Economics of Transition

Economics of Transition
Volume 23(2) 2015, 299–341
DOI: 10.1111/ecot.12064

Informality and mobility

Evidence from Russian panel data[1]

Fabián Slonimczyk* and Vladimir Gimpelson*
*National Research University Higher School of Economics, Moscow, Russia.
E-mail: fslonimczyk@hse.ru and vladim@hse.ru

Abstract

Informality is a defining characteristic of labour markets in developing and transition countries. This paper analyzes patterns of mobility across different forms of formal and informal employment in Russia. Using the Russian Longitudinal Monitoring Survey household panel we estimate a dynamic multinomial logit model with individual heterogeneity and correct for the initial conditions problem. Simulations show that structural state dependence is weak and that transition rates from informal to formal employment are not lower than from non-employment. These results lend support to the integrated view of the labour market.

JEL classification: J6.
Keywords: Informality, labour mobility, initial conditions problem, state dependence.

Received: September 23, 2013; Acceptance: January 21, 2015

[1] The authors thank the Editor and an anonymous referee for their helpful comments. This paper has been presented at the following venues: Stockholm Institute of Transition Economics, Center for Economic Performance (London), Higher School of Economics (Moscow), First RLMS International Users' Conference, Italian Labor Economics Association (Rome). We thank participants for their constructive feedback. We are also grateful to Richard Jackman, Judith Shapiro and Anna Yurko. All remaining errors are those of the authors. Fabián Slonimczyk acknowledges support from NRU Higher School of Economics Academic Fund Program 2012–2013 (research grant No. 11-01-0165). Vladimir Gimpelson acknowledges support from NRU Higher School of Economics Basic Research Program.

Published by Blackwell Publishing Ltd, 9600 Garsington Road, Oxford OX4 2DQ, UK and 350 Main St, Malden, MA 02148, USA

1. Introduction

Widespread informality is a salient feature of transition and emerging economies. It characterizes a broad set of economic activities, including the operations of the myriad small-scale enterprises that are fully run by families or single individuals, but also informally hire employees working for otherwise formal firms.[2] Overall, in these countries a large share of the population is informally employed.[3]

There are multiple reasons why sprawling informality is seen as a negative phenomenon. First, the informal economy operates largely beyond State regulation and tax evasion is the norm rather than the exception. Second, the need to keep activities undetected leads to multiple inefficiencies including suboptimal scale, low investment rates, use of primitive technologies, and close to zero productive innovation. Third, earnings in some informal activities are low and irregular, linking informality and poverty. Finally, informal workers face higher risks of social exclusion because they are not covered by any kind of safety net (except maybe the one provided by family and friends).

Various dimensions of this phenomenon have been thoroughly examined, especially for Latin American countries (Perry *et al.*, 2007). However, the drivers and implications of informality in transition countries remain largely unexplored (for exceptions, see Gimpelson and Kapeliushnikov, 2013b; Lehmann *et al.*, 2012; Slonimczyk, 2012).

An important issue is whether the same individuals participate in the informal sector year after year, or if instead the incidence of informality is spread more equally across the labour force. Given the level of informal employment at a point in time, if informality is a persistent state, most of the negative effects associated with it would be suffered by a limited set of individuals. If the opposite, everyone in the population faces roughly equal chances of experiencing a spell of informal employment.

A closely related question is whether transitions out of informality lead to formal jobs or if, on the contrary, informal workers end up dropping out of the labour force. Does informal employment function as a 'stepping stone' toward formal positions or is it a 'dead end' without exit to better jobs? A *priori* there are good arguments for both views. There are several reasons to think that the probability of finding a

[2] 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).

[3] Even the most advanced transition economies in Europe have a significant informal sector (Packard *et al.*, 2012). According to Gasparini and Tornarolli (2007), in many Latin American countries the share of informal employment exceeds 50 percent of the urban labour force. Existing estimates for Sub-Saharan Africa and Asia are even higher (Jütting *et al.*, 2008). For OECD countries, see Andrews *et al.* (2011).

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 could signal higher levels of ability or other unobservable traits relative to non-employed individuals.

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. Barriers to entry to the formal sector may exist that prevent easy transitions from informality. In particular, certain labour market institutions like the minimum wage and union collective bargaining agreements might restrict labour demand in the formal sector. Alternatively, low transition rates could result 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).

For these reasons, the degree of persistence of informality and the extent to which informal jobs are 'stepping stones' are important empirical questions. The paper addresses these issues using panel data from Russia, a middle-income country with moderate levels of informality. According to various estimates, informal jobs can account for about 20–25 percent of employment (Gimpelson and Zudina, 2011; Slonimczyk, 2012). Using simple transition matrices we document persistence rates in the informal sector of almost 50 percent. The probability of transitioning into a formal sector is also relatively low from the informal sector (about 26 percent, compared to almost 90 percent when the origin state is formality). However, because the state of origin is endogenously determined these figures provide a poor indication of the actual degree of state dependence.

In order to disentangle structural state dependence from selection effects we estimate a dynamic multinomial logit model of sector choice that allows for individual heterogeneity in preferences. We apply the method suggested by Heckman (1981) to take care of the initial conditions problem. We estimate two specifications of the model. In the first the individual heterogeneity is assumed to be normally distributed. In the second the heterogeneity is allowed to have a discrete distribution, as in Heckman and Singer (1984).

Using the model to simulate the behaviour of individuals in the sample when placed in different counterfactual origin states, we are able to obtain estimates of structural state dependence. As opposed to descriptive transition matrices, our model-based estimates control for a series of observable characteristics. In addition, we use Bayesian inference to obtain an estimate of the position of each individual in the distribution of unobservable heterogeneity. Thus, the estimates of state dependence we present also control, to the extent possible, for unobservable heterogeneity in preferences and ability.

We find that state dependence is much lower than what it would appear based on descriptive evidence. Specifically, we find that state dependence for informal employees is only 7.6 percent for males and 9.6 percent for females.[4] Importantly, we also find that the chances of transitioning into a formal job are improved if the origin state is the informal sector rather than non-employment. The simulation results suggest that the specific characteristics and preferences of individuals who occupy the informal sector are the reason behind the relatively high permanence rates and the relatively low transition rates into formal jobs that are observed in simple descriptive transition matrices.

The paper is organized as follows. Section 2 discusses the issue of mobility in the context of the different theories of the informal sector. Section 3 introduces the data, sample selection criteria, and gives details on the definition of informality. It also provides a descriptive analysis of mobility across labour market states using transition matrices. Section 4 describes the empirical model and explains the estimation technique. Section 5 presents estimation results and evaluates how well the model fits the data. In Section 6 we use the model to simulate different counterfactual scenarios and present our estimates of structural state dependence. The final section discusses our findings and concludes.

2. Informality and mobility

Theories that explain informality in the labour market can be divided into two competing schools of thought with regards to the issue of segmentation. According to one view, the existence of a large informal sector is explained by rigidities in the urban labour market. For example, in the classic model by Harris and Todaro (1970), a minimum wage set above the market-clearing wage results in rationing of formal jobs.[5] If unemployment benefits are low or non-existent, workers are left with informal activities as their only option. In other words, there is a perennial excess supply of workers who would want to take formal jobs at the going formal sector wage but are unable to find one. Thus, the formal and the informal sector are segmented.

An alternative perspective sees labour markets as integrated and competitive (Maloney, 1999, 2004). Individuals are endowed with heterogeneous skills, which are valued differently in different sectors (Heckman and Sedlacek, 1985; Magnac, 1991). In addition, jobs vary in non-pecuniary aspects such as amenities and

[4] State dependence (SD) is measured as the average difference between the probability of staying in the same labour market state and the probability of entering from other origin states. These estimates correspond to the semi-parametric specification of the model. When the heterogeneity is assumed to be normally distributed state dependence estimates are 2.8 percent for males and 8.3 percent for females (see Table 7).

[5] Calvo (1978) presents a similar argument where the source of rigidities are union-sponsored collective bargaining agreements.

hazards. Individuals choose among the existing employment opportunities in accordance with their preferences and abilities and there are no strict barriers to entry to formal jobs. In more colloquial terms, workers might have good reasons to prefer informal status over formal alternatives due to various desirable characteristics of informal jobs, the low productivity in formal jobs and the poor quality of government insurance programmes. This is one of the central messages of the influential World Bank report 'Informality: Exit and Exclusion' (Perry *et al.*, 2007).[6]

While segmentation does not preclude the possibility of transitions between formal and informal jobs, it is clear that the two schools of thought have quite different implications regarding the extent of state dependence (are workers trapped in informal jobs?) and the intensity of flows from the informal to the formal sector.[7] If labour markets are segmented, flows from formal to informal jobs should be much larger in volume than those going in the opposite direction. Workers are likely to find themselves trapped in the informal sector in presumably inferior (in terms of pay and employment conditions) positions and stay in a queue waiting for better (formal) openings. In contrast, the integrated labour markets view implies that there are no real grounds for state dependence in informality and that flows between formal and informal jobs should go in both directions with roughly the same intensity.[8]

Existing studies are inconclusive about which of these theories better represents the reality of labour markets in developing economies. Our knowledge of labour markets in transition countries is particularly shallow.

Gong *et al.* (2004) explore mobility patterns using panel data from Mexico. They document relatively large flows across non-employment, formal and informal employment. Using predicted probabilities from a dynamic multinomial model they test the hypothesis that the transition patterns between sectors are in line with the symmetric view of formal and informal sector jobs. These symmetry restrictions on transitions between sectors are not rejected. However, they also find some evidence of entry barriers for low educated individuals.

Pagés and Stampini (2009) provide a comparative study of labour mobility and segmentation in three Latin American countries (Argentina, Mexico, Venezuela) and three transition economies (Albania, Georgia and Ukraine). For all countries they document high mobility rates between formal and informal salary employment but

[6] In more recent work, Bosch and Maloney (2010) are less assertive suggesting that while 'a substantial part of the informal sector, particularly the self-employed, correspond to voluntary entry, . . . informal salary workers may correspond to the standard queuing view'.

[7] A third important question involves sectoral wage differentials but it is beyond the scope of this paper.

[8] The two schools of thought are partially reconciled by Gary Fields's idea that the informal sector in developing countries is two-tiered (Fields, 2009). The lower-tier is composed of free-entry jobs and the upper-tier contains skilled jobs. In terms of mobility, the lower tier is expected to be stagnant with one-way entry and with queuing for exit, while the upper tier is integrated with the formal sector. This third position has fewer clear cut implications regarding the extent of state dependence and the direction of flows between formality and informality.

low rates between formal salary and self-employment. For post-socialist countries symptoms of segmentation seem to be clearer than in Latin America. Tansel and Kan (2012) also argue for the existence of segmentation and a static employment structure in Turkey.

Two studies provide evidence on transition countries. Lehmann and Pignatti (2007) analyze flows in the Ukrainian labour market using panel data for the period 2003–2004. They conclude that there is evidence of both dynamism and segmentation, as argued by Fields (1990). In a more recent paper, Lehmann *et al.* (2012) focus on whether displaced workers and voluntary quitters in Russia are more exposed to informality than new labour market entrants or incumbents. They find that displacement entraps workers in involuntary informal employment. Quitters, in turn, experience voluntary informality for the most part, but a minority of them end up in involuntary informal jobs too. The lock-in effect is stronger for workers with low human capital and for those who separate from informal jobs. The latter result also implies that informal employment is persistent. However, the fraction of those involuntary separated in the sample is quite low, so the results are not conclusive.

3. 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.[9] We use data from rounds XI–XX covering the period 2002–2011. 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') is 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 '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 something else that you were paid for?' The questionnaire structure is such that no one may answer

[9] The RLMS-HSE is conducted by the National Research University Higher School of Economics and the 'Demoscope' team in Russia, together with the Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS. The RLMS website (http://www.cpc.unc.edu/projects/rlms-hse) contains extensive documentation and details on the sampling design.

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 percent 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 labour income.

3.1 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 18 and 65 years of age.[10] 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 8,547 males and 10,203 females making a total of 42,871 and 53,046 observations, respectively. Since mobility patterns are bound to be different across gender lines, we analyze males and females separately.

3.2 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 labour 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.[11] In principle, it would be

[10] The official retirement age for women is 55 years, but a large fraction of retirement age women keep working until much later. In our empirical model we include controls for age group and pension receipts.

[11] This classification is based on four items from the adult questionnaire: (1) 'do you work at an enterprise or organization? We mean any organization or enterprise 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'. Enterprise workers are considered entrepreneurs if they answer positively to both (2) 'Are you personally an owner or co-owner of the enterprise where you work?' and (3) 'In your opinion, are you doing entrepreneurial work at this job?' The distinction between entrepreneurs and employees for non-enterprise individuals is based on: (4) 'At this job are you ... (a) involved in an employer's or individual labour activity or (b) work for a private individual?'

possible to distinguish between formal and informal entrepreneurs. As shown in Slonimczyk (2013) the two resulting sub-categories are very small relative to the size of the labour force and have very similar characteristics in terms of hours worked, earnings, turnover rates and mobility patterns. Since each category considered is computationally (processing time) and statistically (degrees of freedom lost due to extra parameters) costly, we opted for keeping all entrepreneurs together in one group.

We separate between formal and informal employees as follows. First, following the productive definition, employees not working at firms or organizations (i.e., those without an employer or whose employer is not incorporated) are considered informal. Second, for those working at firms or organizations the RLMS questionnaire includes an item that permits determination of whether they are registered, i.e., working officially.[12] The Russian labour code mandates that all employees sign a written contract and deposit their 'labour book' with the employer. Therefore, following the social protection criterion, we classify unregistered employees as informal. Finally, individuals without a primary job but who perform irregular activities for pay are also considered informal employees.

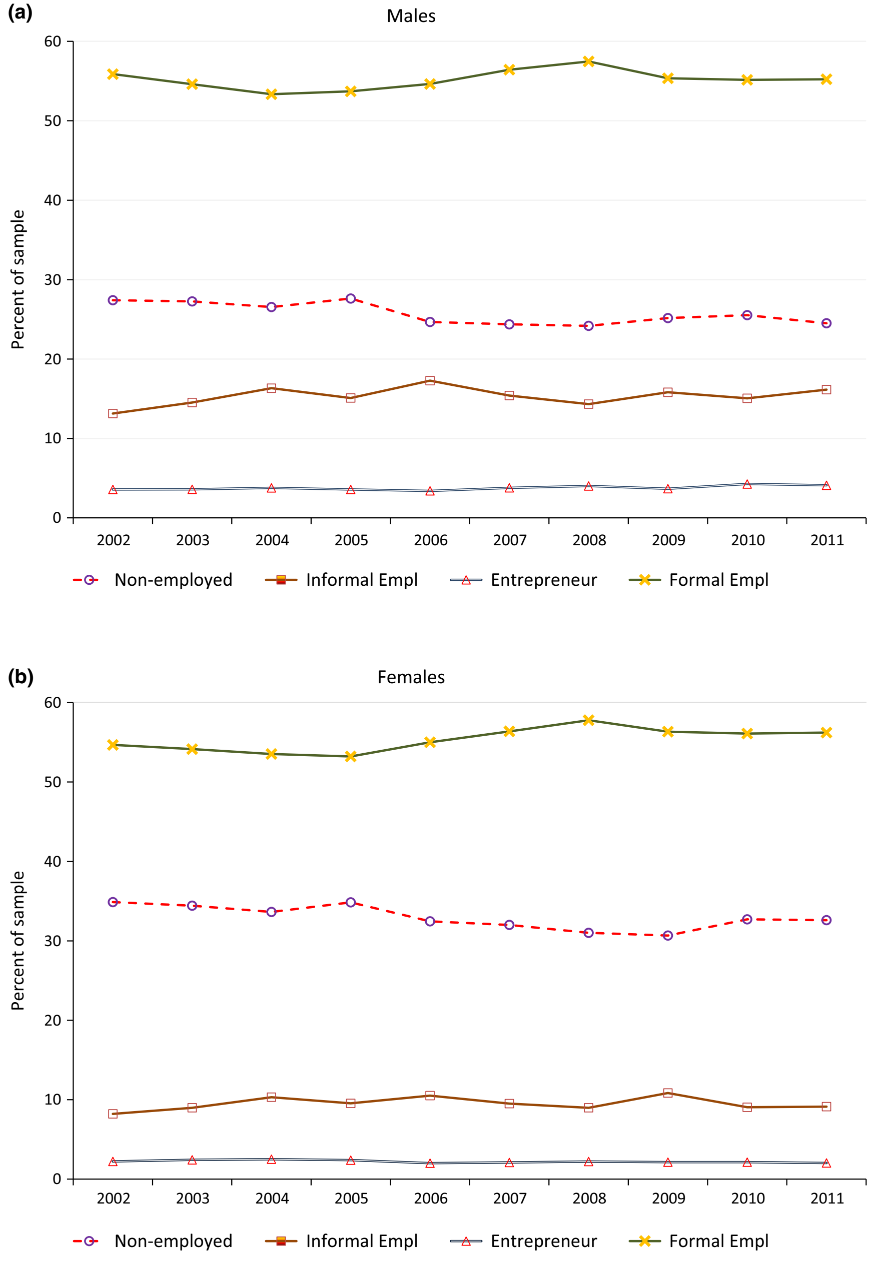
Figure 1 shows the distribution of employment status over time. It is important to emphasize the lack of any strong trends in the data. Although we allow for time shocks by including year dummies, the main empirical exercise in the paper assumes the economy is in steady state. Both for females and for males, employment rates have slightly increased over the period. For males, the increase has taken the form of growing informal employment, while entrepreneurship and formal employment have remained roughly constant.[13] Among women, in contrast, the employment gains were in formal jobs, with informality and entrepreneurship constant.

There are visible differences between males and females. First, even though Russian women have relatively high participation rates by international standards, there still exists a gender gap of about seven percentage points. Second, formal employment is relatively more prevalent among women than men. This might reflect the fact that the large public sector is predominantly female. As a fraction of those employed, roughly 74 percent of males and 83 percent of females in the sample are formal employees. Correspondingly, there are substantially lower shares of women informally employed and in entrepreneurial roles.

[12] The question is: 'Tell me, please: are you employed in this job officially, in other words, by labour book, labour agreement, or contract?'

[13] Russia's working age population slightly decreased over the period. See Slonimczyk and Yurko (2014) for a review of the issues and an evaluation of a major pro-natalist policy.

Figure 1. The evolution of labour market status



Source**:** Authors' calculations based on RLMS data.

3.3 Labour market dynamics

The focus of this study is on individual level mobility in employment status. Tables 1 and 2 present transition matrices for the period under analysis for males and females, respectively. The top panel in each table (P-matrix) presents the conditional distribution of labour market destinations given each of the possible states of origin (p_{ij}), as well as the marginal distributions of states of origin and destination ($p_{i\cdot}$ and $p_{\cdot j}$, respectively).

First, note that both for men and women the marginal distributions for origin and destination states are very similar to each other, which is consistent with the steady state assumption. In fact, the small differences between $p_{i\cdot}$ and $p_{\cdot j}$ are of the same sign as the overall changes shown in Figure 1a,b above. For example, the tables show that the proportions of men and women exiting non-employment are slightly higher that the corresponding entry probabilities, leading to a small long-run increase in employment rates. Second, the diagonal elements in the conditional distributions show that non-employment and formal employment are very persistent states. Both among males and females, for example, less than 15 percent of formal employees leave the state in a given period.[14] In contrast, informal employees appear to be significantly more mobile. A third and final point illustrated by the P-matrices is that, when a change of state takes place, the state of origin seems to affect the likelihood of the possible destinations. For example, men transitioning out of entrepreneurship are much less likely than men leaving informal employment to become jobless.

Analysis based on P-matrices is troubled by the fact that different origin states have very different turnover rates. Also, because the different destination states have different sizes, the conditional distributions are not necessarily informative about the propensities to move from one state to another. Bernabè and Stampini (2009) apply a measure of the propensity to transit from state i to state j that corrects for the turnover rate of the state of origin, as well as for the share of jobs created in each possible destination state. Formally, the elements of their transition matrix are given by:

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

where N_{ij} is the number of individuals in state i in $t-1$ and state j in t, and $N_{i\cdot}$ and $N_{\cdot j}$ are the row and column totals, respectively.

The lower panels of Tables 1 and 2 present the adjusted transition matrices. The results confirm some of the disparities in transition propensities across origin states.

[14] Because the tables do not consider job changes within states, the relative persistence of formal employment does not *per se* imply low levels of overall mobility. Throughout the paper we use the terms 'mobility' and 'persistence' in a narrow sense as they apply to transitions across labour market states only.

Table 1. Transition matrices: Males

	Non-employed	Informal employee	Entrepreneur	Formal employee	$p_{i\cdot}$
P-matrix					
Non-employed	70.9%	15.0%	0.7%	13.3%	25.5%
Informal employee	20.4%	49.5%	4.0%	26.2%	15.2%
Entrepreneur	3.3%	15.0%	68.8%	12.9%	3.8%
Formal employee	5.5%	6.9%	0.9%	86.7%	55.5%
$p_{\cdot j}$	24.4%	15.7%	3.9%	56.0%	
SD	61.2%	66.8%	69.2%	37.2%	
T-matrix					
Non-employed		1.09	0.33	1.01	
Informal employee	0.99		0.92	1.02	
Entrepreneur	0.38	1.31		1.17	
Formal employee	1.04	0.99	0.86		

***Notes*:** Calculations based on 34,324 transitions over the period 2002–2011. The top panel shows the conditional distribution of transitions given the origin state, as well as marginal distributions ($p_{i\cdot}$ and $p_{\cdot j}$). The T-matrix is defined in the main text.

Table 2. Transition matrices: Females

	Non-employed	Informal employee	Entrepreneur	Formal employee	$p_{i\cdot}$
P-matrix					
Non-employed	78.0%	9.4%	0.4%	12.2%	32.3%
Informal employee	25.2%	46.4%	2.5%	25.9%	9.5%
Entrepreneur	5.7%	9.5%	73.6%	11.2%	2.2%
Formal employee	6.7%	3.8%	0.5%	89.0%	56.0%
$p_{\cdot j}$	31.5%	9.8%	2.3%	56.5%	
SD	65.6%	72.3%	72.6%	38.8%	
T-matrix					
Non-employed		1.01	0.35	1.06	
Informal employee	1.02		0.99	0.99	
Entrepreneur	0.62	1.23		1.17	
Formal employee	1.20	0.79	0.87		

***Notes*:** Calculations based on 42,843 transitions over the period 2002–2011.

For example, both for females and for males it is comparatively harder to become an entrepreneur starting from non-employment relative to other origin states. There are also differences in the ease of access to formal employment but these are relatively small. The T-matrices also show that formal and informal employment are not too different with respect to the risk of non-employment. In fact, the non-employment propensities for formal employees are a little higher than those for informally employed individuals, males and females. Entrepreneurs, in contrast, are very unlikely to become jobless.

How does the Russia's labour market compare to those of other countries? Pagés and Stampini (2009) provide similar statistics for three Latin American countries (Argentina, Venezuela, Mexico) and three transition countries (Albania, Georgia, Ukraine). Their data come from panel studies or cross-country surveys with a panel element collected toward the end of the 1990s and the beginning of the new century. Their statistics are pooled across genders and disaggregated into 'low-skill' and 'high-skill' categories. We take the average of the two categories to make comparisons.

First, formal employees in Russia have a relatively high permanence rate. On average, in the comparison countries, 82 percent of formal employees stayed in the sector from one period to the next. Only Georgia had a permanence rate for formal employees (91 percent) higher than those given in Tables 1 and 2. In contrast, informal employees in Russia have about average permanence rate when compared with other countries. Second, and consistent with the first point, the Russian labour market shows relatively infrequent transitions from formal to informal employment and about average transitions in the reverse direction. In the comparison countries, formal employees become informal at a rate around 8 percent, while in Russia the comparable rate when pooling males and females is only 5 percent. The figures for transitions from informal to formal employment are 27 percent in the comparison countries and 26 percent in Russia. Finally, the T-matrix suggests that the Russian labour market is less mobile than those of the comparison countries. The statistic for formal to informal transitions is 0.9 in the former and on average 1.1 in the latter. For informal to formal transitions, the corresponding statistics are 1.0 and 1.5.

In sum, these comparisons suggest that Russia provides a good experimental setting to answer our main research questions: what is the degree of state dependence on informality? and is informal employment a stepping-stone to formal positions? Permanence rates in Russia's labour market are as high or higher than in other middle-income countries and mobility is relatively low.

3.4 Difference in observable characteristics across sectors

While transition matrices, adjusted or otherwise, offer interesting descriptive evidence, they can be misleading because the characteristics of the individuals in the different states are bound to be very different. As an example, suppose there are comparatively more unskilled individuals in non-employment relative to formal and informal employment. If entrepreneurship has high skill requirements, both P- and T-matrices will show relatively lower transition propensities to entrepreneurship from non-employment than from the other two origin states even if the propensities were the same conditional on skill level.

Table 3 presents summary statistics for a number of observable characteristics of the individuals in the sample that are likely to affect transition propensities. It is clear from the table that individuals in different states differ widely in their observable characteristics. Thus, transition matrices are bound to present a biased picture. The empirical model we present in the next section is meant to address this issue.

In addition to the problem of differences in observable characteristics, transition matrices do not take into consideration heterogeneity in preferences and skills that are unobservable to the researcher. In particular, if individuals with strong preferences favouring stability are relatively very prevalent in one labour market state, estimated transition propensities out of this state will be biased downwards. A related limitation is that transition matrices do not differentiate between transitions corresponding to the same individual in two different periods and transitions corresponding to different individuals. In contrast, the model we present below incorporates an individual heterogeneity term representing unobserved variation in preferences and other individual characteristics. This term is integrated out in the estimation process, so within- and between-individual variation are given different treatment.

4. Methodology

We model flows among four different labour market states:[15] non-employment ($j = 1$), informal employee ($j = 2$), entrepreneur ($j = 3$), and formal employee ($j = 4$). The individual's utility in each state is specified as:

$$U_{itj} = X_{it}\beta_j + Z_{i,t-1}\gamma_j + \alpha_{ij} + \eta_{itj}, \quad j = 1, \ldots, 4 \tag{1}$$

where i and t index individuals and time, respectively. The X vector represents observable characteristics influencing state-specific utility. These include variables affecting potential earnings in each state – which we proxy with measures of highest completed education and age – preferences over non-pecuniary characteristics of jobs as determined by marital status and family structure, and shifts in labour demand over time and across regions. Z_{t-1} is a set of binary

[15] The exact definitions are explained in the data section.

Table 3. Descriptive statistics by labour market state

	Males				Females			
	Non-employed (%)	Informal employee (%)	Entrepreneur (%)	Formal employee (%)	Non-employed (%)	Informal employee (%)	Entrepreneur (%)	Formal employee (%)
Age composition								
15–24 years	44.8	21.2	3.7	9.5	33.9	21.5	3.2	9.0
25–34 years	9.8	29.2	29.6	29.8	14.4	25.5	21.5	26.7
35–44 years	9.5	22.7	35.0	23.9	9.4	21.3	31.3	25.4
45–54 years	12.9	18.7	26.1	23.9	12.4	19.6	33.8	26.5
55–65 years	23.1	8.1	5.6	12.9	30.0	12.1	10.3	12.4
Education completed								
Less than secondary	32.3	19.1	5.4	8.2	24.6	11.8	3.8	4.3
Secondary school	31.9	28.9	20.7	20.1	30.6	28.0	15.3	14.5
Vocational school	19.2	31.8	19.5	30.7	15.1	24.4	19.0	18.1
Technical school	8.8	11.2	22.6	18.4	18.9	23.6	36.5	30.9
University or higher	7.8	9.0	31.9	22.5	10.8	12.3	25.5	32.1
Region								
Moscow & St. Petersburg	9.5	8.5	8.7	12.0	10.5	8.5	6.1	12.2
North & North Western	6.1	4.7	5.8	7.1	5.6	5.9	4.4	8.4
Central & Black-Earth	15.8	15.8	18.0	19.8	16.3	14.3	22.8	19.7
Volga	18.3	19.4	17.5	17.0	17.8	16.3	16.6	17.5
North Caucasian	19.1	19.7	16.4	10.7	17.5	19.3	14.4	9.9
Ural	13.1	12.3	15.0	15.7	13.0	14.9	13.3	15.6
Western Siberian	9.6	10.6	10.9	7.8	9.4	10.3	11.5	8.0
East Siberia & Farther	8.6	9.1	7.8	9.9	9.8	10.5	10.9	8.7

Table 3. (Continued)

	Males				Females			
	Non-employed (%)	Informal employee (%)	Entrepreneur (%)	Formal employee (%)	Non-employed (%)	Informal employee (%)	Entrepreneur (%)	Formal employee (%)
Other characteristics								
Russian National	70.9	70.6	70.6	79.6	75.0	75.4	75.5	81.9
Urban location	65.0	64.0	82.5	75.7	67.8	69.4	80.7	78.1
Married	41.0	65.5	89.7	81.1	51.9	56.9	75.1	66.9
Pension	30.7	8.1	4.6	9.6	37.6	14.1	10.8	15.1

Notes: The number of observations is 42,896 and 53,090 for males and females, respectively.

variables indicating the labour market state chosen in the previous period (non-employment is the omitted category). The lagged state affects utility through multiple channels, including sector-specific human capital that increases potential earnings, costs associated with job search in different sectors, signalling of unobservable ability, etc. We assume the dynamic process is Markov, so the first lag includes all relevant information regarding sector-specific experience.[16]

Non-observable individual heterogeneity in preferences is represented by α, which is assumed constant over time and independent of the observable characteristics of the individual.[17] Finally, η is a time-varying random component to utility that is assumed independent of the other determinants and has an extreme value distribution.

With these assumptions, the model is a particular case of the mixed multinomial logit (MMNL) class. McFadden and Train (2000) show that any discrete choice model derived from random utility maximization has choice probabilities that can be approximated to any degree by a MMNL model. In particular, MMNL models allow for correlation among state-specific utilities through the individual heterogeneity term, so the independence of irrelevant alternatives assumption is not imposed.

As it is only possible to identify differential effects across alternatives, the parameters associated with non-employment $(\beta_1, \gamma_1, \alpha_1)$ are set equal to zero. Conditional on X, Z_{t-1}, and α, utility maximizing individuals choose labour market state l with probability:

$$P\left(Z_{it} = l \,|X_{it}, Z_{i,t-1}, \boldsymbol{\alpha}_i\right) = \frac{\exp(X_{it}\beta_l + Z_{i,t-1}\gamma_l + \alpha_{il})}{1 + \sum_{j=2}^{4} \exp(X_{it}\beta_j + Z_{i,t-1}\gamma_j + \alpha_{ij})}$$

where $\boldsymbol{\alpha}_i \equiv (\alpha_{i2}, \alpha_{i3}, \alpha_{i4})$. Since the random shocks to preferences are i.i.d., the probability of a sequence of choices is simply the product of the time-specific probabilities. Specifically, if individual i chooses a sequence $S_i = (j_1, \ldots, j_{T_i})$, we have:

$$P(S_i|\mathbf{X}_i, Z_{i0}, \boldsymbol{\alpha}_i) = \prod_{t=1}^{T_i} P\left(Z_{it} = j_t|X_{it}, Z_{i,t-1}, \boldsymbol{\alpha}_i\right) \tag{2}$$

where $\mathbf{X}_i$ represents the time sequence of observable characteristics. Importantly, the likelihood in equation (2) is conditional on Z_{i0}, the *initial conditions* of the process.

[16] Considering further lags would severely complicate the initial conditions problem. It could also lead to sample selection bias as only individuals with at least three consecutive observations could be considered. At a more fundamental level, expanding the lag structure would require a different definition of state dependence as interactions across different lags would need to be considered.

[17] A fixed effects specification leads to the well-known 'incidental parameters' problem.

Since the initial conditions are unobservable, in principle they would have to be integrated out of the likelihood together with the individual heterogeneity. Instead, we proceed as suggested in Heckman (1981) and re-specify the probabilities associated with individuals' first observed period as follows:

$$P(Z_{i1} = l\,|X_{i1}, \boldsymbol{\psi}_i) = \frac{\exp(X_{i1}\pi_l + \psi_{il})}{1 + \sum_{j=2}^{4}\exp(X_{i1}\pi_j + \psi_{ij})}$$

where π_j are first-period-specific parameters and $\boldsymbol{\psi}_i$ is an individual heterogeneity term.[18] Using this approximation, the likelihood can be rewritten without the need to condition on Z_{i0}:

$$P(S_i|\boldsymbol{X}_i, \boldsymbol{\alpha}_i, \boldsymbol{\psi}_i) = P(Z_{i1} = j_1|X_{i1}, \boldsymbol{\psi}_i) \times \prod_{t=2}^{T_i} P\big(Z_{it} = j_t|X_{it}, Z_{i,t-1}, \boldsymbol{\alpha}_i\big). \qquad (3)$$

To complete the model it is necessary to specify a distribution for the individual heterogeneity ($\boldsymbol{\alpha}$). We have estimated two alternatives.

4.1 Normally distributed heterogeneity

In our initial specification the individual heterogeneity is assumed to be normally distributed. In order to impose positive-definiteness in the variance-covariance matrices, we use a Cholesky decomposition and parameterize the diagonal elements in log space. Formally,

$$\boldsymbol{\alpha}_i = \boldsymbol{W}\boldsymbol{\varepsilon}_i, \quad \boldsymbol{\psi}_i = \boldsymbol{W_1}\boldsymbol{\varepsilon}_i, \quad \boldsymbol{\varepsilon}_i \sim \mathrm{N}(\boldsymbol{0}, \boldsymbol{I}_3)$$

$$\boldsymbol{W} = \begin{bmatrix} e^{v_{22}} & 0 & 0 \\ v_{32} & e^{v_{33}} & 0 \\ v_{42} & v_{43} & e^{v_{44}} \end{bmatrix}, \quad \boldsymbol{W_1} = \begin{bmatrix} e^{\phi_{22}} & 0 & 0 \\ \phi_{32} & e^{\phi_{33}} & 0 \\ \phi_{42} & \phi_{43} & e^{\phi_{44}} \end{bmatrix}$$

It then follows that $\boldsymbol{\alpha}_i \sim \mathrm{N}(\boldsymbol{0}, \boldsymbol{W}\boldsymbol{W}')$ and $\boldsymbol{\psi}_i \sim \mathrm{N}(\boldsymbol{0}, \boldsymbol{W_1}\boldsymbol{W}_1')$. The variance-covariance matrices are uniquely determined by the v and ϕ parameters, which enter the estimation routine completely unrestricted.

[18] The re-specification of the first period probabilities arises from a reduced form approximation to the structural Equation (1). Heckman (1981) provides evidence based on a Monte-Carlo experiment showing that the approximation performs well for a dynamic binary choice model (see also Chay and Hyslop, 2001). Gong *et al.* (2004) apply the same method to a dynamic model with more than two alternatives.

The unconditional individual likelihood can be written:

$$\mathrm{L}_i(\boldsymbol{\theta}) = \int P(S_i|\mathbf{X}_i, \boldsymbol{\alpha}_i, \boldsymbol{\psi}_i)\, \mathrm{d}\boldsymbol{\Phi}(\boldsymbol{\varepsilon}) \tag{4}$$

where $\boldsymbol{\theta}$ represents all model parameters and $\boldsymbol{\Phi}(\cdot)$ is the cdf of a three-dimensional standard normal.

We estimate the model via maximum simulated likelihood (MSL), where the difficult integration in Equation (4) is replaced by a simple average over simulations obtained by taking random draws from $\boldsymbol{\Phi}(\cdot)$. Formally,

$$\mathrm{SL}_i(\boldsymbol{\theta}) = \frac{1}{R}\sum_{r=1}^{R} P\left(S_i|\mathbf{X}_i, \boldsymbol{\alpha}_i = \boldsymbol{W}\boldsymbol{\varepsilon}_i^r, \boldsymbol{\psi}_i = \boldsymbol{W_1}\boldsymbol{\varepsilon}_i^r\right) \tag{5}$$

where $\boldsymbol{\varepsilon}_i^r$ is a three-dimensional vector containing draws from a standard normal. The MSL estimator is consistent and asymptotically equivalent to the usual ML estimator if the number of simulations R grows to infinity at a rate higher than the square root of the number of observations (Hajivassiliou and Ruud, 1994; Train, 2009). For this application, we use $R = 30$ simulations per individual.

The objective function of the MSL procedure is the sum of the log of Equation (5) over the N individuals in the sample:

$$\mathrm{SLSL}\,(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \mathrm{SL}_i(\boldsymbol{\theta}).$$

In order to accelerate convergence, the estimation procedure also calculates the score function:

$$\mathrm{g}(\boldsymbol{\theta}) = \frac{\mathrm{dSLSL}}{\mathrm{d}\boldsymbol{\theta}} = \sum_{i=1}^{N} \frac{1}{\mathrm{SL}_i(\boldsymbol{\theta})} \frac{1}{R} \sum_{r=1}^{R} P\left(S_i|\mathbf{X}_i, \boldsymbol{\alpha}_i^r, \boldsymbol{\psi}_i^r\right)$$
$$\times \left(\frac{\mathrm{d}\log P\left(Z_{i1} = j_1|X_{i1}, \boldsymbol{\psi}_i^r\right)}{\mathrm{d}\boldsymbol{\theta}} + \sum_{t=2}^{T_i} \frac{\mathrm{d}\log P\left(Z_{it} = j_t \mid X_{it}, Z_{i,t-1}, \boldsymbol{\alpha}_i^r\right)}{\mathrm{d}\boldsymbol{\theta}} \right)$$

where, for l = 2,3,4 and $h \leq l$ the relevant derivatives are:

$$\frac{\mathrm{d}\log P\left(Z_{it}=j_t|X_{it},Z_{i,t-1},\boldsymbol{\alpha}_i^r\right)}{\mathrm{d}\beta_l}=X_{it}\left[j_{tl}-P\left(Z_{it}=l|X_{it},Z_{i,t-1},\boldsymbol{\alpha}_i^r\right)\right]$$

$$\frac{\mathrm{d}\log P\left(Z_{it}=j_t|X_{it},Z_{i,t-1},\boldsymbol{\alpha}_i^r\right)}{\mathrm{d}\gamma_l}=Z_{i,t-1}\left[j_{tl}-P\left(Z_{it}=l|X_{it},Z_{i,t-1},\boldsymbol{\alpha}_i^r\right)\right]$$

$$\frac{\mathrm{d}\log P\left(Z_{it}=j_t|X_{it},Z_{i,t-1},\boldsymbol{\alpha}_i^r\right)}{\mathrm{d}v_{lh}}=\sum_{j=2}^{4}\left[j_{tj}-P\left(Z_{it}=j|X_{it},Z_{i,t-1},\boldsymbol{\alpha}_i^r\right)\right]\frac{\mathrm{d}\alpha_j}{\mathrm{d}v_{lh}}$$

$$\frac{\mathrm{d}\alpha_j}{\mathrm{d}v_{lh}}=\mathbb{I}(j=l)\left\{\left[\exp(v_{lh})\right]^{\mathbb{I}(l=h)}\varepsilon_{ih}^r\right\}$$

$$\frac{\mathrm{d}\log P\left(Z_{i1}=j_1|X_{i1},\boldsymbol{\psi}_i^r\right)}{\mathrm{d}\pi_l}=X_{i1}\left[j_{1l}-P\left(Z_{i1}=l|X_{i1},\boldsymbol{\psi}_i^r\right)\right]$$

$$\frac{\mathrm{d}\log P\left(Z_{i1}=j_1|X_{i1},\boldsymbol{\psi}_i^r\right)}{\mathrm{d}\phi_{lh}}=\sum_{j=2}^{4}\left[j_{1j}-P\left(Z_{i1}=j|X_{i1},\boldsymbol{\psi}_i^r\right)\right]\frac{\mathrm{d}\psi_j}{\mathrm{d}\phi_{lh}}$$

$$\frac{\mathrm{d}\psi_j}{\mathrm{d}\phi_{lh}}=\mathbb{I}(j=l)\left\{\left[\exp(\phi_{lh})\right]^{\mathbb{I}(l=h)}\varepsilon_{ih}^r\right\}.$$

In practice, convergence to the optimum required iterating between analytical and numerical derivatives. The estimating routine was written in MATLAB based on code by Kenneth Train.[19]

4.2 Discrete distribution

In the second specification, following Heckman and Singer (1984), the individual heterogeneity is assumed to have a discrete distribution. Formally, ($\boldsymbol{\alpha}$, $\boldsymbol{\psi}$) takes a value in a finite set of vectors (the support set):

$$(\boldsymbol{\alpha},\boldsymbol{\psi})\in\left\{(\boldsymbol{a},\boldsymbol{b})^1,\ldots,(\boldsymbol{a},\boldsymbol{b})^D\right\}\equiv\boldsymbol{\Omega}$$

where the number of points in the set (D) must be specified *a priori*. As is common in the literature, we will refer to each element in the support set as an individual 'type'. Since the model includes constant terms, identification requires setting the first type equal to zero ($\boldsymbol{a}^1 = \boldsymbol{b}^1 = \boldsymbol{0}$). The other points in the support set are estimated jointly with the discrete type probability distribution.

The objective log-likelihood function is now the log of the 'mixed likelihood'

[19] The revised code is available upon request from the authors.

$$\mathrm{SLML}(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log\left[\sum_{d=1}^{D} p^d \times P\left(S_i|\boldsymbol{X}_i, (\boldsymbol{\alpha}, \boldsymbol{\psi}) = (\boldsymbol{a}, \boldsymbol{b})^d\right)\right] \tag{6}$$

where p^d is the probability that a random individual belongs to type d.

In practice, maximizing SLML directly is a very difficult computational task. Instead, we applied a version of the expectation-maximization (EM) algorithm that worked well (Arcidiacono and Jones, 2003).

The EM algorithm consists of two parts. Given initial values for all the model parameters, the first (expectation) part obtains new type probabilities as follows. From Bayes' theorem, the posterior probability that an individual belongs to unobservable type d is given by:

$$\mathrm{P}(d|S_i, \boldsymbol{X}_i) = \frac{p^d \times \mathrm{P}\left(S_i|\boldsymbol{X}_i, (\boldsymbol{\alpha}, \boldsymbol{\psi}) = (\boldsymbol{a}, \boldsymbol{b})^d\right)}{\mathrm{P}(S_i|\boldsymbol{X}_i)}. \tag{7}$$

The new type probabilities are obtained as follows:

$$\begin{aligned} p^d_{\text{next}} &= \frac{1}{N}\sum_{i=1}^{N} \mathrm{P}(d|S_i, \boldsymbol{X}_i) \quad d = 2, \ldots, D \\ p^1_{\text{next}} &= 1 - \sum_{d=2}^{D} p^d_{\text{next}}. \end{aligned}$$

The second (maximization) part obtains new trial values for the remaining parameters. Specifically, new parameters are obtained from the problem:

$$[\boldsymbol{\theta}_{\text{next}}, \boldsymbol{\Omega}_{\text{next}}] = \arg\max_{\boldsymbol{\theta}, \boldsymbol{\Omega}} \sum_{i=1}^{N}\sum_{d=1}^{D} \mathrm{P}(d|S_i, \boldsymbol{X}_i) \times \log P\left(S_i|\boldsymbol{X}_i, (\boldsymbol{\alpha}, \boldsymbol{\psi}) = (\boldsymbol{a}, \boldsymbol{b})^d\right)$$

which is a (numerically) simpler problem because the posterior probability is fixed (rather than a parameter to be estimated) and the log is pushed inside the summation over types. In addition, the score function in this case is relatively straightforward compared to the case with normally distributed individual heterogeneity.

We started the algorithm with $D = 2$ and increased the number of types until the AIC and BIC stopped improving. This procedure led to our final specification with 10 types for women and 12 types for men.

5. Estimation results

In this section we present the estimation results for the dynamic multinomial logit model. We also explore how well the model fits the data.

5.1 Parameter estimates

Tables A1 and A2 in the Appendix present estimates of the coefficients of the dynamic multinomial logit model for the normally distributed specification (S1) and the discretely distributed heterogeneity specification (S2), respectively.[20]

The coefficients capture the effect of the independent variables on the probability of choosing each of the employment alternatives relative to joblessness. However, because the model is nonlinear it is difficult to interpret the magnitude of the effects. In the next section we use simulations to get a better sense of the economic significance of some of the factors affecting choices. Here we focus on some salient qualitative results. Most of these results are the same for S1 and S2. We discuss differences between the two specifications when relevant.

First, we find that all the coefficients corresponding to the previous state are positive and statistically significant. This result is unsurprising as one would expect that any form of employment increases the probability of having a job in the next period. The coefficients in the main diagonal are directly related to the extent of state dependence. Both for females and for males, we find that entrepreneurship and formal employment are the states which more strongly attach workers. There is no clear indication that male informal employees are more likely to stay in that state vis-a-vis other forms of employment. Comparing our model with a dynamic multinomial logit without individual heterogeneity, we find that in almost all cases the diagonal coefficients are substantially higher in the latter (on average 22 percent higher).[21] We interpret this as evidence that the individual heterogeneity is removing at least part of the spurious state dependence.

The model incorporates controls for age group. For men, employment probabilities are highest in the 25 to 34 year old category and then decrease with age. The most senior individuals are less likely to be informal employees or entrepreneurs than the baseline group. The pattern for women is somewhat different, with employment probabilities peaking later in life and never quite decreasing to the same level as for 18 to 24 year olds.

The highest completed education level also has a strong impact on employment type. Formal employment and entrepreneurship become more likely as schooling increases. The effect on informal employment seems to be nonlinear, with a university degree decreasing the probability of entering this state relative to those with a vocational or technical degree.

We find that ethnic Russians are more likely to get a formal job. Interestingly, Russian women are less likely than women from other nationalities to become entrepreneurs. The main difference across gender lines involves the role of

[20] Estimates for the initial conditions equations are omitted to save space.

[21] The only exception is the entrepreneurship diagonal coefficient in the male sample, which is 1 percent higher in the model with individual heterogeneity. Estimates for the model without individual effects are omitted to save space but are available from the authors upon request.

marriage. Married men are more likely to be employed, specially in formal occupations and entrepreneurship. In general, we find the opposite is true for women (the coefficient in the entrepreneurship equation is still positive and significant but small in S1 and positive and not statistically significant in S2). The number of children in the household has a reinforcing effect for males, leading to even higher employment probabilities. For women, the coefficients are also positive but smaller in size.

One possible explanation for informal employment involves a life-cycle component. According to this view, individuals are more likely to choose to work in the informal sector early in life (to accumulate human and physical capital) and also after retirement (when further formal work might be penalized by the pension system). We find no support for this hypothesis. According to our estimates, individuals of retirement age (post 55 for women, post 60 for men) and who receive a pension are less likely to be in informal employment.

Finally, the model picks up some geographic differences. For example, formal employment and entrepreneurship are more likely in cities than in rural areas and less likely in the North Caucasus than in Moscow or St. Petersburg. None of the year dummies are statistically significant.

5.2 Model fit

How well does the model fit the data? Table 4 compares data on individuals' choices to predictions based on S1 and S2. The upper panel presents choices for the initial period and an average of the choices for the other periods. In both cases and regardless of the specification for the individual heterogeneity distribution, the model does a remarkable job at predicting the average behaviour of the sample.

The lower panel presents transitions disaggregated by origin state. Note that, in contrast to the transition matrices above here we present joint probabilities. While overall the model does a reasonable job tracking the data, there are some small misalignments. The only clear pattern is that the model tends to slightly over-predict transitions to formal employment. However, it also slightly under-predicts the fraction of formal employees who stay in the state.

Overall, S2 performs slightly better than S1 in predicting transitions as measured by the root mean square error. However, the differences across specifications are very small in magnitude.

6. Simulations

In this section we use the model to explore the effect of individual characteristics on sector choice. We also analyze the issue of state dependence, i.e., to what extent individuals in one state are bound to stay there.

Table 4. Model fit

	Males				Females			
	Non-employed (%)	Informal employee (%)	Entrepreneur (%)	Formal employee (%)	Non-employed (%)	Informal employee (%)	Entrepreneur (%)	Formal employee (%)
Choice probability								
Initial period	30.5	14.0	3.5	52.1	38.5	8.4	1.8	51.3
	30.3	14.1	3.5	52.1	38.6	8.6	2.0	50.8
	30.5	14.0	3.4	52.2	38.5	8.3	1.9	51.4
Other periods	23.1	15.8	4.2	56.9	29.9	9.8	2.4	57.9
	23.0	16.1	3.6	57.4	30.3	9.9	1.8	58.1
	22.9	16.1	2.9	58.1	30.7	9.3	1.9	58.1
Transition probability								
Non-employed	16.6	3.7	0.2	3.1	23.4	2.8	0.1	3.6
	14.7	3.6	0.1	5.0	21.1	3.0	0.1	5.8
	14.4	3.9	0.2	5.1	20.6	3.0	0.1	6.2
Informal employee	3.2	7.9	0.6	3.8	2.4	4.7	0.2	2.4
	3.1	5.1	0.5	6.8	2.7	2.6	0.1	4.3
	3.3	4.8	0.5	6.9	2.9	2.4	0.2	4.3
Entrepreneurs	0.1	0.6	3.0	0.5	0.2	0.2	1.8	0.3
	0.1	0.6	2.1	1.3	0.3	0.2	1.0	1.0
	0.2	0.8	1.1	2.1	0.2	0.3	0.8	1.1
Formal employee	3.2	3.7	0.5	49.5	3.9	2.1	0.3	51.6
	5.0	6.8	0.8	44.2	6.2	4.1	0.6	47.1
	5.0	6.7	1.1	44.0	7.0	3.7	0.8	46.5

***Notes*:** White cells contain actual probabilities (data). Light and dark gray cells contain model predictions with normally distributed heterogeneity and a discrete distribution, respectively. Transition probabilities are unconditional.

6.1 *The effect of observable and unobservable characteristics*

6.1.1 Education and age

In order to get a better idea of the economic significance of the effect of observable characteristics, we run simulation exercises in which all individuals in the sample were assigned a counterfactual age or education.[22] Specifically, we assign a fixed value of the characteristic under study while keeping other observables unmodified.

Panels A and B of Table 5 present the results for males and females, respectively. Simulations from S1 and S2 and presented side by side for comparison. For males, S2 tends to provide larger estimates of the fraction formally employed and lower estimates of entrepreneurship (especially when the origin state is entrepreneurship). These differences are constant across different simulations (i.e., they affect the predicted *levels* of the different categories). Therefore, both specifications show almost identical results with respect to the effect of *changing* observable characteristics. In the case of females, S1 and S2 present relatively minor differences in levels and almost no difference in the estimated effect of changing observables.

To get at the effect of education, we present simulations in which individuals are assumed to have a secondary degree and a university degree, respectively. Both for females and for males, higher education levels lead to a significant increase in formal employment. Specifically, having a college degree leads to an increase of around 16 (20) percentage points in the fraction of men (women) with a formal job. Interestingly, education has a very small effect on the fraction of entrepreneurs. The increase in formal employment is explained both by lower levels of non-participation and informality. The transition probabilities show that higher levels of education lead to higher retention rates in formal employment and higher exit rates from informality and non-employment. In particular, the probability that a non-employed individual finds a formal job more than doubles.

We also investigated the effect of age. Employment rates increase at the beginning of the life cycle and then decrease. Interestingly, there is almost no effect across the distribution of employment types. This finding can be interpreted as evidence against the existence of queuing for formal jobs (see also Gong *et al.*, 2004, who find similar results in their study of the Mexican labour market).

6.1.2 Unobservables

The model allows for heterogeneity in preferences and other unobservable determinants of sector choice. How important are these factors vis-a-vis observable characteristics? In Table 6 we present results from simulations in which we vary the value of the unobservable heterogeneity leaving other characteristics unchanged.

Panel A presents results from S1. In this case we assign to all individuals an heterogeneity vector with value equal to plus or minus one standard deviation in one dimension and a value of zero in all other dimensions. Predictably, assigning

[22] Simulation results for other characteristics are omitted to save space.

Table 5. Simulating the effect of observable characteristics

	Normally distributed heterogeneity				Discrete heterogeneity			
	NE (%)	IE (%)	ENT (%)	FE (%)	NE (%)	IE (%)	ENT (%)	FE (%)
Panel A. Males								
Secondary complete								
NE	67.1	14.6	0.5	17.8	65.7	15.6	0.7	18.0
IE	23.9	33.3	3.3	39.5	25.7	31.2	2.7	40.4
ENT	4.1	17.9	49.4	28.6	8.7	24.5	22.0	44.8
FE	12.8	14.1	1.5	71.6	12.9	13.9	1.7	71.6
All	27.0	17.3	3.5	52.2	27.2	17.4	2.5	53.0
University complete								
NE	49.8	12.5	1.2	36.5	47.1	13.5	2.1	37.4
IE	12.9	21.6	5.9	59.7	13.3	20.3	5.9	60.5
ENT	1.4	7.5	57.0	34.2	3.0	11.1	32.1	53.8
FE	5.3	6.7	1.9	86.1	5.1	6.6	2.9	85.4
All	16.8	10.4	4.7	68.2	16.2	10.5	4.4	68.9
Young (18–24 years old)								
NE	64.8	15.8	0.5	18.9	63.6	16.4	0.6	19.3
IE	24.7	33.5	2.4	39.4	27.1	30.4	1.9	40.6
ENT	3.9	17.4	45.4	33.4	8.1	22.0	19.4	50.5
FE	11.2	13.5	1.2	74.1	11.4	12.8	1.4	74.5
All	25.7	17.3	3.0	54.0	26.0	16.8	2.0	55.2
Midage (35–44 years old)								
NE	56.3	19.3	0.9	23.4	53.4	21.1	1.5	24.0
IE	18.2	35.2	4.0	42.7	19.2	33.3	3.7	43.8
ENT	2.1	14.0	54.5	29.5	4.5	19.8	28.6	47.1
FE	7.8	13.5	1.8	76.9	7.5	13.5	2.5	76.5
All	20.7	18.2	4.1	57.0	20.1	18.6	3.5	57.8
Senior (55–65 years old)								
NE	69.4	9.9	0.3	20.4	68.1	10.9	0.4	20.6
IE	29.4	23.8	1.9	44.9	31.5	22.1	1.5	45.0
ENT	5.3	13.5	39.6	41.7	10.1	16.6	15.8	57.5
FE	12.3	8.6	0.8	78.2	12.5	8.4	0.9	78.1
All	28.2	11.5	2.5	57.9	28.5	11.4	1.5	58.5
Panel B. Females								
Secondary complete								

Table 5. (Continued)

	Normally distributed heterogeneity				Discrete heterogeneity			
	NE (%)	IE (%)	ENT (%)	FE (%)	NE (%)	IE (%)	ENT (%)	FE (%)
NE	76.0	10.0	0.4	13.7	74.8	10.1	0.2	14.9
IE	34.3	29.4	1.1	35.3	36.7	26.2	1.9	35.1
ENT	17.1	9.5	40.8	32.6	9.7	15.5	38.8	36.1
FE	18.1	10.0	1.0	70.9	19.8	9.0	1.5	69.7
All	37.0	11.9	1.8	49.4	37.6	11.2	2.1	49.1
University complete								
NE	56.5	8.4	0.7	34.4	54.5	8.6	0.4	36.5
IE	18.0	18.7	1.6	61.7	19.4	16.7	2.3	61.5
ENT	6.9	4.3	40.9	48.0	3.8	7.5	33.3	55.4
FE	6.4	4.2	0.9	88.5	7.4	3.8	1.3	87.6
All	22.5	6.9	1.9	68.8	22.5	6.6	1.9	69.0
Young (18–24 years old)								
NE	76.3	8.5	0.3	15.0	75.9	8.3	0.1	15.7
IE	36.1	25.4	0.8	37.7	39.9	22.3	1.0	36.9
ENT	18.2	8.9	32.7	40.2	12.3	15.2	26.2	46.3
FE	15.9	7.3	0.6	76.2	18.5	6.5	0.7	74.3
All	36.0	9.5	1.3	53.3	37.6	8.8	1.2	52.4
Midage (35–44 years old)								
NE	62.9	12.7	0.6	23.8	61.1	12.8	0.3	25.8
IE	22.8	29.1	1.3	46.8	24.6	26.0	2.1	47.3
ENT	9.0	7.6	41.4	41.9	5.1	12.9	34.3	47.8
FE	8.6	7.4	1.0	83.1	9.8	6.6	1.3	82.3
All	26.2	11.1	1.9	60.8	26.4	10.6	1.9	61.2
Senior (55–65 years old)								
NE	73.6	8.8	0.5	17.2	71.3	9.2	0.3	19.2
IE	33.0	24.9	1.4	40.7	34.1	22.2	2.4	41.2
ENT	13.6	6.4	43.0	36.9	7.4	11.0	39.8	41.8
FE	13.7	6.7	1.1	78.4	14.7	6.1	1.6	77.6
All	33.5	9.1	2.0	55.4	33.4	8.7	2.2	55.7

Notes: Simulated choices when all individuals in the sample are assigned counterfactual characteristics. NE = non-employed, IE = informal employee, ENT = entrepreneur, FE = formal employee.

Table 6. Simulating the effect of unobservable heterogeneity

	Males				Females			
	NE (%)	IE (%)	ENT (%)	FE (%)	NE (%)	IE (%)	ENT (%)	FE (%)
Panel A. Normally distributed heterogeneity								
High FE component								
NE	45.4	7.9	0.3	46.4	57.2	5.1	0.2	37.6
IE	9.9	12.5	1.0	76.6	15.6	11.5	0.4	72.6
ENT	1.4	5.9	25.1	67.7	5.7	3.9	19.4	71.1
FE	2.0	1.7	0.2	96.2	2.9	1.1	0.1	95.9
All	13.5	5.0	1.4	80.1	20.5	3.4	0.6	75.6
Low FE component								
NE	77.1	17.3	0.9	4.7	85.2	9.1	0.3	5.4
IE	30.1	49.4	5.9	14.6	41.6	37.4	1.4	19.6
ENT	3.6	16.4	73.2	6.9	14.8	11.2	58.8	15.3
FE	19.1	23.2	3.5	54.2	21.7	10.2	1.1	67.0
All	33.9	25.5	6.1	34.5	42.5	12.5	2.3	42.7
High ENT component								
NE	67.4	13.8	0.7	18.1	74.3	7.4	2.6	15.8
IE	21.4	31.7	3.5	43.4	27.7	22.7	8.3	41.3
ENT	2.7	12.2	57.8	27.3	2.6	1.7	86.9	8.8
FE	7.6	7.6	1.0	83.8	8.7	3.6	3.6	84.1
All	23.7	13.0	3.7	59.7	30.1	6.5	5.7	57.7
Low ENT component								
NE	67.4	13.9	0.6	18.2	75.9	7.6	0.0	16.4
IE	21.5	31.9	3.0	43.7	29.9	24.8	0.1	45.3
ENT	2.9	13.2	54.1	29.8	16.6	12.8	6.6	64.0
FE	7.6	7.6	0.9	84.0	9.0	3.7	0.0	87.2
All	23.7	13.0	3.3	59.9	31.3	7.1	0.2	61.4
Panel B. Discrete distribution (selected types)								
	Type 5				*Type 6*			
NE	86.9	6.9	0.3	5.9	72.2	1.9	0.3	25.6
IE	49.4	24.4	1.7	24.5	30.0	5.3	2.1	62.6
ENT	16.7	19.8	29.4	34.2	4.8	2.0	42.9	50.3
FE	23.8	9.2	1.0	66.1	6.6	0.6	0.5	92.2
All	42.4	11.4	2.1	44.2	28.5	1.5	1.7	68.4

Table 6. (Continued)

	Males				Females			
	NE (%)	IE (%)	ENT (%)	FE (%)	NE (%)	IE (%)	ENT (%)	FE (%)
	Type 7				*Type 8*			
NE	56.1	29.4	7.6	6.9	43.1	4.7	0.0	52.2
IE	15.4	48.8	22.2	13.7	10.4	7.7	0.2	81.7
ENT	1.3	9.7	84.7	4.4	2.2	4.0	4.9	89.0
FE	8.7	23.3	17.7	50.4	1.6	0.7	0.0	97.7
All	20.7	28.1	18.7	32.5	14.9	2.6	0.2	82.3
	Type 9				*Type 9*			
NE	72.8	24.5	0.7	2.1	58.3	35.3	0.5	5.9
IE	29.3	61.3	2.9	6.5	16.8	69.2	2.3	11.7
ENT	8.1	42.5	41.7	7.8	3.1	32.1	54.2	10.7
FE	22.1	41.0	3.2	33.7	11.6	28.9	2.0	57.5
All	34.6	40.2	4.2	21.0	25.9	34.8	2.8	36.5
	Type 12				*Type 10*			
NE	39.0	4.0	0.1	56.9	91.3	6.0	0.8	2.0
IE	8.4	5.2	0.1	86.3	57.7	26.1	8.0	8.3
ENT	1.5	2.8	2.0	93.8	6.0	5.7	85.0	3.3
FE	1.4	0.7	0.0	97.9	39.8	10.9	7.3	42.1
All	11.4	2.2	0.1	86.2	56.1	10.8	7.3	25.8

***Notes*:** Simulated choices when all individuals in the sample are assigned counterfactual individual shocks or types. NE = non-employed, IE = informal employee, ENT = entrepreneur, FE = formal employee.

individuals unobservable heterogeneity value in the formality dimension leads to an increase in the fraction who choose formal employment. What seems remarkable in these simulations is the size of the effect. The gap in the fraction of formal employees with a positive one standard deviation shock and those with a negative shock is 45 and 33 percentage points for men and women, respectively. The unobservable component also affects the transition matrices. For example, the probability that an informal employee finds a formal job is 62 and 53 percentage points higher for males and females, respectively. These are very strong effects when compared to the findings for education and age.

It should be noted, however, that choice probabilities are not as sensitive with respect to other dimensions of the unobservable heterogeneity. Panel A of the table also presents simulations when we introduce a plus and minus one standard deviation shock in the entrepreneurship component. The impact of this shock on choice probabilities is negligible for men. For women, the shock to preferences leads to differences in the fraction of entrepreneurs. But even this effect is an order of magnitude smaller than we find when shocking the formality dimension.

Panel B presents results from S2. In this case we assign the same unobservable 'type' to all individuals in the sample. To save space, we present simulations for only some selected types. The selected types are those at the extremes of the predicted range of probabilities. For example, type 5 for males and type 10 for females have the highest non-participation rates, which are roughly four times higher than the comparable rates for types 12 and 8 respectively.

In sum, the simulation exercises presented in this section tell us that individual characteristics, both observable and unobservable, have an economically significant effect on sector choice. Estimates that ignore these sources of heterogeneity can be misleading.

6.2 State dependence

A key question traversing the informality literature is to what extent informal employment is an absorbing state without open exit to formal positions. In order to investigate this issue, we have conducted simulation experiments in which every individual in the sample is assigned a counterfactual previous state. Table 7, panels A and B, presents the results for males and females, respectively.

In panels A1 and B1, labeled 'prior heterogeneity distribution', we obtained the simulated response by integrating the conditional likelihood over the distribution of the unobservables. These results should be compared against the empirical transition rates (P-matrices) in Tables 1 and 2.

The most remarkable feature of the simulated transition matrices is the substantial reduction – relative to the empirical counterparts – in the fraction of individuals who choose to remain in their sector of origin. For example, roughly 50 percent of informal employees in the data do not change sectors. The simulation results suggest that this statistic is severely inflated by the peculiar observable characteristics of these individuals. Specifically, the S1 specification predicts that only 28.5 percent of males and 24 percent of females would remain informal after one period if the characteristics of informal workers corresponded to that of the overall sample. Similar reductions are observed for other labour market states. The predictions based on S2 show reductions in the diagonal elements that are a couple of percentage points larger in absolute value.

Uhlendorff (2006) suggests measuring state dependence by the average difference between the probability of staying in the state of origin and the probability of arriving at the state from the other possible origins. We report this statistic in the final rows of the panels. According to this measure, both for males and for females and regardless of the specification, state dependence is weakest for informal employment. For males, we find that state dependence is strongest among entrepreneurs and formal employees. We also find that, with the exception only of entrepreneurship in the S1 specification, state dependence tends to be higher for females than for males. In particular, non-employment appears to have stronger retention rates among women. In sum, the simulation results confirm that a naive measure of

Table 7. Simulating dynamics

	Normally distributed heterogeneity				Discrete heterogeneity			
	NE (%)	IE (%)	ENT (%)	FE (%)	NE (%)	IE (%)	ENT (%)	FE (%)
Panel A. Males								
A1. Prior heterogeneity distribution								
NE	42.7	18.6	1.4	37.3	40.5	19.9	2.1	37.5
IE	20.8	28.5	3.8	46.9	22.2	26.8	3.4	47.6
ENT	7.7	19.6	41.1	31.6	13.3	23.3	18.0	45.5
FE	13.3	13.4	1.3	72.0	13.3	13.0	1.7	71.9
SD	28.8	11.3	39.0	33.4	24.2	8.1	15.6	28.4
A2. Posterior distribution								
NE	25.2	30.1	2.4	42.3	41.0	18.1	1.7	39.3
IE	15.5	32.7	7.9	43.9	22.5	25.0	2.7	49.9
ENT	3.2	29.3	25.9	41.6	13.9	22.5	14.9	48.8
FE	15.4	30.0	6.2	48.4	13.3	11.5	1.3	73.8
SD	13.8	2.8	20.4	5.7	24.4	7.6	13.1	27.8
Panel B. Females								
B1. Prior heterogeneity distribution								
NE	57.6	11.5	0.7	30.2	55.6	11.6	0.4	32.5
IE	28.0	24.0	1.3	46.7	29.9	21.1	2.0	47.0
ENT	16.9	8.4	35.6	39.1	10.2	13.8	32.2	43.8
FE	15.2	7.9	0.9	76.0	16.8	7.2	1.2	74.8
SD	37.5	14.7	34.7	37.4	36.6	10.3	31.0	33.7
B2. Posterior distribution								
NE	30.1	16.8	15.4	37.6	56.1	10.2	0.3	33.5
IE	24.1	19.8	15.8	40.3	30.0	19.5	1.5	49.1
ENT	22.0	3.2	36.7	38.1	10.8	13.1	29.5	46.5
FE	22.1	14.5	18.0	45.4	16.4	6.1	0.9	76.7
SD	7.4	8.3	20.3	6.7	37.0	9.6	28.6	33.6

***Notes*:** Simulated choices when all individuals in the sample are assigned counterfactual previous state. Panels A1 and B1 assign a normal distributed heterogeneity term. Panels A2 and B2 assign the Bayesian posterior mean given the observed choices. NE = non-employed, IE = informal employee, ENT = entrepreneur, FE = formal employee, SD = state dependence.

state dependence based on empirical transition rates would be misleading. For example, using the empirical P-matrices would lead to estimates of state dependence of informal employment of 37.2 percent and 38.8 percent for males and females, respectively. These figures are roughly three times as large as those we found using model simulations based on S1, and roughly four times larger than simulations based on S2.

The reduction in measured state dependence found using simulations would not be too significant if it were compensated with an increase in transitions to undesirable states. Specifically, it would be problematic if the decrease in the fraction of employees that remain informal was explained by an increase in the transitions to non-employment (and vice versa for the lower fraction that remain non-employed). However, this is far from being the case. The simulations show that, both for non-employed and informal employees, the transition rates to formal employment absorb most of the decrease in state dependence. Finally, note that the model symmetrically predicts that, after adjusting for the composition of observables, the transitions from formal employment to non-employment and informal employment would also be larger than is observed in the empirical P-matrices.

As with the simulation exercises in the previous section, the experiments presented here use the model to answer the question of what individuals in the sample would do under counterfactual circumstances. In this context, using the prior distribution of unobservables to obtain a simulated response is reasonable. However, one could argue that this procedure does not use all available information in an optimal way. An alternative (Bayesian) approach is to use individuals' past choices and characteristics to obtain an estimate of their place in the heterogeneity distribution, which in turn can be used to get simulation results under counterfactual conditions.

We proceed as follows (see Train, 2009, for details). The mean of $\boldsymbol{\alpha}$ in the subpopulation of people who would choose S_i when their characteristics are $\boldsymbol{X}_i$ is:

$$\overline{\boldsymbol{\alpha}_i} = \int \boldsymbol{\alpha} h(\boldsymbol{\alpha}|S_i, \boldsymbol{X}_i, \boldsymbol{\theta})\mathrm{d}\boldsymbol{\alpha} \tag{8}$$

where $h(\cdot)$ is the density of the heterogeneity conditional on choices and characteristics (we refer to it as the posterior distribution of $\boldsymbol{\alpha}$). In the discretely distributed case (S2), this is simply $\mathrm{P}(d|S_i, \boldsymbol{X}_i)$ defined in Equation (7). For the normally distributed case (S1), a simulated counterpart to $\overline{\boldsymbol{\alpha}_i}$ can be obtained as:

$$\widetilde{\boldsymbol{\alpha}_i} = \sum_{r=1}^{R} w^r \boldsymbol{\alpha}^r; \quad w^r = \frac{P\left(S_i|\boldsymbol{X}_i, \boldsymbol{\varepsilon}_i^r, \boldsymbol{\theta}\right)}{\sum_{r=1}^{R} P\left(S_i|\boldsymbol{X}_i, \boldsymbol{\varepsilon}_i^r, \boldsymbol{\theta}\right)}.$$

We ran simulations in which individuals were assigned counterfactual origin states and the heterogeneity term is set equal to the mean of the posterior distribution. The results are presented in panels A2 and B2 of Table 7. We interpret these results as correcting for the composition of observable characteristics *and also*, to the extent possible, for the position of the individual in the heterogeneity distribution.

In this case the results from S1 and S2 differ significantly. While S2 yields predictions that are quite similar to those obtained using the prior distribution (panels A1 and B1), the use of the posterior distribution in the normally distributed specification leads to sizeable reductions in the measure of state dependence. In fact, for S1 there is a trend towards equalization of the conditional probabilities. For example, whereas the probability of landing a formal job for males in panel A1 ranges from 31.6 to 72 percent depending on the state of origin, the corresponding range in panel A2 is 41.6 to 48.3 percent. As a result, the measure of state dependence uniformly decreases, both for females and for males and for every labour market state.

These differences across specifications are probably due to the different estimation methods. Specifically, the EM algorithm uses the posterior distribution to obtain type probabilities. It is therefore not surprising that the predictions using the prior and the posterior distribution are not too different. In contrast, the normally distributed case imposes more structure on the heterogeneity distribution and is estimated without using the posterior distribution, so the potential for divergence between the prior and posterior means of $\boldsymbol{\alpha}$ is higher.

Two results are robust across specifications, the method for obtaining predictions, and indeed also across gender lines. First, state dependence for informal employees in sizeably lower than what is obtained using simple transition matrices. Both for females and for males, state dependence for informal employees is probably around 10 percent. Second, the probability of obtaining a formal position is higher when the origin state is informal employment rather than non-employment. While the exact difference in probabilities varies, its magnitude seems economically significant (often double digits). This stepping-stone effect seems to be somewhat stronger for women than for men.

6.3 Discussion

To our knowledge, there are only two studies with which it is possible directly to compare our findings. Gong *et al.* (2004) estimate a similar model using panel data from Mexico. Note, however, that their data has quarterly frequency and spans a relatively short spell of 2 years (1999–2000). Also, the model they estimate has three sectors (not working, formal, informal) instead of four and includes interactions between the lagged labour market state and a dummy for higher education. Using their reported simulation results (Table 9 in their paper), it is possible to obtain state dependence statistics.[23] Among males, state dependence is about 22 percent for non-employed, 8 percent for informal workers and 21 percent for formal employees. Akay and Khamis (2012) estimate a binary response model (formal/informal) using panel data from the Ukraine. Their estimating sample pools males and females. They report state dependence in informal employment of about 7 percent.

[23] The simulations they perform are slightly different from ours. Rather than averaging the responses over the whole sample, they set observable characteristics to benchmark values and the individual heterogeneity terms to zero. They also present separate simulations for high and low skilled workers. We focus on the results for males, for whom the calculated state dependence does not vary much by skill level.

These studies differ in several important details to ours. However, it is reassuring that a relatively low estimate of structural state dependence in informal employment is not a rare finding.

The relatively low state dependence of informal employment and the fact that starting from informality does not severely hurt the chances of obtaining a formal job both lend support to the idea that the labour market in Russia is relatively competitive and flexible. This conclusion fits well with the growing literature that finds that labour markets in middle-income countries are relatively well integrated and not segmented.

As mentioned in Section 2, existing studies of informality in middle-income countries vary in their conclusions. However, recent studies that better control for observables and unobservables tend to weaken the segmentation hypothesis if not reject it. Maloney (1999, 2004), Bosch and Maloney (2010), and Perry *et al.* (2007), among others, argue that informality in middle-income (specially Latin American) countries is mostly voluntary and unlikely to cause entrapping segmentation. In a separate study of the urban labour market in Mexico, Gong and Van Soest (2002) find that for the lower educated workers, the dualistic view of the labour market is not a good description. For the higher educated, on the other hand, the labour market has important dualistic features.

The scale and composition of informality in Latin America is quite different from Russia. Regarding the Russian labour market, Lehmann *et al.* (2012) note signs of segmentation due to the interaction of displacements and informality but recognize that 'this scenario of entrapment' concerns a minority and falls predominantly on displaced workers with low human capital while the displacement rate is low. So our study provides additional arguments that informality is not synonymous to the dualistic view.

In fact, none of the labour market institutions that are generally seen as potential sources of rigidity and possible causes of informality are strict enough to cause segmentation in the Russian setting (Gimpelson and Kapeliushnikov, 2013a; OECD, 2011). There are a few particular institutional features of the wage setting machinery that make wages very flexible and, therefore, contribute to job-to-job transitions.

First, the minimum wage, public sector pay and unemployment benefits are all set at a low level. Specifically, the minimum wage was around 10 percent of the average wage and the replacement rate of unemployment benefits was in the single digits during the period under our study. Public sector workers earned 20 percent less on average than private sector workers with comparable observable characteristics. This institutional framework kept the wage floor at a low level, allowing for significant downward price adjustment.

Second, trade unions are weak and have little impact on wage setting. In particular, unions in large privatized firms are usually kept under strong managerial control. In new small and medium size firms they are basically non-existent or decorative.

Third, a considerable fraction of total earnings (including various premiums and bonuses) is not rigidly fixed in labour contracts but is variable within a wide range contingent on general economic conditions and firm performance. This means that firms have a cushion of downward wage mobility during bad times. Finally, while labour regulations are strict on paper, they are poorly and selectively enforced. Indeed, the lack of enforcement means that most jobs are neither completely formal nor informal, but rather lie somewhere in between.

All these factors contribute to remarkable wage flexibility in the labour market, which is hardly compatible with strict dualism or segmentation.

However, a few cautionary remarks are in order. First, not all dualistic theories of the labour market imply strong state dependence of the informal state and low transition rates from informal to formal jobs. There are models in which informality is in a gray area between segmentation and integration. Our findings have little import to these models. Second, our simulation results are based on some difficult to verify assumptions. In particular, we assume the individual unobserved heterogeneity is independent of observable determinants of sector choice. Other assumptions include the Markovian structure of the model dynamics and the absence of general equilibrium effects. Finally, our data correspond to a period of relative economic prosperity. We cannot ignore the possibility that segmentation emerges under less favourable macro conditions.

7. Conclusion

Informal employment is a serious issue affecting most countries with underdeveloped or weak institutions. In this paper we address the issue of whether informality is a persistent state in which workers are trapped. We also investigate the related question of to what extent transitions from informal to formal jobs are possible. We specify a dynamic multinomial logit model of sector choice that allows for unobservable individual heterogeneity. We use econometric techniques to address the issue of endogenous initial conditions and the computational challenge of integrating out the individual heterogeneity term. We also estimate a semi-parametric version of the model. The key simulation results are based on estimates of the place occupied by individuals in the distribution of unobservables that are obtained by applying Bayesian inference.

The results provide strong evidence that the mobility patterns observed in empirical transition matrices can be seriously misleading. First, empirical transition matrices ignore the role of education, age, and other observable characteristics in the selection of sector of employment. Model estimates suggest that several of these characteristics have a statistically significant effect on sector choice. Second, neither do the transition matrices account for preferences and other unobservables. Finally, transition matrices do not take into account the panel structure of the data.

The outcome of these biases is that the role of the sector of origin is severely inflated by descriptive evidence. Our simulations show that state dependence is an order of magnitude lower than what P-matrices would imply. A more general point is that the distribution of destination states is much less dependent on the state of origin than it might seem. In sum, the choice of whether and in what sector to work has more to do with fundamentals (preferences, endowments and technology) and less to do with history than what prima facie evidence suggests.

The findings presented in the paper contradict the predictions based on strictly dualistic views of the labour market and lend support to the integrated labour market paradigm. From a policy perspective, the main implication is that the risk of informality is widely spread in the population. Both formal and informal jobs are heterogeneous enough to combine various amenities and costs over which individuals may have differing opinions and preferences.

References

Akay, A. and Khamis, M. (2012). 'The persistence of informality: Evidence from panel data', in Lehmann, H. and Tatsiramos, K. (eds.), *Informal Employment in Emerging and Transition Economies*, Volume 34 of Research in Labor Economics, chapter 7, Bonn: Emerald, pp. 229–256.

Andrews, D., Sánchez, A. C. and Johansson, Å. (2011). 'Towards a better understanding of the informal economy', *Working Paper No. 873*, Paris: OECD Economics Department.

Arcidiacono, P. and Jones, J. B. (2003). 'Finite mixture distributions, sequential likelihood and the EM algorithm', *Econometrica*, 71(3), pp. 933–946.

Bernabè, S. and Stampini, M. (2009). 'Labour mobility during transition: Evidence from Georgia', *Economics of Transition*, 17(2), pp. 377–409.

Bosch, M. and Maloney, W. F. (2010). 'Comparative analysis of labor market dynamics using Markov processes: An application to informality', *Labour Economics*, 17(4), pp. 621–631.

Calvo, G. A. (1978). 'Urban unemployment and wage determination in LDC'S: Trade unions in the Harris–Todaro Model', *International Economic Review*, 19(1), pp. 65–81.

Chay, K. and Hyslop, D. (2001). 'Identification and estimation of dynamic binary response models: Empirical evidence using alternative approaches', *Working Paper*, Berkeley: Department of Economics, University of California.

Fields, G. (1990). 'Labour market modelling and the urban informal sector: Theory and evidence', in Turnham, D., Salome, B. and Schwartz, A. (eds.), *The Informal Sector Revisited*, Paris: OECD. pp. 49–69.

Fields, G. (2009). 'Segmented labor market models in developing countries', in Ross, D. and Kinkaid, H. (eds.), *The Oxford Handbook of Philosophy of Economics*, Oxford: Oxford University Press, pp. 476–510.

Gasparini, L. and Tornarolli, L. (2007). 'Labor informality in Latin America and the Caribbean: Patterns and trends from household survey microdata', *Working Paper No. 46*, La Plata, Argentina: CEDLAS.

Gimpelson, V. and Kapeliushnikov, R. (2013a). 'Labor market adjustment: Is Russia different?' in Alexeev, M. and Weber, S. (eds.), *Handbook of the Russian Economy*, Oxford: Oxford University Press.

Gimpelson, V. and Kapeliushnikov, R., (eds.) (2013b). *In the Shadow of Regulation: Informality in the Russian Labor Market*. Moscow: HSE Publishing House. In Russian.

Gimpelson, V. and Zudina, A. (2011). "'Informals" in the Russian economy: How many and who are they?' *Working Paper Series 'Labour Markets in Transition' No. 6*, Moscow: Higher School of Economics.

Gong, X. and Van Soest, A. (2002). 'Wage differentials and mobility in the urban labour market: A panel data analysis for Mexico', *Labour Economics*, 9(4), pp. 513–529

Gong, X., Van Soest, A. and Villagomez, E. (2004). 'Mobility in the urban labor market: A panel data analysis for Mexico', *Economic Development and Cultural Change*, 53(1), pp. 1–36.

Hajivassiliou, V. A. and Ruud, P. A. (1994). 'Classical estimation methods for LDV models using simulation', in Engle, R. F. and McFadden, D. L. (eds.), *Handbook of Econometrics*, Volume 4, chapter 40, Amsterdam: Elsevier, pp. 2383–2441.

Harris, J. R. and Todaro, M. P. (1970). 'Migration, unemployment and development: A two-sector analysis', *The American Economic Review*, 60(1), pp. 126–142

Heckman, J. (1981). 'The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process', in Manski, C. and McFadden, D. (eds.), *Strutural Analysis of Discrete Data with Econometric Applications*, Cambridge, MA: MIT Press, pp. 179–195.

Heckman, J. and Sedlacek, G. (1985). 'Heterogeneity, aggregation, and market wage functions: An empirical model of self-selection in the labor market', *Journal of Political Economy*, 93(6), pp. 1077–1125.

Heckman, J. and Singer, B. (1984) 'A method for minimizing the impact of distributional assumptions in econometric models for duration data', *Econometrica*, 52(2), pp. 271–320.

Jütting, J., Parlevliet, J. and Xenogiani, T. (2008). 'Informal employment re-loaded', *IDS Bulletin*, 39(2), pp. 28–36.

Lehmann, H. and Pignatti, N. (2007). 'Informal employment relationships and labor market segmentation in transition economies: Evidence from Ukraine', *Discussion Paper No. 3269*, Bonn: IZA.

Lehmann, H., Razzolini, T. and Zaiceva, A. (2012). 'Job separations and informality in the Russian labor market', in Lehmann, H. and Tatsiramos, K. (eds.), *Informal Employment in Emerging and Transition Economies*, Volume 34 of Research in Labor Economics, chapter 8, Bonn: Emerald, pp. 257–290.

Magnac, T. (1991). 'Segmented or competitive labor markets', *Econometrica*, 59(1), pp. 165–187.

Maloney, W. (1999). 'Does informality imply segmentation in urban labor markets? Evidence from sectoral transitions in Mexico', *The World Bank Economic Review*, 13(2), pp. 275–302.

Maloney, W. (2004). 'Informality revisited', *World Development*, 32(7), pp. 1159–1178.

McFadden, D. and Train, K. (2000). 'Mixed MNL models for discrete response', *Journal of Applied Econometrics*, 15(5), pp. 447–470.

OECD (2011). *OECD Reviews of Labour Market and Social Policies: Russian Federation*. Paris: OECD.

Packard, T., Koettl, J. and Montenegro, C. (2012). *In from the Shadows: Integrating Europe's Informal Labor*. Washington, DC: World Bank.

Pagés, C. and Stampini, M. (2009). 'No education, no good jobs? Evidence on the relationship between education and labor market segmentation', *Journal of Comparative Economics*, 37, pp. 387–401.

Perry, G., Maloney, W., Arias, O., Fajnzylber, P., Mason, A. and Saavedra-Chanduvi, J. (2007). *Informality: Exit and Exclusion*. Washington, DC: The World Bank.

Slonimczyk, F. (2012). 'The effect of taxation on informal employment: Evidence from the Russian flat tax reform', in Lehmann, H. and Tatsiramos, K. (eds.), *Informal Employment in Emerging and Transition Economies*, Volume 34 of Research in Labor Economics, chapter 2, Bonn: Emerald, pp. 55–99.

Slonimczyk, F. (2013). 'Informality as a stepping stone', *Working Paper Series 'Labour Markets in Transition' No. 5*, Moscow: Higher School of Economics.

Slonimczyk, F. and Yurko, A. (2014). 'Assessing the impact of the maternity capital policy in Russia using a dynamic model of fertility and employment', *Labour Economics*, 30, pp. 265–281.

Tansel, A. and Kan, E. (2012). 'Labor mobility across the formal/informal divide in Turkey: Evidence from individual level data', *Discussion Paper No. 6271*, Bonn: IZA.

Train, K. (2009). *Discrete Choice Methods with Simulation*, Cambridge, UK: Cambridge University Press.

Uhlendorff, A. (2006). 'From no pay to low pay and back again? A multi-state model of low pay dynamics', *Discussion Paper No. 2482*, Bonn: IZA.

Appendix A

Table A1. Dynamic multinomial logit estimates: Normally distributed heterogeneity

	Males			Females		
	Informal employee	Entrepreneur	Formal employee	Informal employee	Entrepreneur	Formal employee
Previous state						
Informal employee	1.46***	2.11***	1.40***	1.81***	1.84***	1.6***
Entrepreneur	2.32***	6.14***	2.22***	1.63***	6.30***	2.1***
Formal employee	1.17***	1.74***	2.86***	1.24***	2.04***	3.3***
Age group						
25–34 years	0.80***	1.24***	0.96***	0.52***	0.84***	0.57***
35–44 years	0.41***	0.88***	0.50***	0.71***	1.16***	0.88***
45–54 years	−0.02	0.38*	0.40***	0.53***	1.11***	0.89***
55–65 years	−0.60***	−0.46*	0.03	0.09	0.74**	0.23**
Education						
Secondary complete	0.04	0.46***	0.55***	0.28***	0.13	0.65***
Vocational school	0.56***	0.70***	1.23***	0.68***	0.50**	1.28***
Technical school	0.45***	1.47***	1.71***	0.62***	0.86***	1.78***
University or more	0.27***	1.84***	2.03***	0.47***	1.16***	2.28***
Other characteristics						
Russian	0.02	0.09	0.54***	−0.06	−0.36***	0.30***
Married	0.72***	1.30***	1.15***	−0.25***	0.32**	−0.11**
Receives pension	−1.46***	−1.86***	−2.24***	−1.25***	−1.78***	−1.63***
Size of household	−0.04**	−0.14***	−0.12***	−0.09***	−0.23***	−0.10***

Table A1. (Continued)

	Males			Females		
	Informal employee	Entrepreneur	Formal employee	Informal employee	Entrepreneur	Formal employee
Number of children	0.10***	0.34***	0.24***	0.02	0.27***	0.08**
Urban area	−0.02	0.76***	0.45***	0.09	0.45***	0.26***
Region						
North & North Western	−0.22	0.08	0.21	0.18	−0.02	0.66***
Central & Black-Earth	−0.03	−0.01	−0.13	0.11	0.23	0.28***
Volga	0.02	−0.27	−0.52***	0.11	0.00	0.03
North Caucasian	−0.08	−0.23	−0.83***	0.32***	0.01	−0.31***
Urals	0.00	0.25	0.04	0.34***	0.20	0.34***
West Siberia	0.12	0.06	−0.55***	0.27**	−0.02	−0.13
East Siberia	0.05	−0.19	−0.15	0.28**	0.22	0.04
Year						
2003	−0.33	−0.66	−0.25	−0.30	−0.41	−0.22
2004	−0.14	−0.65	−0.33	−0.24	−0.70	−0.33
2005	−0.36	−0.92	−0.40	−0.42	−0.74	−0.47
2006	0.04	−0.59	−0.15	−0.02	−0.52	−0.17
2007	−0.15	−0.45	−0.05	−0.28	−0.64	−0.20
2008	−0.13	−0.31	−0.05	−0.25	−0.43	−0.08
2009	−0.19	−0.90	−0.45	0.01	−0.54	−0.24
2010	−0.16	−0.52	−0.36	−0.27	−0.69	−0.41
2011	−0.08	−0.54	−0.29	−0.34	−0.86	−0.41
Constant	−1.49	−5.55	−2.34	−2.10	−5.50	−2.52

Table A1. (Continued)

	Males			Females		
	Informal employee	Entrepreneur	Formal employee	Informal employee	Entrepreneur	Formal employee
Variance–covariance						
Informal employee	0.6954***			1.1058***		
Entrepreneur	−0.0218	0.0042		1.471***	1.9661***	
Formal employee	−0.0521	−0.0759***	1.7366***	−0.0477	0.0495	1.3899***
Individuals		8,547			10,203	
Observations		42,871			53,046	
Log likelihood		−29,076.8			−31,537.2	

***Notes*:** Baseline categories are 'Not Employed', '18–24 years old', 'No Degree', 'Moscow-St Petersburg', and '2002'. Significance levels: ***1%, **5%, *10%.

Table A2. Dynamic multinomial logit estimates: Discrete distribution

	Males			Females		
	Informal employee	Entrepreneur	Formal employee	Informal employee	Entrepreneur	Formal employee
Previous state						
Informal employee	1.23***	1.58***	1.29***	1.57***	2.43***	1.47***
Entrepreneur	1.85***	4.63***	2.01***	2.36***	6.90***	2.57***
Formal employee	1.05***	1.53***	2.81***	1.08***	2.51***	3.16***
Age group						
25–34 years	0.89***	1.49***	0.99***	0.58***	1.16***	0.60***
35–44 years	0.54***	1.23***	0.56***	0.79***	1.31***	1.00***
45–54 years	0.08	0.62***	0.42***	0.61***	1.25***	1.06***
55–65 years	−0.58***	−0.54**	0.00	0.19*	1.11***	0.36***
Education						
Secondary complete	0.11*	0.42**	0.55***	0.35***	0.29	0.66***
Vocational school	0.68***	0.78***	1.26***	0.77***	0.47*	1.32***
Technical school	0.60***	1.61***	1.73***	0.73***	0.82***	1.84***
University or more	0.43***	2.18***	2.10***	0.60***	1.05***	2.34***
Other characteristics						
Russian	0.02	0.03	0.47***	−0.06	−0.30**	0.31***
Married	0.79***	1.47***	1.15***	−0.27***	0.15	−0.08**
Receives pension	−1.54***	−2.06***	−2.27***	−1.28***	−1.54***	−1.73***
Size of household	−0.04***	−0.15***	−0.12***	−0.09***	−0.15***	−0.12***
Number of children	0.11***	0.45***	0.27***	0.01	0.19**	0.10***
Urban area	0.04	0.90***	0.46***	0.09*	0.49***	0.26***

Table A2. (Continued)

	Males				Females			
	Informal employee	Entrepreneur	Formal employee		Informal employee	Entrepreneur	Formal employee	
Region								
North & North Western	−0.16	0.22	0.23**		0.30**	0.42	0.67***	
Central & Black-Earth	0.02	0.15	−0.09		0.13	0.53**	0.23***	
Volga	0.02	0.00	−0.46***		0.12	0.35	−0.04	
North Caucasian	−0.02	0.27	−0.72***		0.37***	0.36	−0.40***	
Urals	0.03	0.47**	0.11		0.36***	0.53**	0.32***	
West Siberia	0.16	0.44**	−0.46***		0.33***	0.26	−0.14*	
East Siberia	0.12	0.11	−0.07		0.33***	0.62***	0.00	
Year								
2003	0.59	0.16	0.60		0.66	0.37	0.70	
2004	0.79	0.14	0.53		0.73	0.09	0.58	
2005	0.57	−0.15	0.46		0.55	0.07	0.44	
2006	0.98	0.18	0.72		0.93	0.29	0.73	
2007	0.80	0.35	0.82		0.69	0.16	0.71	
2008	0.82	0.50	0.82		0.72	0.37	0.84	
2009	0.76	−0.13	0.43		0.98	0.28	0.68	
2010	0.79	0.27	0.52		0.71	0.08	0.50	
2011	0.87	0.26	0.59		0.63	−0.02	0.49	
Constant	−3.02	−7.17	−3.73		−3.39	−7.05	−3.55	
Support set				p^d				p^d
Type 1	0	0	0	6.7%	0	0	0	8.4%
Type 2	0.99***	1.41***	0.48***	6.0%	−0.99***	−1.51***	−0.47***	8.2%
Type 3	0.89***	−1.55***	0.60***	7.4%	1.01***	−1.51***	0.51***	9.1%

Table A2. (Continued)

	Males				Females			
	Informal employee	Entrepreneur	Formal employee		Informal employee	Entrepreneur	Formal employee	
Type 4	−1.32***	0.45*	1.06***	10.5%	−0.98***	−0.54*	−0.44***	8.2%
Type 5	−0.81***	−1.38***	−1.26***	8.4%	1.09***	0.56**	0.48***	9.0%
Type 6	1.15***	0.05	0.69***	7.1%	−1.14***	0.45*	0.67***	10.6%
Type 7	1.39***	2.92***	−0.24**	6.4%	1.20***	−1.09**	0.71***	9.3%
Type 8	−0.42***	−1.39***	0.27***	8.3%	0.47***	−0.82	2.29***	15.9%
Type 9	0.77***	−0.25	−2.01***	9.4%	2.05***	1.02***	−0.67***	9.2%
Type 10	0.34***	−1.66**	1.72***	10.9%	−0.38***	0.82***	−2.52***	12.1%
Type 11	2.72***	0.10	1.37***	7.5%				
Type 12	−0.10	−1.25	2.68***	11.3%				
Individuals		8,547				10,203		
Observations		42,871				53,046		
Log likelihood		−24,334.1				−26,617.9		

Notes: ***1%, **5%, *10%.