size, number of children, marital status, Russian nationality, urban location, whether receives a pension, and an indicator for good health.

[12] In our application there are seven states: $S = \{\text{nilf}, \text{unemp}, \text{formal entrep}, \text{inf entrep}, \text{formal empl}, \text{inf empl}, \text{irreg act}\}$.

[13] These assumptions are rather strict. The standard in the literature is to allow the α_s to vary across individuals. For example, Gong et al. (2004) let these parameters have a multivariate normal distribution conditional on the other regressors and independent of the error terms (ν_{st}). Another possibility would be to let the αs have a discrete distribution whose parameters are estimated (as recommended in Heckman and Singer, 1984). We leave these alternative specifications to future work.

Coefficients estimates from a multinomial logit are not easily interpretable. Here we focus on the sign and significance of the coefficients and leave a more detailed interpretation to the next subsection, where we discuss simulations based on the model estimates. Most findings are common to males and females. First, the lagged state in the labor market has a strong impact on current choices, even after controlling for a large set of observable characteristics. We know from the transition matrices that, even though there is substantial mobility across states, a large fraction of individuals stay in the same state. Partly for this reason, the model fits the data very well (74% and 79% correctly predicted choices for males and females respectively). Also consistent with this fact is that coefficients across the diagonal are all positive, relatively large, and significant. Second, we observe that a majority of coefficients corresponding to transitions across states are also positive and significant. For example, given the coefficient corresponding to the lagged state 'informal employee' in the formal employee equation for males, we can estimate that the relative odds of becoming a formal employee are approximately twenty times larger ($\exp(2.98) \approx 20$) from state 'informal employee' than from state 'nilf'.

3.4 Are there stepping stones?

In this subsection we present simulation results based on the dynamic multinomial logit estimates. Simulations are computed by first fixing the lagged state to the same value for all individuals and then using the estimated coefficients to predict the probability of each state in the current period. This procedure is repeated for each possible lagged state.

Table 8 shows the results of this exercise, for males and females separately. The results confirm once more that high levels of mobility across labor market states in Russia. Of particular interest to us are transitions across formality lines. Both for females and for males we see strong flows between formal and informal entrepreneurship. For example, the probability of becoming a formal entrepreneur for

Table 7 – Dynamic Multinomial Logit Estimates: Females

	(1) Unemp.	(2) Formal Entrep.	(3) Inf Entrep.	(4) Formal Empl.	(5) Inf Empl.	(6) Irreg. Activ.
Lagged State						
Unemp.	1.67***	-13.08***	1.27***	1.56***	1.51***	0.95***
Formal Entrep.	1.63**	9.16***	6.86***	3.58***	3.44***	1.92***
Inf Entrep.	-0.12	6.68***	7.26***	1.73***	3.15***	1.86***
Formal Empl.	1.60***	3.32***	2.11***	4.68***	2.46***	0.88***
Inf Employee	1.37***	3.51***	3.52***	2.79***	4.17***	1.51***
Irregular Activ.	0.76***	0.30	2.42***	1.12***	1.65***	2.35***
Age Group						
25–34	0.03	0.73	0.98***	0.16**	0.20**	0.51***
35–44	-0.01	1.23**	1.26***	0.30***	0.24**	0.86***
45–54	-0.13	1.30**	1.24***	0.26***	-0.02	0.80***
55–65	-1.05***	0.90	1.16***	-0.30***	-0.62***	0.60***
Education Comp.						
Secondary	0.34***	0.30	0.18	0.43***	0.25**	0.29***
Vocational	0.81***	0.63	0.54**	0.94***	0.77***	0.43***
Technical	0.84***	1.07**	0.92***	1.29***	0.74***	0.45***
University+	1.02***	1.57***	1.16***	1.69***	0.61***	0.51***
Region						
North/North Western	0.22	0.11	0.92**	0.53***	0.40**	0.21
Central	0.13	0.14	1.02***	0.26***	0.28**	-0.09
Volga	0.12	-0.26	0.86***	0.11	0.16	0.23
North Caucasian	0.13	-0.10	0.88***	-0.12	0.24*	0.44***
Ural	0.30**	0.21	0.96***	0.38***	0.49***	0.27*
Western Siberian	0.27**	-0.20	0.84***	0.05	0.27*	0.35**
East Siberia	0.28**	0.43	0.93***	0.16*	0.37***	0.31**
Year						
2004	0.10	-0.55	-0.11	-0.06	0.20	-0.01
2005	-0.03	-0.52*	-0.29	-0.25***	-0.08	-0.26**
2006	-0.29**	-0.36	-0.12	0.00	0.26**	0.04
2007	-0.28**	-1.16***	-0.08	-0.03	0.12	-0.26**
2008	-0.44***	-0.36	-0.21	0.03	0.09	-0.22*
2009	-0.24*	-0.58*	-0.05	-0.06	0.43***	-0.05
2010	-0.18	-0.45	-0.23	-0.21***	0.17	-0.37***
2011	-0.29**	-1.05***	-0.36	-0.24***	0.09	-0.35***
Household Size						
Two	-0.47***	-1.01***	-0.61**	-0.19**	-0.37***	0.09
Three	-0.52***	-1.01**	-1.06***	-0.43***	-0.56***	-0.07
Four	-0.64***	-1.81***	-1.33***	-0.49***	-0.72***	-0.29*
Five	-0.64***	-2.22***	-1.44***	-0.61***	-0.84***	-0.29
Six	-0.72***	-1.55***	-1.16***	-0.66***	-0.88***	-0.19
Seven	-0.80***	-1.86**	-1.93***	-0.68***	-1.01***	0.01
Eight	-0.81***	-16.48***	-2.22***	-0.75***	-0.97***	-0.32
Nine or more	-0.42	-1.05	-2.02**	-0.77***	-1.19***	0.29
# of Children						
One	0.11	0.78***	0.65***	0.31***	0.31***	0.02
Two	-0.05	1.32***	0.79***	0.29***	0.18	0.04
Three	0.02	0.89*	0.34	0.11	-0.15	0.21
Four or more	-0.24	-14.48***	-0.03	-0.29	-0.36	-0.31
Other Charact.						
Married	-0.15*	0.50**	0.26*	-0.17***	-0.27***	-0.38***
Russian National	0.04	-0.11	-0.16	0.18***	0.16**	-0.08
Urban Location	0.28***	0.41*	0.44***	0.22***	0.29***	-0.21***
Pension	-1.18***	-1.89***	-1.79***	-1.30***	-1.24***	-1.20***
Good Health	-0.13**	0.59***	-0.05	0.05	-0.10	-0.02
Constant	-2.21***	-7.38***	-6.78***	-2.55***	-3.21***	-2.65***

Notes: Standard errors clustered at individual level are omitted. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Reference categories are: NILF, 15–24 years of age, Less than secondary education, Moscow and St.Petersburg, and Year 2003. Estimates based on 41,230 observations and 10,191 individuals. Log-likelihood= -28,482; Pseudo-R^2= 0.422; 79.18% correctly predicted.

Table 8 – Simulated Transition Probabilities (%)

$t-1$ Counterfactual	NILF	Unemp.	Formal Entrep.	Inf Entrep.	Formal Empl.	Inf Empl.	Irreg. Activ.
				Males			
NILF	50.6	7.1	0.4	1.5	20.0	7.2	13.1
Unemp.	24.6	15.3	0.4	1.5	35.7	9.5	13.0
Formal Entrep.	11.3	0.5	35.1	18.9	25.7	4.7	3.7
Inf Entrep.	6.4	1.5	9.4	44.9	11.2	15.1	11.6
Formal Empl.	5.3	2.7	0.3	0.5	83.7	4.8	2.7
Inf Empl.	8.7	4.6	0.9	4.1	33.4	40.5	7.8
Irregular Activ.	22.9	7.4	0.6	3.5	23.7	12.9	29.0
$t-1$ Counterfactual	NILF	Unemp.	Formal Entrep.	Inf Entrep.	Formal Empl.	Inf Empl.	Irreg. Activ.
				Females			
NILF	66.6	6.9	0.2	0.5	15.3	4.5	6.0
Unemp.	35.9	16.1	0.0	0.8	30.9	8.9	7.4
Formal Entrep.	5.8	1.8	41.1	18.7	23.2	7.0	2.5
Inf Entrep.	10.6	0.7	8.4	57.2	7.8	10.8	4.5
Formal Empl.	6.8	2.1	0.2	0.2	86.5	3.2	1.1
Inf Empl.	14.2	3.9	0.7	2.4	33.6	40.8	4.5
Irregular Activ.	33.7	6.4	0.1	2.5	19.9	10.0	27.5

Notes: Simulations based on counterfactually setting the lagged state to each of the respective 7 categories. Observations: 32,692 and 41,230 for males and females respectively.

an unemployed woman is predicted to be zero. In contrast, female informal entrepreneurs become formal at a rate of 8.4% per period. In this sense, informal entrepreneurship can be considered a stepping stone into formal entrepreneurship.

Is there a stepping stone effect for other forms of informality. Informal employees face probabilities of becoming formal employees of 33.4% and 33.6% for males and females respectively. However, because unemployed individuals face similar probabilities there is little evidence that experience as an informal employee increases the chances of getting a formal position. It is nevertheless true that male informal employees have relatively high simulated transition probabilities to informal entrepreneurship. Thus, there might be a stepping stone channel that is more indirect: from informal employee to informal entrepreneur and from informal entrepreneurs to formal entrepreneurs.

Finally, individuals performing irregular activities have poor employment prospects. For males, there are almost 60% that the continuation state will be either non-employment or more irregular activities. This statistic is even higher (68%) for females.

4 Informality, Earnings and Happiness

In this section we examine differences in earnings and life satisfaction across employment types. In particular, we are interested in the effect that movements across formality lines has on these outcomes. The analysis is complicated by selection and other issues. We proceed as follows. First, we analyze how differences in hours worked across categories influence monthly earnings and hourly wages. Next, using Hausman-Taylor and fixed-effects regressions, we document earnings differentials across sectors. Finally, we estimate ordered-probit regressions using two different measures of life satisfaction.

4.1 Earnings, Hours and Wages

Table 9 presents descriptive statistics on earnings, hours, and wages. There are strong patterns in the distribution of monthly earnings. First, both for males and females, there are wide variations in earnings across employment types. A clear ranking emerges with formal employees on top and irregular activities at the bottom. Second, regardless of the job type, there is an important earnings gap between males and females. The gap is largest for informal employees, where the average male receives 60% higher earnings. Third, the distribution of earnings is right-skewed, with median earnings substantially below the mean in all cases. Finally, earnings vary widely *within* job types. The coefficient of variation of earnings is highest for irregular activities, probably reflecting the very high heterogeneity of jobs grouped under this rubric.

The statistics for monthly hours show that the higher earnings for entrepreneurs are explained at least in part by longer work days and weeks. In the opposite extreme, individuals performing irregular activities report less than 50% the number of hours worked in other job types.

With few exceptions, there is little meaning to an hourly rental price for labor in Russia. The vast majority of labor contracts, both

Table 9 – Earnings, Hours, and Wages

	Males			Females		
	Mean	Median	CV	Mean	Median	CV
Monthly Earnings						
Formal Entrep.	27,828.4	21,344.9	0.85	24,853.1	18,018.5	1.04
Inf Entrep.	22,573.0	18,000.0	0.81	14,818.2	11,543.7	0.83
Formal Empl.	15,698.4	12,732.0	0.86	11,130.7	8,538.0	0.88
Inf Empl.	14,462.0	11,543.7	0.92	8,997.4	7,115.0	0.83
Irregular Activ.	9,365.7	5,375.1	1.42	6,364.0	3,557.5	1.77
Monthly Hours						
Formal Entrep.	221.2	216.0	0.30	191.9	180.0	0.35
Inf Entrep.	210.4	200.0	0.35	180.8	177.0	0.45
Formal Empl.	180.7	176.0	0.29	161.3	168.0	0.28
Inf Empl.	197.5	192.0	0.35	169.4	176.0	0.38
Irregular Activ.	89.1	60.0	0.98	77.9	48.0	1.05
Hourly Wage						
Formal Entrep.	139.1	103.3	1.02	135.0	90.4	1.13
Inf Entrep.	125.7	88.2	1.20	113.2	67.0	2.01
Formal Empl.	96.8	72.2	2.08	76.3	54.0	1.30
Inf Empl.	82.4	59.3	1.29	59.9	42.8	1.13
Irregular Activ.	329.7	85.5	5.40	181.3	65.6	2.79

Notes: Earnings are the after-tax amount actually received the previous month and are expressed in rubles from year 2011. Hours are actual hours worked the previous month. Sample restricted to individuals with positive hours. Hourly wages are obtained dividing earnings by hours.

written and orally agreed, are set in month time units. However, given the wide differences in hours, we present hourly wages as a way to gauge to what extent longer hours explain earnings differentials. For individuals with a primary job, the ranking of hourly wages is the same as that of monthly earnings —although the wage differentials are smaller than earnings differentials. In deep contrast, irregular activities now emerge as the top paying job category. In part, this is due simply to a few outliers with very low hours. But the differences in the rankings are remarkable even if considering median earnings and wages (median hourly wages put irregular activities in third place in the ranking, behind entrepreneurs).

One interpretation is simply that individuals use casual and irregular activities as a substitute for part-time work. In this case, the hourly wage statistics are relevant and it would be incorrect to conclude that this type of work is poorly remunerated. An alternative interpretation is that low average monthly hours are observed because the typical irregular "job" typically lasts less than a month. This pos-

Table 10 – Earnings Transitions for Males

	Formal Entrep.	Inf Entrep.	Formal Empl.	Inf Empl.	Irreg. Activ.	All
Formal Entrep.	1,428 1 -1.0	2,559 -4 19.1	6,913 -17 35.4			2,826 -5 63.3
Inf Entrep.	1,052 -7 16.4	1,912 -2 6.6	-4,615 -39 14.7	585 -5 3.2	-164 -66 238.8	803 -12 27.3
Formal Employee	-5,512 5 -19.6	1,682 2 34.0	953 0 3.1	2,402 12 8.5	-1,466 -89 143.4	957 -1 5.9
Inf Employee		1,834 9 31.5	967 -9 0.6	369 1 0.9	-2,975 -94 97.9	336 -9 8.9
Irregular Activ.			4,351 86 -96.2	2,690 73 -69.2	715 9 -143.2	2,248 44 -115.6
All	-286 2 -7.2	2,176 4 5.3	1,021 1 1.1	1,327 12 -3.9	-403 -35 -2.2	991 0 0.4

Notes: Restricted to positive hours in both periods. Observations: 16,358. Only cells with 40 or more transitions are shown. The figures in each cell correspond to the average change in earnings, hours and wages respectively.

sibility is consistent with the analysis of the transition matrices above. Irregular activities have the lowest implied mean duration among all employment types (about 1.5 years). Under this interpretation, the hours statistics for irregular activities can be considered biased downwards, as they do not consider the substantial time necessary to search for new "gigs".

Further insight on earnings differential can be gained by looking at the effect of transitions. Tables 10 and 11 present average changes in earnings, hours, and wages associated with each possible flow (as long as there are enough observations in the cell). In some cases, transitions lead to gains in earnings and wages relative to those who remained in the original state. For example, this is the case for male formal entrepreneurs moving to informal entrepreneurship or formal employee, or for female informal employees moving into formal employee. Most of these transitions are likely to be voluntary. In other cases, there are earnings losses but gains in terms of a shorter working

Table 11 – Earnings Transitions for Females

	Formal Entrep.	Inf Entrep.	Formal Empl.	Inf Empl.	Irreg. Activ.	All
Formal Entrep.	-228 4 -2.1					-766 -1 -4.5
Inf Entrep.		-181 -6 10.3				-211 -10 36.0
Formal Employee			880 1 5.4	682 2 6.6	-1,751 -73 111.8	878 0 6.4
Inf Employee			1,039 -2 8.7	749 3 3.3	-488 -35 42.4	998 -1 8.9
Irregular Activ.			2,101 73 -96.1	2,405 65 -64.0	359 3 35.9	1,349 36 -24.6
All	2,224 3 9.1	1,096 0 12.1	894 2 4.3	757 7 -1.0	-212 -24 77.0	868 1 6.1

Notes: Restricted to positive hours in both periods. Observations: 18,795. Only cells with 40 or more transitions are shown. The figures in each cell correspond to the average change in earnings, hours and wages respectively.

day or week (e.g., males and females going from formal employee to irregular activities). These transitions may be voluntary to the extent that individuals are looking for more flexible hours, or they might represent some form of under-employment. Finally, there are cases in which transitions imply increases in hours and earning.

4.2 Regression Analysis

The comparison of earnings across job types is complicated for two reasons. First, selection across employment types means that simple comparisons of average earnings will be misleading. Individuals choose sectors based on their comparative advantages. Average earnings in a sector are not a good proxy for the counterfactual earnings that individuals in other sectors would get. Second, as described in the previous subsection, different job types imply not only different earnings but also different hours.

Table 12 – Partial Effects

	PE at mean log hours			PE at mean hours		
	Pooled OLS	H-Taylor	FE	Pooled OLS	H-Taylor	FE
Males						
Inf Entrep	-0.13	0.06	0.08	-0.10	0.06	0.09
Formal Empl	-0.37	-0.12	-0.11	-0.37	-0.12	-0.10
Inf Empl	-0.47	-0.13	-0.09	-0.42	-0.09	-0.08
Irreg Act	-0.49	-0.14	-0.10	-0.51	-0.17	-0.13
Females						
Inf Entrep	-0.30	-0.09	-0.08	-0.29	-0.11	-0.10
Formal Empl	-0.68	-0.33	-0.29	-0.68	-0.31	-0.30
Inf Empl	-0.78	-0.33	-0.33	-0.77	-0.35	-0.34
Irreg Act	-0.82	-0.36	-0.33	-0.89	-0.42	-0.40

Notes: Partial effects are based on coefficient estimates from tables A.1 and A.2 in the appendix. Average log hours are 5.05 and 4.97 for males and females respectively. Average hours are 176.9 and 159.4.

In order to address the first challenge, we estimate earnings regressions that control for a number of observable characteristics, as well as for individual heterogeneity. In turn, the second challenge is addressed by including interaction terms between employment type and hours, and estimating wage differential at mean hours calculated for the whole sample. Specifically, we estimate the following equation

$$\log(earn_{it}) = X'_{it}\alpha + Z'_i\beta + \boldsymbol{J}_{it}\gamma_0 + (\boldsymbol{J}_{it} \times hours_{it})\,\gamma_1 + c_i + \varepsilon_{it} \quad (2)$$

where the dependent variable is log monthly earnings, and X_{it} and Z_i are time-varying and time-constant observable characteristics. As above, $\boldsymbol{J}_{it}$ is a vector of indicators for employment type. Note that for this exercise we consider only employed individuals.[14] We also estimate an alternative to equations (2) where hours worked are included in logs.

The first columns of tables A.1 and A.2 in the appendix present pooled OLS estimates for males and females respectively. Standard

[14] A more sophisticated specification would include a selection equation and allow for the possibility of differential returns to skills in different sectors (eg. Gong and Van Soest, 2002).

errors are robust to heteroscedasticity across individuals, as well as autocorrelation over time. The estimates clearly show that more hours lead to higher earnings in all jobs. However, extra hours have a much stronger impact for informal wage and salary workers and irregular activities. To summarize the effect of job type on earnings, table 12 presents the partial effects evaluated at mean hours and mean log hours (PEA). For individual i, the effect of working in job type j (relative to working as a formal entrepreneur) is given by $\gamma_{0,j} + \gamma_{1,j}\overline{hours}$. Since the results for mean hours and mean log hours are similar, I focus on the former.

The calculation of the PEAs is based on the assumption that regression estimates can be used to create a reliable counterfactual. For example, the calculation of counterfactual earnings in irregular activities uses the same mean hours statistic as the counterfactual for informal entrepreneurs. However, casual or irregular employment for 176.8 hours a month (the average hours in the sample) hardly exists in Russia. Therefore, the PEAs have to be interpreted with care.

Looking at the results, note first that formal entrepreneurs earn on average $\exp(0.37) - 1 \approx 44.7\%$ (males) and 116% (females) higher earnings than formal wage workers keeping other factors constant. Informal entrepreneurship leads to lower wage premiums. Second, informal salary workers face a small penalty relative to formal salaried workers. Finally, according to the PEA analysis, workers in casual and irregular activities are indeed at the bottom of the distribution of earnings.

The other estimates in the earnings equation have the expected signs. The effect of age on earnings is concave. While higher levels of schooling receive higher pay, vocational education does not seem to contribute to earnings more than completing secondary education. For males, we also find statistically significant premiums on earnings for married people, urban locations, and good health, while pensioners face penalties in earnings. For women, only urban location, pension, and good health have statistically significant effects.

The pooled OLS estimator is consistent under the assumption of contemporaneously exogenous regressors. There are several reasons why this assumption might fail in this case. Most importantly, employment types are probably correlated with unobservable characteristics. As long as the unobservables do not vary over time, a panel fixed effect (FE) estimator is effective in dealing with the endogeneity problem. Tables A.1 and A.2 present fixed effects estimates for the same specification. They also present estimates for the Hausman-Taylor (HT) type random effects model. In the latter models only the employment status (and the hours interactions) are assumed to be correlated with the individual unobserved effects, so they can be seen as an intermediate specification between fixed effects and pooled OLS. Moreover, the FE transformation leaves parameters associated with time-constant variables unidentified. In contrast, the HT model uses between-variation so these parameters can be identified. The fixed effects estimator has very low precision for regressors that vary little over time. For this reason it is not surprising to find insignificant estimates for factors like marital status. In contrast, estimates for factors that vary significantly over time, like hours worked and age, are similar to the POLS estimates. The HT estimates for these regressors tend to fall somewhere in between the FE and POLS estimates.

Looking at the PEA estimates in table 12, we find that according to the FE estimates, after controlling for time-constant unobservables informal entrepreneurship is the job type with the highest remuneration among men. The results for other job types are attenuated. Both for males and females, there is little difference in earnings among formal employees, informal employees, irregular activities. But the separation between entrepreneurs and employees seems to be robust to this exercise.

4.3 Employment type and life satisfaction

The RLMS regularly includes questions on life satisfaction.[15] In this subsection we study the effect of labor market state on responses to these items. There are several advantages to using life satisfaction (rather than earnings) as a dependent variable. First, responses are available from non-employed individuals, so we can compare employment states with unemployment and individuals not in the labor force. Second, life satisfaction does not directly depend on hours worked in the same way as earnings do. Finally, life satisfaction covers non-pecuniary aspects of the job that are not reflected on earnings or wages.

Tables A.3 and A.4 in the appendix present estimation results for ordered probit models of life satisfaction in general and satisfaction with economic conditions (both variables have five possible levels, from very satisfied to not at all satisfied).

The results reinforce the idea the irregular activities are not a desirable outcome, since in general people in this state are less satisfied than those out of the labor force and only slightly more satisfied than the unemployed. Formal entrepreneurs appear to be at the top of the satisfaction rank, followed by informal entrepreneur, formal employees, and informal employees.

5 Discussion and Concluding Remarks

While informal employment in the Russian labor market is still relatively low compared to Latin American and other developing countries, it has been continuously rising in recent years. Moreover, labor market dynamics imply that a large fraction of the population is likely to experience an informal spell at one point or another of their pro-

[15] The two items we use are: "To what extent are you satisfied with your life in general at the present time?" and "How satisfied are you with your economic conditions at the present time?".

ductive lives.

In this paper we analyze patterns of mobility in the labor market to determine, first, whether there is evidence of segmentation and, second, whether some experience at an informal job might provide workers with a stepping stone into more desirable positions. Using transition matrices, we find little evidence of entry barriers to the formal sector. There are significant flows between informal and formal states. The main exception involves casual and irregular activities, which seem to be weakly integrated to the rest of the labor market. A dynamic multinomial logit model shows that controlling for observable characteristics does not affect these findings. We use the model estimates to simulate counterfactuals in which the whole sample is set to the same origin state. Both for males and for females, the probability of transitioning into formal entrepreneurship is greatly aided by experience as an informal entrepreneur. This type of informality can be said to be a stepping stone. In contrast, we find little evidence of similar effects associated with experience as an informal employee.

The literature has focused on to what extent flows to and from informal states are voluntary. The analysis of earnings and life satisfaction suggest that flows to any form of entrepreneurship are probably voluntary, since these positions are the best paid and are associated with the highest levels of life satisfaction. There are important differences in working hours across employment types, so some transitions might represent a tradeoff between earnings and a more flexible schedule. Finally, irregular activities seem to be the least desirable state.

The analysis in this paper has some clear limitations. Most importantly, the dynamic multinomial logit model does not correct for any form of unobservable individual heterogeneity. Future work will be directed toward this goal.

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A Appendix

Table A.1 – Earnings Regressions: Males

	Log Hours			Hours		
	Pooled OLS	H-Taylor	FE	Pooled OLS	H-Taylor	FE
Employment Type						
Inf Entrep.	-2.00***	-1.71***	-1.64***	-0.47***	-0.26***	-0.23**
	(0.40)	(0.25)	(0.43)	(0.11)	(0.08)	(0.11)
Formal Empl.	-1.53***	-0.98***	-0.97***	-0.64***	-0.33***	-0.32***
	(0.13)	(0.08)	(0.12)	(0.06)	(0.05)	(0.06)
Inf Empl.	-2.59***	-1.90***	-1.86***	-0.86***	-0.48***	-0.45***
	(0.23)	(0.15)	(0.21)	(0.08)	(0.06)	(0.07)
Irreg. Act.	-3.12***	-2.51***	-2.47***	-1.75***	-1.23***	-1.19***
	(0.10)	(0.06)	(0.11)	(0.07)	(0.05)	(0.07)
Hours Interactions						
Inf Entrep.	0.37***	0.35***	0.34***	0.0021***	0.0018***	0.0018***
	(0.07)	(0.05)	(0.08)	(0.0004)	(0.0003)	(0.0004)
Formal Empl.	0.23***	0.17***	0.17***	0.0015***	0.0012***	0.0012***
	(0.02)	(0.01)	(0.02)	(0.0001)	(0.0001)	(0.0001)
Inf Empl.	0.42***	0.35***	0.35***	0.0025***	0.0022***	0.0021***
	(0.04)	(0.03)	(0.04)	(0.0003)	(0.0002)	(0.0002)
Irreg. Act.	0.52***	0.47***	0.47***	0.0070***	0.0060***	0.0060***
	(0.02)	(0.01)	(0.02)	(0.0003)	(0.0002)	(0.0003)
Age Group						
25–34	0.15***	0.17***	0.14***	0.16***	0.17***	0.14***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
35–44	0.13***	0.14***	0.10***	0.13***	0.14***	0.10***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.04)
45–54	0.04*	0.10***	0.08*	0.05**	0.10***	0.08*
	(0.02)	(0.02)	(0.05)	(0.03)	(0.02)	(0.05)
55–65	-0.08***	-0.05*	-0.05	-0.08***	-0.04	-0.06
	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)	(0.06)
Education Compl.						
Secondary	0.17***	0.10***	-0.01	0.16***	0.10***	-0.00
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Vocational	0.14***	0.12***	0.06**	0.14***	0.13***	0.07**
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Technical	0.26***	0.23***	0.12***	0.27***	0.24***	0.13***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)
University+	0.47***	0.39***	0.15***	0.47***	0.41***	0.18***
	(0.03)	(0.02)	(0.05)	(0.03)	(0.03)	(0.05)
Other Charact.						
Russian National	-0.01	-0.01		-0.01	-0.01	
	(0.02)	(0.02)		(0.02)	(0.02)	
Urban Location	0.34***	0.37***		0.34***	0.37***	
	(0.02)	(0.02)		(0.02)	(0.02)	
Married	0.20***	0.13***	0.03	0.20***	0.13***	0.03
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Pension	-0.15***	-0.16***	-0.14***	-0.15***	-0.16***	-0.15***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Good Health	0.08***	0.04***	0.03**	0.08***	0.05***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	9.01***	8.73***	8.76***	8.98***	8.70***	8.74***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)
R-squared	0.41		0.28	0.39		0.26

Notes: Robust standard errors clustered at individual level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Year and region dummies (not shown) were included in all regressions. Restricted to individuals with positive hours. Based on 25,292 observations for 6,833 individuals.

Table A.2 – Earnings Regressions: Females

	Log Hours			Hours		
	Pooled OLS	H-Taylor	FE	Pooled OLS	H-Taylor	FE
Employment Type						
Inf Entrep.	-1.44***	-1.03***	-1.02***	-0.53***	-0.32***	-0.31***
	(0.29)	(0.21)	(0.32)	(0.11)	(0.08)	(0.10)
Formal Empl.	-2.32***	-1.37***	-1.38***	-1.13***	-0.60***	-0.60***
	(0.12)	(0.07)	(0.11)	(0.08)	(0.05)	(0.08)
Inf Empl.	-3.22***	-2.27***	-2.27***	-1.36***	-0.78***	-0.77***
	(0.19)	(0.13)	(0.21)	(0.09)	(0.05)	(0.09)
Irreg. Act.	-3.40***	-2.70***	-2.67***	-2.09***	-1.44***	-1.42***
	(0.13)	(0.07)	(0.14)	(0.10)	(0.05)	(0.10)
Hours Interactions						
Inf Entrep.	0.23***	0.19***	0.19***	0.0015***	0.0013***	0.0013***
	(0.06)	(0.04)	(0.06)	(0.0005)	(0.0003)	(0.0004)
Formal Empl.	0.33***	0.21***	0.22***	0.0028***	0.0018***	0.0019***
	(0.02)	(0.01)	(0.02)	(0.0001)	(0.0001)	(0.0001)
Inf Empl.	0.49***	0.39***	0.39***	0.0037***	0.0027***	0.0027***
	(0.03)	(0.02)	(0.04)	(0.0003)	(0.0002)	(0.0003)
Irreg. Act.	0.52***	0.47***	0.47***	0.0075***	0.0064***	0.0064***
	(0.02)	(0.01)	(0.03)	(0.0004)	(0.0002)	(0.0005)
Age Group						
25–34	0.09***	0.13***	0.14***	0.10***	0.14***	0.15***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
35–44	0.12***	0.16***	0.18***	0.13***	0.17***	0.18***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
45–54	0.09***	0.13***	0.14***	0.10***	0.14***	0.14***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.04)
55–65	-0.03	0.06**	0.08*	-0.02	0.07***	0.08*
	(0.03)	(0.02)	(0.05)	(0.03)	(0.02)	(0.05)
Education Compl.						
Secondary	0.20***	0.16***	0.08**	0.21***	0.18***	0.08**
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)
Vocational	0.13***	0.14***	0.10**	0.15***	0.15***	0.10**
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)
Technical	0.28***	0.26***	0.17***	0.30***	0.28***	0.18***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)
University+	0.61***	0.50***	0.27***	0.63***	0.52***	0.28***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)
Other Charact.						
Russian National	-0.05***	-0.05***		-0.04***	-0.05**	
	(0.02)	(0.02)		(0.02)	(0.02)	
Urban Location	0.28***	0.31***		0.28***	0.31***	
	(0.02)	(0.02)		(0.02)	(0.02)	
Married	0.00	0.02	0.03*	0.00	0.02*	0.03*
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Pension	-0.04**	-0.11***	-0.13***	-0.04*	-0.11***	-0.13***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Good Health	0.06***	0.02***	0.01	0.06***	0.02***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	9.17***	8.70***	8.48***	9.14***	8.66***	8.46***
	(0.09)	(0.06)	(0.08)	(0.09)	(0.06)	(0.09)
R-squared	0.44		0.34	0.43		0.33

Notes: Robust standard errors clustered at individual level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Year and region dummies (not shown) were included in all regressions. Restricted to individuals with positive hours. Based on 28,563 observations for 7,517 individuals.

Table A.3 – Satisfaction Ordered Probit Regression: Males

	General Life Satisfaction		Satisfaction Economic Cond.	
	No Income Control	Income Control	No Income Control	Income Control
Labor Market State				
Unemployed	-0.5***	-0.4***	-0.6***	-0.5***
Formal Entrep.	0.6***	0.3***	0.7***	0.1*
Inf Entrep.	0.5***	0.1***	0.5***	-0.0
Formal Empl	0.3***	0.1**	0.2***	-0.2***
Inf Empl	0.1**	-0.2***	0.2***	-0.3***
Irregular Activ.	-0.1***	-0.2***	-0.1***	-0.4***
Age Group				
25–34	-0.6***	-0.5***	-0.4***	-0.4***
35–44	-0.7***	-0.7***	-0.4***	-0.4***
45–54	-0.7***	-0.7***	-0.4***	-0.4***
55–65	-0.7***	-0.6***	-0.3***	-0.3***
Education Compl.				
Secondary	-0.0	-0.0	-0.0	-0.0
Vocational	-0.1***	-0.1**	-0.1***	-0.1***
Technical	0.1*	0.1*	-0.0	-0.1**
University+	0.2***	0.1***	0.1***	0.0
Region				
North/North Western	0.1***	0.1***	0.1*	0.1
Central	0.0	0.1***	0.0	0.1***
Volga	-0.2***	-0.1*	-0.1***	0.1***
North Caucasian	-0.0	0.1*	0.1***	0.2***
Ural	-0.1***	-0.0	0.1*	0.2***
Western Siberia	-0.1***	-0.0	-0.1*	0.1**
Eastern Siberia	-0.3***	-0.2***	-0.2***	-0.1
Year				
2003	-0.1**	-0.1***	0.0	-0.0
2004	0.1***	0.0	0.0	-0.1**
2005	0.1***	0.1**	0.1***	0.0
2006	0.1**	-0.0	0.0**	-0.1***
2007	0.1***	0.0	0.1***	-0.1***
2008	0.2***	0.1**	0.1***	-0.0
2009	0.2***	0.1**	0.1***	-0.1***
2010	0.2***	0.1***	0.1***	-0.0
2011	0.3***	0.2***	0.1***	-0.1**
Other Charact.				
Russian National	0.0	0.0	-0.1***	-0.1***
Urban Location	0.1***	-0.0	0.1***	-0.0
Married	0.3***	0.3***	0.1***	-0.0
Pension	0.1**	-0.1**	0.2***	-0.0
Good Health	0.4***	0.4***	0.3***	0.3***
log($Income$)		0.2***		0.3***
cut1	-1.3***	-0.1	-0.6***	1.4***
cut2	-0.4***	0.9***	0.4***	2.5***
cut3	0.3***	1.6***	1.0***	3.1***
cut4	1.7***	3.0***	2.1***	4.3***
Observations	42,521	34,745	42,452	34,742
Individuals	8,567	8,085	8,562	8,080
Log-likelihood	-58,957	-47,434	-59,207	-47,673
Pseudo-R2	0.047	0.047	0.027	0.035

Notes: Satisfaction variables are ordered in five categories. Standard errors clustered at individual level are omitted. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.4 – Satisfaction Ordered Probit Regression: Females

	General Life Satisfaction		Satisfaction Economic Cond.	
	No Income Control	Income Control	No Income Control	Income Control
Labor Market State				
Unemployed	-0.4***	-0.3***	-0.4***	-0.3***
Formal Entrep.	0.6***	0.5***	0.9***	0.6***
Inf Entrep.	0.4***	0.2***	0.6***	0.3***
Formal Empl	0.1***	0.0	0.1***	-0.1***
Inf Empl	-0.0	-0.1***	0.0	-0.1***
Irregular Activ.	-0.2***	-0.2***	-0.1***	-0.2***
Age Group				
25–34	-0.5***	-0.5***	-0.3***	-0.4***
35–44	-0.6***	-0.6***	-0.4***	-0.5***
45–54	-0.7***	-0.7***	-0.4***	-0.5***
55–65	-0.6***	-0.6***	-0.3***	-0.4***
Education Compl.				
Secondary	0.0*	0.1**	0.0	0.0
Vocational	-0.1*	-0.0	-0.1***	-0.1***
Technical	0.0	0.0	-0.0	-0.1*
University+	0.2***	0.2***	0.2***	0.1***
Region				
North/North Western	-0.0	-0.0	-0.0	-0.0
Central	-0.1***	-0.1**	-0.1***	-0.0
Volga	-0.2***	-0.1***	-0.1***	-0.0
North Caucasian	-0.1***	-0.0	-0.0	0.1***
Ural	-0.2***	-0.1***	-0.1***	0.0
Western Siberia	-0.2***	-0.2***	-0.1***	-0.0
Eastern Siberia	-0.3***	-0.2***	-0.2***	-0.2***
Year				
2003	-0.1***	-0.1***	-0.0	-0.1**
2004	0.0**	0.0	0.0	-0.0
2005	0.1***	0.1***	0.1***	0.0
2006	0.1***	0.1**	0.1***	0.0
2007	0.2***	0.1***	0.1***	-0.0
2008	0.2***	0.1***	0.2***	0.1***
2009	0.2***	0.2***	0.1***	-0.0
2010	0.3***	0.2***	0.2***	0.0*
2011	0.4***	0.3***	0.2***	0.0*
Other Charact.				
Russian National	-0.0**	-0.1**	-0.1***	-0.1***
Urban Location	0.1***	0.0	0.1***	-0.0
Married	0.3***	0.3***	0.2***	0.2***
Pension	0.1***	-0.0	0.1***	0.0
Good Health	0.4***	0.4***	0.3***	0.3***
log($Income$)		0.1***		0.2***
cut1	-1.4***	-0.5***	-0.6***	1.0***
cut2	-0.4***	0.5***	0.3***	2.1***
cut3	0.3***	1.3***	0.9***	2.7***
cut4	1.6***	2.6***	2.1***	3.9***
Observations	52,704	44,209	52,701	44,254
Individuals	10,242	9,700	10,238	9,701
Log-likelihood	-73,610	-61,171	-72,214	-59,564
Pseudo-R2	0.045	0.047	0.025	0.036

Notes: Satisfaction variables are ordered in five categories. Standard errors clustered at individual level are omitted. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Препринт WP3/2013/05
Серия WP3
Проблемы рынка труда

Слонимчик Фабиан

Ведет ли неформальность к хорошей работе?

(*на английском языке*)