Skills training and development: Russia in comparative perspective

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Summary

The acquisition and maintenance of human capital are considered key drivers of productivity and economic growth. However, recent literature shows that in the case of Russia, this relationship is not obvious, which raises a question concerning the nature of human capital accumulation, despite the significant expansion of tertiary education in this country. The existing literature, much of it relying on a theory of market imperfections, tends to explain low incidences of training by the lack of employer incentives to invest in the human capital of their employees. This dissertation adds to this view confirming the negative role of 'bad' jobs and social origins in obstructing employees from skills development in BRIC-like countries. Skills training in Russia is constrained by stratifying occupational forces comprising jobs with low requirements to skills development, which conserves the working population in generic labour. This reveals the phenomenon of skills polarisation 'at the bottom' in a late-industrial country, thus, contributing to the growing critique of the knowledge society theory. For those few workers who occupy 'good' jobs, skills training is strongly linked to personal-specific traits, such as qualifications and computer and language skills; and this is common in both Russia and India. However, in contrast to Russia, India is still forming their knowledge society. This is confirmed by the statistically significant impact of socio-demographic origins (e.g. age, household size, marital status, and religion) on the incidence of training, which reveals a crucial role of ascription in human capital acquisition in contemporary India. The present thesis contributes to the growing literature on structural prerequisites for successful advancement and the contradictory development of the BRIC countries.

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INTRODUCTION

The world has changed dramatically over the past three decades. The extraordinary economic potential and actual economic achievements of Brazil, Russia, India, and China since the 1980s* have caused these countries to be commonly grouped under the well-known acronym 'BRIC'†. Rapid economic growth, higher-than-average natural endowments, structural reforms, and institutional and technological modernisation promoted by the national governments were supposed to bring these countries to the frontier of economic development, or at least 'catch up' (Krasilshchikov, 2008) with societies 'of advanced industrialism' (Grusky, 2001). However, this catching-up has yet to occur in these countries, the most famous example being Russia.

In the early 1990s, Russia began 'shock therapy' reforms that were primarily focused on diminishing the state's socialist socio-economic system and transitioning to a market economy through liberalisation and privatisation (Gerber & Hout, 1998), based on the premise that these reforms would constitute fruitful ground for further socio-economic development, i.e. the transition to 'modern capitalism' (Lane, 2007), 'competitive systems', and meritocracy (Davis & Moore, 1945). However, inefficient transformations and a protracted transition to meritocracy (Anikin, 2013; Shkaratan, 2007) have lead some critics to argue that Russia is experiencing an involuntary transition to merchant capitalism (Burawoy, 2002), Weberian political capitalism (Hanson & Teague, 2007), 'Marx's account of the development of capitalism' (Clarke, 2007), or a resource-based economy socially supported by estates rather than

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* The 1980s were a prominent decade for several important countries and regions, such as the United States, Russia, South Korea, India, China, Brazil, and others. To 'examine politics, economics, and social change' in such countries over the past three decades the Cambridge University Press designed the series 'The World since 1980'. See: http://admin.cambridge.org/sb/academic/subjects/politics-international-relations/politics-general-interest/series/world-1980.

† Although Lord O'Neill Gatley devised the abbreviation 'BRIC' during his work with Goldman Sachs, this acronym has gained widespread academic use particularly in recent years.

classes (Kordonsky, 2016). In such an economy, human capital (Becker, 1975; Kaare, 1965) does not play a significant role; that is, the role of human capital in the productivity of the Russian economy remains minimal (Connolly, 2012; Timmer & Voskoboynikov, 2014). Therefore, it is surprising that Russia's recent achievements in tertiarization have placed the Russian Federation in second place among Organisation for Economic Co-operation and Development (OECD) countries in terms of the relative share of population with tertiary education (OECD, 2016). Essentially, Russia has become a knowledge-based society although it has failed to build the fully fledged knowledge economy – i.e. an economy based on human capital. Therefore, given the lack of investment in human capital and particularly low volume of formal training – less than 10% of Russia's working population develop their skills and qualifications through vocational courses and training (Anikin, 2017a), it can be stated that Russia is a country of human potential, but not a state of human capital (Anikin, 2017b).

This is atypical for a late industrial society[*]. Moreover, successful catching-up also implies increasing the role of human capital in development. This involves creating structures and institutions that can effectively 'organize and manage modern technologies' so that developing countries will be able to 'not simply copy the technology and practices of the countries at the frontier, but… develop technologies suited to their own conditions' (Nelson, 2015, pp. 331-332). Successful examples of catch-up development, such as Japan, South Korea, Singapore, and Taiwan, indicate that these countries made human capital a cornerstone of socio-economic development; they created a nationwide system for the development of human capital

[*] Late industrial society is based on an economy that recognizes knowledge and skills as new forms of valuable property that generate premiums for its owners. We should remember that the core of the human capital theory presented by Schultz (1960, 1961), Becker (1962, 1965, 1975), and Mincer (1958, 1962, 1974) was established in the 1960s-1970s, a period of synchronized development of knowledge economy and knowledge society in the USA.

that was based on advanced training and continuing education, analogous to that of Western countries (O'Connell, 1999; OECD, 2017; Sala & Silva, 2013).

These reasons explain why the issue of human capital in BRIC is significant. This research examines the following questions: *How do individuals within a certain level of development represented by BRIC-like countries build and maintain their human capital through training acquisition? What are the factors that obstruct the development of human capital in a knowledge-based society, particularly for Russian workers? Are these factors distinct from those in countries with different levels of development and particularly in those that have yet to become a knowledge society? To what extent do individual patterns of human capital acquisition really matter in economies that are barely driven by knowledge and skills?*

We assume that different levels of development produce distinct barriers to building and maintaining human capital, supposing that in advanced industrial societies like Russia, market-based structures and individual traits are more significant than ascription – i.e. demographic characteristics such as gender, age, religion, race, caste, locality, etc. (Grusky, 2001). In so-called pre-industrial societies, by contrast, ascription plays a dominant role; for instance, India is consistent in retaining the features of a pre-industrial society, and these features are more salient than in Russia (see Table 1).

Two-thirds of Indians inhabit rural areas; the agricultural sector comprises almost half the total employment. According to the National Sample Survey (2013), almost 65% of Indians perform manual work, and approximately half of them work as unskilled labour while others are employed as low- and semi-skilled employees. The majority of these people work without written agreements and face the unavoidable risks of informal employment. Ultimately, the role of religion and the caste system is still relevant in contemporary India (Corbridge, Harriss, & Jeffrey, 2013).

Table 1

Socio-economic statistics of Russia and India, 1980-2012

	GDP per capita, PPP (current international $)						**Unemployment total, % of total labour force (modelled ILO estimate)**				
	1980	*1990*	*2000*	*2005*	*2012*		*1991*	*1998*	*2000*	*2005*	*2012*
Russia	-	8013	6825	11822	25317	Russia	12.2	13.3	10.6	7.1	5.5
India	420	1146	1999	2861	4923	India	4.3	4.1	4.3	4.4	3.6
	Employment in agricultural sector, % of total employment						**Informal employment, % [a)]**				
	1980	*1994*	*2000*	*2005*	*2012*		*1985-89*	*1990-94*	*2000-07*	*2010*	*2012*
Russia	-	16.1	14.5	10.2	7.3	Russia	-	-	8.6	12.1	
India	-	60.5	59.9	55.8	47.1	India	76.2	73.7	83.5	83.6	84.7
	Urban population, %						**Age dependency ratio, %**				
	1980	*1990*	*2000*	*2005*	*2012*		*1980*	*1990*	*2000*	*2005*	*2011*
Russia	69.8	73.4	73.4	72.9	74	Russia	46.8	49.6	44.1	40.5	38.9
India	23.1	25.5	27.7	29.2	31.6	India	75.9	71.7	63.8	59.1	54.3

Source: The World Bank.
Notes: [a)] The current table shows a percentage of informal employment in total non-agricultural employment. Data on informality in India and Russia over the period of 1985–2007 are compiled from Jutting and Laiglesia (2009). The Federal State Statistics Service of Russia does not provide data on informal employment, so we used data from ILO statistics questionnaires (ILO, 2012); however, these figures may be underestimated. See Kapelyushnikov (2012) for estimations of the analytical power of different concepts of informal activity in contemporary Russia.

Thus, although both Russia and India, as two BRIC countries, have displayed similar economic performance over the past decades, we should not expect a similar volume of training given the countries' varied demographic and socio-economic contexts. However, both India and Russia do have almost a similar level of formal training among working population; this is surprising given the different development levels in these countries. This makes India an important and even more exciting counterfactual case for a comparative analysis of training acquisition in Russia.

Researchers rarely conceptualise demographic features in the course of ascription hypothesis as they study training in societies with advanced industrialism where the stratifying role of ascription is significantly lower than in developed nations. Conversely, most of the studies on training are conducted within the framework of economic approach, which only employs demographic characteristics as mere ‘controls’. However, the effects of demographics—particularly gender and marital status—on training in developed nations are somewhat contradictory. Some earlier findings argue for convergence regarding access to training for women and men (Aisa, Gonzalez-Alvarez, & Larramona, 2016; Green & Zanchi, 1997; Tharenou, 1997), whereas other studies insist on gender bias in human-capital acquisition (Cho, Kalomba, Mobarak, & Orozco, 2013; Polavieja, 2012; Stier & Yaish, 2014). In pre-industrial societies, by contrast, demographics are considered to have a straightforward impact on training.

The dominant strand in the literature belongs to labour economists who pay considerable attention to a wide range of economic factors in training. Social factors are usually considered without sociological argumentation. In late industrial society, skills, expertise, on-the-job training, experience, formal education, and knowledge are examples of human assets, which represent ‘the principal stratifying forces’ (Grusky, 2001, p. 13) that have replaced traditional assets such as labour-power assets, capital assets, and organisational assets (Roemer, 1982; Wright, 1989, p. 306). The primary structural outcome of the stratification based on human and cultural capital is revealed in the pivotal role of ‘skill-based occupational groupings’, which are the major strata in advanced industrial societies (Grusky, 2001, p. 9; Weeden & Grusky, 2012). Hence, the representation of human capital acquisition in advanced industrial society remains incomplete without thorough consideration of occupational structure (Chen, 1947; Dunkerley, 1975) and the occupation-specific constraints (Bukodi & Goldthorpe, 2011) of training. From a theoretical perspective, a focus on occupational structure as a contextual source of unexplained heterogeneity contributes to a rather innovative strand in training literature.

Another major approach to training, however, alternative to that developed by labour economists, belongs to social psychologists (Salas & Cannon-Bowers, 2001; Wexley, 1984) and researchers who consider individual specificity to be significant determinants of investments in human capital. These are the social attitudes of employees and their motivation (Anikin, 2013; Tharenou, 1997, 2001), as well as personal traits, such as disabilities (Pagán-Rodríguez, 2015) and health conditions (Brunello, 2004). The general expectation here predicts the growing importance of individuals' incentives in labour markets and developing human capital in modern society based on meritocratic principals. Thus, a study on the acquisition of skills in a late-industrial society, ceteris paribus, must track individual trends of training. Essentially, acquisition of human capital must depend not only on effective institutions maintaining the existence of 'good' jobs, but also on workers' individual traits.

In agreement with the aforementioned logic, our study comprises three papers. The first paper explores the gap between knowledge-based society and knowledge-based economy targeting some contradictions regarding the catching-up. We explore social factors that obstruct Russian workers from skills training with a primary focus on occupational structure and the occupation-specific constraints of training in Russia. Paper 1 presents a multilevel analysis of the propensity for training across a range of occupations and against various socio-demographic factors. We believe that the first paper makes a significant contribution to the growing critique of knowledge economy literature because the unusual conditions of Russia's labour market highlight certain contradictory dynamics in the general understanding of training- and skills-acquisition in developed nations.

The second paper explores the aspects that obstruct (and encourage) individuals from developing their human capital in India, another BRIC country, which is experiencing a different mode of development than Russia, i.e. arriving at a knowledge society. At this stage of research, we reassess Grusky's notion that ascription represents the primary stratifying force, and thus dominates the socio-economic life in pre-industrial society. On the other hand, India invests heavily in tertiary education and schemes that target employment of educated people, particularly women, which may principally alter the association between female gender and training reception in supposedly pre-industrial societies. In the second paper, we thus state two opposing hypotheses examining ascription and tertiarization traces in training. It postulates the contradictory nature of training acquisition in India, i.e. non-market inequalities have a greater impact on training here than in Russia; however, the occupational structure and working place characteristics are also significant. These results contribute to the growing literature on structural prerequisites for successful catching-up and the contradictory development in BRIC countries (Wood & Lane, 2012).

The third paper highlights Russia's perspectives regarding successful catching-up, as it focuses on the role of individuals in training acquisition within individual times in the context of Russia's economic growth between 2001 and 2014. The final paper presents a longitudinal analysis of the individual propensity for training over a range of individual-specific and socio-economic determinants. We demonstrate that at least 26% of the variation in training is attributable to unobserved individuals' characteristics, after accounting for their important observed parameters changing over the period of economic growth. Social structures best explain the low incidence of training among interchangeable and disposable labour, whereas individual traits are more important for hardworking skilled labour with competitive jobs. Even in systems that have yet to arrive at knowledge economy, individuals build and maintain their human capital in more confined areas limited to a few occupations and sectors in big metropolitan areas than their peers in post-industrial economies. Above all, the obtained results support the concepts of structural functionalism and justify the use of this approach to analyse both obstacles and perspectives of post-transition countries. The cases of India and Russia, as two BRIC countries experiencing different modes of development, indicate that the simple promotion of training seems to be inefficient without complex institutional rearrangements and labour market reforms.

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METHODOLOGICAL PREFACE

This section describes Russian and Indian data in detail, as well as the methodology used in the analysis, particularly, the Bayesian methods that have been used across the three papers. Both papers on Russia draw on the data from the Russian Longitudinal Monitoring Survey (RLMS—HSE), which was designed as a series of nationally representative surveys. The main purpose of this project was to collect longitudinal microdata on the effects of the Russian reforms of the 1990s, on the health and economic welfare of households and individuals in the Russian Federation. According to the official conductors of the data, these effects are measured by a variety of means: detailed monitoring of individuals' health statuses and dietary intake, precise measurement of household-level expenditures and service utilization, and collection of relevant community-level data, including region-specific prices and community infrastructure data[*].

Concurrently, the full data cover almost the whole period of transformation of Post-Communist Russia, between 1992 and 2016. However, the official conductors do not distribute the first rounds of the data (1992–1994), as these data were collected during the experimental phase of the project. For Phase II, which started in 1995, the Carolina Population Center at the University of North Carolina in Chapel Hill, which has run this survey jointly with the Institute of Sociology of the Russian Academy of Science (RAS) in Russia, applied a new representative sampling. Today, the Institute of Sociology RAS and the National University Higher School of Economics distribute only data conducted according to the new sampling procedures – that is,

[*] For further details, see the official web page of the RLMS—HSE: http://www.cpc.unc.edu/projects/rlms-hse.

data covering the period from 1995 onwards. Phase II of the RLMS—HSE data is described rigorously by Kozyreva, Kosolapov, and Popkin (2016).

Paper 1 draws on a representative sample of the RLMS—HSE from 2012, as this year was one of the most prosperous years before the recession occurred in Russia from 2014 to 2016. Paper 1 especially provides a cross-section analysis within a single time-point. Paper 3 gains from using a panel nature of the RLMS—HSE data. Since the major focus of Paper 3 is on skills training over the recent period of economic growth, we eliminate the data rounds of economic transition and limit our panel to 14 rounds, between 2001 (round X) and 2014 (round XXIII). The data have no missing time points, as, during the considered period, surveys were conducted once a year, in the autumn months. However, we selected respondents who are currently working. Thus, 99,101 observations of 23,870 respondents are left in the longitudinal data-sequence that we use in Paper 3. This compound dataset consists of the unbalanced panel with embedded round gaps. It is common practice to eliminate observations within a panel that exhibit gaps in their data-sequences (Baum, 2006). However, it may involve a loss of efficiency in coefficient estimation (Biørn, 2016). Thus, we do not eliminate gaps to keep these losses at a minimum.

Unfortunately, we cannot avoid sample attrition because we deal with a panel study of micro-level changes and the conductors do not usually follow individual household members that have moved away from the original sample dwelling unit. Although some households and individuals who have moved are followed (like in Round VII) to complete the interview, this is rare as true panels are expensive to maintain. Therefore, attrition is a very common issue for most known panel studies. For the RLMS—HSE data, ‘the influence… of household turnover does not seriously distort the geographic distribution of the sample or its size or household-head characteristics', even though the influence of sample attrition of the RLMS—HSE rounds for a panel of individual respondents on the percent of individuals from the Moscow and St. Petersburg regions and the more general urban domain is the greatest (Heeringa, 1997). Furthermore, Heeringa (1997) warns researchers that attrition may cause a general ageing effect of the panel of individuals and a loss of panel respondents from higher income groups. More recent and rigorous studies on sample attrition in the RLMS—HSE (Denisova, 2010; Gerry & Papadopoulos, 2015) confirm that attrition in these data is systematically related to demographic, health, and other socioeconomic characteristics. However, Gerry and Papadopoulos (2015) admit that a carefully specified model can minimise attrition bias. Thus, the authors' preliminary findings support the 'state dependence' hypothesis (Maddala, 1987), and confirm the importance of unobserved individual heterogeneity in the longitudinal studies based on the RLMS—HSE data. Their findings additionally justify the methodological framework chosen for Paper 3.

Paper 2 uses microdata from the National Sample Survey (NSS) 68th Round, Schedule 10 'Employment & Unemployment Survey', carried out between July 2011 and June 2012 by the National Sample Survey Office, the Ministry of Statistics and Programme Implementation, Government of India (the first round was set up in 1950). In general, the NSS data resembles the RLMS—HSE data since the former is designed to monitor detailed information on various socioeconomic aspects of the population. These data are based on stratified sampling and provide a representative selection of the household population. The NSS 68th Round data are abundant when it comes to information on household characteristics, demographic particulars, educational levels, status of current attendance and vocational training, usual principal activity status of all the people, and particulars of the enterprise for all the usual status workers and other related information. They also represent geographical distribution of population for rural and urban areas, and by states divided into NSS regions and districts*.

The NSS 68th Round covers 100,957 households (59,129 in rural areas and 41,828 in urban areas) and 459,784 individuals (281,327 in rural areas and 178,457 in urban areas). The NSS 68th Round data measures training by asking the question: '*whether they are receiving/have received any vocational training or not*', which is applicable only to 63.1% of the respondents, that is, the population within the age range of 15 to 59 (the 'adult population'). Further, data on job contracts and other dimensions of employment relationships are collected only from employees who are institutionally employed; that is, regular salaried or wage employees, casual wage labour in public and casual wage labour elsewhere. Consequently, household workers, helpers, and self-employed people are not counted. Moreover, several employment indicators such as job contracts or enterprise types are applicable only for persons from certain industries, which do not exclude crop and animal production, hunting, and related service activities (Division 01 in National Industrial Classification (NIC) 2008). Information on wages also affects the sample size. As a result, the sample reduces to 30,007 households and 36,430 individuals.

Both NSS 68th Round and RLMS—HSE data contain almost similar classifications of occupations. The RLMS—HSE data provide the International Standard Classification of Occupations (ISCO) developed by the International Labour Organization. Concurrently, the RLMS—HSE data adopt the most recent version of classification, ISCO-08. However, we use the previous version of occupation classification, ISCO-88, which was distributed by the official conductors of the

* Further details about the sampling design of the NSS 68th Round are described elsewhere: http://mail.mospi.gov.in/index.php/catalog/143/study-description

RLMS—HSE data until 2014. Both, Papers 1 and 3, apply the modified version of ISCO-88.

The modified version of ISCO-88 is applied to match the reality of the Russian labour market and to get rid of classification mismatches. Regarding mismatches in occupation coding in RLMS—HSE, see Sabirianova (2002). In the adapted version of ISCO-88, we attribute, as professionals, only those specialists who have a university degree or a related equivalent. By this, we mean that the number of years of education in Russia is less important than formal credentials are. ‘Managers’ are those with more than five employees under their direct supervision. Managers with less than five subordinates are treated as supervisors and coded as a separate category among professionals. Professionals who have no university degree or a related equivalent are encoded as a separate category among ‘semi-professionals’. The latter are filtered accordingly in relation to the level of education required for that group (tertiary education: unfinished undergraduate or vocational training). Some of the minor occupations are directly recoded as lower occupations because of the specifics of their work and its value in the labour market. For more details, see Anikin (2012).

The official maintainers of NSS and RLMS—HSE recommend the use of post-stratification weights in a descriptive analysis, as it ‘may correct non-coverage biases in the frame used to derive the original sample of … individuals’ (Heeringa, 1997). The RLMS—HSE data sets were created to contain post-stratification weights that adjust for both design factors and deviations from the multivariate census characteristics, such as locality, age, and gender. Although experts suggest that researchers should construct weights on their own, if necessary (e.g. weights that adjust to other variables), in the present thesis, we avoid computing weights in addition to the existing ones or using any post-stratification weights in the multivariate regression analysis. This coincides with the general recommendation to plug variables that explain the vast amount of sampling variation in the model as fixed effects. Again, for the RLMS—HSE data, these are as follows: regional and urban/rural residency, age, and sex. As considered, all three constructs (except regional diversity as the RLMS—HSE data do not represent regions) are included in the multivariate analysis of the probability of training in Russia.

In the Indian case, we follow similar tactics. Moreover (and in contrast to Russia), I used all the information at the regional and household levels by modelling region-specific and household-specific variables as higher-level entities. In other words, I allowed the variation between regions and households that drags the most sampling variation to contribute to the variation of the probability of vocational training. This is more effective (than to use them as dummies) as it substantially decreases the number of degrees of freedom consumed.

In general, this recommendation provides additional support as to why we keep gender and age in the regression models, despite the statistically insignificant impact of these variables on the probability of training in Russia, as revealed by the cross-section analysis (see Paper 1). The models specified accordingly do not require extra weighted estimation since additional weighting can result in a model that is not correctly specified (*Ibid*).

Since we deal with survey data, it is likely that respondents do not know the right answer, or are reluctant to provide an answer. Both cases lead to sporadically missing values for the multivariate regression analysis. Some researchers plug in dummies for missing values, controlling, thus, for these respondents. This strategy seems to be somewhat redundant as it consumes additional degrees of freedom and decreases the model's parsimony. Instead, one may take into account multiple imputations of missing data for multilevel models with binary outcomes. However, this is quite a new stream in the literature (Audigier et al., 2017; Grund, Lüdtke, & Robitzsch, 2018) which requires deeper study and independent research. Multiple imputations require the researcher to correctly specify which components of the studying process need to be included in the imputation models in order to obtain unbiased results. However, with the full Bayesian approach, there is no need to explicitly specify how the longitudinal outcome enters the imputation models (Erler et al., 2016). Moreover, multiple imputations work well with missing data at random assumptions, which may be violated by the variables included in the imputation model.

As regards methodology, all three papers use the Bayesian approach to produce estimations of parameters of interest (e.g. regression coefficients). The advantages of the Bayesian approach are as follows: a) it discovers a posterior distribution of a parameter of interest, which allows us to estimate mean, median, and modes, as well as to quantify the amount of variations of the estimated parameters, whereas the frequentist approach produces only a single value; b) it does not require any prior assumption concerning the form of distribution of the parameters to be estimated, whereas the frequentist approach starts with distributional assumptions (likelihood) about the estimated parameters; c) it allows to estimate complex models, such as multilevel models with cross-classifications.

These valuable characteristics of the Bayesian inference are followed from its 'sequential learning' nature (Browne, 2015):

> 'The Bayesian approach is sequential in nature as we can now use our posterior beliefs/ideas as prior knowledge and collect more data. Incorporating this new data will give a new posterior belief'.

In technical terms, Bayesian inference is '…the process of fitting a probability model to a set of data and summarising the result by a probability distribution on the parameters of the model and on unobserved quantities such as predictions for new observations' (Gelman et al., 2014, p. 1). Bayesian methods are designed to utilize the probability for direct quantification of uncertainty in relationships revealed in data analysis. Bayesian inference considers population parameters of interest θ in terms of probability statements, which are conditional on the observed data $p(\theta|Data)$. In order to summarise $p(\theta|Data)$ in appropriate way, Bayesian analysis begins with a joint probability distribution for parameters of interest and observed data $p(\theta, Data)$, which is a product of prior distribution $p(\theta)$ and sampling distribution $p(Data|\theta)$:

$$p(\theta, Data) = p(\theta)p(Data|\theta). \quad (1)$$

Equation (1) represents a formula for conditional probability. Formula (2) represents the basic property of such distribution known as Bayes' rule for yielding posterior distribution:

$$p(\theta|Data) = p(\theta, Data) \,/\, p(Data) = p(\theta)p(Data|\theta) \,/\, p(Data). \quad (2)$$

Finally, we get posterior distribution for θ (3):

$$p(\theta|Data) \propto p(\theta)p(Data\,|\,\theta), \quad (3)$$

where the term $p(Data\,|\,\theta)$ denotes the function that maximum likelihood methods maximize. This posterior is the distribution from which inferences about population parameters of interest θ are then arrived at. Finding the exact form of the posterior distribution usually requires heavy computations due to multidimensional integration. Methods that cope with this problem are known as Markov chain Monte Carlo (MCMC) methods. MCMC methods 'do not calculate the exact form of the posterior distribution, but instead, produce simulated draws from it' (Browne, 2015), which is why they are widely used in a Bayesian framework.

All three papers apply MCMC methods. MCMC gives less biased estimates than frequentist methods do (Browne, Subramanian, Jones, & Goldstein, 2005), particularly in the case of a small number of units at higher levels (Goldstein, 1995). However, in cross-class interaction models, even with a bigger number of units, the known issues (biased estimates and too-short confidence intervals) of deterministic methods become more apparent (Stegmueller, 2013).

MCMC analysis requires specification of prior information to start with. Starting values can be specified manually, or produced by diffuse priors, or obtained from frequentist estimations. In all three papers, we store the estimations returned by the iterative generalized least squares model (Goldstein, 1986) and use them as the starting values for the Bayesian analysis, thus, remarkably optimising the simulation procedures. Paper 1 estimates a two-level model and considers occupations at a higher level, which allows the capturing of structural heterogeneity of training and receiving precision-weighted estimates of occupational propensity for training in contemporary Russia. Papers 2 and 3 apply multilevel cross-classified modelling (Kim, Mohanty, & Subramanian, 2016). This approach allows identifying important contextual factors operating at the state, occupation, and household levels, in India, and individual and occupation levels, in Russia.

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OCCUPATIONAL PROPENSITY FOR TRAINING IN A LATE INDUSTRIAL SOCIETY: EVIDENCE FROM RUSSIA

Abstract

What factors best explain the low incidence of skills training in a late industrial society like Russia? This research undertakes a multilevel analysis of the role of occupational structure against the probability of training. The explanatory power of occupation-specific determinants and skills polarisation are evaluated, using a representative 2012 sample from the Russian Longitudinal Monitoring Survey. Applying a two-level Bayesian logistic regression model, we show that the incidence of training in Russia is significantly contextualised within the structure of occupations and the inequalities between them. The study shows that extremely high wage gaps within managerial class jobs can discourage training, an unusual finding. Markets accumulating interchangeable and disposable labour best explain the low incidence of training; workers within generic labour are less likely to develop their skills formally, except in urban markets. Although we did not find strong evidence of skills polarisation, Russians are yet to live in a knowledge economy.

Introduction

In a late industrial society, acquisition of human capital through skills development is regarded as a cornerstone of economic development, productivity growth, job quality, and social equity (Grugulis, Holmes and Mayhew, 2017; Keep and Mayhew, 2010; Konings and Vanormelingen, 2015). Late industrial society is also described as a ‘society of advanced industrialism’, since it is based on human assets – e.g. skills, expertise, on-the-job training, experience, formal education, and knowledge (Becker, 1975; Kaare, 1965) – to the same extent that early industrial society was based on the production of goods (Bell, 1973). The main holders of such assets are non-manual workers and particularly ‘skill-based occupational groupings’ (Grusky, 2001) such as managers, professionals, and their associates. In late industrial society, development of skills is crystallised through most of these occupations, so that human capital is recognised as an occupation-specific phenomenon (Groen, 2006; Kambourov and Manovskii, 2009; Sullivan, 2010).

The per cent participation rate in continuing adult education and training is generally considered very high worldwide (Arulampalam, Booth and Bryan, 2004; Bosch and Charest, 2012; O’Connell, 1999; Sala and Silva, 2013) and the returns of training are positive and substantial (Booth and Bryan, 2005; Brunello, Comi and Sonedda, 2012; Dearden, Reed and Van Reenen, 2006). However, there are signs of falling training volumes among non-manual occupations in some of the advanced industrial societies, representing a trend away from the knowledge economy (Green, Felstead, Gallie, Inanc and Jewson, 2016). Further evidence comes from Russia. Although it has reached the mature stage of industrial development, researchers are still sceptical of the idea that Russia can be characterized as a fully fledged knowledge economy (Anikin, 2012, 2013a). The training participation rate in Russia is unexpectedly low and training is mainly received within a few occupations (Anikin, 2013b; Sabirianova, 2002; Travkin and Sharunina, 2016), which contributes to a considerable critique of the knowledge economy theory (Green et al., 2016; Livingstone, 1999).

What are the constraints that explain such a low incidence of training in Russia? Our research suggests that factors related to social structure best explain human capital acquisition in Russia. Although we confirm the occupational specificity of human capital in Russia, the main idea of the present paper is to show that in advanced industrial society, rigid occupational niches comprising ‘bad jobs’ can depreciate human capital negatively, affecting the likelihood of the incidence of training. This research in particular reassesses the ‘skill polarisation’ assertion led by economists (Goos and Manning, 2007; Goos, Manning and Salomons, 2009) and sociologists (Castells, 2000) to explain the low incidence of training in late industrial society. We also found that within-occupation heterogeneity (measured via occupation-specific wage gaps) – particularly found among employees engaged with occupations in market sectors – can drastically reduce the probability of undertaking training. These results contribute to our understanding of the depreciation of human capital in Russia and certain other advanced industrial societies.

The focus on occupational structure:
A third strand in the training literature

There is a vast literature on both the economic and social factors of training. The dominant strand in the literature belongs to those labour economists who mostly pay attention to economic factors, such as unemployment (Berger, Earle and Sabirianova, 2001; Sabirianova, 2002), tenure, work experience, position in the wage distribution, and educational attainments (Arulampalam et al., 2004; Booth and Bryan, 2005; Nikolai and Ebner, 2012), labour market institutions (Gimpelson, Kapeliushnikov and Lukiyanova, 2010), industrial and sectoral differences (Lazareva, 2006; Lazareva, Denisova and Tsukhlo, 2006; Méndez and Sepúlveda, 2016), local density of firms (Brunello and Gambarotto, 2007; Rzepka and Tamm, 2016), and organisation-specific determinants, such as ownership etc. (Booth and Bryan, 2005; Hansson, 2007; Parker and Coleman, 1999; Travkin and Sharunina, 2016). Most of these researchers promote their findings as a contribution to the recent theory of market imperfections (Acemoglu and Pischke, 1999; Picchio and van Ours, 2011).

Another stream in the literature comes from social psychologists (Salas and Cannon-Bowers, 2001; Wexley, 1984) considering social attitudes of employees and their motivation as significant determinants of training (Anikin, 2013b; Tharenou, 1997, 2001). We can also mention some of the economists highlighting the importance of personal traits, such as disability (Pagán-Rodríguez, 2015) and health conditions (Brunello, 2004).

The sociological tradition focuses on the role of social structure, placing occupational structure (Chen, 1947; Dunkerley, 1975) and occupation-based groupings and classes (Bukodi and Goldthorpe, 2011) within the broader societal framework of employment relations that contextualises skills acquisition in advanced industrial societies. In light of this, **Hypothesis 1** predicts that *the inequality between occupations significantly explains the variation in the incidence of training*.

Since occupations 'make very natural indicators of individuals' positions within social structures of inequality' (Lambert and Bihagen, 2016, 14), there is a growing empirical interest in the occupational specificity of human capital (Groen, 2006; Monnier, Tschöpe, Srbeny and Dietzen, 2016). For example, Sullivan (2010) showed the importance of occupation-specific human capital for skilled workers, namely professionals, service workers, and craftsmen; and the importance of general human capital for semi-skilled non-manual workers like sales workers and office clerks. As a result, training became a hallmark of workforce members of a certain quality being associated with top positions in the wage distribution and in educational attainment (Arulampalam et al., 2004; Brunello, 2004; Nikolai and Ebner, 2012). The incidence of training is much greater among skilled workers, such as managers, professionals, and technical workers (Berger et al., 2001; Lazareva, 2006; Lazareva et al., 2006; O’Connell, 1999; Rzepka and Tamm, 2016). According to Acemoglu, Aghion and Zilibotti (2006), skilled managers play a more important role than institutions when a country is absorbing a set of new technologies.

Occupational classes and skills development

In a late industrial society, ‘skills provide a grouping of occupations’ (Capatina, 2014, 52). In line with the skill polarisation argument, Castells (2000) proposed two useful categories of such occupational groupings: *self-programmable labour* and *generic labour*. Self-programmable labour is equipped with the ability and resources to upgrade skills and qualification by means of continuing education and training; these workers easily adapt to new tasks, processes, information and technologies. This group comprises people in highly educated, skilled, and flexible occupations, such as managers, experts, health and teaching professionals, business consultants, financial and marketing analysts, scientists, technical professionals, and related professions that normally deal with information and new technologies. On the other hand, generic labour is routine, exchangeable, and disposable; generic workers deal with ‘menial tasks’ and instructions, representing semi- and low-skilled occupations, such as clerks, sales and service workers, operators, drivers, labourers, unskilled farmhands, and related trades.

Thus, we expect that *the impacts of upper and lower occupational classes on the probability for skills training will be opposite*. **Hypothesis 2A** predicts *a low likelihood of training for generic workers*. **Hypothesis 2B**, by contrast, suggests that *members of the upper occupational class (self-programmable labour) will be more likely to undertake training*.

Occupation-specific wage differentials and training

The main challenges for training in late industrial societies occur when: a) non-manual workers are substantially comprised by generic labour; and b) occupations supposed to be held by self-programmable labour show falling training participation rates (Green et al., 2016). The latter challenge can be examined both across and within occupations. Since occupation-specific skills play an important role in earnings (Akerman, Helpman, Itskhoki, Muendler and Redding, 2013; De Beyer and Knight, 1989; Kambourov and Manovskii, 2009), heterogeneity within occupations can be effectively captured by occupation-specific wage differentials. We assume that both employees and employers are usually well informed about the wage[*] spreads within 'their' occupations (Hansen, 1963; Wodtke, 2016), so that labour market participants can rely on this information for skills development and career track decisions (Cover, 2014). If wage differentials within occupations indicate skills differentials, small occupation-specific wage gaps can encourage people to undertake training, while huge gaps discourage workers from training.

[*] In this paper, we use wages and salaries as synonyms. The main reason is that, in Russia, employment contracts are based on monthly paid salaries, and not on hourly paid wages. We also consider the term 'wage gaps' in the sense of 'wage differentials' and vice versa.

Following this, we assume that in a late industrial economy, occupation-specific wage differentials can explain why people undertake training. **Hypothesis 3** predicts that *wage differentials within occupations have a non-linear, quadratic, effect on the probability of training in Russia*. The quadratic form of the relationship between wage differentials and the probability of training is conjectured in order to capture the possible negative impact of high wage gaps on workers' incentives to upgrade their qualifications. That is, unbridgeable wage differentials within occupations may discourage employees from investing in their human capital, as the 'extraordinary' wage gaps across relatively similar jobs may reflect 'non-competitive' – i.e. non-meritocratic – forms of distribution of income and other valued assets such as social capital and loyalty rents (Wright, 1989).

Human capital acquisition in Russia

The theory of industrial society suggests that the excessive role of occupational structure and occupation-based classifications (Lambert and Bihagen, 2016) has resulted from three processes (Grusky, 2001, 12), described as: 1) the rise of a service economy, 2) the increasing centrality of theoretical knowledge in the transition to a new 'information age' and the growing power of so-called informational labour (Castells, 2010), and 3) the consequent emergence of technical expertise, educational degrees, and training certificates as new forms of property (Wright, 1997) or 'cultural capital' (Bourdieu, 1986).

The foregoing transformations, which have been taking place all around the world since the 1980s, suggest that the three processes outlined intensified in societies that were far beyond the Western type of industrial development. The results of these structural changes are also clearly seen in the economies of the 'Asian

Tigers' (Hong Kong, Singapore, South Korea, and Taiwan) and the BRIC countries (Brazil, Russia, China, and India). In Russia, these transformations have been spectacular; in the early 1990s, the nation undertook 'shock therapy' reforms primarily focused on diminishing the state socialist socioeconomic system and on transitioning to the market economy by means of liberalisation and privatisation (Gerber and Hout, 1998).

The dissolution of the Soviet Union led to a rapid depreciation of human capital at state-owned enterprises and caused a deep crisis for most branches of manufacturing industry and services. This was especially the case for those segments based on human capital, including the defence and aircraft industries, science and scientific services, informational and computing services, health and social security, public education, culture and art. 'Perestroika' also urged a 'great reallocation' of human capital (Sabirianova, 2002) that was necessary to support growing new activities (e.g. finance and insurance, accommodation and food services, administrative and support services, retail trade, professional and technical activities) in the private sector with higher premiums, although with higher norms of exploitation. These reforms were premised on the idea that they should become a fruitful ground for further socioeconomic development, and in particular, for the transition to a new 'information age' representing a fully fledged knowledge economy.

However, this information age has not yet arrived, although Russia has recovered the monetary value of stock of human capital and become one of the most educated nations in the world (OECD, 2016). Authors usually interpret this paradox as an institutional legacy of the state socialist system (Didenko, 2015; Shkaratan, 2007), which coincides with recent findings that differences in national skill systems and their functionality are likely to persist (Bosch, 2017; Bosch and Charest, 2012). During the 20th century, Russia and other republics of the USSR had been accumulating the quantitative indicators of human capital. Before the transition, the average number of years of schooling in Russia was at the average level of the European countries. Nevertheless, the Soviet Union's planners did not prioritise the role of human capital against traditional capital assets, labour power assets, and organisational assets. During the early phases of industrialisation, this agenda was successful in supporting the substantial accumulation of material assets and the resulting socioeconomic development. However, by the 1970s-1980s, this approach had led to a depreciation of the role of human capital (as compared with material forms of capital) in production and became the main factor that obstructed Russia's transition to a knowledge economy (Didenko, 2015).

Recent studies show that, even during the post-transition period, the role of human capital has not increased significantly; that is, its role remained minimal during the recent growth and productivity of the Russian economy (Connolly, 2012; Timmer and Voskoboynikov, 2014). Neither perestroika nor the recent economic growth of the 2000s led to substantial increases in the relative share of experts and highly skilled professionals in the Russian economy; furthermore, the recent deindustrialisation of Russia has been accompanied by growing shares of semi- and low-skilled non-manual workers (Anikin, 2012, 2013a). According to Gimpelson and Kapeliushnikov (2013), incentives to upgrade human capital are hardly promoted by institutional arrangements on the Russian labour market that allow low-productivity firms to survive and hire workers with relatively low levels of human capital (Gimpelson and Kapeliushnikov, 2013), thus producing significant skills mismatches (Demmou and Wörgötter, 2015). The findings of Timmer and Voskoboynikov (2014) suggest that the only industries for which human capital can be a growth factor are the finance and business services sectors, even though these industries do not necessarily encourage training, because much of their productive performance ‘is of some basic catching-up character’ (Timmer and Voskoboynikov, 2014, S418), which is also very typical for other newly industrialising societies (Krasilshchikov, 2008).

This supports the ‘varieties of capitalism’ approach (Hall and Soskice, 2004; Lane, 2007; Wood and Lane, 2012) and leads some critics to argue that Russia is following ‘Marx’s account of the development of capitalism’ (Clarke, 2007). Thus, there is a notable contradiction in the socioeconomic system of Russia. On the one hand, Russia overcame the turbulent times of restructuring (Gimpelson and Lippoldt, 2001; Sabirianova, 2002) and transitioned into a market economy, shifting to a ‘normal country’ (Shleifer, 2005); on the other hand, the desired transformations of institutions and sociocultural contexts have not occurred, so that most jobs in Russia remain of low quality, discouraging employees from undertaking training.

Data and variables

The present paper uses the representative 2012 sample of the Russia Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE)[*]. The RLMS-HSE data measure skills training via the following question: ‘During the last 12 months, were you studying professional courses, advanced training, or other any courses, including foreign language classes?’ The response is a binary variable with the value of 1 for ‘yes’, otherwise 0. The RLMS-HSE 2012 sample applies the International Standard Classification of Occupations (ISCO-88) as a measure of occupational

[*] For further details, see the official web page of the RLMS-HSE: http://www.cpc.unc.edu/projects/rlms-hse

structure[*]. To get rid of classification mismatches, we have adapted the official version of ISCO-88[†]. The adapted version of ISCO-88 contains 341 occupations on the lowest tier, which is a four-digit level. The first-digit level ISCO-88 occupations – capturing ten major occupational categories – are also used in the analysis.

We use the most detailed list of minor occupations to obtain occupation-specific differences in wages measured regarding the intra-occupational standard deviations of monthly salaries. According to prior research, we assume that a sufficient measure of wage differentials is one standard deviation (Hox, 2010) of salary (in thousands of rubbles) earned monthly within each minor occupation. To control for non-linearity, we take a polynomial of the 2nd order (termed 'Wage gap' and 'Wage gap^2' and denoted accordingly in the output tables).

Table 1 describes the occupational composition of those who undertook formal training in 2012. First, we see that occupational structure plays a pivotal role in training. Second, the structure obtained provides empirical grounds for grouping occupations into macro-occupational classes (see Castells, 2010; Goldthorpe, Llewellyn and Payne, 1987; Wright, 1997).

The highest rates of those who received training were among those holding either skilled or semi-skilled jobs within non-manual labour and managerial positions. There is a significantly higher share of managers (11.7%), professionals (14.4%), and semi-professionals (9.7%) among trained people than the mean (6.9%)[‡].

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[*] In 2012, ISCO-88 was an official classification scheme applied by the International Labour Organization (ILO).

[†] An adapted version of ISCO-88 is applied to match the reality of Russian labour market and get rid of classification mismatches. Regarding mismatches of coding occupations in RLMS-HSE, see Sabirianova (2002). In the adapted version of ISCO-88, we attribute professional status only to those specialists who have a university degree or a related equivalent. We consider 'managers' to be those who have more than five subordinates under their direct supervision. For more details about the recoding strategy used in this paper, see Anikin (2012).

[‡] The statistical significance of this result is at the level α<0.01, as the value of 'adjusted standardized residuals' (used to measure the significance of difference between theoretical and observed distribution of two nominal variables) is equal to or exceeds 3.3. In statistical terms, this means that according to

Table 1

Occupational composition of training in Russia, 2012

Major Occupations, Adapted ISCO-88	Received formal training during last 12 months, %	
	Yes	No
Managers	11.7***	88.3
Professionals	14.4***	85.6
Semi-professionals	9.7***	90.3
Clerks	6.2	93.8
Sales workers	3.9	96.1***
Craft workers	3.5	96.5***
Industrial workers	3.6	96.4***
Unskilled workers	3.3	96.7***
Total		
%	6.9	93.1
n	*520*	*7051*

Note. Armed forces and farm workers are encoded within the other occupational groups regarding their highest degree of qualification.
*** Statistically significant difference from the average ($\alpha<0.01$).

We use these results to construct a variable measuring macro-occupational classes. This is a binary variable with the value of 1 for 'self-programmed labour' to indicate the upper occupational class, otherwise 0 for 'generic labour' denoting the lower occupational class. Generic labour embraces occupations that are less likely to improve their qualifications: unskilled workers, industrial workers, craft workers, sales workers (occupied with simple jobs in sales and services), and clerks. The upper occupational class contains managers who have more than five subordinates, employees who deal with either information or health (professionals), and associate professionals (semi-professionals). For simplicity, we call this grouping 'Qualified non-manual workers'.

Despite the fact that the relative number of trained workers is significantly higher among professionals than in other occupational groups, only few of them still

the 3-sigma rule, the probability of occupational status and fact of training being independently distributed is much less than 0.1 per cent.

undertake formal training; and this is generally under the influence of organisational and job-specific contexts. About 70% of trainees were fully funded by their employers, while only 23% were self-funded. To control for the organisation-specific context, we use data on ownership and organisation size. In Russia, almost half (47%) of the national labour force works in organisations that are directly or indirectly owned by the Russian government, and over 60% of those who received training worked in one of these state-owned enterprises. The qualification attributions of occupations in relation to state-owned enterprises are firmly regulated by explicit procedures. That is, both salary and occupational status in state bureaucracies are the result of employees' qualification ranks, which also determine their occupational mobility within and between these organisations as a result of this skill heterogeneity within occupations.

We measure job-specific levels related to gainful employment through a set of indicators, such as working more than eight hours a day, being paid without delays, and holding a formal job contract. Table 2 presents the detailed information concerning these factors and indicators and their expected impact on the probability of training (the full description of the respective variables is given in Appendix A in a supplementary file). We also take into account the individual traits of employees, such as skills-specific characteristics and efforts related to the knowledge-based economy (using foreign languages and personal computers at the level of the job or the workplace). According to the theory of skills-biased technological change, information and communication technology is more effectively used by better-educated workers, hence raising both their relative productivity and wages (Goos and Manning, 2007). Following the existing literature, we suggest that computer use at work can be associated with 'better use of available knowledge and abilities, and an increased emphasis on skills development training'(Felstead, Gallie, Green and Henseke, 2016).

Table 2

Observed single-level factors of training, indicators, and expectations

Factors	Indicators	Anticipated impact
Socio-demographics	Males	Positive
	Urban area	Positive
	Age	Positive
	Age squared	Negative
Class situation	Lower occupational class, Generic labour	Negative
Skills-specific characteristics related to knowledge-based economy	Using personal computer at work	Positive
	Foreign language skills	Positive
Job-specific level	Working time, more than eight hours a day	Positive
	Paid without delays	Positive
	Formal job contract	Positive
Individual-specific level	Intention to change a job	Positive
	Good and excellent self-rated health	Positive
	High self-rated qualification	Negative
	Satisfaction with opportunities for professional growth at work	Positive
Organization-specific level	State ownership	Positive
	Size of organisation	Positive
	Size of organisation squared	Negative

Furthermore, we also check for self-rated qualification, self-rated health, intention to change a job, and satisfaction with opportunities for professional growth at work. Although this list of controls for training is not the only one possible, we find the chosen factors applicable and relevant to the specific case of Russia.

Hierarchical modelling of occupational propensity for training

The selected data support binary response multilevel modelling of the occupational propensity for training. A relatively young, yet vast literature on multilevel modelling prompts researchers to use specific models to account for the structural nature of professional hierarchies in the analysis. Manley, Johnston, Jones and Owen (2016) show that the occupational hierarchy contains structural information that significantly contributes to a segregation on labour markets; thus, in line with prior studies (Goldstein, 2011; Hox, 1998; Jones, 2011; Peugh, 2010) these researchers advise that the occupational segregation be assessed accordingly by applying multilevel modelling to the stratified data. In more general terms, if the hierarchy is theoretically justified, we can model the unobserved structural-specific heterogeneity of the given process by applying multilevel modelling (Nezlek, 2008)

Thus, multilevel regression is more than an extension of the random regression model (Baayen, 2004), being a more efficient instrument than the naïve use of occupational dummies in regression equation (1):

$$Y_{ij} \sim \text{Binomial}(\text{cons}_{ij}, \pi_{ij})$$

Fixed-effects part (micro-level):

$$\begin{aligned}
\text{Logit}(\pi_{ij}) = \boldsymbol{\beta_{0j}}\text{cons}_{ij} &+ \beta_1\text{Wage-gaps}_{ij} + \beta_2\text{Wage-gaps}^2_{ij} + \\
&+ \beta_3\text{Age}_{ij} + \beta_4\text{Age}^2_{ij} + \beta_5\text{Male}_{ij} + \beta_6\text{Urban}_{ij} + \\
&+ \beta_7\text{Generic labour} + \\
&+ \beta_8\text{Generic labour * Male * Urban}_{ij} + \\
&+ \beta_9\text{Not using foreign language}_{ij} + \beta_{10}\text{Not using PC}_{ij} \\
&+ \beta_{11}\text{Not willing to change a job}_{ij} + \\
&+ \beta_{12}\text{Health professionals * cons}_{ij} + \\
&+ \beta_{13}\text{Paid without delays}_{ij} + \\
&+ \beta_{14}\text{Private ownership}_{ij} + \beta_{15}\text{Working more than 8 hours}_{ij} \\
&+ \beta_{16}\text{Generic labour * Not using PC}_{ij}
\end{aligned}$$

$$+\beta_{17\text{-}18}\text{Self-rated health}_{ij} + \beta_{19}\text{Self-rated qualification}_{ij} +$$
$$+\beta_{20}\text{Satisfaction of professional growth}_{ij}$$
$$+\beta_{21}\text{Size of organisation (ln)}_{ij} + \beta_{22}\text{Size of organisation(ln)}^2_{ij}$$

Random part (macro-level):

$$\boldsymbol{\beta}_{\mathbf{0j}} = \beta_0 + u_{0j}$$

Full-length model: (1)

$$\text{Logit}(\pi_{ij}) = \beta_0 + \beta_1\text{Wage-gaps}_{ij} + \beta_2\text{Wage-gaps}^2_{ij} + \ldots +$$
$$+\beta_{22}\text{Size of organisation(ln)}^2_{ij} +$$
$$+ (u_{0j}\ \text{cons}_{ij})$$

$$\text{var}(Y_{ij}|\pi_{ij}) = \pi_{ij}(1 - \pi_{ij})/\text{cons}_{ij}$$
$$\left[u_{0j}\right] \sim \text{N}(0, \Omega_u) : \ \Omega_u = \left[\sigma^2_{u_{0j}}\right]$$

The dependent variable Y_{ij} denotes the probability of training. It is considered to be a binomial process because the main quantity of interest has a binary outcome. In the given formula (1), $cons_{ij}$ relates to the cell number (which is simply a vector of ones) and π_{ij} is the population mean proportion for an individual from the *i*-th cell (Goldstein, 1991). The index *j* of an estimated coefficient $\boldsymbol{\beta}_{\mathbf{0j}}$ is used to evaluate the hypothesis of a structural nature of an outcome for a given occupation; each occupation *j* from a set of occupations *J* is sorted.

From (1), the final model contains occupation-specific wage differentials and occupational classes with their multiple interactions with other factors – such as gender, type of locality, and skills characteristics (including foreign language skills and using a computer at work) – as well as outlier occupations for which training is mandatory, such as health professionals. Figure 1 visualises this particular outlier.

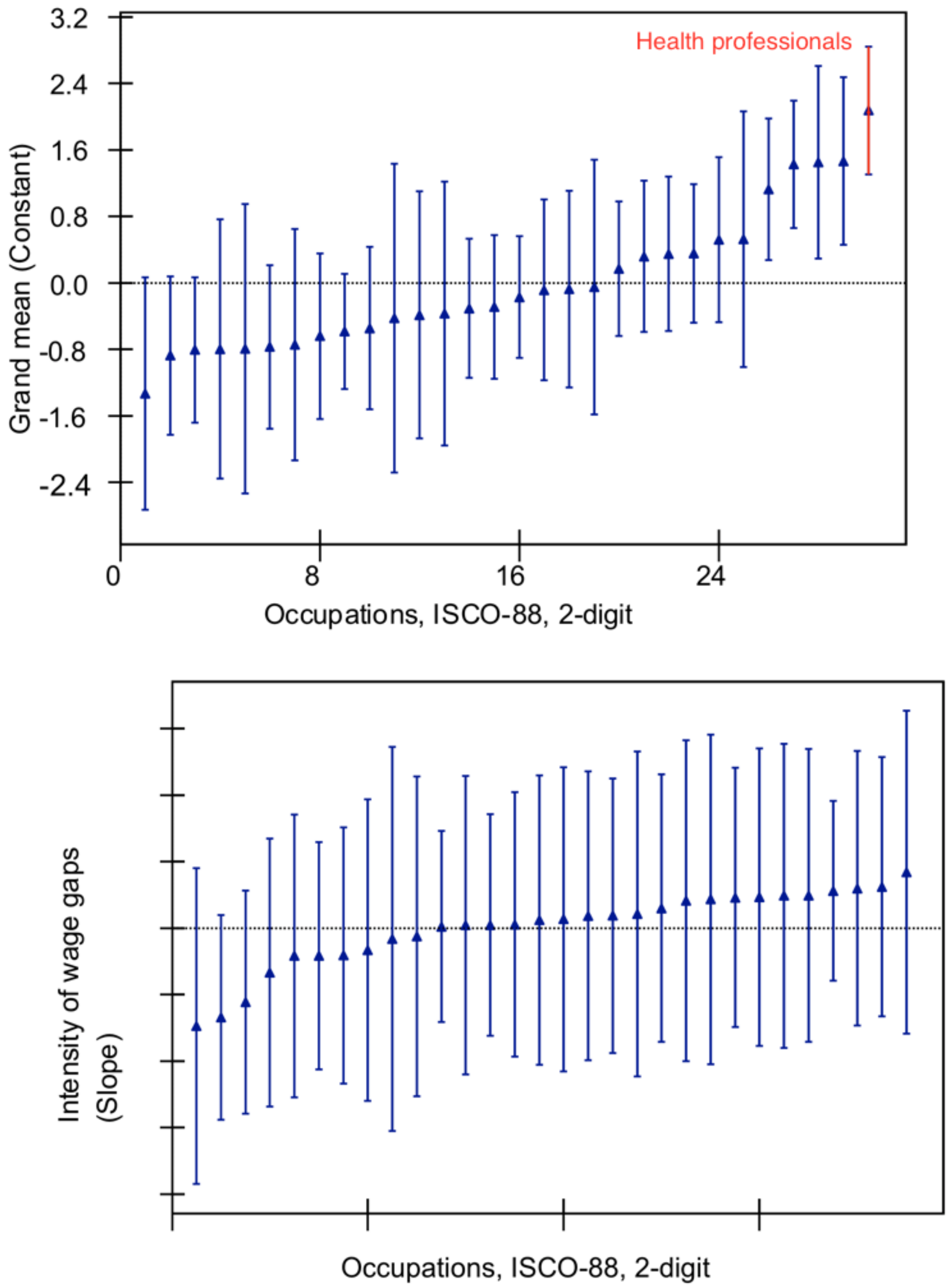


Figure 1. Level-2 residuals from model 1 (empty model + wage-gaps). Both graphs depict structural residuals with their credible intervals for 30 ISCO-88 sub-major groups. 'Health professionals' appears to be an outlier.

Model (1) is estimated by the Bayesian approach, i.e. Markov chain Monte Carlo (MCMC) methods. MCMC methods are used to avoid the known issues (biased estimates and too-short confidence intervals) of deterministic methods (Stegmueller, 2013). At the first step, we apply the iterative generalized least squares (IGLS) approach and its more flexible version, restricted IGLS (RIGLS) (Goldstein, 2011), to obtain the estimates of the parameters that will serve as initial values in the MCMC estimation (Browne, 2015; Browne, Subramanian, Jones and Goldstein, 2005). For the second step, we apply the multivariate Metropolis Hastings sampling with hierarchical centring at level 2 (Browne et al., 2005, 605; Gelfand, Sahu and Carlin, 1995). Starting with a burn-in length of 5,000 and 100 thousand simulations, we end up with 400 thousand simulations in the final model. We also apply group-mean centring to some continuous predictors, following the argument of Afshartous and Preston (2011, 3).

Although there is no universal instrument for selection between MCMC models, one possible solution discussed in the literature is to use the deviances obtained with MCMC sampling to derive a diagnostic similar to the AIC (Spiegelhalter, Best, Carlin and Van Der Linde, 2002). The diagnostic known as the Bayesian deviance information criterion (DIC) returns a value of deviance at each iteration and the deviance at the expected value of unknown parameters (Browne, 2015).

Results and discussion

Our analysis shows that multilevel modelling of training gives a more precise picture of the role of occupations in skills development in contemporary Russia. Occupational structure helps us to understand how the probability of training changes from one occupation to another and also changes within each occupation. The random part of the intercept remains significant whatever the specification (see Appendix B from a supplementary file for the overall modelling routine), thus showing the robustness of the occupational propensity of training.

Table 3

Fit diagnostics of the models

	Simulations	DIC	Decrease in DIC	pD	Increase in pD
Model 1: Inter- and intra-occupational diversity	100 k	3,514	n/a	27.955	n/a
Model 2: Socio-demographics and occupational class	100 k	3,451	63	27.143	-0.812
Model 3: Health professionals, Late-industrial skills, willingness to change a job	200 k HC	2,924	527	30.821	3.671
Model 4: Job-specific level	200 k HC	2,541	383	32.006	1.185
Model 5: Cross-class interaction with skills	400 k HC	2,539	2	32.655	0.649
Model 6: Individual-specific level	400 k HC	2,359	180	36.426	3.771
Model 7: Organization-specific level	400 k HC	1,891	468	36.225	-0.201

Note. k = thousands. HC = simulations with hierarchical centring at level 2. DIC = Bayesian Deviance Information Criterion. pD = the ‘effective’ number of parameters. n/a = data are not available.

In Table 3, we show how the quality of the model changed when increasing the number of simulations and adding new predictors, such as macro-occupational variables, an outlier (health professionals), skills-specific indicators, working place characteristics, and organisation-level determinants. In the final model (see Table 4), we observe the massive drop in level-one units due to missing samples caused by including some of the predictors (e.g. foreign language skills, using a computer at work, size of the organisation, self-estimation of qualification level). It is possible to compensate for the lack of observations by an increased number of simulations. This approach allows us to avoid the necessity of employing dummies for 'missing values', as widely applied in frequentist analysis; and according to the effective sample size (ESS) criterion, widely used in MCMC diagnostics, it is likely to meet the sufficiency criterion.

From Table 3, the first severe drop in DIC occurs when we model training as a function of late industrial skills (computer and foreign language skills), intentions to change a job, and the occupation outlier that is institutionally related to training (health professionals). Another remarkable increase in the model fit happens when we include job-specific parameters indicating a high intensity of work in gainful conditions (being paid without delays, overwork, and working for private and privatised companies). In other words, job-specific and skills-specific parameters of the labour force are much more important than socio-demographic effects, which appear to be statistically insignificant in the fully adjusted model. The smallest DIC is in the final model, that is, the DIC value drops substantially from 2,359.62 to 1,891.37.

Table 4

Fully adjusted multilevel model of training

Parameter	Mean	Median	CI(2.5%)	CI(97.5%)	ESS
	Fixed effects				
Intercept (grand mean)	−1.96** (0.895)	−1.95	−3.67	−0.223	277
Wage-gaps	0.06* (0.034)	0.058	−0.001	0.134	992
Wage-gaps^2	−0.001* (0.001)	−0.001	−0.003	0	1,137
Age	0.037 (0.038)	0.036	−0.036	0.112	247
Age^2	−0.001 (0)	−0.001	−0.001	0	254
Male	−0.21	−0.208	−0.57	0.144	22,890

Parameter	Mean	Median	CI(2.5%)	CI(97.5%)	ESS
	(0.182)				
Urban	0.195	0.194	−0.135	0.529	10,704
	(0.169)				
Occupational class					
Generic labour	−0.811**	−0.81	−1.435	−0.196	17,581
	(0.315)				
Cross-class interaction with gender and location					
Generic labour * Male * Urban	0.805***	0.804	0.211	1.399	16,787
	(0.304)				
Industrial society skills					
No foreign language skills	−0.056	−0.057	−0.327	0.22	24,522
	(0.139)				
Not using PC at work	−0.355*	−0.352	−0.774	0.049	21,273
	(0.21)				
Cross-class interaction with skills					
Generic labour * Not using PC at work	−0.59**	−0.589	−1.234	0.056	18,343
	(0.329)				
No intentions to change the job	−0.212	−0.214	−0.529	0.109	14,697
	(0.162)				
Outlier:					
Health professionals * Intercept	0.876**	0.879	−0.021	1.76	69,261
	(0.454)				
Job-specific predictors					
Paid without delays during a year	−0.955***	−0.956	−1.429	−0.469	3,827
	(0.245)				
Work for non-state owned organisations	−0.475***	−0.475	−0.771	−0.175	28,450
	(0.152)				
Work for more than 8 hours per day	0.33**	0.331	0.031	0.627	49,942
	(0.152)				
Self-rated predictors					
Self-rated health (Good – ref. cat.)					
Neither good, nor bad	0.28**	0.28	0.013	0.551	24,445
	(0.137)				
Bad	0.258	0.266	−0.419	0.886	60,109
	(0.333)				
Self-rated qualification (Natural log of 10-scale ladder)	−0.006	0.375	0.115	0.638	29,197
	(0.208)				
Satisfaction of professional growth at work	0.375***	−0.009	−0.408	0.412	47,066
	(0.134)				
Organization-specific predictors					
Size of organisation (Natural log, polynomial of the 1st order)	0.092**	0.091	0.006	0.18	34,275
	(0.044)				
Size of organisation ^{2} (Natural log, polynomial of the 2nd order)	0.017	0.018	−0.013	0.046	31,860

Parameter	Mean	Median	CI(2.5%)	CI(97.5%)	ESS
	(0.015)				
	Random parameters				
Variance of intercept					
Intercept/Intercept ($\sigma^2_{u_{0j}}$)	0.237** (0.124)	0.212	0.073	0.545	25,799
	Model diagnostics				
DIC:	1,891.37				
pD:	36.225				
Level 2 units: Occupations, ISCO-88, 2nd digit	30				
Level 1 units: Respondent's Identifier	2,976				

Note. Model 7 is estimated using MCMC methods over 400 thousand simulations; hierarchical centring at level 2 is applied to speed up simulations. Group-mean centring is applied to two variables: Self-rated qualification and Size of the organisation. Standard deviation (SD) from the chain of values in parentheses. CI = confidence interval.
*** Bp <0.01, ** Bp<0.05, * Bp<0.1.

Table 4 presents the estimations of the final model (1). It should be noted that we excluded from the model a set of ascriptive variables, such as marital status, the number of children, immigration experience, and religion, because these factors were statistically insignificant and, moreover, they worsened the overall fit of the model, increasing values of DIC. From Table 4, the impact of gender is also not significant. This coincides with earlier findings on the convergence in access to training for women and men (Aisa, Gonzalez-Alvarez and Larramona, 2016; Green and Zanchi, 1997; Tharenou, 1997); nevertheless, gender has not been excluded from the final model, as it is an important theoretical factor (Cho, Kalomba, Mobarak and Orozco, 2013; Polavieja, 2012; Stier and Yaish, 2014). Other demographic predictors, such as age and location, also do not have any significant effects on training. In general, the findings confirm the argument of Grusky (2001) about the small role of ascription in an advanced industrial society.

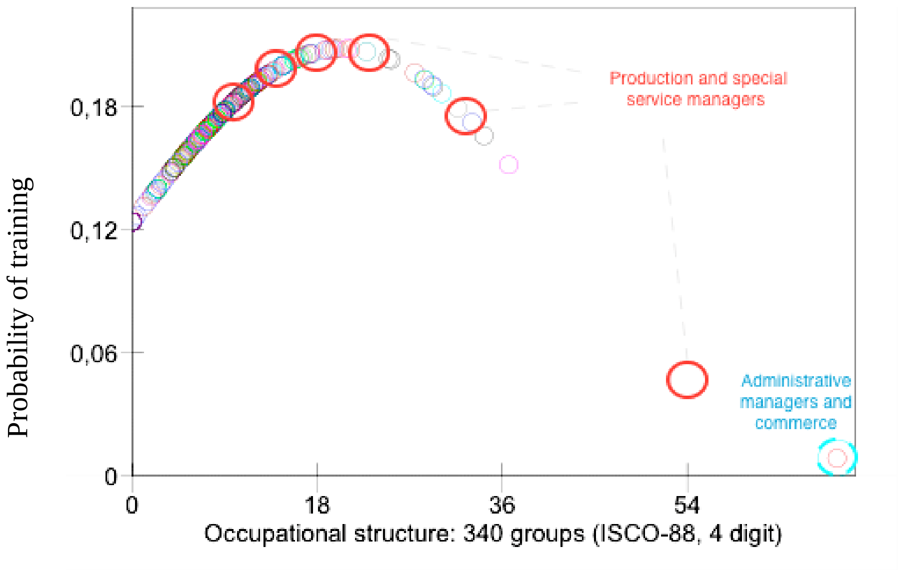
The statistically significant random part of the intercept indicates that the inequality between occupations explains the variation of probability in the intercept.

The traditional way of showing the importance of inequality between occupations is to look at the variance partition coefficient (VPC). Level-1 residuals follow a logistic distribution with variance $\pi^2/3 \approx 3.29$, since the variance of the logistic function is different from the variance of the normal only by the scaling value $\pi^2/3$ (Snijders and Bosker, 2012). Then we have

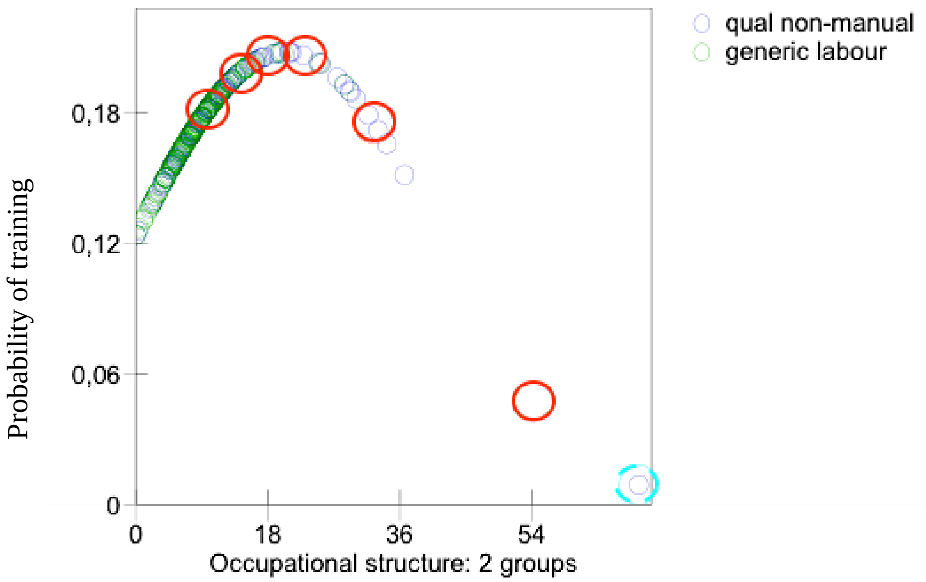
$$\begin{aligned} \text{VPC} &= \text{level-2 variance} / (\text{level-2 variance} + 3.29) = \\ &= 0.237 / (0.237+3.29) \\ &= 0.067 \end{aligned}$$

In other words, approximately 7% of the probability of training is attributable to differences between occupations. Thus, we fail to explain at least about 7% of the probability if we ignore the structural component of training related to the differences between occupations. Taking into account all these results, Hypothesis 1 is fully confirmed: the variation among occupations significantly explains the probability of training.

The fully adjusted model (1) provides evidence of the non-zero impact of occupational wage gaps on the likelihood of training. Hypothesis 3 is therefore also confirmed, which means that the inequality of payments within occupations reflects occupation-specific skills differentials that may encourage workers (particularly those from generic labour) to improve their qualifications in order to have higher salaries.



Occupation-specific wage-differentials in terms of standard deviation of monthly salary



Occupation-specific wage-differentials in terms of standard deviation of monthly salary

Figure 2. Inverted-U shape relationship between wage differentials (horizontal axis) and the probability of training (vertical axis). Different occupational groupings are applied. Zero values on the horizontal axis indicate no deviation of monthly salary from the average wage in a particular occupation. Large values on the horizontal axis indicate cases where monthly salaries exceed the occupational average several times. Light blue and red circles suggest probabilities for ‘Administrative managers and commerce’ and ‘Production and special service managers’, respectively

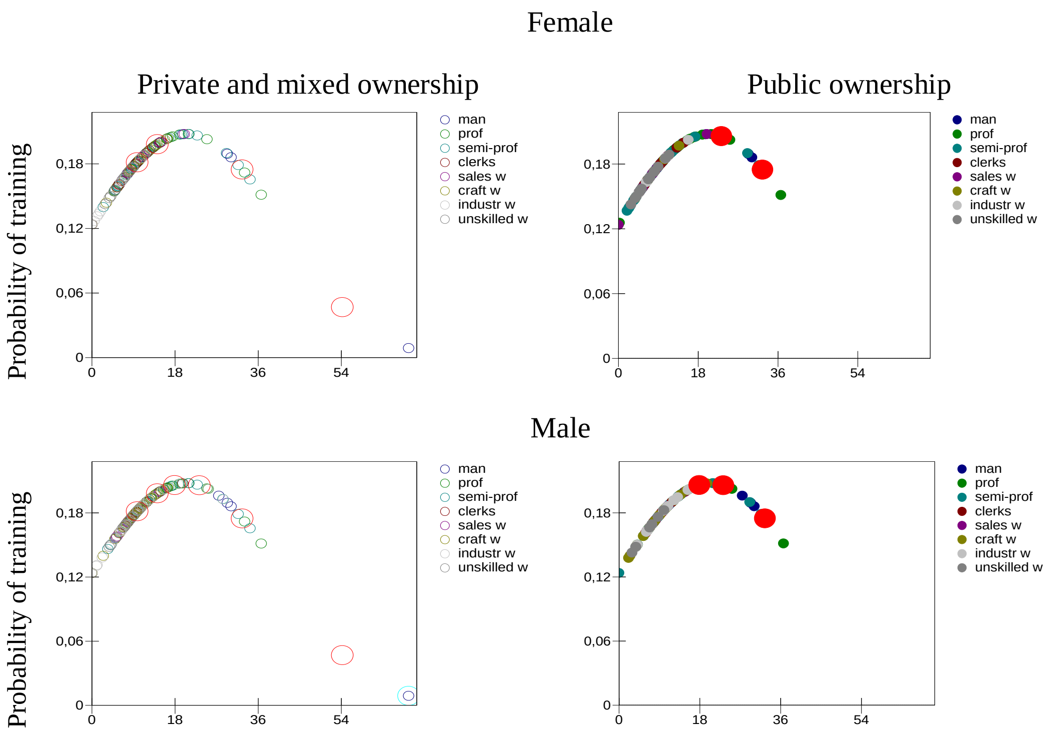


Figure 3. Inverted-U shape relationship between wage differentials (horizontal axis) and the probability of training (vertical axis). Ownership and gender group the given effects insignificantly. Zero values on the horizontal axis indicate no deviation of monthly salary from the average wage in a particular occupation. Large values on the horizontal axis indicate cases where monthly salaries exceed the occupational average several times. Light blue and red circles suggest probabilities for ‘Administrative managers and commerce’ and ‘Production and special service managers’, respectively.

However, the effect of occupation-specific wage differentials on the probability of training is non-linear and takes an inverted-U shape. From Figure 2 and Figure 3, we can see that the impact of wage gaps on the probability of training changes from positive to negative as the parameter reaches high values. In other words, small deviations of monthly salaries from the occupational average increase the probability of workers improving their qualifications from about 12% to 20%, whereas unbridgeable wage gaps within occupations act to discourage workers from training, regardless of their gender or the nature of firm ownership.

These effects remain very sensitive to occupational classes. Workers from ‘generic’ labour, in general, are more likely to undertake training when wage differentials within their occupations increase, whereas employees from upper-occupational classes are less likely to receive training; that is, the probability for the latter drops as monthly salary deviates from the occupational average. The most extreme case belongs to ‘Administrative managers and commerce’, which has the lowest probability of training against the highest occupational wage differentials. These managers are considered by some researchers as working in ‘market sectors’ (Lazareva, 2006) and are therefore expected to show a higher probability of training. Our study confirms this only partially, since these ‘market sector’ managers demonstrate almost zero likelihood of training when the wage differentials within their occupations are extremely high. The majority of jobs in commerce do not require advanced competencies from employees, even when these employees are supervising other people. Knowing this, these managers may perceive the existing wage differentials as being produced by some type of structural shift or market failure that is not related to skills differentials.

Unbridgeable differences of salaries among managerial class jobs may indicate 'unfair' drivers of payments in these occupations. Employers easily merge these payments with market-like payoffs, such as employment rents (Goldthorpe, 2000), loyalty rents (Wright, 1997), industry rents (Katz, Summers, Hall, Schultze and Topel, 1989), premiums for industry-specific human capital (Sullivan, 2010) or other permanent and temporary rents. The fact that extreme wage gaps discourage managers from training supports the trend documented earlier in advanced industrial societies (Busemeyer and Trampusch, 2012, 70):

> A growing differentiation in wages … undermines the country's [Germany's] training regime to the extent that it reduces overall incentives to train at the same time that it feeds the demand for more flexibility in order to accommodate and adapt to a greater differentiation in jobs.

This heterogeneity in the probability of training within self-programmable labour is saliently revealed in Figure 4.

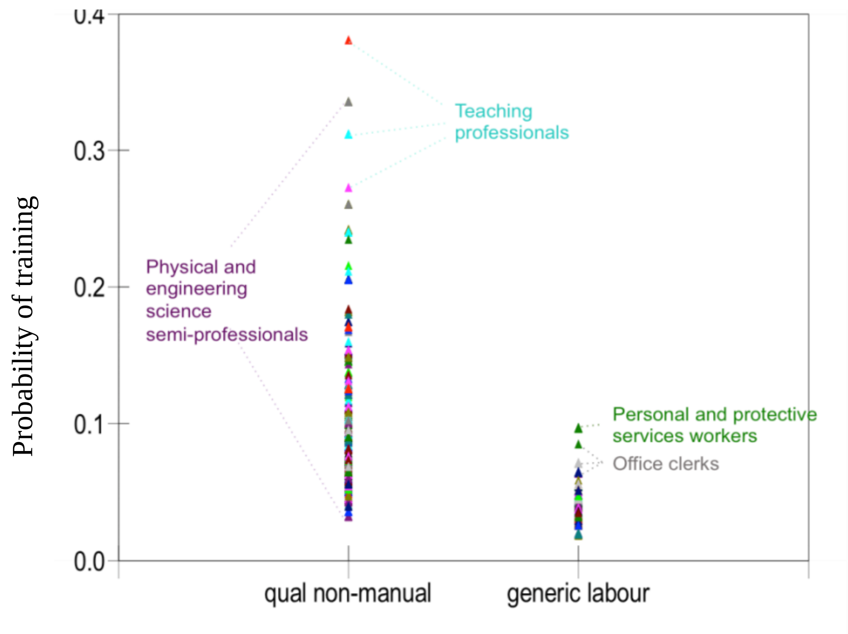


Figure 4. Probability of training in two occupational classes: qualified non-manual workers and generic labour. Figure 4 depicts the estimated probability of undertaking training for minor (1-digit ISCO-88) occupations.

There is a highly scattered variation in the probability of training (vertical axis in Figure 4) within qualified non-manual workers (i.e. managers, professionals, and semi-professionals), varying from zero probability to almost 0.4. This leads to the rejection of Hypothesis 2B, formulated in line with the 'skill polarisation' discourse. Above all, this heterogeneity of skill acquisition among qualified non-manual workers reveals one of the fundamental challenges for training in a late industrial society, since it affects the processes of transition to a knowledge economy.

In contrast with the wide skills acquisition diversity among qualified non-manual occupations, generic labour (clerks, sales workers, and manual labour) is characterised by a low-spread, densely distributed variation in the probability of training. Generic workers are less likely to develop their skills. Hypothesis 2A is therefore confirmed, showing that the grouping of disposable occupations proposed by Manual Castells imposes somewhat homogeneous human capital characteristics and similar training profiles (Weeden and Grusky, 2012). The fact that up to half of Russian generic labour is comprised of non-manual workers, who are normally involved in skills acquisition in other developed nations, illustrates another major challenge for training in this late industrial society.

However, the effect of local labour markets switches the negative impact on generic labour for males who live and work in cities. That is, from Table 4, the interactions between generic labour and gender and area of living are highly significant. It should be noted that the main effects of socio-demographics (gender and location) remain insignificant when this three-way interaction is excluded from the model. The robust positive impact of this interaction term shows that the market situation of the lower occupational class, or generic labour, has a limited negative influence on the opportunities for workers to undertake training. In other words, although being in generic labour significantly reduces the average incidence of training among these employees, this effect disappears in urban labour markets, particularly for male workers. This is quite a positive result, showing the particular perspectives of skills formation in workers residing Russian cities and the possibility of switching to human-capital-intensive production in urban areas.

Among other determinants, organisation-specific characteristics are seen to be significantly influential on training. The positive linear impact of the size of the organisation on the probability of being trained reveals the concentration of investments in human capital in bigger companies. Taking into account the occupational disparities of training, the concentration of continuing education in large enterprises may reveal rewards in terms of gratitude from skilled non-manual employees who display a remarkable propensity for professional growth at work. At the same time, training in a big business is not a privilege, as it goes with hard work of more than eight hours a day. The high intensity of work may be considered as a bargain between employees and the company that invests resources in workers' human capital. Flexible and even unstable schemes of payment in private and privatised companies are likely to add additional costs to this bargain, rather than to break it apart, though these firms are very unlikely to encourage training of their employees. From the experience of the early 1990s, Russian employees are familiar with wage elasticity and are somewhat prepared for salary manipulations (Gimpelson and Kapeliushnikov, 2013), particularly on the part of private and privatised companies. In the early 1990s, enterprises were likely to give up state ownership due to financial distress (Sprenger, 2011). These specifics of Russian non-state ownership may shed some light on the reasons why instability of payment positively interferes with the probability of training among Russian employees.

Conclusion

Previous studies show that the transitional reforms failed to make human capital a major driver of the Russian economy. Although Russia became one of the most educated countries in the world, human capital maintenance has not become widespread among the working population, even across non-manual occupations, thus contributing to the growing critique of the knowledge economy. However, the positive examples of skills acquisition via training courses are more related to market-based incentives and thus display a greater meritocratic nature than was previously believed. Our study shows that skills training in Russia is primarily concentrated in confined, but human-capital-intensive niches of the labour market, found in employment in state-owned enterprises, skilled occupations, and responsible jobs such as managerial positions and professional and semi-professional vocations. These findings support the optimistic view of Russia as a ‘normal country’ becoming open to marketization and the private sector.

However, the transition of Russia to the fully fledged knowledge economy remains obstructed by mass employment in occupational niches representing disadvantaged jobs. This type of employment corresponds with low opportunities for workers in the labour market and thus impairs the chances of undertaking training. That is, the fact that being a part of ‘generic labour’ (which comprises about 60% of the Russian labour force) crucially decreases the probability of workers to undertake training remains one of the main determinants of qualification improvement in Russia. Nevertheless, the urban labour markets compensate for the adverse impacts of generic labour, thereby favouring semi- and low-skilled male workers to develop their skills.

Russia also provides evidence of another important challenge for training in a late industrial economy: a wide heterogeneity of skills formation among qualified non-manual workers. This heterogeneity is revealed in the significant non-linear impact of occupation-specific wage differentials on the probability of training. On the one hand, the wider the occupational wage gaps, the more likely workers are to receive training; on the other, when the occupational wage gaps become unbridgeable, the likelihood of investments in human capital declines sharply. The latter dynamic is notable chiefly for managers from market sectors such as administrative, commerce, production, and special services, thus indicating redistributive processes beyond skills pushing the remarkable wage gaps across these managerial positions.

Finally, the Russian case provides unusual support for the skill polarisation discourse: first, the probability of training among qualified workers varies remarkably; second, a substantial share of non-manual workers in Russia is composed of generic labour. However, there is distinct polarisation of skills formation 'at the bottom', which represents one of the main headwinds of the post-transition of Russia to a fully fledged knowledge economy. These findings add to our understanding of the controversial and diverse character of a late industrial society and Russian capitalism in particular.

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Appendix A

Description of variables

Variable name	Type	Description
Response variable		
Training	Binary [0;1]	Courses for the improvement of professional skills or any other courses over the last 12 months 1- Yes; 0- No
Single-level Independent factors		
Socio-demographics		
Male	Binary [0;1]	1- Male; 0- Female
Urban	Binary [0;1]	1- Urban; 0- Rural
Age	Scale	
Age squared	Scale	
Skills-specific characteristics related to knowledge-based economy		
Using personal computer at work	Binary [0;1]	Used a personal computer personal computer at work over the last 12 months 1- Yes; 0- No
Foreign language skills	Binary [0;1]	Speak foreign language 1- Yes; 0- No
Job-specific level		
Working time, more than eight hours a day	Binary [0;1]	1- Yes; 0- No
Job contract	Binary [0;1]	1- Working officially; 0- Not officially
Paid without delays	Binary [0;1]	1- Working officially; 0- Not officially
Individual-specific level		
Intentions to change the job	Binary [0;1]	Would prefer different work? 1- Yes; 0- No
Self-rated health	Nominal [1;30]	1- Excellent, 2- Good, 3- Bad
Self-rated qualification	Binary [0;1]	Self-evaluation of job skills 1- High step; 0- Low step
Satisfaction with growth opportunities at work	Binary [0;1]	1- Absolutely and mostly satisfied; 0- Neutral, Not very, and Absolutely unsatisfied
Organization-specific level		
Ownership	Binary [0;1]	1- Enterprise owned by the government; 0- Other ownership
Organisation size	Scale	Number of employees working in the organization
Higher level entities		
Occupational structure	Nominal [1;30]	Occupations coded via 2-digit code as per ISCO-88
Occupation-specific wage differentials (wage gaps)	Scale	Standard deviation of monthly wages (in thousands of rubles) by occupation, ISCO-88, 4-digit; taken as polynomial of the 1st order
Occupation-specific wage differentials (wage gaps^2)	Scale	Polynomial of the 2nd order of wage gaps
Occupation class	Binary [0;1]	0- Qualified non-manual workers; 1- Generic labour

Appendix B

Table B1

Fixed Effects Estimates (Top) and Variance-Covariance Estimates (Bottom) for the Models of the Socio-Demographic Predictors of the Probability of Training

Parameter	**Model 1**	Corr	Median	CI(2.5%)	CI(97.5%)	ESS	**Model 2**	Median	CI(2.5%)	CI(97.5%)	ESS
					Fixed effects						
Intercept (grand mean)	-3.783***		-3.772	-4.505	-3.134	127	-2.86***	-2.85	-4.067	-1.744	82
	(0.351)						(0.576)				
Wage-gaps: Standard deviation of monthly wages (in thousands of rubbles) by occupation, ISCO-88, 4-digit; taken as polynomial of the 1st order	0.126***		0.125	0.065	0.199	71	0.078***	0.076	0.029	0.133	289
	(0.035)						(0.026)				
Wage-gaps^2: Standard deviation of monthly wages (in thousands of rubbles) by occupation, ISCO-88, 4-digit; taken as polynomial of the 2nd order	-0.002***		-0.002	-0.004	-0.001	75	-0.002**	-0.002	-0.003	0	348
	(0.001)						(0.001)				
Age							0.03	0.029	-0.015	0.08	72
							(0.024)				
Age^2							-0.001**	-0.001	-0.001	0	75
							(0)				
Male							-0.333**	-0.332	-0.605	-0.065	5,209
							(0.138)				
Urban							0.361***	0.361	0.117	0.613	3,036

(continued)

Parameter	**Model 1**	Corr	Median	CI(2.5%)	CI(97.5%)	ESS	**Model 2**	Median	CI(2.5%)	CI(97.5%)	ESS
							(0.126)				
Occupational class											
Generic labour							-1.342***	-1.339	-1.851	-0.833	906
							(0.263)				
Cross-class interaction with gender and location											
Generic labour * Male * Urban							0.472**	0.472	0.064	0.88	4,510
							(0.209)				
Random parameters											
Variance of intercept											
Intercept/Intercept ($\sigma^2_{u_{0j}}$)	1.411**	1	1.311	0.666	2.737	1,538	0.325***	0.299	0.143	0.656	10,681
	(0.537)						(0.134)				
Covariance of intercept and slope											
Wage-gaps/Intercept ($\sigma_{u_{0j}}\sigma_{u_{1j}}$)	-0.04	-0.907	-0.037	-0.088	-0.012	803					
	(0.02)										
Variance of slope											
Wage-gaps/Wage-gaps ($\sigma^2_{u_{1j}}$)	0.001	1	0.001	0	0.003	712					
	(0.001)										
Model diagnostics											
DIC	3,513.555						3,450.835				
pD	27.955						27.143				
Level 2 units: Occupations, ISCO-88, 2nd digit	30						30				
Level 1 units: Respondent's Identifier	7,588						7,588				

Note. Both models are estimated using MCMC methods with 100 thousand simulations. Standard deviation (SD) from the chain of values in parentheses. Corr = correlation between intercept and slope. CI = Confidence intervals. ESS = Effective sample size. ESS is a parameter of Bayes diagnostics that used as a criterion for a sufficient number of MCMC simulations. It shows the 'restored' number of units of distribution of a parameter of interest. It is conventional practice to stop simulations when ESS is somewhat 350 or bigger. Here and later, when we use MCMC estimation so-called 'Bayesian p-value' (Bp) is calculated. The exception is the significance of parameters in random parts, which is calculated with the Chi-Square test. *** Bp <0.01, ** Bp<0.05, * Bp<0.1.

Table B2

Fixed Effects Estimates (Top) and Variance Estimates (Bottom) for the Models of the Socio-Demographic and Job-Specific Predictors of the Probability of Training

Parameter	**Model 3**	Median	CI(2.5%)	CI(97.5%)	ESS	**Model 4**	Median	CI(2.5%)	CI(97.5%)	ESS
					Fixed effects					
Intercept (grand mean)	-2.384*** (0.617)	-2.384	0.617	-2.384	168	-1.35* (0.694)	-1.321	-2.87	-0.08	159
Wage-gaps	0.064** (0.029)	0.064	0.029	0.064	497	0.081** (0.033)	0.079	0.021	0.152	417
Wage-gaps^2	-0.002** (0.001)	-0.002	0.001	-0.002	561	-0.002** (0.001)	-0.002	-0.004	0	484
Age	0.033 (0.028)	0.033	0.028	0.033	133	0.026 (0.029)	0.023	-0.025	0.091	135
Age^2	-0.001 (0)	-0.001	0	-0.001	136	0 (0)	0	-0.001	0	139
Male	-0.314** (0.144)	-0.314	0.144	-0.314	10,976	-0.311** (0.155)	-0.31	-0.618	-0.01	11,116
Urban	0.207 (0.135)	0.207	0.135	0.207	4,786	0.247* (0.146)	0.246	-0.034	0.533	5,872
Occupational class										
Generic labour	-0.787*** (0.285)	-0.787	0.285	-0.787	28,322	-0.822*** (0.28)	-0.825	-1.368	-0.265	18,617
Cross-class interaction with gender and location										
Generic labour * Male * Urban	0.364 (0.224)	0.364	0.224	0.364	9,588	0.504** (0.248)	0.503	0.019	0.993	9,014
Industrial society skills										
Foreign language skills	-0.162 (0.113)	-0.162	0.113	-0.162	10,757	-0.131 (0.121)	-0.131	-0.368	0.107	11,605

(continued)

Parameter	Model 3	Median	CI(2.5%)	CI(97.5%)	ESS	Model 4	Median	CI(2.5%)	CI(97.5%)	ESS
Not using PC at work	-0.736*** (0.128)	-0.736	0.128	-0.736	22,038	-0.745*** (0.142)	-0.745	-1.025	-0.468	22,221
No intentions to change the job	-0.285** (0.121)	-0.285	0.121	-0.285	7,878	-0.304** (0.131)	-0.305	-0.558	-0.047	7,932
Outlier										
Health professionals * Intercept	0.72* (0.413)	0.72	0.413	0.72	36,652	0.698 (0.428)	0.705	-0.165	1.518	40,046
Job-specific predictors										
Paid without delays during a year						-0.934*** (0.211)	-0.935	-1.341	-0.515	1,898
Work for non-state owned organisations						-0.423*** (0.127)	-0.423	-0.671	-0.176	15,303
Work for more than 8 hours						0.364*** (0.128)	0.364	0.112	0.615	24,942
Random parameters										
Variance of intercept										
Intercept/Intercept ($\sigma^2_{u_{0j}}$)	0.345** (0.146)	0.317	0.147	0.707	26,873	0.278** (0.128)	0.253	0.108	0.596	19,105
Model diagnostics										
DIC	2,924.33					2,540.68				
pD	30.821					32.006				
Level 2 units: Occupations, ISCO-88, 2nd digit	30					30				
Level 1 units: Respondent's Identifier	5,115					4,210				

Note. Both models are estimated using MCMC methods with 200 thousand simulations; hierarchical centring at level 2 is applied to speed up simulations. Standard deviation (SD) from the chain of values in parentheses. CI = Confidence intervals. ESS = Effective sample size. ESS is a parameter of Bayes diagnostics that used as a criterion for a sufficient number of MCMC simulations. It shows the 'restored' number of units of distribution of a parameter of interest. It is conventional practice to stop simulations when ESS is somewhat 350 or bigger. Here and later, when we use MCMC estimation so-called 'Bayesian p-value' (Bp) is calculated. The exception is the significance of parameters in random parts, which is calculated with the Chi-Square test. *** Bp <0.01, ** Bp<0.05, * Bp<0.1.

Table B3

Fixed Effects Estimates (Top) and Variance Estimates (Bottom) for the Models of the Socio-Demographic, Job-Specific and Self-Rated Predictors of the Probability of Training

	Model 5	Median	CI(2.5%)	CI(97.5%)	ESS	**Model 6**	Median	CI(2.5%)	CI(97.5%)	ESS
			Fixed effects							
Intercept	-1.536**	-1.534	-2.999	-0.146	310	-1.885**	-1.897	-3.311	-0.355	307
	(0.718)					(0.748)				
Wag gaps	0.079**	0.077	0.019	0.153	797	0.088	0.086	0.024	0.161	883
	(0.033)					(0.035)				
Wage-gaps^2	-0.002**	-0.002	-0.004	0	924	-0.002**	-0.002	-0.004	-0.001	988
	(0.001)					(0.001)				
Age	0.033	0.033	-0.027	0.097	261	0.036	0.037	-0.028	0.097	259
	(0.031)					(0.032)				
Age^2	-0.001	-0.001	-0.001	0	267	-0.001	-0.001	-0.001	0	268
	(0)					(0)				
Male	-0.298*	-0.297	-0.606	0.003	23,913	-0.283*	-0.282	-0.605	0.032	22,405
	(0.155)					(0.163)				
Urban	0.255*	0.253	-0.026	0.541	11,088	0.304**	0.304	0.007	0.604	10,378
	(0.145)					(0.153)				
Occupational class										
Generic labour	-0.628**	-0.628	-1.19	-0.064	26,456	-0.648**	-0.648	-1.238	-0.061	26,132
	(0.286)					(0.299)				
Cross-class interaction with gender and location										
Generic labour * Male * Urban	0.504**	0.505	0.016	0.994	18,384	0.586**	0.587	0.075	1.098	17,133
	(0.25)					(0.26)				

(continued)

	Model 5	Median	CI(2.5%)	CI(97.5%)	ESS	**Model 6**	Median	CI(2.5%)	CI(97.5%)	ESS
Industrial society skills										
No foreign language skills	-0.128 (0.12)	-0.129	-0.362	0.11	24,525	-0.105 (0.124)	-0.106	-0.348	0.141	24,578
Not using PC at work	-0.472*** (0.185)	-0.471	-0.838	-0.114	19,468	-0.436** (0.192)	-0.434	-0.818	-0.067	20,011
Cross-class interaction with skills										
Generic labour * Not using PC at work	-0.593** (0.276)	-0.593	-1.135	-0.052	17,300	-0.621** (0.29)	-0.622	-1.187	-0.05	17,728
No intentions to change the job	-0.301** (0.131)	-0.302	-0.555	-0.041	17,188	-0.39*** (0.142)	-0.391	-0.665	-0.11	15,701
Outlier										
Health professionals * Intercept	0.721* (0.427)	0.726	-0.131	1.545	72,832	0.782* (0.442)	0.787	-0.1	1.636	71,531
Job-specific predictors										
Paid without delays during a year	-0.941*** (0.212)	-0.944	-1.347	-0.515	3806	-1.02*** (0.215)	-1.023	-1.435	-0.588	4,080
Work for non-state owned organisations	-0.415*** (0.127)	-0.415	-0.663	-0.165	31,488	-0.424*** (0.133)	-0.425	-0.685	-0.164	31,263
Work for more than 8 hours per day	0.362*** (0.128)	0.363	0.112	0.612	49,929	0.35*** (0.135)	0.35	0.083	0.613	47,578
Self-rated predictors										
Self-rated health (Good – ref. cat.)										
Neither good, or bad						0.22** (0.122)	0.22	-0.021	0.46	28,005
Bad						0.278 (0.306)	0.285	-0.347	0.856	69,640

(continued)

	Model 5	Median	CI(2.5%)	CI(97.5%)	ESS	**Model 6**	Median	CI(2.5%)	CI(97.5%)	ESS
Self-rated qualification level (Natural log centred at grand mean)						0.028 (0.185)	0.026	-0.327	0.398	47,179
Satisfaction of professional growth at work						0.344*** (0.121)	0.344	0.11	0.581	28,108
Random parameters										
Variance of intercept										
Intercept/Intercept ($\sigma^2_{u_{0j}}$)	0.256** (0.122)	0.232	0.095	0.558	36,316	0.237* (0.124)	0.212	0.073	0.545	25,799
Model diagnostics										
DIC	2,539.3					2,359.62				
pD	32.655					36.426				
Level 2 units: Occupations, ISCO-88, 2nd digit	30					30				
Level 1 units: Respondent's Identifier	4,210					3,934				

Note. Both models are estimated using MCMC methods over 400 thousand simulations; hierarchical centring at level 2 is applied to speed up simulations. Standard deviation (SD) from the chain of values in parentheses. CI = Confidence intervals. ESS = Effective sample size. ESS is a parameter of Bayes diagnostics that used as a criterion for a sufficient number of MCMC simulations. It shows the 'restored' number of units of distribution of a parameter of interest. It is conventional practice to stop simulations when ESS is somewhat 350 or bigger.

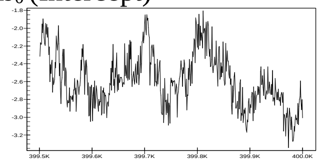
Here and later, when we use MCMC estimation so-called 'Bayesian p-value' (Bp) is calculated. The exception is the significance of parameters in random parts, which is calculated with the Chi-Square test.

*** Bp <0.01, ** Bp<0.05, * Bp<0.1.

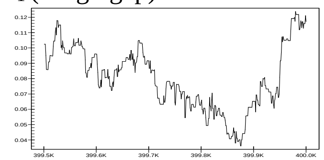
Appendix C

MCMC Diagnostics for the Estimated Parameters, Final Model

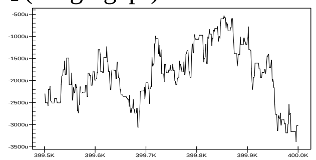
ß$_{0}$ (Intercept)



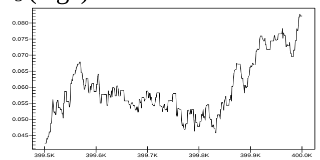
ß$_{1}$ (Wage-gap)



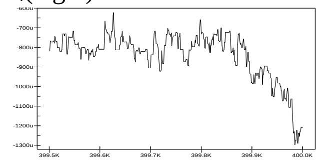
ß$_{2}$ (Wage-gap^{2})



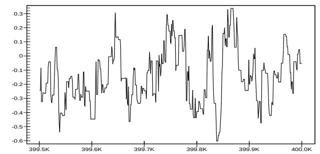
ß$_{3}$ (Age)



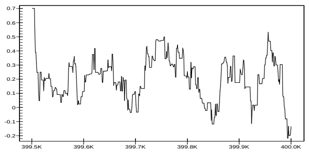
ß$_{4}$(Age^{2})



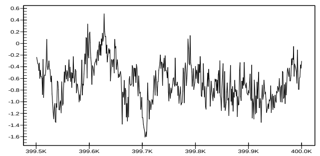
ß$_{5}$ (Male)



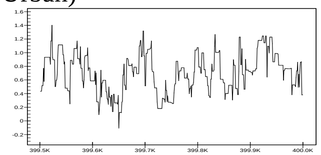
ß$_{6}$ (Urban)



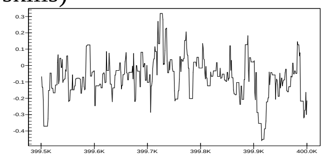
ß$_{7}$ (Generic labour)



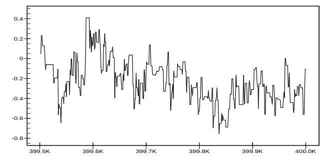
ß$_{8}$ (Generic labour * Male * Urban)



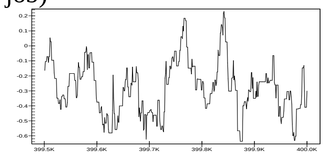
ß$_{9}$ (No foreign language skills)



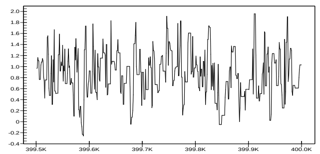
ß$_{10}$ (Not using PC at work)



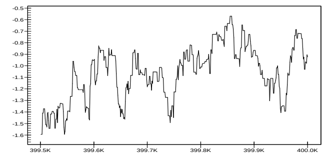
ß$_{11}$ (No intentions to change the job)



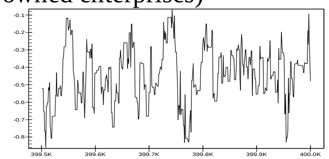
ß$_{12}$ (Health professionals)



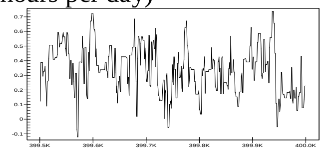
ß$_{13}$ (Paid without delays)



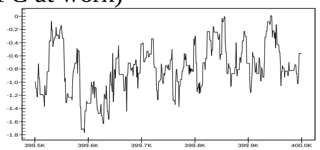
ß$_{14}$ (Work for non-state owned enterprises)



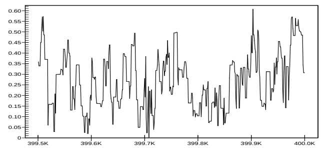
ß$_{15}$ (Work for more than 8 hours per day)



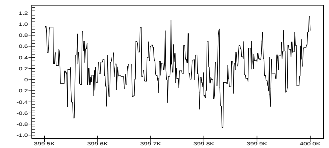
ß$_{16}$ (Generic labour * Not using PC at work)



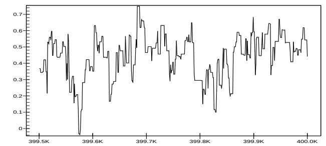
ß$_{17}$ (Self-rated health (neutral)



ß$_{18}$ (Self-rated health (bad))



ß$_{19}$ (Self-rated qualification)



ß$_{20}$ (Satisfied of professional

ß$_{21}$ (Size of organisation, ln)

ß$_{22}$ (Size of organisation, ln^{2})

$\sigma^2_{u_{0j}}$ (Variance of intercept) growth)

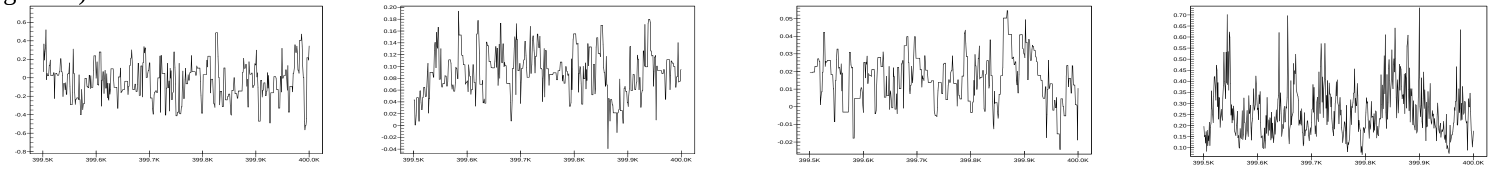
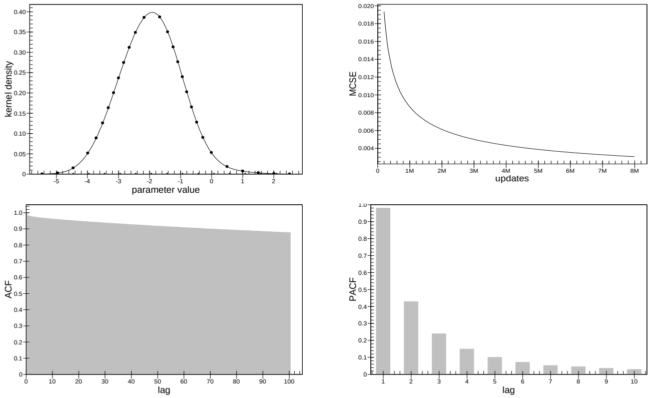
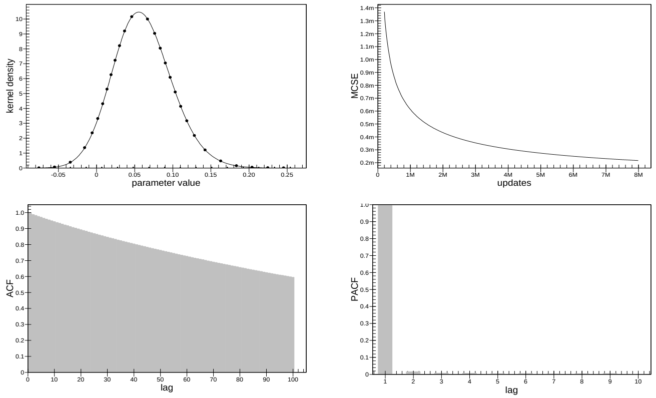
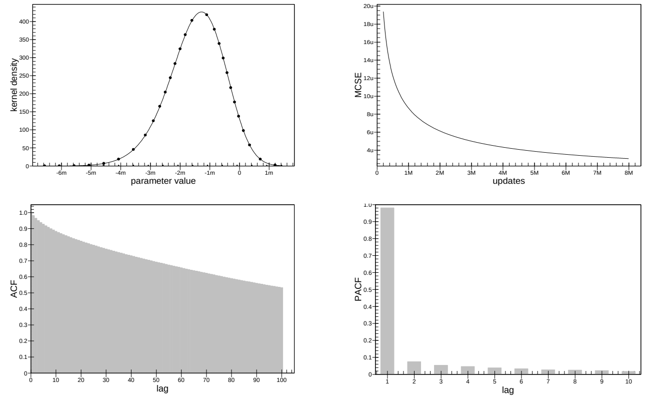


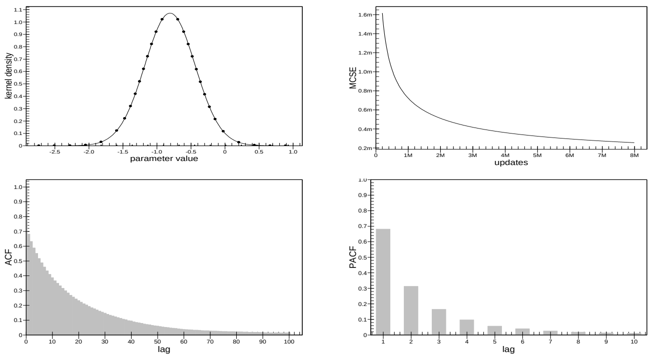
Figure C1. Trajectories of the parameters over the chain for 400 thousand iterations (last 500 shown), from the final model ß$_0$ (Intercept) ß$_1$ (Wage-gap) ß$_2$ (Wage-gap^2)

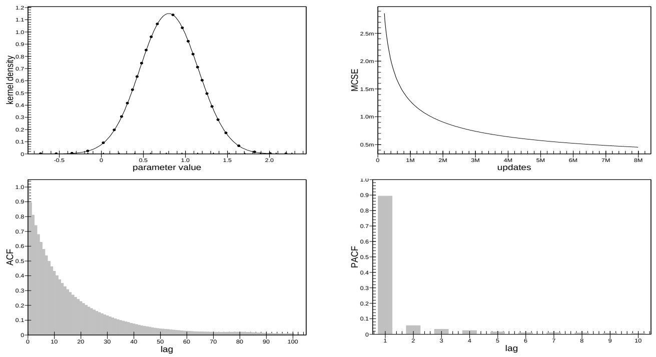


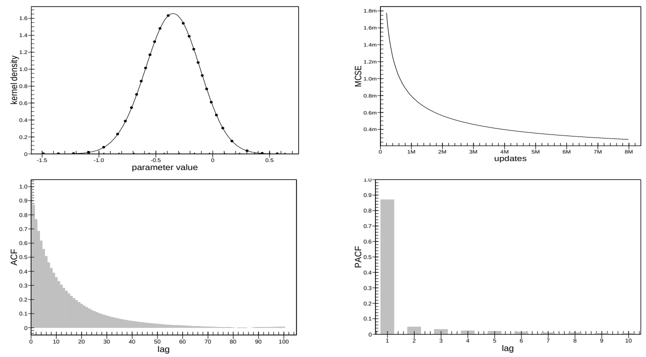




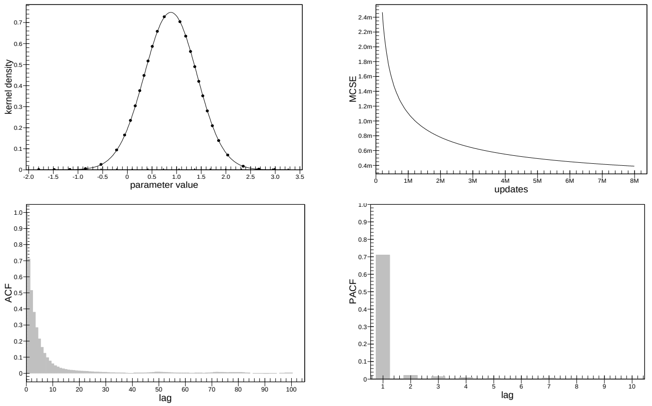
ß$_7$ (Generic labour) ß$_8$ (Generic labour * Male * Urban) ß$_{10}$ (Not using PC)



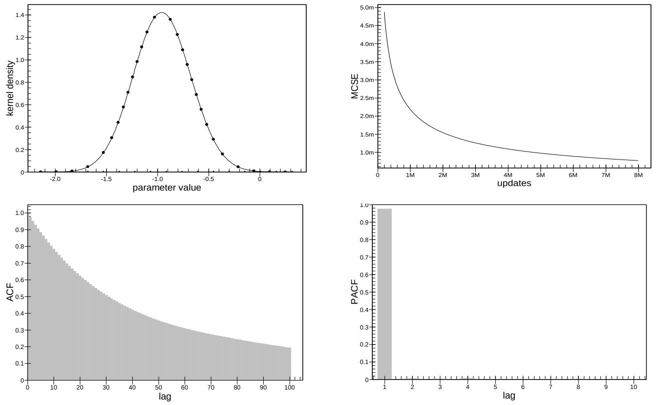




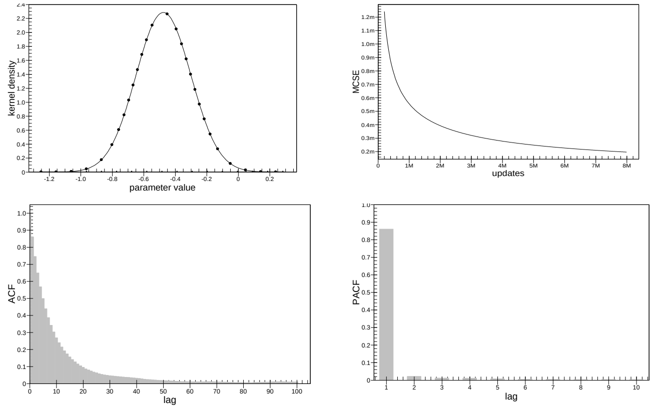
ß$_{12}$ (Outlier interacted to intercept) ß$_{13}$ (Paid without delays) ß$_{14}$ (Work for non-state owned enterprises)



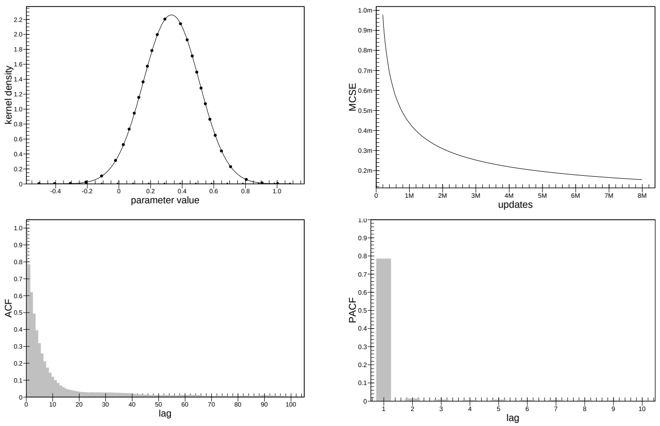
ß$_{15}$ (Working for more than 8 hours per day)



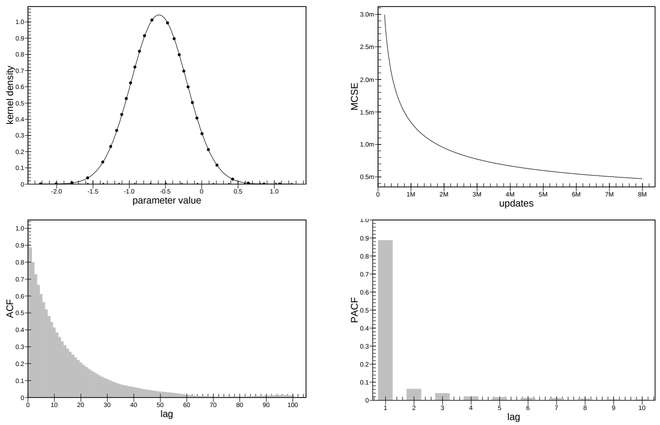
ß$_{16}$ (Generic labour * Not using PC)



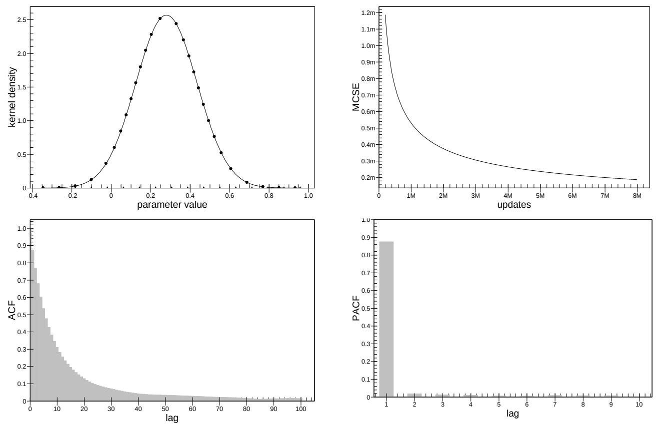
ß$_{17}$ (Self-rated health)



ß$_{19}$ (Satisfied of professional growth)



ß$_{21}$ (Size of organisation, ln)



$\sigma^2_{u_{0j}}$ (Variance of intercept)

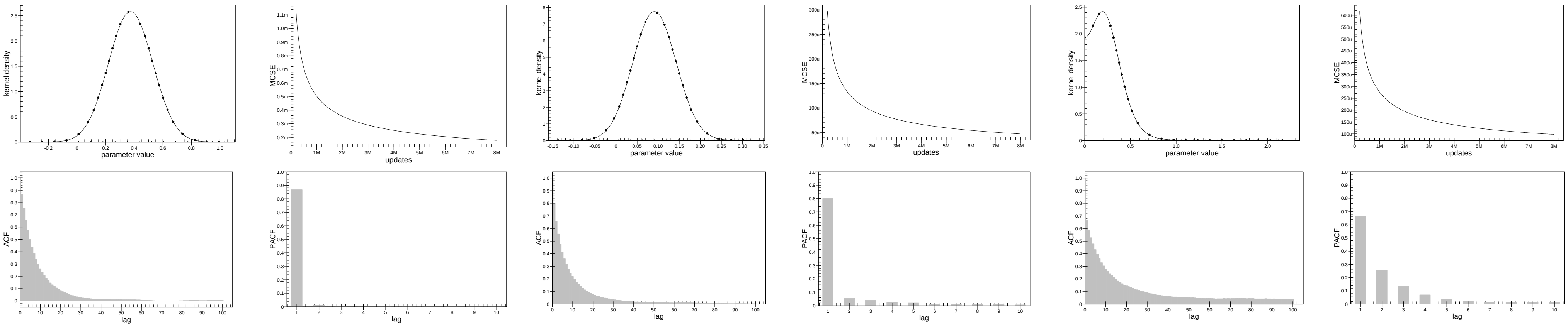


Figure C2. MCMC diagnostics of statistically significant coefficients, from the final model (4). The density of most of the parameters estimated look like kernel plots that show a substantial probability of a value less than zero.

Appendix D

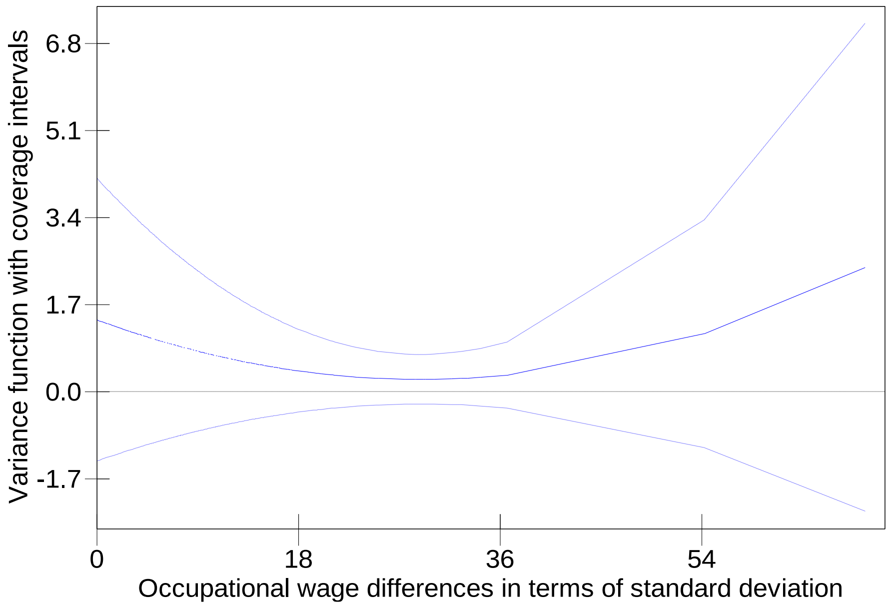
Summary statistics and accuracy diagnostics for the significant coefficients, Final Model

Parameter	Summary statistics				Accuracy diagnostics	
	Posterior mean	MCSE	Mode	ESS	Raftery-Lewis (quintile)	Brooks-Draper (mean)
$ß_0$	-1.960	0.014	-1.915	277	Nhat = (27058,84650)	Nhat = 115237
$ß_1$	**0.060**	**0.001**	**0.055**	**922**	**Nhat = (99260,144744)**	**Nhat = 5768429**
$ß_2$	-0.001	0.000	-0.001	1137	Nhat = (82378,52522)	Nhat = 115525
$ß_7$	-0.811	0.001	-0.807	17580	Nhat = (7099,6837)	Nhat = 80425
$ß_{10}$	-0.355	0.001	-0.349	21273	Nhat = (20970,19622)	Nhat =97121
$ß_{12}$	0.876	0.002	0.884	69261	Nhat = (14496,14742)	Nhat =186922
$ß_{13}$	**-0.955**	**0.003**	**-0.958**	**3827**	**Nhat = (50342,54660)**	**Nhat =731092**
$ß_{14}$	-0.475	0.001	-0.475	28450	Nhat = (19453,20331)	Nhat =47419
$ß_{15}$	0.333	0.001	0.332	49941	Nhat = (16147,16258)	Nhat =29403
$ß_{16}$	-0.590	0.002	-0.590	18343	Nhat = (21156,22873)	Nhat =275562
$ß_{17}$	0.280	0.001	0.279	2445	Nhat = (19922,20940)	Nhat =43273
$ß_{19}$	0.375	0.001	0.375	29196	Nhat = (20886,22070)	Nhat =38836
$ß_{21}$	0.092	0.000	0.091	34275	Nhat = (19218,17315)	Nhat =271289
$\sigma^2_{u_{0j}}$	0.237	0.000	0.195	25799	Nhat = (11530,6460)	Nhat =11711

Note. Estimations from the Raftery-Lewis diagnostic shows that we have no need to run for more times our current run length. The only exception is $ß_1$ (wage-gap) and $ß_{13}$ (paid without delays). These parameters are bold.

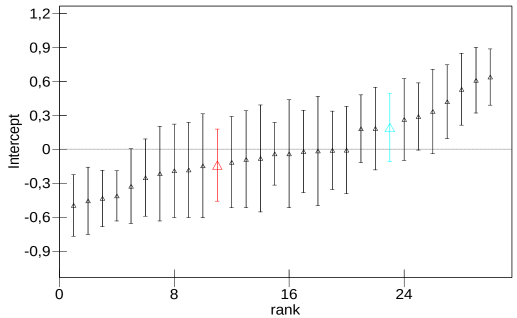
Appendix E

Quadratic Variance Function with coverage intervals, Model 1



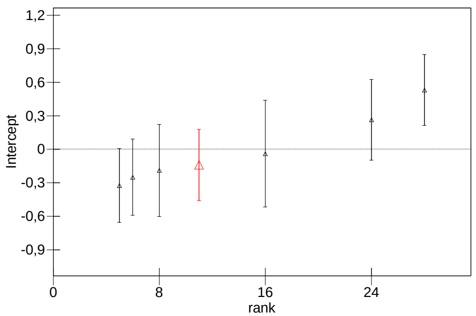
Appendix F

Second-level residuals, by gender and ownership, Model 7

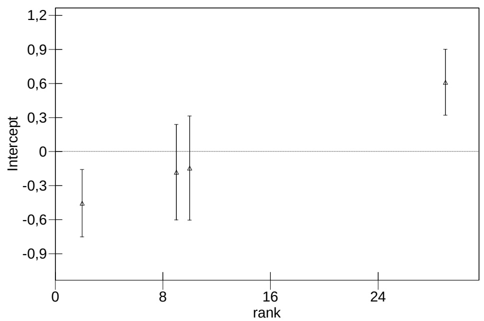


Female

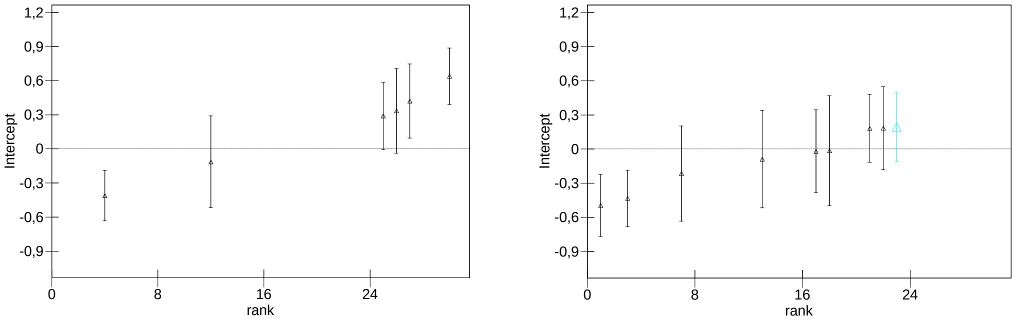
Private and mixed ownership



State ownership



Male


1,2
0,9
0,6
0,3
0
-0,3
-0,6
-0,9
Intercept
0
8
16
24
rank
1,2
0,9
0,6
0,3
0
-0,3
-0,6
-0,9
Intercept
0
8
16
24
rank

A version of this paper was discussed as "Skills Training in India: Market or Privilege?" at the 14-th European Association for Comparative Economic Studies Conference «Comparative Economic Development in the Long Run», 8-10 September 2016, Regensburg, Germany.

SKILLS TRAINING IN INDIA: MARKET OR PRIVILEGE?

Abstract

This paper targets issues relating to the socio-economic development of contemporary India by studying the economic and non-economic contributory factors of formal vocational training. Drawing on data from the 2011–12 National Sample Survey (NSS) 68th Round, the author notes that skills development in India has a contradictory nature as it involves both market and non-market characteristics. Applying the four-level cross-classified Markov chain Monte Carlo (MCMC) logistic regression to the probability of formal training, the author highlights that the market nature of skills training in India is revealed in the significance of some of its economic factors such as the inequality that exists between occupations, enterprises' size, availability of permanent employment, and some human capital characteristics such as tertiary-education attainment and skills. Moreover, this study proves that, in contemporary India, women are more likely to receive formal training than men. However, non-market characteristics of skills acquisition in contemporary India remain very high. They are revealed in the statistically significant impact of ascription – i.e. socio-demographic determinants (such as age, household size, marital status, and religion). This paper indicates that the differences between families and regions explains considerable portion of variations in the probability of acquiring training (60% and 9%, respectively). Obtained results contribute to the literature suggesting India is a society with pre-industrial modes of development and focuses on the importance of within-region diversity in explaining different socio-economic performances of BRIC countries.

Introduction

Skills training is the primary factor in socio-economic development in industrial societies, boosting productivity and growth (Konings & Vanormelingen, 2015; Sala & Silva, 2013) and reducing poverty (Nilsson, 2010). In such societies, skills, knowledge, and expertise are the principal assets that stratify employees' opportunities in the labour market, their negotiation power in their organisations, and their positions in the occupational hierarchy (Bukodi & Goldthorpe, 2011; Erikson & Goldthorpe, 1992; Grusky, 2001). However, India still retains signs of a pre-industrial mode of development, that is, 68.4% of Indians reside in rural areas, while 47% work in the agricultural sector. Thus, at least half of the population 'experience' life of an agrarian society, which involves limited access to knowledge and skills, despite national efforts to promote these capabilities (Jamal & Mandal, 2013). According to the National Sample Survey (NSS) (2012), the very low incidence of formal vocational training in contemporary India is quite obvious, constituting 2.6% of the adult population, while 8.2% undertake varying types of non-formal training; furthermore, most of these people are self-funded.

In such an environment, the 'role of ascription' – i.e. gender, age, race, ethnicity, religion, caste, etc. – is crucial (Grusky, 2001), particularly in determining the acquisition of knowledge and skills. Although the vast literature on training normally includes consideration of demography, most of the estimates are applicable to industrially developed societies of the US (Acemoglu & Pischke, 1999), Australia (Tharenou, 1997), and European countries (Arulampalam, Booth, & Bryan, 2004; Booth & Bryan, 2005; Green & Zanchi, 1997), so there is a lack of research on the determinants of skills training in India, particularly in regard to ascription.

Concurrently, India demonstrates economic growth and the on-going development of urban economy and service infrastructure (Tiwari et al., 2015). In the literature, there is a stream showing that the liberalisation and tertiarization[*] of India during the 1990s is considered to have played a crucial role in the relatively intensive economic development of the country in recent decades (Arora, Arunachalam, Asundi, & Fernandes, 2001). Although tertiarization has affected the secondary sector[†] of the Indian economy, primarily by discouraging growth in manufacturing industries and real production, it has considerably enhanced the volume of educated people. As a complementary part of tertiarization, India overwhelmingly supports women, their welfare, human capital acquisition, and employment. Article 15 of the Indian constitution directly justifies positive discrimination in favour of women and the Ministry of Women and Child Development of the Government of India aims to propose the policy by various programs[‡]. Testing out the tertiarization hypothesis in the Indian context we will thus gain from arguing for institutional explanation of gender bias in human capital acquisition (Dämmrich & Blossfeld, 2017).

All these result in arguments concerning the marketization of human capital and decreasing the role of domestic duties; in contrast, it actualises the more common discourse in Western societies concerning the role of education attainments (Nikolai & Ebner, 2012) and market-based factors of human capital acquisition (Davis & Moore, 1945), wage differentials (Coulombe & Tremblay, 2007), employment relationships, organisation-specific factors, and ‘skill-based occupational groupings’,

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[*] By the term ‘tertiarization’, we mean a promotion of tertiary education that results in a growing number of people graduating from professional (vocational) schools and universities.
[†] We apply a general view on sectors of the national economy: primary (extracting, agriculture, fishery and related activities), secondary (industrial production), tertiary (service economy), and quaternary (information and images services).
[‡] For instance, one can mention ‘Support to Training and Employment Programme for Women (STEP)’ Scheme’ administrated by the Ministry since 1986-87 as a ‘Central Sector Scheme’. See: http://wcd.nic.in/schemes/support-training-and-employment-programme-women-step. Access checked 20 November 2017.

which are the major strata in advanced industrial societies (Grusky, 2001, p. 9). From this perspective, we expect training and skills acquisition in India to be significantly associated with female gender, occupational structure and occupation-specific determinants, the nature of employment, the type of written job contract, the method of payment, and enterprise size and ownership.

Concerning industrial societies, occupational diversity on the job market exists not only between occupations but also within them (Gallie, 1991; Lambert & Bihagen, 2016). Differentials in wages indicate this intra-occupational diversity within occupations. Both workers and employers are aware of wage spreads within their occupation and can rely on this information when making decisions for their career growth. These decisions become related to skills development should the variation in wages within occupations signal premium payoffs for higher-qualified workers in the same occupation. Essentially, the link between training and wage differentials within occupations reveals one of the most important characteristics of industrial society – the differentiation of occupations depends on the skills required, the capacity to work, nature of the work, and job specifications.

We assume that the contradictory nature of skills development in India is a result of India's controversial modernization. India has become a country where high-qualified jobs in skills-intensive enterprises coexist with unskilled and routine labour in agriculture. This inconsistent economy contains quasi-market or even non-market lacunas, which are barely regulated by the mechanisms of demand and supply. In India, markets are notably fragmentized because of 'ascriptive inequalities' (Grusky, 2001; Linton, 1936) that rarely constitute achievements through merit, but are ascribed through status such as gender, age, location, caste, and religion. Furthermore, these so-called 'unfair inequalities' (Li & Wang, 2013) are synthesized with different types of labour market and their diversities. Gender and location greatly disperse occupations in countries engaging in catch-up development, like Russia (Anikin, 2012, 2013); thus, we must account for occupational effects in relation to socio-demographics; however, researchers usually ignore the joint effects of both.

In this paper, we use the NSS (2012), Round 68, Schedule 10 ‘Employment & Unemployment Survey’, issued by the National Sample Survey Office (NSSO), Government of India. These household data are deeply structured containing, besides households, multi-layered data on geography and occupations. In order to estimate both geographical and occupational propensity for qualification improvement by considering the structural heterogeneity of the data, we apply a specific version of multilevel modelling: cross-classified models with interactions, as they provide statistically efficient estimates of regression coefficients (Goldstein, 2011). The Bayesian approach is employed to fit the models. Using Markov chain Monte Carlo (MCMC) method to fit multilevel models with binary response produces precision-weighted estimates (Browne, 1998), especially in cases that comprise few units (Goldstein, 1995).

Flip side of tertiarization in India

Skills development is better understood by analysing the broader socio-economic context and modernization of India over the past 30–40 years. Compared to the other BRIC countries, the modernization of India has been very controversial. Despite intensive technological reform of its non-agricultural sectors, Indian society remains predominantly rural, and one-quarter remain illiterate (see Table 1); the Indian economy predominantly comprises unorganized sectors with weak enforcement.

The socio-economic modernization of India is based on the idea of creating a 'beneficial state' (Corbridge, 2009) governed by a planning commission that produces a series of five-year plans. For this reason, when studying India, it is important to consider the role of the government. The Indian economy is centralised and integrated according to a national plan that is established, executed, and monitored by the planning commission every five years.

It was originally believed that the Indian government would be able to reroute resources from agricultural to non-agricultural sectors 'without much rural backlash' (Tiwari et al., 2015, p. 4); however, the government has instead reduced institutional investments to the infrastructure of the primary sector (Patel & Bhattacharya, 2010). This disparity has also postponed the land issue. According to Montalvo and Ravallion (2010) and Ravallion (2011), the latter seems to be a key issue in regard to India's development because of the overpopulation of rural areas where the majority of peasants do not possess any land. Above all, agriculture and, therefore, population welfare is still greatly vulnerable to climate change and natural disasters.

The informal sector is a major employer in India, even in urban areas. In non-agricultural sectors, informal employment rose 13% in response to the reforms of the 1990s, and remains very high, reaching 83.6% at one point (see Table 1). According to the NSS (2012), only 25.2% of employees in India worked as regular salaried or wage employees; 56.5% had no written job contract with their employer, and 20.1% worked as casual wage labour engaged in different types of work (except public works) without any written job contract (98.6%). Approximately 72% of the employed population did not have written job contracts with their employers, and less than half the working people were in paid employment. Over one-third of employees (37%) worked in household enterprises on a self-employment basis, whereas 14.9%

worked as helpers in household enterprises without any payment. Consequently, it makes sense to expect that formal training and skills acquisition in India may be concentrated towards acquiring gainful employment in more privileged positions, such as those that include written job contracts, permanent employment, regular payments, and jobs in large and industrially advanced enterprises.

Table 1

Developmental Statistics for India, 1980–2012

Socio-economic statistics	*1980*	*1990*	*2000*	*2005*	*2011*
GDP p.c. PPP (current international $)	419.9	873.8	1528	2209	3650
Employment in agricultural sector, %	-	60.5	59.9	55.8	51.1 [a]
	1985-89	*1990-94*	*1995-99*	*2000-07*	*2009-10*
Informal employment in non-agricultural sectors [b]	76.2	73.7	83.4	83.5	83.6
Socio-demographic statistics	*1980*	*1990*	*2000*	*2005*	*2011*
Urban population	23.1	25.5	27.7	29.2	31.6 [a]
Age dependency ratio	72.4	65.6	54	51	47.4
Literacy [b]	43.6	52.2	64.8	-	74
Educational statistics	*1995*	*1999*	*2003*	*2005*	*2011*
Educational expenditure in tertiary as % of total educational expenditure	-	17.5	20.1	16.6	35.9
Current expenditure on education as % of GNI	3.1	4.3	-	3.1	-
	1990	*2000*	*2002*	*2004*	*2006*
Personal computers (per 100)	0	0.4	0.9	1.5	3.2
	1996	*2002*	*2007*	*2010*	*2012*
Internet users (per 100)	0	1.5	4	7.5	12.6

Source: Socio-economic statistics, CIA (2013); IMF (2013); World Development Indicators (2013b)
Socio-demographic statistics and data on India were compiled from United Nations (2013). For detailed sources, see United Nations (2012) and World Development Indicators (2013a).
Educational Statistics, Development Data (2013)
Notes: [a] Employment in the agricultural sector is calculated for 2010. Urban population is calculated for 2012.
[b] Normally, researchers consider the informally employed to be those who work without a written job contract or who are not full-time employees. The pattern of informal employment varies in each country (Charmes, 2012). In India, informal activity is concentrated in the form of unorganized casual labour (Arnal & Förster, 2010). Data on India (2009/2010) were compiled from the ILO statistics questionnaires (ILO, 2012). Data for the other time points are covered by (Jutting & Laiglesia, 2009). Data on literacy in India were compiled from the Census of India 1981/1991/2001/2011.

The majority of India's working population still possess poor skills or none at all, possessing only the capacity to perform simple manual labour. Over one-fifth* of the labour force are illiterate (see Table 1), and almost two-thirds (63%) live in rural areas with restricted access to necessary social services. As observed in Table 2, almost 65% perform manual work, and roughly half of these people work as unskilled labour.

Table 2

Occupational Structure of India as % of labour force, 2012

Occupations [a]	Gender		Area		Literacy		Persons
	Males	Females	Rural	Urban	Non literate	Literate	
1. Managers	**87**	13	42.9	**57.1**	10.4	**89.6**	9.4
2. Professionals	**79.3**	20.7	40.6	**59.4**	2.8	**97.2**	5.7
3. Semi-professionals	72	**28**	49.8	**50.2**	1.5	**98.5**	5.9
4. Clerks	**83.1**	16.9	34.9	**65.1**	0.9	**99.1**	2.8
5. Sales and services workers	**84.5**	15.5	46.8	**53.2**	11.4	**88.6**	11.6
6. Orientated to market agricultural and fishery workers	70.9	**29.1**	**91**	9	**28.1**	71.9	25.7
7. Craft and related trades workers	**82.8**	17.2	54.7	**45.3**	**21.8**	78.2	13.7
8. Plant and machine operators and assemblers	**96**	4	49	**51**	11.7	**88.3**	5.5
9. Elementary occupations	73.5	**26.5**	**69.8**	30.2	**38.8**	61.2	19.5
Total, %	78.4	21.6	63	37	21	79	100
N	123,696	34,052	99,383	58,365	33,176[b]	124,554[b]	157,748

Source: National Sample Survey (2012), calculations computed by the author.
Note: [a] The National Classification of Occupations (NCO-2004) made by the Directorate General of Employment and Training (DGE&T) was used to compile data on occupational groupings. NCO-2004 retains the pattern of classification of occupations adopted in ISCO-88. As a result, DGE&T applies the same labels for 'occupational divisions' – 'major occupation groups' in ISCO-88 terminology.
[b] Instead of N=157,748 we get a total of 157,730 when checking the literacy level of working Indian people – 18 individuals were excluded due to missing values.

* For the rest of this paper, only statistically significant results are published with at least a less than 5% probability of a mistake ($\alpha<0.05$). The numbers are sourced using the chi-square test routine by considering the adjusted residuals in the cross-tabulations of the quantities of interest.

Others relate to a low- or semi-qualified labour force. Notwithstanding a tertiarization trend, the relative share of qualified non-manual workers is still infinitesimal – 5.7%. If we consider that even some 'professionals' are illiterate (which seems paradoxical because being literate is an essential requirement for specialists whose job, by definition, 'requires' higher education) this number would be even smaller. In general, this funnels education investments towards well-educated groups and inhibits the popularisation of formal training programs among unskilled labour. Having no knowledge and skills, employees have few opportunities to improve their qualifications through formal training (Jamal & Mandal, 2013) – they require basic education.

Hypothesis 1 predicts that occupational structure significantly contributes to incidences of training in contemporary India. Moreover, in line with this meritocratic course, **Hypothesis 1.1** says that *skilled occupations are more likely to be associated with the development of human capital than low-skilled or unskilled occupations*. Finally, **Hypothesis 1.2** predicts that *higher educated workers are more likely to be involved in skills acquisition*, which coincides with previous research on Western countries (Booth & Bryan, 2005; Nikolai & Ebner, 2012).

Educational expenditure on tertiary education (taken as a percentage of total educational spending) has increased on two occasions between 2005 and 2011, although current expenditure on education (taken as a percentage of GNI) has remained the same. Combined with the liberalisation of the caste system, the tertiarization has pushed women into the labour market and promoted moderate-skills jobs requiring training; this combination has consequently broadened the social base of people applicable for formal vocational training. In addition, a relative share of Internet users is a very useful indicator, as it provides auxiliary information on the opportunities available for people aiming to improve their qualification. Despite this positive trend, India still has a negligible number of individuals engaged in informational technology (12.6 Internet users per 100) when compared to other BRIC countries. For example, according to World Bank data, in Russia 53.3% used the Internet in 2012; although this is an increase on a survey conducted 10 years earlier, the spread of Internet users among the population remained the same (4.1 users per 100, in 2002). Information technologies as an instrument of acquiring new knowledge and skills are available to a very limited segment of the Indian population. However, it can play a significant role in reducing the costs and barriers of vocational training for the population.

Institutional framework of skills training in tertiarized India

India has set a target of raising the skills of 500 million people by 2022 and is investing heavily in vocational training (Department for Education & Department for Business, 2013). The eleventh Five-Year Plan launched the National Skill Development Mission, and resulted in the creation of a three-tier institutional structure. Some of these programs are considering skills development through programs that focus on both formal and informal sectors, which also encourage vertical mobility – e.g. Vertically Integrated Engineering Programme launched by The Indira Gandhi National Open University. The twelfth Five-Year Plan (2012–2017) announced the necessity of training and equipping workers—especially teachers—continuously with latest skills.

The government of India produces a variety of training programs promoting skills for different categories of workers (e.g. Advanced Vocational Training Scheme for specialists), nature of work and particular occupations (e.g. Craftsman Training

Scheme), and specialty (Apprenticeship Training Scheme); they also address disparities in sectors (e.g. Advanced Vocational Training Scheme) and gender employment (Women-training Scheme, Research and Staff Training). These programs are directly aimed at equipping people with specific on-the-job marketable skills. Such broad governmental initiatives are focused on promoting skills development and learning, however, it is difficult to identify their results (Jamal & Mandal, 2013).

Ascription in contemporary India

Given the institutional barriers for vocational training in India (Hajela, 2012), we assume that the low incidence of training is determined by the 'rigid' socio-cultural background that hampers vertical movements. Indian society is historically stratified by non-merit attributes embedded in castes or *jati* (particularly in Hindu society) that still generate a significant portion of economic discrimination in modern India (Thorat & Neuman, 2012). From a cultural perspective, the 'stratification system of a caste society' (Grusky, 2001) is traditionally maintained by reproductive and non-achievement orientations—'traditional and survival' values (Inglehart, 1997) or the 'tradition, conformity and security' value dimension (Schwartz, 1994)—that are commonly shared by peasant societies named in modernist theories as societies based on 'tradition' (Maine, 1834), Gemeinschaft (Tönnies, 1887), based on ascription and traditional societies (Inglehart & Welzel, 2009; Lerner, 1958). Therefore, **Hypothesis 2**, in contrast to Hypothesis 1, predicts that *ascription best explains the incidence of training in contemporary India*.

Ascription is strongly associated with socio-demographics, particularly with gender. India is a country with a significant gender bias. Demographers use 'Sex

Ratio' (the number of females per 1000 males) to describe this bias. In the Population Census of 2011, the Sex Ratio was 1.06. Although it has lowered considerably over the last decade, the role of gender is still very high. Demographers believe that this bias stems from a structural violence that limits the life chances of women in education. Modernization theory normally expects a higher gender bias in traditionalistic societies because of a strict segregation of male and female roles. Women are supposed to perform domestic duties, whereas men are more active outside their households, selling their labour in the market. Moreover, a gender bias in skills acquisition would be the result of physical assets that play a principal role in pre-industrial societies. Polavieja (2012, pp. 594-595) highlights that more powerful individuals (i.e. male employers, male co-workers, and male supervisors) can exclude status inferiors (i.e. women) from the best and most profitable jobs, which tend to be those requiring specific training (Tomaskovic-Devey & Skaggs, 2002). Ultimately, according to discrimination and social closure identification approaches, firms are more likely to train male workers (Evertsson, 2004; Fernandez-Mateo, 2009).

For gender to be a significant determinant of training, 'the gender hypothesis', **Hypothesis 2.1**, predicts that in a traditional society *males are more likely to undertake training than females*. The alternative **Hypothesis 2.1(A)** concerns the role of tertiarization and formal institutional arrangements, which softens the structural violence against females and, therefore, reduces the disparities in the life chances of men and women. Essentially, tertiarization helps women to swim against the current (Polavieja, 2012), thus making them more active than men in the acquisition of post-schooling learning and training.

Castes and religion

As mentioned above, the caste system can be an important determinant of skills acquisition in contemporary India. The role of caste is saliently obvious in studies that focus on occupations and human capital activities. Individuals from lower (or exterior) castes are still excluded from good education, jobs, activities, and social contacts. Social segregation alone does not promote this form of pre-industrial social exclusion; caste-ground culture (based on prejudices) also contributes heavily to the lack of schooling, self-motivation, and severe poverty.

Some researchers argue that the significance of the 'caste system' in contemporary India should not be exaggerated, despite knowing that Indian politics still continues to be informed by caste identities (Corbridge, Harriss, & Jeffrey, 2013). These scholars suggest that hierarchical rankings of castes are far less accepted now than fifty or hundred years ago. Nevertheless, the caste system is still present and reproduced. The remaining order of India's social hierarchy may be supported by 'a pervasive cultural consensus between the Untouchables and the higher castes…' (Moffatt, [1979] 2015, p. 5), rather than cultural complementarities. The primary evidence provided by Moffatt suggests that the Untouchables replicate the institutions and ranked relations from which they have been excluded. The power of higher castes operates by obedience rather than coercion. Untouchables construct their identity by obtaining an internal locus of control over performing mandatory, socially relevant duties (castes' specific roles).

Above all, past literature indicates that incidences of poverty in scheduled castes (SC) and scheduled tribes (ST)* is significantly higher than in other social

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* The government of India applies a classification of external castes – scheduled castes and other downward classes. Being an author of the *Report on the Census of India*, 1931, which contributed considerably to the system of censuses in India by elaborating the classifications and registration rules for castes nationwide, Hutton (1963) highlights that the facts and considerations taken into account in

groups (Borooah, 2005; Gang, Sen, & Yun, 2008; Tendulkar, Radhakrishna, & Sengupta, 2009). John and Mutatkar (2005) demonstrate that some religious groups in India are more associated with poverty than others. Drawing on the 55th round of NSS data, the authors documented that the average monthly per capita expenditure of Muslims is lowest in both rural and urban India, whereas the average monthly per capita expenditure of Sikhs and Christians is the highest. Following this, **Hypothesis 2.2** *predicts the low incidence of training among these religious groups, as well as scheduled castes (SCs) and scheduled tribes (STs)*. This hypothesis seems quite reasonable if we consider the occupational bias of religious groups and castes in contemporary India. For example, Muslims are more likely to work as casual labourers than other religious groups (John & Mutatkar, 2005).

Administrative geography and location

Geography is also important in regard to the role of ascription in acquiring vocational education and training in contemporary India (Agrawal, 2012). Some arguments stem from political economy concerning climate conditions and distance from the equator, which are presented as important contributing factors to economic performance (Masters & McMillan, 2001). From a sociological perspective, India is a country of numerous local disparities, which exist between geographic entities on different levels (Kim, Mohanty, & Subramanian, 2016). In rural areas, the core elements of social geography are the communities that historically represent settled castes.

Although castes are historically closely associated with local communities, states and castes are not linearly associated with each other. For example, Zinkin (1965, p. 27) highlights that the Brahmins of Orissa do not plough, as compared to

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determining what constitutes a depressed caste should be consistent across India. These criteria are subjectively elaborated, because the disabilities can vary across regions. Political considerations may also outweigh the number of castes being depressed.

the Anavil Brahmins of Gujarat who do; also, in Punjab, Brahmins ‘enjoy a relatively low status’. Historically, social disabilities suffered by Indians of depressed castes on account of their low social position, as well as a result of being prohibited from temples, schools, wells, and other public conveniences or jobs, vary across provinces and districts (Hutton, 1963). Nowadays, these disabilities are still scattered widely and much more severely in the south of India than elsewhere (Corbridge et al., 2013), similar to the conditions in the 1960s (Hutton, 1963, p. 207).

It is typical for students of India to consider the south of India to be distinct from other regions. In his study of Southern India, Kumar ([1965] 2013) indicates that the south can harbour a distinct quantity of interest due to several reasons such as the importance of pre-Aryan elements in its social structure, the relatively shallow impact of Muslim invasion, fluctuating contact between the south and north, and higher social segregation between castes (special schools for exterior castes).

Variation at state and district levels represent distinct causal processes, rather than simply ‘unobserved deviation’ (Browne, Subramanian, Jones, & Goldstein, 2005):

> …in India the levels of state and district are not simply administrative units for data collection and dissemination; rather they represent distinct levels at which causal processes affecting illiteracy occur. Whereas a greater variation at the state level would imply dominance of the sociopolitical and financial processes that influence illiteracy, the dominance of the district level would suggest the relative importance of administrative processes. Given that education in India is primarily the responsibility of the states, we can expect a substantial variation between them; concurrently, the districts within the states are in charge of implementing educational initiatives, and it is not clear how these may differ within the states…

In methodological terms, this paper accounts not only for the differences between states but also distinct differences between parts of India known as ‘above-the-states’ – at least between southern and northern/western India.

Besides socio-political reasons that may distinguish districts within states, developmental issues also arise, since not all the districts advance uniformly following reforms, as they had before during the early industrialisation of India. Relying on urban economists such as Krugman (Fujita, Krugman, & Mori, 1999), Gilbert (Gilbert, 1993), Rosenthal, and others, Chakravorty (2003) provides evidence of 'concentrated decentralization' – i.e. the role of geography in guiding investment locations. In particular, he speaks of geographical shifts within and between regions in the post-reform period: 1) the declining of metropolitan districts; 2) the continuing decline of inland regions; 3) the growth of non-metropolitan areas; and 4) industry concentration and spatial clustering at the district level.

Besides the increasing inter-regional polarisation of industry, these trends enhance intra-regional dispersion, even in leading regions (Ibid.). Both intra- and inter-regional dispersals are mostly inherent to urban areas. For example, Mumbai and Ahmedabad have been centres for Indian industrialisation since colonial times. Although it is believed that after independence Indian cities obtained large proportions of capital investments and attracted more educated workers by embracing 'modernity' (Tiwari et al., 2015), contemporary Indian cities vary quite remarkably. These differences are found not only between cities (old towns and new ones) but also within urban spaces. India still suffers from 'urban bias' (Corbridge et al., 2013), as seen in its social and economic contradictions and problems, such as absences of proactive and responsible urban planning (evidenced by enhanced slums and shanty settlements that co-exist with well-planned service areas) and industrially abandoned lands in old 'cities that have degenerated into low productive usage' (Tiwari et al., 2015, p. 9), as in modern Mumbai.

To summarise, we expect that *inequality between states generates a high portion of unobserved variation in incidences of training*. **Hypothesis 2.3** predicts that *population living in certain states and regions (for example, Southern Indians)* *are less likely to undertake training*. **Hypothesis 2.4** *predicts that urban areas significantly contribute to the encouragement of people to receive formal training*.

Table 4 summarizes our expectations for the single-level impact of different socio-economic and demographic determinants. A detailed description of the variables is presented in Appendix A.

Table 4

Observed Single-level Factors of Training, Indicators, and Expectations

Factors	Indicators	Anticipated impact
Socio-demographics	Male	Positive
	Urban area	Positive
	Age	Positive
	Age squared	Negative
	Marital status (married)	Negative
	Size of household	Negative
	Religion (Sikhism)	Positive
	Scheduled Castes and Scheduled Tribes	Negative
Human capital	Technical education	Positive
	Schooling: further education (diploma, degree)	Positive
Occupation groupings	Skilled (professionals, semi-professionals, clerks, industrial and craft workers),	Positive
	Unskilled (Sales and service workers, farmers, elementary occupations)	Negative
Job-specific level	Job contract (written long-term)	Positive
	Worked regularly	Positive
	Permanent employment	Positive
	Method of payment (regular salary)	Positive
	Full time employment	Positive
Organisation-specific level	Size of organisation	Positive
	Enterprise uses electricity	Positive
	Government /public ownership	Positive

Note: See Appendix A for an extended description of the variables.

Data on training and other variables

As mentioned above, this study applies the NSS (2012), Round 68, Schedule 10 ‘Employment & Unemployment Survey’, issued by the National Sample Survey Office, Government of India (in short, NSS 68th Round). These data are based on household sampling and provide a representative sample of the population. NSS 68th Round data are abundant concerning contextual variables; they also represent geographical distribution of population by states divided into NSS regions and districts.

Formal and non-formal training, by the NSS 68th Round data

The NSS 68th Round data measures training through the question: ‘*whether they are receiving/have received any vocational training*’, which is applicable only to 63.1% of the respondents, – i.e. population in the age range of 15–59, hereafter the ‘adult population’. It is important to note that this age range includes not only economically active population, but also students, pensioners, and people with disabilities. Above all, according to NSSO procedures, data on job contracts and other indicators of employment relationships are collected only from employees who are institutionally employed – i.e. regular salaried or wage employees, casual wage labour in public and casual wage labour elsewhere. Consequently, household workers, helpers, and self-employed are not counted. All these considerably reduces the sample size of individual; that is, from 459,784 to 36,430 persons.

The Ministry of Statistics of India distinguishes those who are currently receiving training (1% of the adult population) from those who have already received any degree of vocational training (10.8%) – 11.8% of the total adult population. Undertaking most training (39.7%, which is 2.6 times higher than the population average) relates to people who have attended an educational institution and, to a lesser extent, (25.5%, but still 1.9 greater than average) – those who have worked as regular salaried or wage employees.

The NSS 68th Round data splits those have already received vocational training into two categories: formal (2.6% of adult population) and non-formal (8.2%). Compared to those Indians that are currently receiving vocational training, only 10% of Indians who have already received formal training have attended educational institutions. Moreover, the relative majority of Indians who have already received training (39.9%) have worked as regular employees receiving a salary or wage. In addition, approximately 6.8% (which is 3.2 times higher than average) of them did not work but were seeking for and/or available for work. The category ‘received formal training’ describes economically active population in possession of regular jobs, or those who are expecting this kind of employment.

In contrast, the incidence rate of non-formal training in India is three times greater. The NSS 68th Round data measures non-formal training through three primary components: hereditary (2.5%), self-learning (1.8%), and learning-on-the-job training (3.4%)[*]. Hereditary training describes the most informal and rudimentary manner of transmitting knowledge and skills. This kind of non-formal training is predominant in pre-industrial societies, where non-market mechanisms regulate employment and job-mobility. In a pre-industrial society, traditions prescribe what should be produced and what should be learned.

From this perspective, hereditary training is a part of intra-family socialisation and social reproduction of its members. Since hereditary training can be considered a right (*miras*, e.g. barber *mirasdars* in Bellary, see (Iyengar, 1933)) passed from parent to offspring, it inevitably strengthens the role of ascribed characteristics in status

[*] Just 0.5% of the adult population are engaged in other forms of non-formal training.

attainment. Hence, even in industrially matured societies (Nock & Rossi, 1978), we consider hereditary training as something that lies beyond the whole concept of skills development.

The majority of those undertaking hereditary 'training' are involved in traditional forms of labour activities – i.e. working self-employed in a household enterprise (38.7%) and helpers (unpaid family workers) in household enterprises (24%). Concurrently, hereditary training is highly uncommon for regular employees receiving salaries or wages (4.1%). Conversely, the association of hereditary training with domestic and non-paid employment reflects the maintenance of traditional institutions that cocoon individuals by placing taboos on certain economic activities and occupations framed by castes and sub-castes. There are several jobs (e.g. trading, curing, finance, science, work with religious cults, etc.) unavailable for untouchables[*]; and several occupations (e.g. ploughing, cleaning, sweeping, grave-digging, fishing, and other forms of casual labour) that people from lower classes are reluctant to perform because they wish to avoid being 'polluted'. Hence, it is 'much simpler to follow in…father's footsteps and take up the family's traditional occupation' (Zinkin, 1965, p. 27).

In contrast to hereditary training, both self-learning and learning on the job are closer to formal employment. For instance, 14.6% of Indians who experienced self-learning and 33.8% of those who received non-formal learning on the job worked as regular salaried or wage employees. However, these forms of training are different from formal training. Self-learning and, to a greater extent, learning on the job, are the primary forms of training used by unqualified (generic) labour. That is, 11.3% and

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[*] There are several views on origins of untouchability including social custom. Though the low position of the scheduled castes originates from a combination of their race, religion, and occupation, Hutton argues that the concept of untouchability originates from fears, taboo, and social stigma of a kind 'which will not permit of association with persons of other profession' (Hutton, 1963, p. 207) that is different from the stigmatised one.

20.4% of those who have experience of self-learning and learning on the job, respectively, work as casual wage labour in different types of work, but within the realm of public work.

Ultimately, formal and non-formal training (except hereditary training) represent differences in employment relationships relating to the life chances of workers in the labour markets. The most important component of employment relationships is a job contract and additional benefits (or compulsory benefits, as in Russia) associated with the employment relationships established between employees and their employers (Goldthorpe & McKnight, 2006).

The incidence of formal training strongly correlates with formal employment embedded in long-term contractual relationships. That is, 41.1% of the Indian employees who undertook formal training in 2012 had three-year written job contracts whereas, on average, there were only 25.3% of such employees. Although the majority of employees (71%) in India still work without any formal agreements with their employers, informality is much less statistically presented among formally trained personnel; that is, only 51% of them had no written job contracts. In regard to non-formal training, between 82.6% of those undertaking on-the-job learning and 85.6% of employees receiving hereditary training work had no written job contract, whereas three-year contracts were signed by only 14.8% and 12.9%, respectively.

The NSS (2012) measures employment relationships and benefits vis-à-vis three indicators: 1) eligibility for paid leave, 2) availability or social security benefits, and 3) regular monthly or weekly payments. All three are significantly associated with the incidence of formal training. Formal vocational training is usually received by employees whose contracts support paid leave (65.3%), whereas only 39.2% of non-formally trained are eligible for this opportunity. Between 74.8 and 83.8% of those undertaking on-the-job learning and hereditary training are not eligible for paid leave. Concerning social security benefits, there are several different types such as health care and maternity benefits, gratuity, and PF/pension. Employees in India are either eligible for the full set of these benefits including a pension, or are ineligible for any social security benefits; the latter is applicable for 65.3% of employees. The availability of welfare benefits is mostly applicable for employees who are only eligible for PF/pension (7.3%) or PF/pension, gratuity, and healthcare and maternity benefits (21.3%).

Specification of the structural variables for the regression analysis

Our primary interest is focused on the formal training received by employees (7.8% in 2012). The response is a binary variable with the value of '1' for employees who have received training, and '0' otherwise. Since some of the predictors (job contract or enterprise type) are applicable only for persons from certain industries, we can exclude crop and animal production, hunting, and related service activities (Division 01 in National Industrial Classification (NIC) 2008), except support activities for agriculture and post-harvest crop activities, trapping, and related service activities (Groups 014, 016, 017 in NIC-2008, accordingly).

Regarding the first hypothesis, the NSS 68th data encode occupations via the Indian National Classification of Occupations (NCO-2004). This is a three-tiered hierarchical scheme relating to the occupations formed in the course of ILO's official International Scheme for the Classification of Occupation (ISCO-88). The Ministry of Statistics of India provides NCO-2004 in a three-digit form – i.e. the structure of 112 occupations, which we apply without any additional adjustments, since NCO-2004 was created as an adaptation of ISCO-88 for the Indian labour market.

Based on NCO-2004, 1-digit code, we created two occupational classes: skilled and unskilled. The skilled occupational class includes managers, professionals, semi-professionals, clerks, craft workers, and assemblers. The unskilled occupational class comprises elementary occupations, farmers, and sales and services workers engaged in simple jobs. We divide labour force on the basis of skills rather than 'disposability' (recall the Castells' dichotomy of 'generic' and 'self-programmable' labour elaborated for the Network society (Castells, 2000)), since the skills-based dichotomy better coincides with the specificity of the stage of development that India is currently experiencing. India is still advancing towards becoming a late- and post-industrial society, so the macro-divisions of labour-force elaborated for these societies are barely applicable to those such as India.

To measure the intra-occupational diversity we employed the wage differences within occupations (see (Hox, 2010)). Appendix B summarizes wage and salary earnings (received or receivable) for the work performed during the week (Rs) for the given occupations. We deleted useless and extreme values – all zeros and those who earn over 702,980 Rs in a week. This number is 590 times higher than the weekly earnings of half the employees in India (the median weekly wage is 1,190 Rs). This figure appears unusual for the weekly salary of one casual worker; hence, we excluded this extreme value and higher. Since occupation-specific wage gaps were the focus of our interest as they can motivate people to improve their qualifications, we conducted a more detailed examination of occupation-specific extreme values for weekly incomes. Appendix B indicates that the highest value belongs to a manager who earns 125,000 Rs per week. No other occupation provides such a large weekly income. The next highest also belongs to a manager, who earns 72,916 Rs per week, which is very close to the amount earned by the most ‘expensive’ professional (65,000 Rs per week). However, the lower extremes are similar across all occupations with the exception of elementary occupations. Hence, by excluding upper income extremes from the dataset, we are taking the risk of obtaining a less remarkable picture of the differences between occupations regarding within-occupation wage differentials.

In addition to detailed information on occupations, The NSS 68th Round dataset provides data on 30,007 households and 88 states, which indicates the demographic and contextual heterogeneity of India and, therefore, considered structural variables in the regression analysis. Regarding geography, we have created a dummy for Southern India with respect to the official classification of regions in 2012: Andhra Pradesh, Karnataka, Tamil Nadu, and Kerala, as well as the union territories of Lakshadweep and Puducherry. Although Goa is one of the richest states in India, it is more suitable to avoid considering it separately from other regions (namely, as a dummy) because of several reasons. First, Goa contributes to the Indian economy because of the tourism sector; this segment of the economy normally does not require intensive skills upgrade and heavy on-going investments in human capital. Moreover, social groups and some advantaged castes are likely to monopolize tourism and thus create conditions that barely foster workers to improve their qualification. Another remarkable reason is language. Southern Indian states are Dravidian-language speaking areas, which is not the case for the majority of people in Goa. Telangana is also not included because this state became a part of Southern India on 2 June 2014.

Methodology

Considering the structural complexity of the Indian sample, we must devise a model that can effectively utilize this information. In socioeconomic research, scholars widely apply sample splitting, selection, and a dummy-approach to control contextual heterogeneity. However, from the methodological perspective, we cannot apply single-level modelling because of the structural heterogeneity in our data (Goldstein, 2011; Hox, 1998; Jones, 2011; Peugh, 2010); otherwise, there will be a risk of losing between-variance components that can also contribute (and they usually do) to the variation of our response variable.

To cope with this issue, researchers use multilevel modelling. In this study, we address four levels: regions, occupations, households, and persons. We assume that these four levels may 'overlap' because they are not necessarily nested inside each other. Since households are expected to send their members to different occupations in the various regions and states, we should continue modelling under the assumption of an inter-classification between the various levels of interest. Thus, a specific version of a multilevel model is required: a cross-classified model with random intercept. Following the given selection of the levels, three random parameters need to be estimated in the final model – the estimate of: 1) between-region variance ($\sigma^2_{u_{0j}}$), 2) within-region-between-occupation variance ($\sigma^2_{u_{0k}}$), and 3) within-occupation-between-household variance ($\sigma^2_{u_{0l}}$, see (1)):

$$\text{Formal training}_{ijkl} \sim \text{Binomial}(\text{cons}_{ijkl}, \pi_{ijkl})$$

Fixed-effects part (micro-level):

$$\begin{aligned}\text{Logit}(\pi_{ijkl}) = \boldsymbol{\beta_{0jkl}}\text{cons}_{ijkl} &+ \beta_1\text{Wage-gaps}_{ijkl} + \beta_2\text{Wage-gaps}^2_{ijkl} + \\ &+ \beta_3\text{Age}_{ijkl} + \beta_4\text{Age}^2_{ijkl} + \beta_5\text{Male}_{ijkl} + \beta_6\text{Urban}_{ijkl} + \\ &+ \beta_{7\text{-}9}\text{Marital status}_{ijkl} + \beta_{10}\text{Household size}_{ijkl} + \\ &+ \beta_{11\text{-}13}\text{Caste}_{ijkl} + \beta_{14\text{-}19}\text{Religion}_{ijkl} +\end{aligned}$$

$$
\begin{aligned}
&+ \beta_{20}\text{Technical education}_{ijkl} + \beta_{21\text{-}23}\text{Schooling}_{ijkl} + \\
&+ \beta_{24\text{-}26}\text{Job contract}_{ijkl} + \beta_{27}\text{Worked regularly}_{ijkl} + \\
&+ \beta_{28}\text{Permanent employment}_{ijkl} + \\
&+ \beta_{29}\text{Full employment}_{ijkl} + \\
&+ \beta_{30\text{-}33}\text{Method of payment}_{ijkl} + \\
&+ \beta_{34}\text{Enterprise uses electricity}_{ijkl} + \\
&+ \beta_{35\text{-}37}\text{Size of organisation}_{ijkl} + \\
&+ \beta_{38\text{-}45}\text{Ownership}_{ijkl} + \\
&+ \beta_{46}\text{Skilled} + \beta_{47}\text{Skilled * Male}_{ijkl} \\
&+ \beta_{48}\text{Skilled * Male * Urban}_{ijkl} + \\
&+ \beta_{49\text{-}51}\text{State outliers}_{ijkl}
\end{aligned}
$$

Random part (macro-level):

$$\boldsymbol{\beta}_{\boldsymbol{0jkl}} = \beta_0 + u_{0j} + u_{0k} + u_{0l}$$

Full-length model:

$$
\begin{aligned}
\text{Logit}(\pi_{ijkl}) = \beta_0 \text{ cons}_{ijkl} + \beta_1 \text{Wage-gaps}_{ijkl} &+ \\
&+ \beta_{49\text{-}51}\text{States and regions outliers}_{ijkl} + \\
&+ (u_{0j} \text{ cons}_{ijkl}) + (u_{0k} \text{ cons}_{ijkl}) + \\
&+ (u_{0l} \text{ cons}_{ijkl})
\end{aligned}
\tag{1}
$$

$$\text{var}(\text{Y}_{ijkl}|\pi_{ijkl}) = \pi_{ijkl}(1 - \pi_{ijkl})/\text{cons}_{ijkl}$$

$$[u_{0j}] \sim \text{N}(0, \Omega_u) : \ \Omega_u = [\sigma^2_{u_{0j}}]$$

$$[u_{0k}] \sim \text{N}(0, \Omega_u) : \ \Omega_u = [\sigma^2_{u_{0k}}]$$

$$[u_{0l}] \sim \text{N}(0, \Omega_u) : \ \Omega_u = [\sigma^2_{u_{0l}}]$$

We will fit the cross-classified model by employing MCMC methods, because in contrast to maximum likelihood methods, MCMC provides less biased estimates; in cross-classified models, the known problems of maximum likelihood methods (biased estimates, confidence intervals that are two low) become more apparent even with more higher-levels units (Stegmueller, 2013). MCMC is particularly recommended for cross-classified models and models with the limited number of the higher-level entities.

Results and discussion

Modelling of training was performed in several stages. At the first stage, the naïve two-level model was estimated with randomized intercept provided to dummies of occupations. We utilized this stage to obtain starting values for further analysis. We employed iterative generalized least squares (IGLS) to obtain rapid estimates for the parameters in the multilevel model. Although there are some limitations when one uses IGLS to estimate the multilevel model, researchers widely use it for relatively simple models (Goldstein, 1986). Table 5 demonstrates that the 'IGLS-model' confirms the basic hypothesis concerning the role of inequality between occupations in explaining the variation of training. It also reveals the significance of the main socio-demographic factors predicting the probability of formal training in India. As expected, age, gender, marital status, household size, and religion play a significant role; however, the signs of some of the effects are somewhat surprising (for example, gender); the negligible effects of SC, ST, and other Backward Classes (BC) are also surprising.

Table 5

Factors of the Probability of Formal Training in India

	Model1		Model2		Model3		Model4	
Parameters	IGLS 2-level Coef.	S.E.	MCMC 2-level Coef.	S.E.	MCMC 4-level Coef.	S.E.	MCMC 4-level Coef.	S.E.
Intercept	**-4.577**	0.478	**-4.368**	0.458	**-8.654**	0.846	**-9.003**	0.939
Wage gaps	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wage gaps^2	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
Socio-demographics								

Age	**0.080**	0.016	**0.082**	0.016	**0.104**	0.031	**0.107**	0.028
Age^2	-0.001	0.000	-0.001	0.000	-0.002	0.000	-0.002	0.000
Male	**-0.411**	0.057	**-0.652**	0.148	**-0.571**	0.240	**-0.579**	0.240
Urban	0.037	0.044	0.194	0.078	0.371	0.140	**0.387**	0.143
Marital status								
Never been married (*reference category*)								
Currently married	**-0.386**	0.064	**-0.403**	0.065	**-0.637**	0.128	**-0.641**	0.125
Widowed	**-0.412**	0.152	**-0.460**	0.162	-0.470	0.290	-0.472	0.290
Divorced/ separated	-0.294	0.259	-0.347	0.275	-0.324	0.467	-0.343	0.470
Household size (centred at grand mean)	**-0.041**	0.009	**-0.043**	0.010	**-0.045**	0.019	**-0.044**	0.019
Social characteristics								
Caste								
Scheduled Caste (*ref cat*)								
Scheduled Tribe	-0.121	0.092	-0.126	0.097	0.058	0.199	0.071	0.199
Other Backward Class	0.045	0.065	0.054	0.068	-0.083	0.133	-0.094	0.134
Others	0.018	0.066	0.021	0.069	0.166	0.134	0.178	0.136
Religion								
Hinduism (*ref cat*)								
Islam	0.060	0.070	0.064	0.072	-0.014	0.152	-0.035	0.152
Christianity	**-0.194**	0.083	**-0.203**	0.087	**-0.387**	0.195	**-0.403**	0.194
Sikhism	**0.656**	0.141	**0.690**	0.149	**1.033**	0.350	**1.089**	0.353
Jainism	-0.635	0.429	-0.724	0.446	-1.336	0.890	-1.331	0.896
Buddhism	0.291	0.172	0.303	0.179	**1.112**	0.367	**1.113**	0.368
Other	-0.578	0.349	-0.646	0.387	0.097	0.699	0.063	0.695
Occupations								
Unskilled (*ref cat*)								
Non-manual workers	**1.202**	0.276						
Sales	**0.689**	0.297						
Famers	0.496	0.442						
Crafters	**1.245**	0.257						
Assemblers	**1.621**	0.262						
Human capital characteristics related to tertiarization trend:								
Technical education	**1.532**	0.056	**1.624**	0.058	**2.965**	0.158	**2.976**	0.165
Schooling								
Secondary (*ref cat*)								
Below primary, incl. non-formal schooling	**-1.256**	0.161	**-1.322**	0.166	**-1.979**	0.273	**-1.982**	0.275
Primary and middle	**-0.542**	0.076	**-0.570**	0.075	**-1.040**	0.135	**-1.041**	0.135
Further education (diploma, grad, postgrad)	**0.344**	0.065	**0.355**	0.066	**0.688**	0.123	**0.694**	0.123
Job-related characteristics								
Job contract								
No written job contract (*ref cat*)								
Written job contract: for 1 year or less	0.148	0.110	0.159	0.113	0.166	0.213	0.170	0.215
Written job contract: more than 1 year to 3 years	0.040	0.133	0.028	0.137	-0.209	0.263	-0.206	0.266

Written job contract: more than 3 years	0.088	0.053	0.092	0.055	0.184	0.109	0.195	0.110
Worked regularly	-0.176	0.097	-0.184	0.102	-0.167	0.192	-0.163	0.188
Permanent employment	**0.180**	0.054	**0.190**	0.055	**0.313**	0.105	**0.307**	0.105
Full time employment	0.353	0.230	0.408	0.243	0.453	0.416	0.492	0.433
Method of payment								
Daily payment (*ref cat*)								
Regular monthly salary	-0.038	0.102	-0.030	0.100	**0.607**	0.189	**0.628**	0.191
Regular weekly payment	**-0.414**	0.134	**-0.436**	0.146	-0.188	0.251	-0.182	0.252
Piece rate payment	-0.083	0.184	-0.075	0.190	0.336	0.339	0.355	0.343
Others	-0.005	0.209	-0.037	0.224	0.410	0.408	0.424	0.410
Organisation level								
Enterprise uses electricity	**0.358**	0.048	**0.381**	0.049	**0.489**	0.098	**0.495**	0.098
Size of organisation								
Less than six employees (*ref cat*)								
6-9 employees	-0.046	0.065	-0.047	0.070	-0.062	0.126	-0.066	0.127
10-19 employees	0.031	0.069	0.033	0.073	-0.011	0.135	-0.015	0.135
20 and more employees	**0.140**	0.062	**0.154**	0.064	**0.325**	0.122	**0.326**	0.123
Ownership								
Proprietary: male	-0.320	0.240	-0.261	0.230	-0.249	0.386	-0.225	0.396
Proprietary: female	-0.007	0.301	0.038	0.301	0.598	0.529	0.634	0.544
Partnership: with members from same household	**-0.714**	0.353	**-0.687**	0.355	-1.009	0.641	-0.972	0.645
Partnership: with members from different household.	-0.456	0.286	-0.414	0.280	-0.626	0.489	-0.612	0.496
Government/public sector	-0.367	0.244	-0.312	0.235	-0.208	0.401	-0.182	0.407
Public/Private limited company	-0.471	0.247	-0.418	0.238	-0.424	0.404	-0.394	0.411
Co-operative societies/trust/other non-profit institutions	-0.304	0.265	-0.253	0.261	-0.278	0.450	-0.254	0.456
Others	**-0.788**	0.272	-0.755	0.266	-0.842	0.450	-0.817	0.459
Occupational class								
Skilled			**0.685**	0.221	**1.407**	0.392	**1.416**	0.385
Interclass Interactions								
Skilled x Male			**0.418**	0.170	0.475	0.277	0.497	0.282
Skilled x Male x Urban			**-0.226**	0.093	**-0.307**	0.161	**-0.318**	0.166
State outliers and regions								
Northern Kerala							**2.781**	1.173
Delhi							**-2.835**	1.220
South Indians							0.616	0.332
Level 4: Regions								
Variance component					**1.502**	0.303	**1.236**	0.266
Level 3: Occupations, NCO-2004, 3rd digit								
Variance component	**0.238**	0.046	**0.283**	0.054	**0.956**	0.198	**0.969**	0.203
Level 2: Households								
Variance component					**8.310**	0.920	**8.468**	0.998
DIC			16855		12789.		12749.	

		.2	2	3
pD		117.6 5	4283. 8	4291. 3
Level 4 units: Regions	88	88	88	88
Level 3 units: Occupations, NCO-2004, 3rd digit	112	112	112	112
Level 2 units: Households	30,00 7	30,00 7	30,00 7	30,00 7
Level 1 units: Respondent's identifier	36,43 0	36,43 0	36,43 0	36,43 0

Note: Using MCMC methods gives an opportunity to extract means, modes, and standard deviations, which are the means, modes, and the standard deviations of the monitoring-chains values generated from the 500,000 values for each parameter drawn from the joint distribution. For simplicity, Table 5 publishes only the mean values of the estimated parameters. Statistically significant values are in bold (Bayesian p-value is less than 0.1).

The IGLS-model also supports the tertiarization hypothesis (Hypothesis 1.2), predicting that the probability of formal training in India will be higher among more educated workers. According to our expectations, training should be positively correlated to workers who have successfully graduated from high school, university, etc. Workers holding a degree in technical education are more likely to receive formal training than others. Below we can see that this effect remains significant once we switch to the more complex models. The significance of job- and enterprise-related characteristics such as permanent employment in large electrified organisations demonstrates the relevance of training in the market context. Concurrently, the negative relationship between training and the regular basis of payment challenges our suggestion that formal training is a privilege. Further modelling is required to obtain a better solution for appropriate data, as well as acquire the most precise estimates for the coefficients.

At the second stage, we conducted modelling with the same hierarchical structure – two levels with a randomised constant given 112 occupations. Instead of IGLS, we used MCMC. To fit multilevel models employing Bayesian methods of estimation, we must first specify starting values for the model parameters. We store the estimations returned by the IGLS model (Model 1) and use them as the starting values for the Bayesian analysis, thus, remarkably optimising the simulation procedures.

Predominantly, all effects (including variance component) obtained by the IGLS-model were confirmed; however, the values were adjusted. At this stage, occupational dummies were reshaped into two macro-occupational classes – skilled and unskilled workers. The class of ‘skilled’ workers concerned non-manual occupations such as professionals, semi-professionals, clerks, including industrial and craft workers. ‘Unskilled’ employees worked in sales and personal service, agriculture, fisheries and forestries, as well as elementary occupations. These two classes were added to the model both as main effects and with regard to their interactions with gender and location. Table 5 indicates that the effect of the macro-occupational classes positively predicted the probability of training. That is, skilled workers were more likely to receive training than unskilled workers, especially if they were male. As we will see below, this result is robust and remains statistically significant in all the models. In general, it confirms the ascription hypothesis that skilled labour is linked to male gender in India.

In the third and fourth models, we switch to cross-classification specifications. The number of levels are increased – the now model includes four levels: state at the highest level (the fourth), occupation at the third level, household at level two, and individuals at level one. All the variance components produce the interrelated unobserved structural heterogeneity, which should be considered.

All three components of the structural variance of training are significant. From the methodological perspective, this implies the existence of a complex structural inequality that is typically ignored in naïve modelling when we include the structural variables as dummies or use nested hierarchical models. The between-state variance is estimated at 1.236 – i.e. 9% of variance of training due to differences between regions; between-occupation variance is estimated at 0.969 (capturing approximately 7% of the variation in the probability of training, the same as in Russia (Anikin, 2017)); between-household variance is estimated at 8.468 – i.e. 60% of variance of training due to differences between households in the same area. To determine the significance of the estimates for the variance components, we examine their posterior distributions. The posterior distributions for the between-household variance are close to normal; this allows us to use the Wald test on variance parameters. In other cases, the Wald test provides an approximate result. The sampling distribution for the between-region variance and between-occupation variance is positively skewed. In all three cases, a joint chi-square test is also applicable; its results indicate the high significance of all the structural variance components of the model.

Regarding ascription, we obtained a controversial result. Table 4 indicates that female gender enhances the probability of training; this effect is highly significant and robust in all models. If we test the relationships between gender and on-the-job training in isolation from the other predictors, i.e. assuming the other predictors' impact is equal to zero, the chi-squared test for gender and formal training equals 0.33 with one degree of freedom, implying that there is no relationship between these variables at a conventional level of significance, alpha < 0.05. However, controlling for other factors (that are obviously ignored in the bivariate statistical analysis) in the regression analysis via multilevel modelling reveals the statistically significant negative inference between male gender and formal training.

We therefore confirm the alternative Hypothesis 2(A) predicting the positive role of female gender in human capital acquisition, although it is only true for single women relatively free from domestic duties, whereas married females are much less likely to invest in their human capital. Considering the strong institutional support of women in contemporary India, the given result coincides with the institutional explanation of such phenomena (Dämmrich & Blossfeld, 2017). This impact is channelled through institutional arrangements that foster schemas targeting female employment, particularly in those occupations that are more likely to require formal training. From cross-tabulations, the relative share of women who receive formal vocational training is statistically higher among the number of non-manual occupations when viewed in the context of the average proportion of women within them. Tertiarization in India has produced most of these occupations that are more likely to require formal training. These are primarily as follows: secondary-education teaching professionals (46.3%, versus the average of 32.6% of women filling this role) and other teaching professionals (56.4%, versus 41.2%), nursing and midwifery associate professionals (87.1%, vs. 77.4%), middle- and primary-education teaching associate professionals (44.1%, vs. 34%), administrative associate professionals (23.9%, vs. 16%) and office clerks (27.2%, vs. 17.5%), personal care workers (55.8%, vs. 31.9%), other personal service workers (84.2%, vs. 16.3%), and even protective service workers (11.1%, vs. 3.4%). This is very similar to what we observe in an industrial society. Considering the positive impact of further education (high school and above) on the probability of training published in Table 5, we reveal the influence of the tertiarization trend on skills development in contemporary India.

Notwithstanding this, we should observe that the effect of gender remains somewhat controversial. From Table 2, we can recall that the traditional segregation of labour by gender with regard to occupations remains significant, primarily in a pre-industrial environment. The relative share of women who received training is statistically higher than the average number in pre-industrial occupations such as handicraft workers in wood, textile, leather and related materials (75%, vs. 52.9%), textile, garment and related trades workers (63.4%, vs. 39.1%), and manufacturing labourers (45.8%, vs. 27.9%). In general, not all occupations reveal their link to training; however, some do – and this occurs because of *ceteris paribus* of women's activity in these occupations, which is strongly supported by official institutions.

Conclusion

The concept of industrial society and modernization theory assumes the growing role of market-oriented factors along with industrialization and socio-cultural transformation of society. Generally, in cases of top-down and catch-up modernization, some elements are imported from different socio-economic environments (Polterovich, 2001). This occurred in India, where training became an example of the institutions imported along with the tertiarization trend. Our study revealed that training only partially links the market. This happens when a country fails to develop their institutions from the foundations such as in India, which 'leap-frogged the industrial revolution' (Corbridge, 2009).

Despite the comprehensive efforts of the Indian Government, few people receive formal vocational training in the country – less than eight percent of the working population. Although this number is surprisingly similar to what we observe in other BRIC countries (e.g. Russia), the nature of human capital acquisition in India is entirely different. Formal training in India is deeply ingrained in the advantaged socio-economic reality associated with certain unique privileges in the labour market – formal employment with long-term contracts, support from enterprises during leave, social benefits, stable payment, and so forth. In contrast, non-formal training seems to be an alternative to those who have weak positions in the labour market due to their low level of education attainment and feeble social background, being from SC or other downward classes. This corresponds to recent findings suggesting that informal training may be considered a specific form of educating low-skilled workers in some Asian countries (Kim, Hawley, Cho, Hyun, & Kim, 2016).

Traditional agencies and ascriptive inequalities still play a substantial role in economic life of India. Certain socio-demographic factors have a significant impact with regard to predicting the probability of training such as age, marital status, locality, and religion. However, the industrialization hypothesis predicts that the role of ascription in market-oriented processes should decrease during industrialization. In India, these factors are still present. From a theoretical perspective, these findings reveal the limitations of the theory of market imperfections about explaining human-capital acquisition as it fails to conceptualize the role of demography. In contrast, the theory of industrial society and particularly Grusky's model of stratification systems provides a fruitful framework that that accounts for structural and non-market forces.

Ultimately, we found that workers in better positions obtain benefits in the labour market. Formal training is a specific example of these benefits, as the majority of the population cannot obtain it; it is difficult even for those who have previously invested in their human capital. This is easily observed by considering the associations between low social status and non-formal training. From this perspective, we consider formal training a prerogative for a better position on the labour market rather than a result of merit and achievements within a competitive framework. However, we discovered a notable exception to this trend –men are less likely than women to develop their skills via the mechanisms of formal training. In contemporary India, the story of working women is one of meritocracy rather than honorific or cult-based assets. Therefore, it is understandable to believe that female labour may be a possible avenue towards effective modernization in the future.

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Appendix A

Description of Variables

Variable name	**Type**	**Label**	**Description**
Response variable			
Training	Binary [0;1]	Formal training, whether receiving or received by employees	
Independent factors			
Urban	Binary [0;1]	Area of living	
Household size	Scale	Household size	Household (hh) size centred at its mean
Religion	Nominal [1;8]	Religion	1- Hinduism, 2- Islam, 3- Christianity; 4- Sikhism; 5- Jainism; 6- Buddhism; 7- Zoroastrianism; 8- Others
Social group	Nominal [1;4]	Social group	1- Scheduled Tribe, 2- Scheduled Caste; 3- Other Backward Class; 4- Others
Male	Binary [0;1]	Gender	0- Female, 1- Male
Age	Scale	Age	
Marital status	Nominal [1;4]	Marital status	1- never married; 2- currently married; 3- widowed; 4- divorced/separated
Schooling	Nominal [1;4]	General education	1- Below primary; 2- Primary and middle; 3- Secondary; 4- Further education: diploma, graduate/ postgraduate degree
Technical education	Binary [0;1]	Technical education	
Occupations	Nominal [1;9]	Occupations	Occupations coded via 1-digit code as per NCO-2004
Skilled	Binary [0;1]	Occupational classes: Skilled/Unskilled labour	Skilled: professionals, semi-professionals, clerks, industrial and craft workers Unskilled:

Variable name	Type	Label	Description
Ownership	Nominal [1;9]	Enterprise type	1- Proprietary: male 2- female 3- Partnership: with members from the same hh 4- with members from different hh. 5- Government/public sector 6- Public/Private limited company 7- Co-operative societies/trust/other non-profit institutions 8- Employer's households (i.e., private households employing maidservant, watchman, cook, etc.) 9- Others
Use electricity	Binary [0;1]	Whether the enterprise uses electricity for its production of goods and services	1- Yes, 0- No
Size	Scale	Number of workers in enterprise	
Job contract	Nominal [0;4]	Type of job contract	1- No written job contract; 2- written job contract for 1 year or less; 3- more than 1 year to 3 years; 4- more than 3 years
Method of payment	Nominal [1;4]	Method of payment	1- Regular monthly salary; 2- Regular weekly payment; 3- Daily payment; 4- Piece rate payment
Wage	Scale	Wage & Salary Earnings –Total (Cash and Kind)	
Full-time job	Binary [0;1]	Engaged in full time/ part time work	

Variable name	**Type**	**Label**	**Description**
Regular work	Binary [0;1]	Whether worked regularly	
Permanent employment	Binary [0;1]	Nature of employment (temporary /permanent)	
Level variables			
Occupational structure	Nominal [1;112]	Usual principal activity as per the National Classification of Occupations (NCO-2004)	Occupations coded via 3-digit code as per NCO-2004
Regions	Nominal [1;88]	States given regions	States divided into NSS regions
Household	Nominal [1; 30,007]	Number of households	Representative sampling of households

Appendix B

Descriptive Statistics of Wage and Salary

Weekly Earned by Employees in India, 2012

			Bootstrap [a)]			
					95% Confidence interval	
Tendency	**Statistic**	**Std. Error**	**Bias**	**Std. Error**	**Lower**	**Upper**
N	71,260		0	0	71,260	71,260
Range	124,980					
Minimum	20					
Maximum	125,000					
Mode	700					
Median	1,190		2.21	8.18	1,169	1,200
Mean	2,133.14	9.53	0.07	9.73	2,113.83	2,151.3
Std. Deviation	2,543.55		-1.42	52.5	2,451.9	2,654.81
Percentiles:			0.12	1.2	700	700.24
25	700					
75	2,500		11.43	24.85	2,500	2,571
Skewness	5.63	0.01	-0.121	1.28	3.74	8.17
Kurtosis	118.8	0.02	-7.42	65.46	30.93	247.34
Valid N	7,1260		0	0	71,260	71,260

Notes: [a)] Bootstrap results are based on 1,000 stratified bootstrap samples

Appendix C

Extreme values of weekly wages and salaries (Rs), given occupations

Upper and lower extremes		Case Number	Value	Case Number	Value	Case Number	Value
		1. Managers		4. Clerks		7. Craft workers	
Highest	1	42,223	125,000	14,4430	35,000	236,675	25,000
	2	159,930	72,916	14,3916	28,000	277,603	25,000
	3	35,009	52,111	29,1515	24,000	26,213	16,250
	4	47,183	51,500	46,655	20,000	28,6210	15,500
	5	159,923	50,000	17,5484	15,000[a)]	32,206	15,167
Lowest	1	238,568	100	43,6996	110	228,908	40
	2	358,119	117	80,378	125	319,161	50
	3	126,805	140	22,3947	138	344,305	56
	4	370,430	144	22,1982	150	374,245	60
	5	428,060	175	45,248	210 [a)]	368,743	60 [a)]
		2. Professionals		5. Sales workers		8. Industrial workers	
Highest	1	108,081	65,000	3862	50,500	435,177	41,870
	2	170,736	46,667	49,039	21,950	251,443	35,200
	3	108,082	40,000	143,701	21,000	83,605	25,030
	4	58,525	36,000	288,992	20,000	42,463	20,200
	5	310,840	35,750	250,579	18,000 [a)]	143,919	18,000
Lowest	1	48,599	90	234,953	35	98,414	60
	2	240,367	117	350,266	47	57,736	90
	3	144,781	120	235,175	60	307,855	100
	4	104,745	120	225,454	70	237,580	100
	5	277,941	125	2,0916	70	47,139	100
		3. Semi-Professionals		6. Farmers		9. Elementary occupations	
Highest	1	103,576	35,000	283,901	15,000	23,195	21,000
	2	149,346	30,000	449,842	10,500	143,927	21,000
	3	255,339	25,600	26,651	10,000	12,857	16,000
	4	143,604	25,000	59,906	10,000	129,126	15,000
	5	47,279	24,200	73,169	8,000	133,895	14,000
Lowest	1	12,377	90	402,632	50	309,325	20
	2	16,021	117	355,421	50	310,091	30
	3	16,020	117	431,381	100	137,587	30
	4	121,598	119	417,755	100	245,661	48
	5	265,813	120	387,397	100 [a)]	245,660	48

Note: [a)] Only a partial list of cases with these values are shown in the table of upper and lower extremes, accordingly.

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INDIVIDUAL PROPENSITY FOR TRAINING AND ECONOMIC GROWTH: EVIDENCE FROM RUSSIA

Abstract

The literature tends to neglect the role of individuals in formal skills training in Russia during the period of economic growth between 2001 and 2014. The present paper addresses this oversight. Although to a certain extent, studies have associated the prosperous years of the recent economic growth in Russia with training, they have not considered that the Russian population insisted on better qualifications. The present study shows that such insistence came primarily from skilled non-manual workers who resided in cities, worked more than eight hours per day, had second jobs, and were in great demand by organizations. Drawing on the panel data of the Russian Longitudinal Monitoring Survey—Higher School of Economics (RLMS—HSE), we argue that individual heterogeneity over the studied period significantly contributed to unobserved variation in training and cannot be ignored in applied social and economic studies on human capital. Further, we contend that there may be important structural factors operating at the occupational level. After accounting for important within- and between-person characteristics, we found that 26% of the variation in training during the studied years is attributable to individuals and 7% to occupations. We used multilevel probit models with cross-classifications to partition the variation in training into individual and occupational levels in the context of Russia's economic growth between 2001 and 2014. Consequently, we can confirm the superiority of a random effects model which allows for distinct within and between effects (a 'random effects' within–between (REWB) model) and which provides efficient estimates of a cluster-specific random effect.

Introduction

Observers agree that the period between late autumn 2014 and winter 2016 was a time of crisis for the Russian economy. It was caused by large-scale Western sanctions against Russia in relation to the Ukraine Crisis in July 2014 and by a fall in oil prices. These external events rendered the Russian stock market and rouble more volatile and consequently less predictable (Obizhaeva, 2016; Schmidbauer, Rösch, Uluceviz, & Erkol, 2016). This recent intense difficulty for the Russian economy poses questions regarding the role of the internal drivers of economic prosperity during 2001–2014, with a particular focus on the contribution of human capital to such prosperity and the importance of skills development for Russian employees.

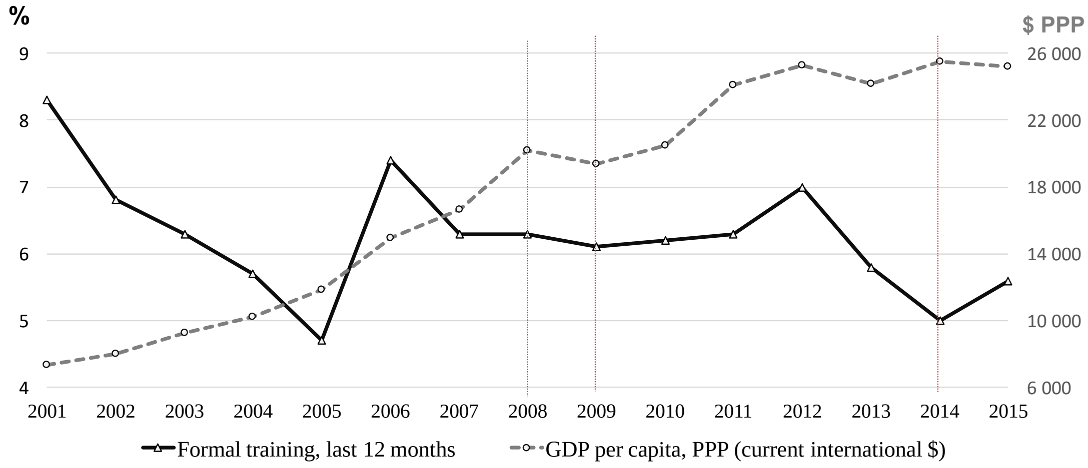
The recent literature on knowledge-based societies reconsiders the role of education and examines the inflated optimism about the expansion of education and its social value (Alvesson & Benner, 2016). In this regard, one study in particular expects ‘to see higher levels of workplace skill formation to generate both the work skills that cannot be learned during school and college education’ (Green, Felstead, Gallie, Inanc, & Jewson, 2016, p. 424). The literature on knowledge-based societies suggests that training and skills acquisition increases during a period of economic growth, if such growth is based on human capital, and thereby marks a transition towards a knowledge economy.

The period 2001–2014 was a time of expansion for higher education in Russia (Gimpelson & Kapeliushnikov, 2016; Kyui, 2016). According to the Organization for Economic Cooperation and Development (OECD) (2016), Russia has the second highest share of adults attaining tertiary education of all OECD members: the relative share of employees with tertiary education increased notably from approximately 20% in 2000 to more than 30% in 2013 (Gimpelson & Kapeliushnikov, 2016). The growing number of university (tertiary-type A) graduates, more than half of which were enrolled part-time, mainly supported this expansion.

This growth of higher education coincides with the specificity of Russia as a knowledge society; however, Russia has yet to become a knowledge economy. The incidence of training in Russia remained low and stable, and even slightly declined, during 2001–2014. The recent literature on training explains such 'training poverty' in developed nations in terms of 'a falling demand for skills formation', which is 'inherent in a "low skills" trajectory for large swathes of the … economy' (Green et al., 2016, p. 441). In light of this, we assume that the main reason for the low level of training in Russia is a reluctance in parts of the labour market for skills upgrading and innovation. As a result, people employed in certain industries and occupations are unwilling to invest time and effort in acquiring new knowledge and skills. At the same time, employees from more efficient and advanced niches of the labour market tend to develop their skills on a regular basis through their personal experience with training. Thus, the present research focuses on the individual patterns of skills acquisition (Tharenou, 1997, 2001) in Russia during the prosperous years of economic growth between 2001 and 2014.

Economic growth and skills acquisition in contemporary Russia

The year 2001 was a tipping point for the Russian economy. By then, the economy had passed through the murky waters of perestroika, which were marked by social instability and economic fluctuations (Gerber & Hout, 1998). In the early 2000s, the economic situation became broadly favourable to the absorption of new capital and expectations; in other words, the new era in the socio-economic and political life of Russia had begun (Voigt, 2006). By this time, most of the remaining Soviet industrial infrastructure had been reused within the institutions of the market economy. Such institutions were formed as a result of the completed transition to a market economy and the ‘great reallocation of human capital’ (Sabirianova, 2002). However, this reallocation has not led to widespread skills acquisition in Russia. As Figure 1 shows, the average annual share of workers who received training from 2001 to 2015 is approximately 6% of the working population, a share which is much lower than in Europe (Arulampalam, Booth, & Bryan, 2004; Bosch & Charest, 2012; O'Connell, 1999).



Source: Training data retrieved from the Russian Longitudinal Monitoring Survey—Higher School of Economics (RLMS—HSE) data, with representative samples weighted by post-stratification weight. GDP per capita data retrieved from the World Bank.
Notes: % is the percentage of the working population. GDP is gross domestic product. PPP is purchasing power parity.

Figure 1. Formal training (solid line) and gross domestic product (GDP) per capita (dashed line) in Russia

One of the main reasons for this lack of skills acquisition is that the growth of the Russian economy has been led by natural resources. Gaddy and Ickes (2013) document the abundance of tradable natural resources during Russia’s recent economic growth, suggesting that the country’s extensive input-driven growth trajectory is a legacy of the late Soviet era. The recent slowdown in growth strongly supports the view that the rapid economic expansion before the crisis was due to external drivers related to the positive situation in foreign markets, namely rising oil and gas prices, rather than the productivity of human capital (Connolly, 2012). Hence, Hypothesis 1 proposes that *prosperous years of economic growth will have no effect on the probability of training*.

Timmer and Voskoboynikov (2014) calculate that the average productivity growth of Russia had been only approximately 2.25% a year since the mid-1990s. In many industries, employees' salaries grew faster than their productivity, a factor which, among others, may have contributed to the lack of incentive to develop human capital and upgrading the quality of skills. This situation was widespread; moreover, it was significantly enhanced by the institutional arrangements of the Russian labour market which allowed low-productivity firms to survive and the hiring of workers with relatively low levels of human capital (Gimpelson & Kapeliushnikov, 2013), thereby producing significant skill mismatches (Demmou & Wörgötter, 2015).

Recent findings suggest that the human capital of Russian employees had been systematically overpaid during the period of economic growth. Because salaries were detached from workers' competencies, we suggest that employees and employers had less of a need to direct their efforts and time to lifelong education and skills. Ultimately, when 'the gap between productivity and wage is independent of the skill level of the worker, the firm has no interest in increasing the worker's skills' (Acemoglu & Pischke, 1999, p. F120). According to Gimpelson and Kapeliushnikov (2013), it is assumed that there is little incentive to upgrade human capital in low-productivity firms and, consequently, among poorly skilled labour. Thus, Hypothesis 2 proposes that *employees from generic (i.e. routine, exchangeable, and disposable) labour will be less willing to receive training*.

The findings of Timmer and Voskoboynikov (2014) suggest that the only industries where human capital can be a factor of growth are finance and business services; however, even these industries do not necessarily encourage training because much of their productive performance ‘is of some basic catching-up character’ (Timmer & Voskoboynikov, 2014, p. S418). With regard to such ambiguity, the industry-specific level is less informative than occupational structure.

Occupations and occupation-based groupings are of great importance (see Castells, 2010; Goldthorpe, Llewellyn, & Payne, 1987; Wright, 1997), particularly in an advanced industrial society (Grusky, 2001) or an information society (Castells, 2010). In such societies, skilled occupations form the major strata. Thus, skilled employees may seek training to retain their positions in the occupational and status hierarchy (Goldthorpe & McKnight, 2006). Moreover, skilled managers are more important than institutions when a country is absorbing a set of new technologies (Acemoglu, Aghion, & Zilibotti, 2006). In OECD countries, the incidence of training is statistically higher among managers and professionals (O'Connell, 1999). With regard to Russia, Berger, Earle, and Sabirianova (2001) show that during the period of economic restructuring (1994–1998), managers and skilled professionals were more likely to undertake training than other occupations. Following this strand of the literature, we control for administrative power at work; namely, whether or not employees have any subordinates. Further, in line with the functionalist perspective, hardworking employees should also reveal a positive inclination for training as a criterion for promotion (Ding, Fields, & Akhtar, 1997) or retaining employment in the public sector (Arulampalam et al., 2004; Méndez & Sepúlveda, 2016).

There are also contradictory findings. These relate to demographic differences, with a particular focus on gender. For example, empirical evidence suggests that, in advanced industrial societies such as the UK, disparities in the incidence of training between men and women are converging (Green & Zanchi, 1997), whereas others argue that these differences are still important and even non-linear (Cho, Kalomba, Mobarak, & Orozco, 2013; Fitzenberger & Muehler, 2015; Polavieja, 2012). Although recent findings on Russia support the former strand in the literature (Anikin, 2017; Berger et al., 2001), it remains important to control for gender because of a gender division of labour among occupations and, in particular, the predominance of women in semi- and low-skilled occupations despite their high levels of education (Anikin, 2012; Klimova, 2012).

Another significant demographic parameter which is usually considered in models of training is age. With panel studies, the age variable has become a very important individual-specific indicator because it enables such studies to capture the ageing effect on workers' investments in human capital. Further, belonging to a specific age group may effect workers' participation in training. For instance, younger employees are more likely to receive training than senior employees. The explicit modelling of this so-called 'cohort effect' enables research to capture important differences between individuals of various age groups compared with other socio-economic indicators.

Following the classic papers on human capital (Lemieux, 2006; Mincer, 1962, 1974), researchers suggest tenure (specific work experience) as a relevant determinant of training. The importance of this indicator is even higher in a longitudinal study, enabling the researchers to capture whether or not the experience of growth leads employees to engage in training. In line with prior estimates, we expect that the impact of tenure on training is either negligible or negative (Bartel & Sicherman, 1998; Berger et al., 2001; Loewenstein & Spletzer, 1999). Further, a panel study makes it possible to account for the person-specific cohort effects of tenure. The human resource management routines which are applied in many organizations are likely to categorize workers into different 'tenure groups' and use these categorizations to decide on whether or not workers need formal training.

From this perspective, newcomers and, in particular, those who have recently changed their occupations are more likely to receive training. Such a perspective was quite worthwhile when studying the earlier transition period of the Russian economy (Berger et al., 2001), during which inter-occupational flows were much more intensive (Sabirianova, 2002). However, from 2001 to 2014, occupation–job flows may also have been a significant factor of retraining. Thus, because we do not split training into different components (additional training and retraining), it seems crucial to consider occupation–job mobility and the experience of unemployment.

The reason why we disregard the distinction between additional training and retraining comes from the general statement that, by the year 2000, Russia had overcome the turbulent times of restructuring (Berger et al., 2001; Gimpelson & Kapeliushnikov, 2016; Gimpelson & Lippoldt, 2001). After the 2000s, the Russian economy had already moved beyond the major phase of transition and, by this time, stabilized its institutions and structures. In the earlier stages of transition, workers could 'leapfrog' from low- to high-level occupations by acquiring new knowledge and skills on training courses (e.g. some accountants became chief executive officers); however, even then this was not a widespread phenomenon (Gerber & Hout, 2004). In Russia nowadays, these 'jumps' are hardly possible. Instead, researchers have noted downward intergenerational mobility, while 'social origins became a more salient factor in sorting workers into privileged and impoverished positions' (Gerber & Hout, 2004).

Based on the literature and empirical results, we can arrange observed factors of training as in Table 1. We should clarify that the list of factors we are going to use to model the probability of training is not the only one possible. For instance, our multivariate analysis excludes several observed factors which have recently been considered important determinants of training incidence such as occupation-specific wage differentials; types of employment relationships; employment in the quaternary sector; education and other explicit human capital characteristics which measure cognitive skills, such as computer and language skills; organization-specific indicators, such as ownership and organizational size; and self-rated health and other self-assessed parameters, such as work satisfaction and opportunities for professional growth associated with a job (Anikin, 2017).

Table 1

Observed and Unobserved Factors of Training, Indicators, and Expectations

Factors	Indicators	Anticipated impact
Single-level part	*(Observed)*	
Socio-demographics	Males	Positive
	Age (years)	Negative
	Residence in cities	Positive
Occupation- and job-specific level	Tenure (years)	Negative
	Qualified non-manual labour	Positive
	Working time, average hours per day	Positive
	Working time, more than eight hours per day	Positive
	Have subordinates	Positive
	Occupation–job mobility	Positive
	Unemployment in a previous year	Negative
	Have second job	Positive
Multilevel part	*(Unobserved)*	
Individuals	Individual-specific variation across persons	Sign.
Occupations	Variation between occupations	Sign.
Time	Variation between years	Insign.

Notes: The abbreviations 'Sign.'/ 'Insign.' mean that we anticipate a particular component will have a statistically significant (or insignificant) contribution to the variation in training. See Appendix A for an extended description of the variables.

Some of these indicators are included in the measurement of certain other indicators. For example, the horizontal variability between minor occupations is attributable to sectoral differences, whereas the hierarchical variation across occupations reflects educational and skill-specific differentials. Other variables are omitted because they either produce unacceptable amounts of missing data in the longitudinal panels or contain significant measurement errors (see Appendix B). For instance, self-rated health is very sensitive to panel attrition and ageing, an issue which is covered in more detail in the 'Data' section. Further examples are some 'objective' variables such as organizational size and ownership, which are measured on the basis of survey respondents' answers. In this regard, respondents are not always sure about the relevant numbers and actual information related to their employers and real owners (a situation which may occur to employees working in the military-industrial field); thus, such respondents may provide false data unintentionally.

Data

This study uses the panel samples of the Russian Longitudinal Monitoring Survey—Higher School of Economics (RLMS—HSE). The survey started in 1995 by the Carolina Population Centre at the University of North Carolina in Chapel Hill, USA, and the Institute of Sociology of the Russian Academy of Sciences. The data are primarily maintained and distributed by the National Research University Higher School of Economics, in Moscow. The RLMS—HSE data are rigorously described by Kozyreva, Kosolapov, and Popkin (2016).

Since the major focus of the present study is on skills training over the recent period of economic growth, we limit our panel to 14 rounds between 2001 (round 10) and 2014 (round 23). This selection of data has no missing time points because surveys were conducted once a year in the autumn months. However, we selected respondents who are currently working. Thus, we used 99,101 observations of 23,870 respondents in the longitudinal data sequence (see Appendix C). This compound data set consists of an unbalanced panel with embedded round gaps. Although it is common practice to eliminate observations within a panel which exhibit gaps in their data sequences (Baum, 2006), this approach may involve a loss of efficiency in coefficient estimation (Biørn, 2016). Thus, we do not eliminate gaps in order to keep these losses to a minimum.

The RLMS—HSE data enable us to model skills training via the following question: ‘During the last 12 months, were you taking part in professional courses, advanced training, or other any courses, including foreign language classes?’ This question is a binary variable with a value of 1 for ‘yes’ and 0 for ‘no’. Appendix D (Table D2) shows that this variable contains a significant disproportion of answers. Most answers are ‘no’; only a few respondents say that they received training during the year. As aforementioned, we apply this question only to the working population.

The RLMS—HSE data do not enable a distinction to be drawn between on-the-job training, periods of training-related unemployment, and affirmative action training. The presented data contain limited direct information concerning prior periods of unemployment (for example, ‘Did not work in November last year’: see Appendix A); however, we can check the current primary activity of respondents. Based on the chi-square test, we study the relationship between unemployment and training and do not find any statistically significant correlation. Among unemployed Russians (see Appendix D, Table D1), the percentage of those who received training in the prior 12 months does not statistically differ from the percentage of those who did not. Moreover, this finding applies to all the years of monitoring considered in the present study. Appendix D (Table D2) summarises the data on training in terms of the working and non-working populations.

The International Standard Classification of Occupations (ISCO-88) is used to encode the occupations of working respondents and, consequently, the occupational structure. According to the International Labour Organization, ISCO-88 has four different levels of aggregation. The modified* version of ISCO-88 contains 430 minor, four-digit occupational levels. ISCO-88 is used to produce two occupational classes: qualified non-manual workers and generic labour. Aggregated forms of occupations are supposed to represent the basic structural elements of the situation in the labour market. The highest percentage rates of those who received training are among the respondents with either skilled or semi-skilled jobs within the non-manual labour and managerial groups. From the year-to-year transition matrices, it can be seen that the average percentage of trained workers is significantly higher among managers, professionals, and semi-professionals, who are combined under the category 'qualified non-manual workers'. Office clerks, salespeople, farmers, craftworkers, operators and assemblers, and elementary occupations fall within the category of 'generic labour'.

As aforementioned, the period 2001–2014 fully covers the recent economic growth of Russia before the crisis which occurred in autumn 2014. In Figure 1, we

* The modified version of ISCO-88 is applied in order to meet the reality of the Russian labour market and to eliminate classification mismatches. Regarding mismatches in the occupational coding of RLMS—HSE, see Sabirianova (2002). In the modified version of ISCO-88, we classify professionals as specialists who have a university degree or a related equivalent. By this, we mean that the number of years of education in Russia is less important than formal credentials. 'Managers' are those with more than five employees under their direction. Those managers with less than five subordinates are treated as supervisors and coded as a separate category among professionals. Those professionals who have no university degree or a related equivalent are encoded as a separate category among 'semi-professionals'. The latter are filtered accordingly in relation to the level of education required for each group (tertiary education: unfinished undergraduate or vocational training). Some of the minor occupations are directly recoded as lower occupations because of the specifics of their work and its value on the labour market. For more details, see Anikin (2012).

can see that the growth trajectory of Russia was not sustainable during these years because the global economic crisis affected the Russian economy in 2009. However, economic growth had fully recovered by 2010. In order to trace these and other time-specific peculiarities, we utilize a year-specific variable: its 14 values are intended to capture the variations between 2001 and 2014 at the year level which represent the so-called period effect.

Unfortunately, we cannot avoid sample attrition because we are using a panel study of micro-level changes. Here, the conductors do not usually follow individual household members who have moved away from the original dwelling unit. Although some households and individuals who have moved are followed (as in round VII) in order to complete the interview, this is rare because true panels are costly to maintain. Thus, attrition is a very common issue for most panel studies. With regard to the RLMS—HSE data, 'the influence … of household turnover does not seriously distort the geographic distribution of the sample or its size or household-head characteristics' (Heeringa, 1997). This situation applies even though the influence of sample attrition of the RLMS—HSE rounds for a panel of individual respondents on the percentage of individuals from the Moscow and St. Petersburg regions and more general urban domains is the greatest (Heeringa, 1997). Further, Heeringa (1997) warns researchers that attrition may cause a general ageing effect regarding the panel of individuals and lead to losses of panel respondents from the higher income groups.

More recent and rigorous studies on sample attrition using RLMS—HSE data (Denisova, 2010; Gerry & Papadopoulos, 2015) confirm that attrition is systematically related to demographic, health, and other socio-economic characteristics; however, Gerry and Papadopoulos (2015) admit that a carefully specified model can minimize attrition bias. Thus, the authors' preliminary findings support the ‘state dependence’ hypothesis (Maddala, 1987) and confirm the importance of unobserved individual heterogeneity in longitudinal studies based on RLMS—HSE data. In the present paper, we do not test the ‘state dependence’ hypothesis because a lagged variable for training leads to a significant amount of missingness; however, we accept the advice to apply models which assess unobserved individual heterogeneity.

Methodology

A panel analysis of micro-data objectifies one of the basic issues of econometric analysis, that of the fundamental heterogeneity problem. In longitudinal regression analysis, the parameters of interest may vary, either across individuals or time, or both. In ‘canonical’ econometric literature, variation across individuals is expressed in terms of ‘individual heterogeneity’ (Hausman & Taylor, 1981) because it may be related to a set of individual-specific features which stay unchanged over time but vary across individuals. The most salient example of such features may be gender or temperament. In the literature on training, unobserved individual heterogeneity, u_i, may relate to unobserved individual abilities (or talents) which are expected be very rigid over time. Random effects (RE) models are required to capture this portion of heterogeneity.

Individual heterogeneity

When individual heterogeneity is present, RE models have greater efficiency than counterfactual methods, which are models with fixed, or constant, effects (FE); however, there is a penalty for such efficiency. In general, a model is inconsistent if the revealed heterogeneity is correlated to the covariates. With regard to RE models, which may be considered simple examples of multilevel models (MLMs), this issue occurs because of the omission of FE. According to Antonakis, Bendahan, Jacquart, and Lalive (2010), MLM followers are likely to fit the models using random coefficients without checking whether the level 1 variables correlate with fixed, or constant, effects which are due to the higher-level entity. Antonakis et al. (2010) warn that one cannot use RE if level 1 variables, x_{it}, are correlated with FE: the FE are an omitted cause. Thus, RE modellers must check the correlation between higher-level residuals, u_i, and level 1 regressors in order to meet the following assumption:*

$$Cov\,(u_i, x_{it}) = 0 \qquad (1)$$

If assumption (1) is met, one should choose the model which captures the additional variance in favour of FE models, presuming the variance of u_i to be zero. Therefore, if assumption (1) is true, RE models are consistent. If assumption (1) is violated, RE models are considered inconsistent, in which case researchers are expected to continue modelling with the 'consistent' specification.

In order to check assumption (1), econometricians use the Hausman specification test. This test is widely known as a statistical tool which helps researchers to choose between FE and RE models. Despite its popularity and statistical power, though, one should be careful when using the test. While conducting the Hausman specification test, applied economists tend to assume that the RE estimator is fully efficient; however, this is usually not the case. The latter circumstance may be one of the reasons why RE models are rejected more often relative to FE models. For example, the literature on training in Russia always suggests rejecting the particular specifications of RE models and accepting less

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* The full list of assumptions includes the restrictions to a correlation between level 1 residuals (e_{it}) and level 1 regressors (x_{it}). We assume $Cov(e_{it}, x_{it}) = 0$. Because level 1 residuals are constant in binary response models, we omitted this assumption from (4).

efficient FE models under the assumption that inconsistency exists in RE models per se. Thus, human capital acquisition in Russia is modelled as a homogeneous phenomenon (Berger et al., 2001; Lazareva, 2006; Sabirianova, 2002). However, if this homogeneity is assumed incorrectly, the FE estimates will be biased.

In this regard, Cameron, Gelbach, and Miller (2008) suggest conducting a panel bootstrap of the Hausman specification test or using the Wooldridge robust version of it. Nonetheless, even these techniques do not solve the issue of endogeneity in RE models: such an issue is not a routine matter that simply needs technical correction. Essentially, in the case of a violation of assumption (1), instead of neglecting the RE model, one should explore the reasons for the violation and thereby reassess the RE model critically in terms of omitted variables and the misspecification of disregarded heterogeneity.

FE models are somewhat problematic because they only estimate so called within effects, thereby producing heterogeneity bias. In order to avoid this problem, all the higher-level entities are included in the model as dummy variables (Allison, 2009). Then, the mean of the higher-level entities is deducted from both sides of the regression equation. This method should free a researcher from estimating a parameter for each higher-level unit.

The growing critique of FE models is usually built around Mundlak's (1978) approach, which offers an RE solution for heterogeneity bias by 'attempting to model two processes in one term' (Bell & Jones, 2015, p. 141). With regard to a panel data example, where individuals, i, are considered at level 2 as they observed on multiple occasions (level 1), t, the Mundlak formulation explicitly models FE by adding one extra term on the right-hand side of the regression equation, thereby averaging each time-variant covariate across time points (see equation (2)):

$$y_{it} = ß_0 + ß_1 x_{it} + ß_3 x.mean_i + ß_4 z_i + (u_i + e_{it}). \quad (2)$$

Equation (2) represents a model with a continuous dependent variable, y_{it}, specified in two-level terms; notations are utilized for a panel data structure. With regard to models with binary outcomes, the form of the equation will be the same but with no level 1 error term, e_{it}. Term x_{it} denotes a vector of time-variant level 1 covariates, whereas $x.mean_i$ denotes a vector of individual-specific means of x_{it}. $ß_3$ represents the contextual effect because it explicitly models the difference between the within and between effects (Bell, Jones, & Fairbrother, 2017). $ß_4$ accounts for the effects of time-invariant variables (z_i) which exist at a higher level (i). Term u_i represents homogeneous RE at level 2; namely, higher-level (individual-specific) residuals which are assumed to be normally distributed (see equation (5)).

Equation (2) is quite efficient and is recommended for use in cross-sectional repeated studies (Bell & Jones, 2015). With panel data, the contextual effect is not that informative because level 1 units represent occasions, namely individual–time observations; thus, the within and between effects are of more interest. For this reason, Bell and Jones (2015) rearrange equation (2) to obtain an RE within–between (REWB) model.

$$y_{it} = ß_0 + ß_1 (x_{it} - x.mean_i) + ß_2 x.mean_i + ß_4 z_i + (u_i + e_{it}). \quad (3)$$

Equation (3) represents a simplified version of REWB because it still assumes homogeneous RE, u_i, meaning that randomization is applied only to the intercept and that the slopes are kept fixed. In contrast to equation (2), in equation (3), $ß_1$ represents the estimate of the within effect of a time-variant variable, x_{it}, and the between effect of the same variable. Equation (3) is a general form of a two-level REWB model which considers individuals as ‘clusters’.

Following the conventional recommendations (Maddala, 1987), we use a probit link function to specify an REWB model with a binary response because probit models do not have a conditional likelihood. A general form of a probit specification for an REWB model with homogeneous RE is as follows (equations (4) and (5)):

$$y_{it} \sim \text{Binomial}(\text{const}_{it}, \pi_{it})$$

Micro-level:

$$\text{Probit}(\pi_{it}) = \boldsymbol{\beta_{0i}} + \beta_1(x_{it} - x.mean_i) + \beta_2 x.mean_i + \beta_4 \text{z}_i$$

Macro-level:

$$\boldsymbol{\beta_{0i}} = \beta_0 + u_i$$

Full-length model:

$$\text{Probit}(\pi_{it}) = \beta_0 + \beta_1(x_{it} - x.mean_i) + \beta_2 x.mean_i + \beta_4 \text{z}_i + (u_i) \quad (4)$$

$$\text{var}(y_{it} \mid \pi_{it}) = \pi_{it}(1 - \pi_{it}) / \text{const}_{it}$$

$$[u_i] \sim \text{N}(0, \Omega_u) : \Omega_u = [\sigma^2_{u_i}] \quad (5)$$

The value of the individual-specific variation of a person’s unobserved characteristics, $\sigma^2_{u_i}$, is our particular interest.

Structural heterogeneity

Applied economists assume that individual heterogeneity, which is expected to account for people’s unmeasured abilities, absorbs the major portion of the entire heterogeneity of an outcome. However, sociology suggests that structures may also play a significant role in predicting the agency. Social, cultural, and other contextual differences (e.g. geographical) absorb a notable share of the variation of many socio-economic phenomena (Kim, Mohanty, & Subramanian, 2016); thus, the role of individual abilities is usually overestimated. Further, if one ignores structural heterogeneity, the issue of endogeneity arises. Bell and Jones (2015) call this type of endogeneity a 'heterogeneity bias' which affects the parameters' estimates if one does not specify the structure-specific variance. Given that an REWB model contains greater flexibility and generalizability, it offers an opportunity to account for not only individual but also structural heterogeneity (Bell & Jones, 2015); thus, it is an REWB model with structural effects.

In the context of this advice, our second model considers both individual and structural heterogeneity. Our REWB model with structural effects considers occupation-specific units and the variation between them. In technical terms, we keep the intercept (the grand mean) random, given both individual-specific (level 2, '*i*' lower index) and structural-specific (level 3, '*k*' lower index) variables. Equation (6) represents the model as follows:

$$y_{itk} \sim \text{Binomial}(\text{const}_{itk}, \pi_{itk})$$

Micro-level:

$$\text{Probit}(\pi_{itk}) = \boldsymbol{\beta_{0ik}} + \beta_1(x_{itk} - x.mean_{ik}) + \beta_2 x.mean_{ik} + \beta_4 \text{z}_{ik}$$

Macro-level:

$$\boldsymbol{\beta_{0ik}} = \beta_0 + u_{ik} + v_k$$

Full-length model:

$$\text{Probit}(\pi_{itk}) = \beta_0 + \beta_1(x_{itk} - x.mean_{ik}) + \beta_2 x.mean_{ik} + \beta_4 \text{z}_{ik} + (u_{ik} + v_k) \qquad (6)$$

$$\text{var}(y_{itk} \mid \pi_{itk}) = \pi_{itk}(1 - \pi_{itk}) / \text{const}_{itk}$$

$$[u_{ik}] \sim \text{N}(0, \Omega_u) : \ \Omega_u = \left[\sigma^2_{u_{ik}}\right]$$

$$[\ v_k\ ] \sim \text{N}(0, \Omega_v) : \ \Omega_v = \left[\sigma^2_{v_k}\right]$$

In equation (6), the structural variance component, $\sigma^2_{v_k}$, is considered to capture the structural variation. Because the multilevel process we address in the REWB model with structural effects does not refer to a clear hierarchy, we allow for cross-classification; namely, individuals (level 2) can move between occupations (level 3) over time.

Time-specific heterogeneity

Equation (3) has some useful properties. With regard to a panel with no missingness, if x_{it} denotes age, then $x.mean_i$ would represent individuals' cohort; thus, $ß_2$ contains the estimate of the 'cohort effect'. This point leads to an age–period–cohort (APC) discourse. The final model of interest accounts for time-specific heterogeneity, which is needed to test Hypothesis 1. However, the specification of periods (years) in an APC model is not straightforward because we cannot use age, period, and cohort as explanatory components in the fixed part of the regression equation. The reason is that age, period, and cohort are linearly related (a circumstance which is known as the APC identification problem). Although the identification problem is recognized as hard to solve, researchers are still seeking for an efficient solution. For instance, drawing on repeated cross-sectional data, Bell and Jones (2017) propose a hierarchical age–period–cohort (HAPC) which solves the APC identification problem by specifying both period and cohort as cross-classified RE. With our panel study, we treat only periods as RE, not cohorts. This approach may not solve the APC identification problem. However, we still try to minimize the amount of unexplained variation in the model, a method which coincides with the general strategy applied by Bell and Jones (2017) . Equation (7) represents the model as follows:

$$y_{itkl} \sim \text{Binomial}(\text{const}_{itkl}, \pi_{itkl})$$

Micro-level:

$$\text{Probit}(\pi_{itkl}) = \boldsymbol{ß_{0ikl}} + ß_1(x_{itkl} - x.mean_{ikl}) + ß_2 x.mean_{ikl} + ß_4 z_{ikl}$$

Macro-level:

$$\boldsymbol{\beta}_{\mathbf{0}ikl} = \beta_0 + u_{ikl} + v_{kl} + f_l$$

Full-length model:

$$\text{Probit}(\pi_{itkl}) = \beta_0 + \beta_1(x_{itkl} - x.mean_{ikl}) + \beta_2 x.mean_{ikl} + \beta_4 z_{ikl} + (u_{ikl} + v_{kl} + f_l) \qquad (7)$$

$$\text{var}(y_{itkl} \mid \pi_{itkl}) = \pi_{itkl}(1 - \pi_{itkl}) / \text{const}_{itkl}$$

$$[u_{ikl}] \sim \text{N}(0, \Omega_u) : \Omega_u = [\sigma^2_{u_{ikl}}]$$

$$[v_{kl}] \sim \text{N}(0, \Omega_v) : \Omega_v = [\sigma^2_{v_{kl}}]$$

$$[f_l] \sim \text{N}(0, \Omega_f) : \Omega_f = [\sigma^2_{f_l}]$$

At the final stage, we estimate a four-level model which comprises of three pieces of unexplained variation in training: the individual-specific variance component, $\sigma^2_{u_{ikl}}$; the occupation-specific variance component, $\sigma^2_{v_{kl}}$; and the period(year)-specific variance component, $\sigma^2_{f_l}$. All the listed unexplained components are treated as cross-classified RE.

Cross-classified multilevel models are quite complicated; hence, they are hard to fit using traditional deterministic methods applicable to binary response outcome models, which are (quasi) maximum-likelihood methods. This is why Bayesian methods of estimation are required. The Markov chain Monte Carlo (MCMC) method gives precision-weighted estimates, particularly when we have few units at higher levels (Goldstein, 1995), which is exactly the issue in our final model (we have only 14 years). Ultimately, in cross-class interaction models, even with a larger number of units, the known issues (biased estimates and too-short confidence intervals) of deterministic methods become more apparent (Stegmueller, 2013). Hence, we fit the cross-classified REWB probit models using the MCMC method, monitoring a chain length of 100,000 and a burn-in length of 500.

Results and discussion

We confirm the significance of individual-specific heterogeneity in skills training. As can be seen in Tables 2 and 3, individual-specific (level 2) variance is significantly different from zero and remains significant in all three models. In Model 1, the variance partition coefficient (VPC), which may be used to identify the amount of variation in the probability of training attributable to differences between higher-level entities of interest (Browne, Subramanian, Jones, & Goldstein, 2005), is equal to 0.344. This finding indicates that differences between time-invariant characteristics of individuals explain up to 34.4% of the variation in the probability of formal skills training in Russia, after accounting for important individual characteristics and within and between effects of time-variant socio-economic parameters such as age, tenure, and working hours.

Table 2

Determinants of Skills Training, 2001–2014

	Model 1	[S.E.]	**Model 2**	[S.E.]	**Model 3**	[S.E.]
Fixed Part						
Constant	-1.574***	[0.040]	-1.609***	[0.051]	-1.611***	[0.055]
Male	-0.165***	[0.021]	-0.135***	[0.026]	-0.135***	[0.025]
Residency						
Town (ref. cat.)						
Cities	0.077***	[0.023]	0.092***	[0.022]	0.093***	[0.022]
Villages	-0.109***	[0.029]	-0.115***	[0.029]	-0.115***	[0.029]
$\text{Age}_{\text{within}}$	-0.038***	[0.003]	-0.037***	[0.003]	-0.037***	[0.004]
$\text{Age}_{\text{between}}$-gm	-0.017***	[0.001]	-0.014***	[0.001]	-0.014***	[0.001]
Job-specific						
$\text{Tenure}_{\text{between}}$ -gm	0.012***	[0.002]	0.003**	[0.002]	0.003**	[0.002]
Subordinates	0.206***	[0.021]	0.233***	[0.023]	0.233***	[0.023]
Working $\text{hours}_{\text{within}}$	0.012***	[0.004]	0.007**	[0.004]	0.008**	[0.004]
Working $\text{hours}_{\text{between}}$-gm	0.004	[0.004]	-0.001	[0.004]	-0.001	[0.004]
Overwork	0.054**	[0.024]	0.093***	[0.025]	0.091***	[0.025]
Generic labour	-0.558***	[0.022]	-0.503***	[0.049]	-0.508***	[0.048]
Occupation–job flows						
Changed either job or profession (ref. cat.)						
Profession and job remain the same	-0.119***	[0.032]	-0.140***	[0.031]	-0.138***	[0.032]
Changed profession, but not a job	0.290***	[0.057]	0.282***	[0.056]	0.282***	[0.057]
Changed both job and profession	0.148***	[0.039]	0.168***	[0.038]	0.168***	[0.039]
Did not work in November last year	-0.001	[0.046]	0.023	[0.045]	0.025	[0.045]
Second job	0.318***	[0.035]	0.280***	[0.034]	0.279***	[0.034]
Random parameters						
Level 4: years						
$\sigma^2_{f_l}$					0.003	[0.002]
Level 3: occupations						
$\sigma^2_{v_{kl}}$			0.114	[0.013]	0.114	[0.014]
Level 2: individuals						
$\sigma^2_{u_{ikl}}$	0.525	[0.024]	0.394	[0.020]	0.396	[0.019]
Model diagnostics and number of units						
DIC:	38,872.2		38,232.7		38,210	
pD:	4,795.37		4,202.73		4,216.78	
Units: years (level 4)					14	
Units: occupations (level 3)			430		430	
Units: individuals (level 2)	23,382		23,382		23,382	
Units: occasions (level 1)	95,040		95,040		95,040	

Notes: All three models utilize ‘random intercept’ specification. Individual-specific group means are centred around the grand mean (‘gm’) and do not predict beyond the range of the data (Bell & Jones, 2015). The ‘S.E.’ column presents the standard errors of the estimated parameters. The mean values of the estimated parameters are also presented. The asterisks denote Bayesian p-values (Bp), specified in accordance with the following rule: *** Bp <0.01, ** Bp<0.05, * Bp<0.1. For more details, see Appendices E, F, and G.

Table 3

Significance of Homogeneous RE Using Chi-square Tests

Variance component	**Model 1**	**Model 2**	**Model 3**
Individual-specific $\sigma^2_{u_{ikl}}$	495.436 (p = 0.000)	400.616 (p=0.000)	418.604 (p=0.000)
Occupation-specific $\sigma^2_{v_{kl}}$	-	72.234 (p=0.000)	70.184 (p=0.000)
Year-specific $\sigma^2_{f_l}$	-	-	2.636 (p=0.052)

Notes: The results of the chi-square tests are computed independently for each term in each model; directional H_0 hypotheses are used. The p-values are in parentheses. See Appendix H for further examination about the posterior distributions of the variance components.

This considerable amount of unexplained variation may be omitted if a researcher models the longitudinal likelihood of training within an FE framework. From the theoretical perspective, unobserved characteristics of individuals are crucial in order to understand the reasons why some workers receive formal training and others do not. This finding notably helps to reassess and enrich the dominant view among applied economists that skills training in advanced industrial societies (and in Russia) is a function of employers' inclinations to invest in the human capital of their workers. During the recent economic growth in Russia, workers had opportunities to improve their qualifications; or at least, these opportunities were not heavily restricted by their employers. Conversely, most employees seemed to be reluctant to use these opportunities and develop their skills.

Further, the effect of unobserved individual heterogeneity is robust, although its value changes when controlling for other sources of unexplained variation in the model. As can be seen in Model 2, the estimated value of the variance of unobserved individual heterogeneity, $\sigma^2_{u_{ik}}$, reduces from 0.525 to 0.394, after controlling for the occupational variance component, $\sigma^2_{v_k}$, the value of which is 0.114. Then, the VPC for the individual-specific variance within occupations is 0.261. In other words, individual heterogeneity embraces up to 26.1% of total residual variance, after accounting for structural heterogeneity. The VPC for occupation-specific variance is 0.076; thus, 7.6% of the variation in the likelihood of training is related to the inequality between occupations. Variation at both levels explains up to 33.7% of the total variation in the probability of training during 2001–2014. Hence, unobserved individual heterogeneity is the most remarkable source of the unexplained variation of training compared with other sources. Accounting for this heterogeneity helps greatly to uncover the individual-based nature of skills development in contemporary Russia, thereby explaining, in particular, the enormous diversity of the training probability among qualified non-manual workers in contemporary Russia (Anikin, 2017).

Although the contribution of structural RE to the likelihood of training is less salient than that of individual RE, Table 3 confirms that the estimated value of the occupation-specific variance component is significantly different from zero. Further, such a remarkable difference in the estimated values of the occupation-specific and individual-specific variance components originates from the different number of units at these levels. Indeed, a larger number of units at the individual level boosts the value of the estimated parameter and increases its contribution to the unexplained part of the model.

Could we omit the structural heterogeneity parameter? Our answer is fairly positive because we find a significant reduction in the Bayesian deviance information criterion (DIC) value after accounting for occupation-specific variation in Model 2; namely, from 38,872.2 to 38,232.7, given the same number of observations at level 1 (95,040). Thus, we cannot ignore structural heterogeneity when assessing for individual heterogeneity in panel studies on training, otherwise the ‘pure’ individual-specific RE will be slightly exaggerated. Unfortunately, in 'traditional' RE models, most authors terminate modelling at the individual heterogeneity stage, thereby losing (and leaving unexplained) up to 7.6% of the structural heterogeneity of training in Russia.

The year-specific variation, in contrast, barely increases the fit of the model and leads to a relatively slight reduction in DIC (from 38,232.7 to 38,210.0). Despite this decrease in DIC (which can be considered a substantial improvement of the model), the results of the chi-square test (see Table 3) lead to an acceptance of H_0, assuming $\sigma_{f_l}^2 = 0$ at the conventional significance level of 0.1 (p = 0.052). However, we seem to reject the null hypothesis at the significance levels of 0.05 and 0.01. Consequently, the unobserved variance between years barely contributes to an explanation of the unobserved variation in training. As can be seen in Table 2, the estimated value of the parameter $\sigma_{f_l}^2$ is 0.003 and the VPC value for the year-specific variation is 0.002; thus, only 0.2% of the variation in the likelihood of training is attributable to the inequality between years. Hence, these results confirm Hypothesis 1, which proposes that the years of economic prosperity have had no effect on the probability of training.

With regard to the contribution of observed characteristics to the variation in training, the main results are as follows. First, we confirm that separation between the within- and between-person effects produce tangible results. As shown in Table 2, there are three time-variant scale-measured terms to be estimated: age, tenure, and working hours. All three terms represent observed individual-specific time-variant characteristics; however, only two of them are significant determinants of training during the period of interest; namely, age and working hours per average day.

The negative effect of the within-person variation of age indicates that while a worker is becoming older (relative to the worker's average age observed during the considered period), the likelihood for training significantly decreases (assuming all other parameters remain unchanged). The time-invariant cohort effect (i.e. the between-person effect centred around the grand mean, $Age_{between}$-*gm*, see Table 2) is also negative and highly statistically significant.

It is important to note that we revert the models without non-linear (quadratic) effects for these terms and the within-person effect for tenure.[*] We adopt this approach because all of the terms appear subtly indifferent from zero; moreover, they affect the fit with increased complexity and DIC. This finding indicates that the considered within-person effects of age and working hours seem to have a linear impact on training, whereas a worker's tenure contributes a cohort effect; namely, the time-invariant between-person effect of tenure.

As can be seen in Table 2, workers who stay in the same jobs at companies for a greater number of years (considered relatively to the average working experience within the labour market, $Tenure_{between}$ -*gm*) demonstrate a lower incidence of training than their less experienced peers. This finding is particularly important because it reveals the nature of skills development utilized in Russian enterprises, which are reluctant to invest in the human capital of senior and well-experienced workers. In other words, this finding illustrates a stumbling block for lifelong learning in Russia. Unfortunately, existing studies on training in Russia have tended to disregard this effect and focus only on the insignificance of the within-person effect for tenure (Berger et al., 2001). Thus, the tenure-specific cohort effect seems to be a significant

[*] We omit the within effect from the 'fixed part' of a regression equation in accordance with the corresponding property of REWB models (Bell et al., 2017).

FE variable which is omitted in these studies, a situation which could lead to the publication of relatively biased estimates.

In contrast to year-measured working experience, an FE for working hours per average day (*Working hours$_{between}$-gm*) is not significant, while the within-person effect (*Working hours$_{within}$*) is positive and statistically significant. Thus, hardworking individuals are more likely to receive training than other workers. Taking into account the positive affect of additional employment and hard work, this finding indicates that skills development during 2001–2014 was partly supported by the high demand from Russian enterprises for employees who ‘can work’; that is, skilled labour.

Second, our findings support Hypothesis 2, which proposes the crucial role of macro-occupational classes in obstructing individuals from training. As shown in this study, working in the powerless generic labour significantly decreases the incidence of training which coincides with previous estimates (Anikin, 2017). Moreover, employees residing in villages are less likely to receive training than their counterparts living in towns and cities. Recalling the inverse relationship between older cohorts and training, we conclude that older semi- and low-skilled workers residing in rural parts of Russia were a social group whose skills were barely formally developed during the recent years of economic prosperity.

Finally, we confirm the proposal that new people at work are more likely to receive training than others, particularly if they hold managerial positions or have just changed their occupations. Although we do not know whether these employees received training before or after occupation–job mobility, this finding indicates that occupation–job flows are matched to skills development practices. Ultimately, such a finding challenges the popular viewpoint that occupations and jobs are significantly mismatched with skills in contemporary Russia (Demmou & Wörgötter, 2015).

Conclusion

Skills training in Russia reflects individual heterogeneity; hence, it may be linked to meritocracy to a greater extent than expected. Personal time-variant and time-invariant determinants of training substantially contribute to skills acquisition, even in societies which have yet to establish knowledge-based economies. Unobserved differences between individuals gain a larger share in the prediction of training, explaining up to 26.1%–34.4%. This finding helps to explain the immense diversity of training probability among qualified non-manual workers in contemporary Russia (Anikin, 2017). From a methodological perspective, this finding justifies the importance of RE models on training which allow for distinct within and between effects. However, skills training remains a strongly confined phenomenon; as a result, it does not have a considerable influence on the Russian economy compared with external and structural factors. For instance, we find that only a 0.2% variation in training is attributable to the years of economic prosperity, after accounting for other important parameters.

Why is the incidence of training in Russia relatively low, even during a growth period? Some scholars consider the problem to be significantly aggravated by specific institutional arrangements which disparage productivity based on human capital and thus result in significant skill mismatches (Demmou & Wörgötter, 2015). Another possible explanation comes from the finding that organizations have low incentives to invest in workers' human capital because of high personnel turnover (Travkin & Sharunina, 2016). Our study considerably reassesses these views.

Structural determinants of training are clearly revealed in the significant role of the occupational structure in contributing to the concept of the industrial society and our understanding of the social origins of skills in such a society (Green, 2013). Further, the differences between occupations significantly predict the probability of training, capturing up to 7.6% of the variation in the likelihood of training.

The negative prediction of training is explained to a large extent by numerous ‘bad’ jobs which retain workers in generic labour; the categorization of employees by enterprises, resulting in skills-development discrimination against older cohorts; and the rural location of labour. In contrast, the positive prediction of training is more likely to be embedded in a post-industrial context. This study shows that the probability of training can be determined by qualification-level matching of workers with ‘good’ jobs and the usefulness of employees as represented by those who work more than eight hours per day, apply themselves, and seek additional employment. Such a finding demonstrates the indirect link between training and labour market demand during the recent economic growth.

Thus, our findings highlight the crucial role of the individual in skills development during the years of economic prosperity, although these years per se barely affected training. With regard to policy recommendations, our results help to reassess the existing discourse on skills development in contemporary Russia. Nowadays, experts develop recommendations at organizational level and seek efficient mechanisms which will encourage businesses to develop their employees’ skills. Despite the significance of such a policy stream, policymakers and experts should perhaps switch their focus from organizations to individuals and develop instruments which enhance the personal inclinations of workers, particularly older cohorts, for skills acquisition.

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Appendix A

Description of Main Variables

Variable name	Type	Description
Response variable		
Training	Binary [0; 1]	Courses for the improvement of professional skills or any other courses over the last 12 months 0- No; 1- Yes
Single-level independent factors		
Socio-demographics		
Gender	Binary [0; 1]	0- Female; 1- Male
Residency	Nominal [1; 3]	1- City; 2- Town; 3- Village
Age	Scale	
Age squared	Scale	
Occupation- and job-specific level		
Tenure	Scale	Year started the primary job subtracted from the year of survey
Tenure squared	Scale	
Occupational class	Binary [0; 1]	0- Generic labour: office clerks, sales workers, famers, craft workers, operators and assemblers, and elementary occupations 1- Qualified non-manual labour: managers, professionals, and semi-professionals;
Have any subordinates	Binary [0; 1]	0- No; 1- Yes
Working time, hours in average workday	Scale	
Working time, more than eight hours in average workday	Binary [0; 1]	0- No; 1- Yes
Occupation-job flows since November last year	Nominal [1; 6]	1- Profession and place of work remain the same; 2- Changed profession, but not place of work; 3- Changed place of work, but not profession; 4- Changed both place of work and profession; 5- Changed either place of work or profession; 6- Did not work in November last year
Second job	Binary [0; 1]	0- No; 1- Yes
Higher level entities		
Level 2: Individuals	Nominal [1; 23,870]	Unique longitudinal person ID
Level 3: Occupations	Nominal [1; 430]	Occupations coded via 4-digit code as per ISCO-88
Level 4: Years	Nominal [1; 14]	Years (waves) of survey covering the period 2001–2014

Appendix B

Variables and Missingness

Variables, short labels	Missing, N	Missing time points
Selected variables		
Gender	0	
Residency	0	
Age	3	
Training	94	
Second job	110	
Changed job since November last year	169	
Subordinates	180	
Occupational structure (ISCO-88)	245	
Occupational class	789	
Tenure	997	
Working hours	2,958	
Omitted variables		
Job satisfaction	5,563	2001
Ownership, government	12,463	
Ownership, foreign enterprise	12,516	
Ownership, Russian enterprise	13,731	
Official employment	13,867	2001
Economic sector / industry	17,008	2001-2003
Organizational size	33,628	
Use of personal computer at work	39,604	
Lagged training	52,525	

Source: The RLMS—HSE data, panel samples.

Appendix C

Description of Waves, 2001-2014

Year	**All observations**		**Observations for working respondents**	
	Frequency	**Percent**	**Frequency**	**Percent**
2001	12,121	5.4	4,871	4.9
2002	12,523	5.6	5,102	5.2
2003	12,656	5.6	5,282	5.3
2004	12,641	5.6	5,339	5.4
2005	12,237	5.4	5,245	5.3
2006	14,689	6.5	6,547	6.6
2007	14,505	6.4	6,589	6.7
2008	14,026	6.2	6,476	6.5
2009	13,991	6.1	6,392	6.4
2010	21,343	9.5	9,703	9.8
2011	21,993	9.8	9,842	9.9
2012	22,534	10.0	9,995	10.1
2013	21,753	9.7	9,655	9.7
2014	18,372	8.2	8,063	8.2
Total	225,384	100.0	99,101	100.0

Source: The RLMS—HSE data, panel samples.

Appendix D

Table D1

Proportions of working and non-working population, 2001-2014, %

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Employed	40.3	40.3	40.6	42.4	42.5	44.3	45.4	46.2	46.0	47.0	47.8	47.9	48.2	47.6
Out-of-Labour Force	52.6	52.7	52.6	50.0	50.2	49.3	49.3	48.9	50.1	48.3	47.3	47.7	47.8	47.4
Unemployed, the RLMS-HSE data	7.1	7.0	6.8	7.6	7.3	6.4	5.3	4.9	3.9	4.7	4.9	4.4	4.0	5.0
Unemployment, the official rate*	10.6	9.0	7.9	8.2	7.8	7.1	7.1	6.0	6.2	8.3	7.3	6.5	5.5	5.5

Source: The RLMS—HSE data, representative samples; The official rate of unemployment is compiled from the Federal State Statistics Service data, see elsewhere: http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/en/main/
Notes: The RLMS—HSE data are weighted by the post-stratification sampling weight (provided with the data). Out-of-Labour Force includes pensioners and students.

Table D2

Proportions of working and non-working population within Russians who received formal training in the same year, 2001-2014, %

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Employed	71.4	73.7	77.2	72.7	66.3	82.2	79.2	76.8	79.0	81.8	85.3	85.8	88.1	84.1
Out-of-Labour Force	22.9	21.5	17.6	23.9	26.0	15.0	17.6	18.7	16.2	12.6	10.8	10.0	9.1	12.5
Unemployed	5.7	4.8	5.2	3.4	7.7	2.8	3.2	4.5	4.8	5.6	3.9	4.2	2.8	3.4

Source: The RLMS—HSE data, representative samples
Notes: The RLMS—HSE data are weighted by the post-stratification sampling weight (provided with the data).

Appendix E

Model 1, Estimated Parameters

Parameter	**Posterior mean**	**S.E.**	**Credible Interval 2.5%**	**Credible Interval 97.5%**	**ESS**	**Bayesian p-value**
Fixed Part	Fixed Part					
Constant	-1.574	0.040	-1.652	-1.496	504	0.000
Male	-0.165	0.021	-0.207	-0.123	5,173	0.000
Residency						
Town (ref. cat.)						
Cities	0.077	0.023	0.033	0.121	3,270	0.000
Villages	-0.109	0.029	-0.166	-0.051	4,916	0.000
Age_{within}	-0.038	0.003	-0.043	-0.032	21,295	0.000
$Age_{between}$-gm	-0.017	0.001	-0.019	-0.015	5,775	0.000
Job-specific						
$Tenure_{between}$ -gm	0.012	0.002	0.009	0.015	5,127	0.000
Subordinates	0.206	0.021	0.164	0.247	6,759	0.000
Working $hours_{within}$	0.012	0.004	0.004	0.019	11,103	0.001
Working $hours_{between}$-gm	0.004	0.004	-0.003	0.012	5,105	0.120
Overwork	0.054	0.024	0.006	0.102	4,683	0.013
Generic labour	-0.558	0.022	-0.601	-0.517	4,297	0.000
Occupation-job flows						
Changed either job or profession (ref. cat.)						
Profession and job remain the same	-0.119	0.032	-0.183	-0.055	712	0.000
Changed profession, but not a job	0.290	0.057	0.179	0.401	3,570	0.000
Changed both job and profession	0.148	0.039	0.071	0.224	1,322	0.000
Did not work in November last year	-0.001	0.046	-0.090	0.089	1,905	0.486
Second job	0.318	0.035	0.250	0.385	14,002	0.000
Random Part						
Level 2: individuals						
$\sigma^2_{u_i}$	0.525	0.024	0.478	0.571	738	
Model diagnostics and number of units						
Units: individuals (level 2)	23,382					
Units: occasions (level 1)	95,040					
Estimation:	MCMC					
DIC:	38,872.2					
pD:	4,795.4					
Burnin:	500					
Chain Length:	100,000					

Appendix F

Model 2, Estimated Parameters

	Posterior mean	S.E.	Credible Interval 2.5%	Credible Interval 97.5%	ESS	Bayesian p-value
			Fixed Part			
Constant	-1.609	0.051	-1.708	-1.510	414	0.000
Male	-0.135	0.026	-0.185	-0.085	3,540	0.000
Residency						
Town (ref. cat.)						
Cities	0.092	0.022	0.049	0.135	3,624	0.000
Villages	-0.115	0.029	-0.171	-0.058	5,375	0.000
$\text{Age}_{\text{within}}$	-0.037	0.003	-0.043	-0.032	20,907	0.000
$\text{Age}_{\text{between}}$-gm	-0.014	0.001	-0.016	-0.012	5,775	0.000
Job-specific						
$\text{Tenure}_{\text{between}}$ -gm	0.003	0.002	-0.000	0.006	5,417	0.026
Subordinates	0.233	0.023	0.188	0.278	6,228	0.000
Working $\text{hours}_{\text{within}}$	0.007	0.004	-0.000	0.015	10,750	0.032
Working $\text{hours}_{\text{between}}$-gm	-0.001	0.004	-0.009	0.006	4,845	0.394
Overwork	0.093	0.025	0.044	0.141	4,442	0.000
Generic labour	-0.503	0.049	-0.600	-0.407	674	0.000
Occupation-job flows						
Changed either job or profession (ref. cat.)						
Profession and job remain the same	-0.140	0.031	-0.200	-0.079	1,070	0.000
Changed profession, but not a job	0.282	0.056	0.172	0.391	4,453	0.000
Changed both job and profession	0.168	0.038	0.094	0.241	2,086	0.000
Did not work in November last year	0.023	0.045	-0.065	0.111	2,761	0.301
Second job	0.280	0.034	0.214	0.347	13,900	0.000
			Random Part			
Level 3: occupations						
$\sigma^2_{v_k}$	0.114	0.013	0.087	0.140	8,226	
Level 2: individuals						
$\sigma^2_{u_{ik}}$	0.394	0.020	0.355	0.433	588	
			Model diagnostics and number of units			
Units: occupations (level 3)	430					
Units: individuals (level 2)	23,382					
Units: occasions (level 1)	95,040					
Estimation:	MCMC					
DIC:	38,232.744					
pD:	4,202.7					
Burnin:	500					
Chain Length:	100,000					

Appendix G

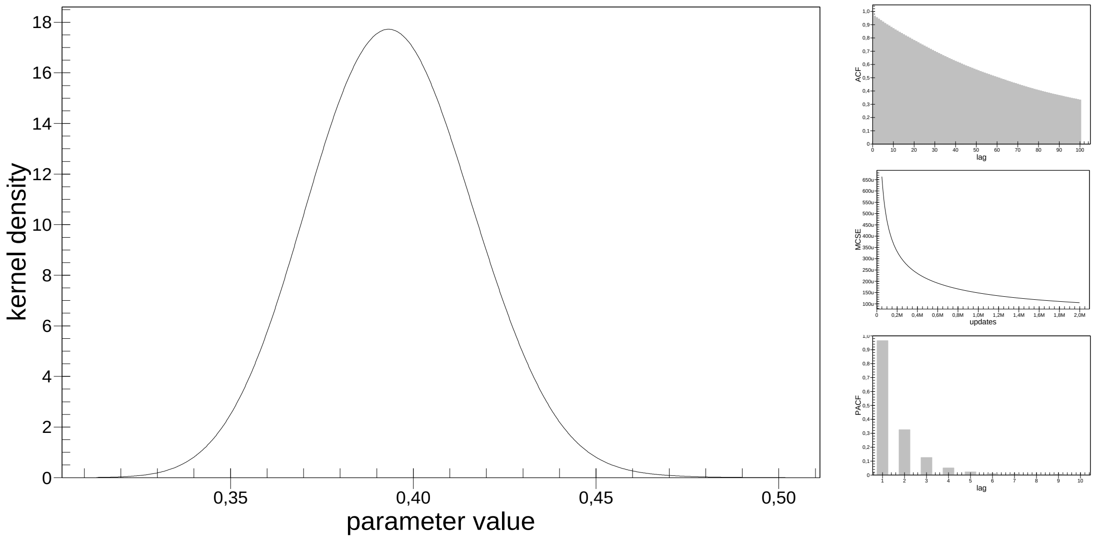
Model 3, Estimated Parameters

	Posterior mean	**S.E.**	**Credible Interval 2.5%**	**Credible Interval 97.5%**	**ESS**	**Bayesian p-value**
		Fixed Part				
Constant	-1.611	0.055	-1.719	-1.505	283	0.000
Male	-0.135	0.025	-0.186	-0.087	3,451	0.000
Residency						
Town (ref. cat.)						
Cities	0.093	0.022	0.050	0.137	3,562	0.000
Villages	-0.115	0.029	-0.172	-0.057	5,090	0.000
$\text{Age}_{\text{within}}$	-0.037	0.004	-0.044	-0.030	8,828	0.000
$\text{Age}_{\text{between}}$-gm	-0.014	0.001	-0.017	-0.012	5,630	0.000
Job-specific						
$\text{Tenure}_{\text{between}}$ -gm	0.003	0.002	-0.000	0.006	5,165	0.029
Subordinates	0.233	0.023	0.187	0.279	6,069	0.000
Working $\text{hours}_{\text{within}}$	0.008	0.004	-0.000	0.015	10,765	0.030
Working $\text{hours}_{\text{between}}$-gm	-0.001	0.004	-0.008	0.007	4,926	0.413
Overwork	0.091	0.025	0.042	0.139	4,324	0.000
Generic labour	-0.508	0.048	-0.600	-0.414	753	0.000
Occupation-job flows						
Changed either job or profession (ref. cat.)						
Profession and job remain the same	-0.138	0.032	-0.202	-0.075	655	0.000
Changed profession, but not a job	0.282	0.057	0.171	0.392	2,781	0.000
Changed both job and profession	0.168	0.039	0.092	0.245	1,126	0.000
Did not work in November last year	0.025	0.045	-0.064	0.114	1,827	0.291
Second job	0.279	0.034	0.212	0.346	14,092	0.000
		Random Part				
Level 4: years						
$\sigma^2_{f_l}$	0.003	0.002	-0.001	0.006	17,832	
Level 3: occupations						
$\sigma^2_{v_{kl}}$	0.114	0.014	0.087	0.141	7,518	
Level 2: individuals						
$\sigma^2_{u_{ikl}}$	0.396	0.019	0.358	0.433	659	
	Model diagnostics and number of units					
Units: years (level 4)	14					
Units: occupations (level 3)	430					
Units: individuals (level 2)	23,382					
Units: occasions (level 1)	95,040					
Estimation:	MCMC					
DIC:	38,209.9					
pD:	4,216.8					
Burnin:	500					
Chain Length:	100,000					

Appendix H

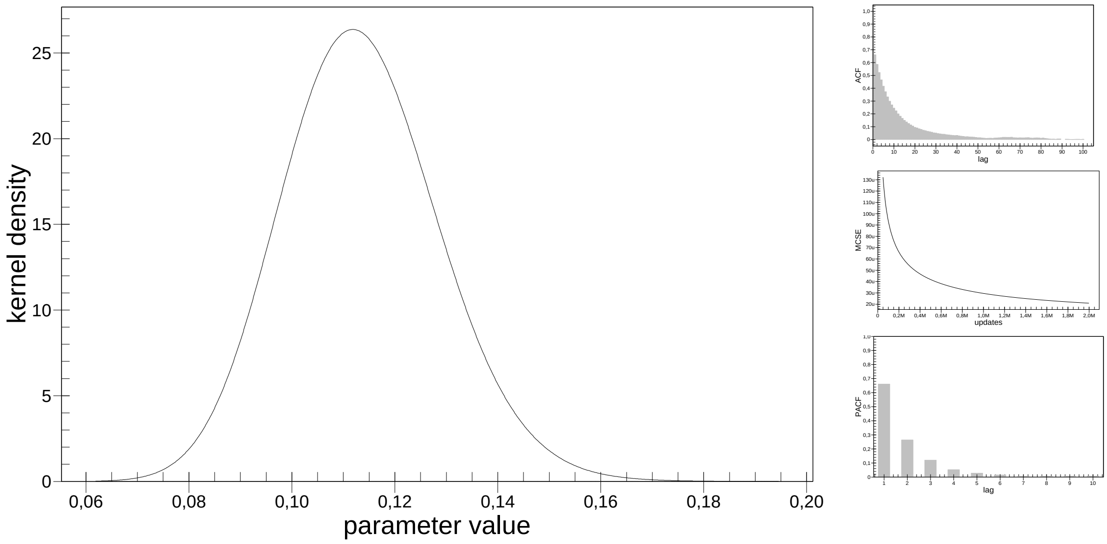
Variance Components, Key MCMC Diagnostics (Based on Model 2)

Unobserved individual-specific variance $\sigma^2_{u_{ik}}$



Posterior mean = 0.394 (0.000), SD = 0.020,
mode = 0.393. ESS = 588

Unobserved occupation-specific variance $\sigma^2_{v_k}$



Posterior mean = 0.114 (0.000), SD = 0.013,
mode = 0.112. ESS = 8,226

Notes: SD = Standard Deviation. ESS = Effective sample size. ESS is a parameter of Bayes diagnostics that used as a criterion for a sufficient number of MCMC simulations. It shows the 'restored' number of units of distribution of a parameter of interest. It is conventional practice to terminate simulation chain when ESS exceeds 250.

CONCLUSION

Successful economic advancement involves developing human capital. Consequently, the BRIC governments must bring the issue of human capital to the forefront of their development agendas. In contrast to the ‘Asian Tigers’ (Japan, South Korea, Singapore, and Taiwan), which have had successful experiences of development, the BRIC countries have yet to arrive at what is called the knowledge-based economy. The most contradictory example is Russia. Although Russia’s population is one of the most educated in the world, training and skills acquisition are still poorly presented among Russian workers. The incidence of formal training hardly exceeds 10%; moreover, the volume of formal training decreased during the period of recent economic growth between 2001 and 2014. The goal of the present study is to explore the factors that obstructed individuals from obtaining skills training in Russia in the context of a BRIC country, which has a different mode of socio-economic development.

We selected India as a counterfactual case for Russia. Although India, another BRIC country, has a socioeconomic and demographic context that is different from (and even opposite to) Russia’s, the two countries reveal almost the same incidence of training among the working population. To solve this puzzle, we postulate that the nature of human capital differs in societies with different modes of development. India represents a society with a pre-industrial form of a stratification system; in such a society, ‘human capital’ exists in the form of honorific or cult-based assets rather than in occupation-specific knowledge, skills, and expertise. The latter, by contrast, is considered principal assets in advanced industrial societies. Thus, the factors that obstruct individuals from building and maintaining human capital in the course of formal training and skills acquisition are considered distinct as well.

In general, the present study confirms this expectation. Formal training in Russia is significantly associated with the occupational structure and occupation-specific determinants. Although the incidence of training in Russia is extraordinarily low, it is highly concentrated in confined, but human-capital-intensive, niches of the labour market found in skilled and gainful occupations, such as managerial positions and professional and semi-professional vocations. Above all, a qualification improvement in Russia is statistically associated with skills and individual-specific characteristics related to language and computer skills, self-rated health and professional growth, as well as personal valuability of workers for the labour market during the years of economic prosperity; although these years explain only 0.2% of the variation in training.

At the same time, Russian workers within ‘generic’—i.e. interchangeable and disposable—labour, elder cohorts, and rural areas are less likely to develop their skills formally unless they are employed in urban labour markets. Further, our study reveals high heterogeneity in the incidence of training among qualified non-manual employees, especially managers. For instance, when the occupational wage gaps become unbridgeable, the likelihood of investments in human capital among production and special service managers sharply declines, and thus, possibly indicates non-merit redistributive processes pushing the remarkable wage gaps across these managerial positions in Russia. This heterogeneity is produced by person-specific differences. We found at least 26% of variation in training to be attributable to individuals. The given finding provides strong support to a deliberate policy to involve skilled workers of elder cohorts in the schemes of lifetime learning and skills development programmes.

The nature of human capital acquisition in Russia is remarkably less influenced by demographic disparities in the labour markets than in other developed nations, and much less than in India, as it is a country with a pre-industrial mode of socio-economic development. Our study shows that the incidence of training in India is significantly associated with locality, marital status, religion and household- and region-specific differences. Married Indians with large families residing in rural Christian communities, ceteris paribus, are less likely to upgrade their skills through formal institutions than their unmarried counterparts who live in cities and regions like Northern Kerala and belong to Sikh or Buddhist groups. Ultimately, 9% of the variance of training is due to unobserved differences between states and 60% between households in the same area.

However, our findings also suggest that market-influenced factors play an important role in acquiring training in contemporary India, thus revealing a modernisation potential for this BRIC country. First, there is a positive incidence of training for Indian women who, like their European peers, are more likely than men to challenge the status quo, thus making them more active in acquiring post-schooling learning and training. Like in Russia, the acquisition of formal training in India is significantly higher among educated and skilled employees. In contrast, Indian employees with little education (primary and middle, and below primary schooling) are discouraged from obtaining formal training. In this peculiarity, India and Russia resemble each other. In both countries, inequality between occupations explains a significant portion of the variation in the probability of training—from 7% to 8%.

The obtained results reveal the complex nature of human capital in Russia and India and thus contribute to the growing literature on structural prerequisites for successful development and on the contradictory development of the BRIC countries. However, policies tackling human capital issues in both countries should differ. Russia may win from developing incentives of educated workers and create ‘good’ jobs for human capital holders, whilst, in India, workers will gain from comprehensive employment and human capital policy to equalise life chances for training and further employment of people living in socially disadvantaged conditions. We believe that these initiatives will help provide an impetus to substantive development of a fully fledged knowledge economy in Russia and smooth transition to a knowledge-based society in India.