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WAGE DIFFERENTIALS IN EU TRANSITION ECONOMIES (2009-2016): HOW LARGE A PENALTY FOR FEMALES AND INFORMAL EMPLOYEES?

Abstract:

The paper tackles the wage differentials issue upon a large sample of employees in eight EU transition countries over 2009-2016 with respect to human capital theory vs. labour market segmentation theory and according to gender. Using several measurement methods, the results display a significant penalty in average real monthly wages for informal employees, which is always higher for females; hence, informal female employees face a double penalty. In regard of individual and job characteristics, earnings functions investigate the wage penalty for informality, which declines respectively to 20 per cent and 12 per cent for males, and 27 per cent and 17 per cent for female employees. Next, fixed effects model demonstrates that wage penalty reaches 23 per cent for females and over 10 per cent for males. Last, according to the decomposition model, explained variables (individual and job characteristics) account for two-thirds of the wage differentials, which prove better explained on the demand side of firms and supports the segmentation theory.

Keywords:

Decomposition model; EU-SILC; informal employment; Mincer model; panel data; quantile regression; transition economy; wage differentials

JEL Classification: E26, J16, J31

1. Introduction

As Malta et al (2019) put it, informality and gender gaps are closely related. We tackle this issue in terms of wage differentials upon a sample of eight EU transition countries over 2009-2016 using the data from the European Union Survey on Income and Labour Conditions (EU-SILC). Two distinct explanations address the supply side as for gender and the demand side from employers. Such differentials arise due to differences in the personal characteristics (e.g. gender) of workers. Instances are there when a female worker is paid less than her male counterpart for doing the same job. The rationale behind wage differentials is twofold. One is positive and it is due to differences in demand and supply of jobs alongside variations in job requirements (skills, aptitude, experience, etc.) from workers differing by their human capital (Mincer, 1974). The other one is normative whereby the role of labour regulations is to minimise income inequalities, especially the gender wage gap, according to the ‘equal pay for equal work’ principle.

Wages also depend on the level of labour market segmentation, in as much as informal employment is widespread in transition countries from Central and Eastern Europe that shifted from a planned to a market based economy and experienced strong socio-economic transformation. Labour market segmentation refers to wage differentials that cannot be explained by the individual attributes of labour supply (e.g. human capital), and that would be associated with certain characteristics of labour demand related to the job itself. It applies if two workers with similar personal attributes perceive a different remuneration because respectively one is in formal employment and the other in informal employment. Segmentation occurs because existing barriers to entry the formal segment such as unions, professional associations and specific rules minimum wage (Fields, 2005). Against this segmentation thesis, Maloney (1999) contends that informal employment it a matter of choice and not necessity. Neither this issue nor the transitions from informal to formal employment fall within the scope of this paper.

We assess wages differentials with four measurement methods. (i) Mincer earnings functions estimate ordinary least squares (OLS) as the average differences, which result in particular from differences in human capital (education and experience). (ii) Quantile regressions assess whether wage differentials remain constant or vary with income distribution. (iii) Fixed effects regression takes into account unobservable individual characteristics. (iv) The Oaxaca-Blinder model enables to decompose average income gaps between formal and informal employees; it identifies the "endowment effects" resulting from the differences in characteristics of each category of employees, distinct from the "coefficient effects" corresponding to the differences in the returns of these characteristics, testing human capital vs. segmentation, and the "interaction effect".

From the aforementioned and based on the data availability and purpose of the study, we selected eight EU member countries formerly in transition: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland and Slovakia. These countries are especially interesting because they did experience a major shock due to transformation and the global recession (EBRD, 2016) and had promoted gender equal pay policy.

We document figures and trends for informal wage employment, and wage gap as for formal vs informal employment, according to gender divide. According to literature review and to the best of our knowledge, among the very few papers that tackle informal employment using the EU-SILC, we provide the first analysis devoted to a set of eight EU transition countries, applying panel data and wages decomposition over the years 2009-2016. Hence, we bring in value added with a thorough investigation of wage differentials with respect to human capital theory vs. labour market segmentation theory.

The remainder of the paper is designed as follows: Section 2 presents a literature review on the topic of informal employment and labour market segmentation in EU transition countries. Section 3 compares data sources and estimates of informal wage employment. Section 4 is devoted to the EU-SILC dataset and descriptive statistics. Section 5 provides the findings from three models: pooled OLS regression regarding the Mincer earnings functions, pooled quantile regression as for income distribution and Oaxaca-Blinder wages decomposition. Section 6 concludes.

2. Literature review

The following review focuses upon informal employment and labour market segmentation in transition countries.

Lehmann and Pignatti (2007) study informal employment and analyse informal-formal wage gaps in Ukraine, using very short panels of the 2003 and 2004 waves of the ULMS longitudinal survey. They show positive wage differentials for voluntary informal employees and for both formal and informal self-employed, while there is no significant wage differential between formal and involuntary informal employees. The difference-in-differences estimates of log hourly real earnings for movers versus stayers confirm the fixed effects regression results.

Pagés and Stampini (2009) assess labour market segmentation across formal and informal salaried jobs and self-employment in six countries. They document evidence of a formal wage premium relative to informal salaried jobs in the three Latin American countries, but not in the three transition economies. These patterns suggest a preference for formal over informal salaried jobs in all countries. For wage differentials however, there is no statistical difference across skill (education) levels, suggesting that the markets for skilled and unskilled labour experience similarly segmentation.

Hazans (2011) investigates informal employment in Europe before the great recession in 2008. Comparing two datasets: Fourth European Working Conditions Survey (EWCS) of the year 2005, European Social Survey (ESS) of 2004/2005 and of 2006/2007, some estimates prove pairwise consistent while others do not match. The share of informal employment as of 2007, including workers without an employment contract, is distributed across eight transition countries as follows: 11.3 per cent (Bulgaria), 7.2 per cent (Latvia), 5.9 per cent (Poland), 4.2 per cent (Estonia), 3 per cent (Lithuania), 2.9 per cent (Slovakia), 2.7 per cent (Czech Republic) to 2.6 per cent (Hungary).

Fialová and Schneider (2011) compare the 12 new EU members (i.e. 10 transition countries Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia, plus Cyprus and Malta) with the older EU members over 1999-2007. They find that the tax wedge upon labour is not associated with several "shadow employment" indicators and data sources: a lower share of employment in small firms, fewer workers not contributing to social insurance (EU-SILC), a reduced rate of self-employment and a smaller share of temporary workers or without an employment contract (LFS) that is in line with Hazans (2011).

Packard et al (2012) collected data from repeated waves of the ESS during Europe's high-growth period (2004–07), the economic slowdown (2008) and then actual contraction (2009) in many European countries. The data show an inverse relationship between the changes in the share of the labour force that is unemployed (and discouraged) and the share that is employed informally (non-professional self-employed, employees without a contract, unpaid family workers; and those who do not make social insurance contributions). When unemployment rises, informal employment does not expand to fill the gap. Social protection as a tax on labour force is a disincentive to formal work and an impetus for informal employment. Rising minimum wages reduces informal salaried employment but may fuel informal self-employment.

Santos and Sequeira (2013) address skills mismatch and its influence throughout the distribution of wages upon a sample of 31 European countries from the 2005 EWCS. The effect of mismatch between skills and labour market requirements on wages widely differ across countries and proves non-significant in most countries. However, it becomes significant for the pooled sample, wherein over-educated workers tend to face a wage penalty, whereas under-educated workers get a wage premium. The first finding is consistent with the prevailing literature on this issue, but the second one is quite rare a finding, although Lehmann and Pignatti (2007) and Staneva and Arabsheibani (2014) provide a similar finding for Ukraine and Tadjikistan.

Staneva and Arabsheibani (2014) define informal sector employment and decompose the difference in earnings between formal and informal sector employees in Tajikistan for 2007. According to quantile regression and self-selection of individuals into different employment types, they find a significant informal employment wage premium across the whole earnings distribution. Wage premium that may be due to different observed characteristics of formal and informal workers is checked with a matching approach, which confirms the existence of a wage gap in favour of informal sector workers.

According to Tkachenko and Mosiychuk (2014), high informal employment and unbalanced labour market have serious consequences for the official economy, via an impact of human capital availability on the growth rate. On a first panel of 8 developed (Belgium, USA, Denmark, France, Germany, Italy, Finland, Great Britain) is investigated alongside a second panel of 7 post-socialist countries (Russia, Poland, Hungary, Slovak republic, Romania, Czech Republic, Ukraine) over 2000-2010. Informal employment is low-paid and does not provide social protection for the worker from the labour legislation of the country, raising barriers to economic inclusion.

Flórez and Perales (2016) use five waves of data (2004, 2006, 2008, 2010, and 2012) from the European Social Survey (ESS), i.e. an eight-year span upon a total sample of 20 countries, including only six transition countries (circa 9,000 observations): Czech Republic, Estonia, Hungary, Poland and Slovakia. As in Hazans (2011), informal employees are those who have no verbal or written contract, whereas formal workers are those who have a verbal or written contract, irrespective of whether this is of limited or unlimited duration. On average, the share of informal labour force declines before 2008 and increases up to 2012 with a trough in 2010 as for employees whereas self-employed experience a peak the same year.

Kukk et al (2018) investigate income underreporting by the self-employed using a cross-country study upon nine EU transition countries as of 2010 that shows large discrepancies. A small 8 per cent share for Poland, and between 18 per cent and over 30 per cent for Romania, the Czech Republic, Estonia, Hungary, Lithuania and Latvia; self-employment is insignificant for Bulgaria and Croatia. There is no association between the tax rates and the estimated shares of underreporting. There are several biases due to sampling size across countries, restriction to households wherein the head is aged 24–59 and industry; excluding households wherein the household head is reported as being a farmer provides lower shares.

Very few papers use EU-SILC and are devoted to the post-global recession period. None is addressing wage penalty from labour market segmentation and from gender divide.

3. Informal employment: Comparing data and estimates

In 2003, the 17th International Conference of Labour Statisticians adopted guidelines endorsing the following framework as an international statistical standard. “Informal employment includes total number of informal jobs, whether carried out in formal sector enterprises, informal sector enterprises, or households; including employees holding informal jobs; employers and own-account workers employed in their own informal sector enterprises; members of informal producers' cooperatives; contributing family workers in formal or informal sector enterprises; and own-account workers engaged in the production of goods for own end use by their household." Informal wage employment is a subset of the former and includes "all employee jobs characterized by an employment relationship that is not subject to national labour legislation, income taxation, social protection or entitlement to certain employment benefits" (ILO, 2016, p. 86). Noteworthy is that the informal employment rate is defined as the percentage of persons (and not the number of jobs) in total employment whose main job is in informal employment. The percentage of employees without formal contracts on total number of employees is not available in the EU-Labour Force Survey (EU-LFS).

Table 1. Estimates of informal wage employment (%) in eight EU transition countries

Approach	Direct									Indirect
Sources	Eurobarometer, undeclared work		ESS, no contract		EWCS, no contract,		EU-SILC, no social protection and non-permanent contract			LIM
Country/Year	2013	2013*	2010	2012	2010	2015	2010	2013	2015	2013
Bulgaria	5	6	7.1	6.0	4.4	6.0	7.39	5.46	5.73	17.8
Czech Rep.	4	5	6.2	3.5	1.0	4.3	0.58	0.77	0.92	7.7
Estonia	11	5	6.5	12.2	5.1	3.1	1.23	1.03	0.29	14.8
Hungary	4	6	3.4	4.6	1.6	5.1	0.84	1.06	0.61	17.3
Latvia	11	11	N/A	N/A	3.7	7.3	3.46	4.05	1.60	18.3
Lithuania	8	6	6.2	5.9	3.4	2.0	0.42	1.06	0.49	19.8
Poland	3	5	4.3	6.5	5.0	15.7	11.25	10.60	10.53	20.8
Slovakia	5	7	3.2	5.0	2.3	3.1	0.98	1.38	0.90	13.2
Average	*6*	*7*	*5.4*	*6.8*	*3.3*	*5.6*	*6.2*	*5.83*	*5.45*	*16.5*
Sample size	9,144	N/A	16,491	17,184	7,867	8,240	58,413	55,261	50,959	N/A

*Note: * Dependent employees paid with 'envelope wages' is a subset of undeclared work.*
Source: Authors' compilation of different surveys, all data weighted

Five sources provide estimates of informal employment in the EU countries: The Labour Input Method (LIM), the 2013 Eurobarometer, the European Social Survey (ESS), the European Working Conditions Survey (EWCS) and the European Union Survey on Income and Living Conditions (EU-SILC). We examine which sources allow us to estimate best the size of informal employment in the eight selected transition countries (see Table 1).

The LIM estimates the magnitude of undeclared work from the discrepancy between the reported supply of labour according to the LFS and labour demand data on recorded enterprise surveys or records, and tax or social security declarations. This indirect method, being used only in Italy is controversial (Adair (2012). There is no explicit assumption regarding the size of businesses and labour productivity on the supply side, whereas there are loopholes in business data sets on the demand side. In addition, it does not provide information upon wages. On average, 16.5 per cent of total labour input in the private sector in the EU is undeclared with Poland and Lithuania facing the highest undeclared work rate (Williams et al., 2017).

Among direct methods, Eurobarometer investigates undeclared work from both demand and supply side from a cross-section analysis upon an average sample of 1,500 individuals taking place in each EU country as of year 2013 (European Commission, 2014). The share of undeclared work derives from the following question "*Did you yourself carry out any undeclared paid activities in the last 12 months (which were not or not fully reported to the tax authorities*)"*?* Here, the proxy for informal wage employment is dependent employees paid with ‘envelope wages’, a small subset of the overall sample of individuals as for the eight selected transition countries.

The European Social Survey (ESS) investigates social conditions every other year upon an average sample of 1,500 individuals in each EU country. According to the question; “*Do/did you have a work contract of unlimited duration, limited duration, or do/did you have no contract?*” The absence of contract provides a proxy for informal wage employment.

The same proxy for informal wage employment applies to the European Working Conditions Survey (EWCS), devoted to the working life and conditions, employment status and income. It only takes place every five years upon a sample of 1,000 individuals in each EU country. The relevant question from EWCS is “*What kind of employment contract do you have in your main paid job?*”

Direct approaches vary across surveys and within countries. In the Eurobarometer, Estonia, Latvia and Lithuania are the transition countries with the highest unregistered workforce in 2013. According to the ESS, Bulgaria, Estonia and Lithuania experience the largest number of workers without contract in 2010, whereas the ranking changes in 2012 with Estonia and Poland standing among the top three transition countries. As for the EWCS, Estonia, Poland, Latvia and Bulgaria have the highest percentage of “no contract” workers in 2010; whereas the ranking of these countries changes in 2015 and includes Hungary. In the EU-SILC*,* Poland, Bulgaria, Hungary have the highest percentage of workers “without social protection coverage” as of 2010; the ranking of these transition countries has slightly changed in 2013.

The weighted average for informal wage employment in selected transition countries it pretty close, standing between 5.5 per cent at least and seven per cent at most as of comparable years 2012/2013. The figure for Eurobarometer is understated, due to a high rate of refusal (8% for Hungary) and missing answers that were not adjusted. The figure for LIM is not comparable with respect to methodology.

The trend within countries differs according to surveys and proves on rise as for ESS and EWCS compared with a mild decline in EU-SILC.

4. Descriptive statistics from EU-SILC

The justification for using the European Union Survey on Income and Living Conditions (EU-SILC) is that the sample size is far larger for the eight selected countries as compared to other surveys and it includes wages, which is also the case for EWCS, but neither for ESS nor for Eurobarometer.

First launched in 2003, EU-SILC is the main data source for comparative analysis and indicators on income and living conditions in the EU. It provides two kinds of data: cross-sectional data for a given time with variables on income, poverty, social exclusion and other living conditions; and longitudinal survey and multidimensional statistics on income. Detailed data are collected on income components, mostly on personal income, although a few household income components are included (Eurostat, 2016, 2019).

In EU-SILC, weighting factors were calculated in order to take into account the probability of selection and non-response of the units. The sample was adjusted to external data relating to the distribution of households and persons in the target population, such as sex, age (five-year age groups), household size and composition and region, or relating to income data from other national sources, in so far the Member States concerned consider such external data to be sufficiently reliable” (Eurostat, 2010).

We use income and labour market statistics, in as much as labour market conditions (gross national income per capita, net wages and labour productivity) stand as a set of main criteria and a widespread characteristic of how well a country economy develops and provides earning possibilities to its citizens. EU-SILC provides quantitative database on net earnings, gross earnings and structure of earnings. For this survey, we use a cross-sectional and panel data. Initial cross-sectional samples for the years 2009-2016 consist from 132,289 to 153,108 observations[1]. However, when the sample of interest is excreted and the observations with missing values are dropped, final sample is about twice as little from 50,959 to 59,946[2].

Table 2 reports the distribution of individuals in the initial samples according to their economic statuses: active (including employees, self-employed and unemployed) and inactive.

Table 2. Economic status of individuals in the eight selected transition countries (2016)

Economic status	Frequency	Per cent of total population	Per cent of active population
Active population sub-total	**120 869**	**87.4**	**100**
Employee	106 662	77.1	88.3
Self-employed	13 052	9.4	10.8
Unemployed	1 155	0.8	0.9
Inactive population sub-total	**17 406**	**12.6**	
Total	**138 275**	**100**	

Source: Authors' calculations based on EU-SILC 2016 survey

Most individuals belonging to the active population sub-total are employees (106,662 individuals, or 77.1 per cent in the whole sample), self-employed represent 9.4 per cent (13,052 individuals), unemployed are 0.8 per cent (1155 individuals). Thus, active population is 87.4 per cent (120,869 individuals) and inactive – 12.6 per cent (17,406 individuals).

We focus our study on employees, the largest employment category, in order to investigate informal wage employment. This is justified by the homogeneous character of wage distribution within employees, as the wages of self-employed are more skewed and polarized, especially at the top of wage distribution (Schneck, 2018; Dahl & Kaiser, 2020). Second, it is impossible to use the same definition of "informal" in EU-SILC for self-employed as they do not receive social security contribution.

As the EU-SILC questionnaire does not provide a direct division into formal and informal employment, we design the category of "informal" for the employees who receive no employer's social insurance contribution and at the same time do not have a permanent contract at the main job. It is worth noting that there is no intersection between formal and informal employment. These two groups are defined separately. In addition, the EU-SILC provides a limited information on multiple jobs holding that does not inform about the nature of second job in terms of its formal or informal status. At the same time, the share of employees who report having another job is only 3.9 per cent. Hence, the focus of the study is on the employees with one job.

The distribution of employees into formal and informal is reported in Figure 1.

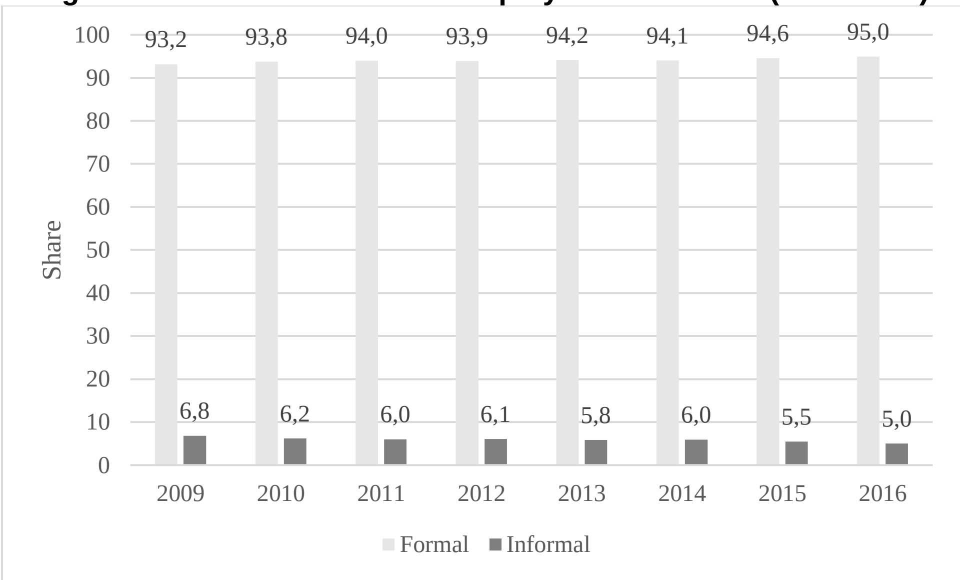
According to Figure 1, from 2009 to 2016, the share of formal employees is gradually increasing from 93.2 to 95 per cent of employed population. Conversely, the informal employed population

[1] The initial samples have following numbers of observations: 2009 – 150,394; 2010 – 150,225; 2011 – 153,108, 2012 – 150,325; 2013 – 143,289; 2014 – 139,315; 2015 – 132,289; 2016 – 138,275.

[2] The final samples have following number of observations: 2009 – 59,946; 2010 – 58,413; 2011 – 58,892; 2012 – 58,648; 2013 – 55,261; 2014 – 54,407; 2015 – 50,959; 2016 – 53,895.

is declining from 6.8 to 5 per cent for the same period. The average of formal employment for the period 2009-2016 is 94.1 per cent and the average for informal – 5.9 per cent.

Figure 1. Formal and informal employee distribution (2009-2016)



Source: Authors based on EU-SILC weighted data

The dependent variable, log real monthly income, is calculated as follows: all income variables in EU-SILC are reported for a twelve-month reference period. We sum up “gross employee cash or near cash income” and “gross non-cash employee income”. Later on, we divide it by a full-time equivalent, which is derived separately for each individual based on the data on the number of months spent at full-time and part-time work as employee. Full-time equivalent ranges from 0.83 to 12 months; full-time equivalent is 12 for 82 per cent of the whole sample, which means that 82 per cent of the sample work on average 21 working days. Hence, the dependent variable does not depend on the duration of work during the month, this information being used to derive the variable of monthly income. Eventually, we adjust the monthly income variable to the CPI (World Bank, 2017a) with 2010 as a base year. See Table A1 (in the appendix) for the description of other variables.

Tables A2 and A3 (in the appendix) reports summary statistics for formal and informal employees, respectively, of the selected dataset of countries detailing the variables, their standard deviation and number of observations for each of the four years in the sample: 2009, 2013 and 2016. The average real monthly income of formal employees is € 730 in 2009, declining to € 658.5 in 2013 and rising to € 724.8 in 2016. The average real monthly income of informal employees is 512.9 euro in 2009, 449.8 euro in 2013 and 510 euro on 2016. Thus wages of informal employees are on average 30 per cent less than of formal employees, irrespective of gender that may be explained by personal and job characteristics, according to supply side and demand side. As regards the gap in educational attainment, there are about 10 per cent more employees with a university degree in formal employment and about 10 per cent more employees with no secondary education in informal employment. Average experience over 2009-2016 of formal employees is 24.1 and informal – 20.1 years, because average age of formal employees is 43.4 and informal – 38 years old. There are more married individuals among formal employees. At the same time, formal employees tend to have more fulltime job arrangements compared to informal employees. Formal employees work on average 39.9 hours a week and informal – 39 hours. About 60 per cent of informal employees have low-skilled occupations. About 30 per cent of formal employees are either a director or a professional. As regards the firm size, there are about 20 per cent more employees working in medium and large firms in formal employment.

5. Model and results

5.1. Pooled OLS regression

To study wage determinants for formal vs. informal employees, we designed the following Mincer model:

$$\ln Income_{it} = \alpha_j + \beta_j Informal_{it} + \sum_r \gamma_j x_{it} + \delta_j Education_{it} + +\varepsilon_j Experience_{it} + u_{it} \quad [1]$$

Where ln *Income*$_{ij}$ denotes the log real monthly income of the employee *i* at time *t* and in country *j*. The dummy variable *Informal* takes the value of one if the individual is in informal employment and zero otherwise; *x* is the set of individual, household and job characteristics; *Education* and *Experience* are the main explanatory variables in our model; *α*, *β*, *γ* and *δ* are unknown coefficients; and *u* represents a random disturbance and measurement error.

Table 3 presents the coefficients of Mincer equations using pooled OLS regressions for male employees (models (1) - (3)) and female employees (models (4) - (6)). We start with a simple model with "informal" dependent variable and year dummies. This model suggests large wage penalty for participation in the informal employment. When individual characteristics from the supply side are added to the model, this wage penalty falls, and when job characteristics from the demand side are taken into consideration, the wage penalty for informality drops again. Hence, taking into consideration both individual and job characteristics, wage penalty declines without fading away.

Initial wage penalty for informality affecting of male employees is 39 per cent. When adding individual and job characteristics, wage penalty for informality declines respectively to 20 per cent and 12 per cent. The analysis of standardizing regression coefficients allows the estimation of the explanatory share certain variables have. For males, the individual characteristics related to human capital theory (education and experience) explain 43.5 per cent of the wage gap, whereas job characteristics not related to human capital theory (industry, occupation, fulltime job arrangements, working hours and firm size) explain 49.4 per cent. Hence, human capital variables on the supply side explain less wage penalty than job characteristics on the demand side, suggesting the latter is consistent with segmentation theory.

Table 3. Pooled OLS Mincer regression (2009-2016)

	Male			Female		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Informal	-0.391***	-0.203***	-0.120***	-0.474***	-0.268***	-0.174***
Working hours		0.015***	0.012***		0.021***	0.018***
Age		Ref. 16-24	Ref. 16-24		Ref. 16-24	Ref. 16-24
Age_25-39		0.047***	0.031***		0.013	-0.006
Age_40-54		0.037***	0.014		0.031**	-0.001
Age_55-64		0.085***	0.035**		0.121***	0.048***
Age_65+		0.229***	0.140***		0.157***	0.047*
Experience		0.030***	0.026***		0.027***	0.023***
Experience2		-0.001***	-0.001***		-0.001***	-0.000***
Education		Ref. secondary	Ref. secondary		Ref. secondary	Ref. secondary
Below secondary		-0.216***	-0.157***		-0.216***	-0.121***
University		0.444***	0.195***		0.475***	0.200***
Student		0.059***	-0.014		0.032***	-0.029***

Married		0.115***	0.086***		-0.023***	-0.029***
Industry			Ref. Other			Ref. Other
Agriculture			0.005			0.059***
Manufacturing			0.115***			0.110***
Construction			0.116***			0.104***
Trade			0.076***			-0.002
Transportation			0.168***			0.148***
Accommodation			0.088***			0.021*
Finances			0.102***			0.150***
Public administr			0.097***			0.094***
Education			-0.016			-0.007
Occupation			Ref. Low-skill			Ref. Low-skill
Director			0.511***			0.695***
Professional			0.423***			0.547***
Technician			0.247***			0.363***
Semi-skilled			0.012**			0.175***
Fulltime			0.101***			0.045***
Firm size			Ref. Micro			Ref. Micro
Small			0.093***			0.114***
Medium-Large			0.243***			0.226***
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country differ	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.860***	4.829***	4.605***	5.656***	4.395***	4.225***
Observations	225,013	203,760	201,814	225,408	203,900	203,297
F-test (P<0.001)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.210	0.374	0.448	0.179	0.390	0.489

*Note: Robust standard errors omitted. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: log real monthly income*
Source: Authors

Initial wage penalty for informality for female employees reaches 47 per cent. When adding individual and job characteristics, wage penalty drops respectively to 27 per cent and 17 per cent. For females, the individual characteristics related to human capital theory (education and experience) explain 35.1 per cent of the wage gap, whereas job characteristics not related to human capital theory (fulltime job arrangements, working hours and firm size) explain 60.3 per cent. Once again, human capital variables on the supply side explain less than job characteristics on the demand side (discrimination or else), suggesting the latter is consistent with segmentation theory.

Beyond individual and job characteristics that explain about 69 per cent of wage penalty for informal male employees and 63 per cent for female employees, 31 per cent for male and 37 per cent for female employees remain unexplained. For instance, we ignore why male employees and married individuals tend to have higher income.

On the one hand, in a segmented labour market, entry barriers to formal employment explain why informal employment may be due to involuntary choice (Fields, 2005). On the other hand, one labour market theory states that individuals may self-select themselves into different sectors due to better opportunities in informal employment or inefficiencies of labour regulations in formal employment (Maloney, 1999).

We run Hausman-Wu-Durbin test for endogeneity and accordingly *Informal* is an endogenous variable. Hence, we perform a two-stage Heckman correction (Heckman, 1979) as follows:

$$\begin{cases} Informal_{it} = \alpha_j + \sum_r \gamma_j x_{it} + \delta_j Education_{it} + \varepsilon_j Experience_{it} + \mu_j Z_{it} + u_{it} \\ \ln Income_{it} = \alpha_j + \beta_j Informal_{it} + \sum_r \gamma_j x_{it} + \delta_j Education_{it} + \varepsilon_j Experience_{it} + \mu_j \hat{\lambda}_{it} + u_{it} \end{cases} \quad [2]$$

Where Z_{ij} includes the two instrumental variables and λ_{it} is the Inverse Mills ratio used to correct for selection bias in the dummy *Informal*. As instrumental variables, we use the *level of trust to police* (available at the individual level) that reflects the level of trust to the Government or State in general, and *unemployment rate* at country level (ILOSTAT) that explains the state of the labour market for a specific country and specific year. Of course, instruments that work look like lucky heuristics. However, the rationale for using these instruments consists in the fact that they both have impact on the status of employment (formal or informal), but do not affect the wages as displayed in Table 4.

Trust to police explains trust to the legal institutions and *unemployment rate* reflects the state of the labour market where individuals seek employment. The data for the variable *trust to police* is available for 2013 only, so we approximate the fact of trust in police from 2013 for all years for this particular model.

By accounting for selection bias, we observe in Table 4 a decline in wage penalty for informal employment both for males and females. Wage penalty for males drops from 12.0 to 10.7 per cent and for females, from 17.4 to 16.4 per cent. It is worth noting that informal wage penalty is still five percentage points higher for females. Also noteworthy is the significant and negative inverse Mills ratio as for the dummy *Informal*.

Table 4. Pooled OLS Mincer regression, with Heckman correction (2009-2016)

	Probit – Informal		**Heckman corrected**	
Variables	**Male**	**Female**	**Male**	**Female**
Informal			-0.107***	-0.164***
Age	Ref. 16-24	Ref. 16-24	Ref. 16-24	Ref. 16-24
_25-39	-0.179***	-0.117***	0.066***	0.045***
_40-54	-0.071	-0.113	0.023*	0.055***
_55-64	-0.083	-0.125	0.048***	0.114***
_65+	-0.068	0.017	0.142***	0.001
Experience	-0.043***	-0.066***	0.037***	0.060***
Experience2	0.001***	0.001***	-0.001***	-0.001***
Education				
Below secondary	Ref	Ref	Ref	Ref
Secondary	-0.458***	-0.369***	0.252***	0.316***
University	-0.639***	-0.540***	0.490***	0.610***
Student	0.083*	0.040	-0.042***	-0.057***
Married	-0.193***	-0.111***	0.133***	0.028***
Industry	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Fulltime	-0.568***	-0.462***	0.378***	0.531***
Firm size	Ref. Micro	Ref. Micro	Ref. Micro	Ref. Micro
Small	-0.187***	-0.170***	0.129***	0.207***
Medium-Large	-0.388***	-0.305***	0.323***	0.401***
Trust in police	-0.073**	-0.049		

Unemployment rate	-0.000	-0.004		
Inverse Mills Ratio			-0.251***	-0.628***
Year	Yes	Yes	Yes	Yes
Country difference	Yes	Yes	Yes	Yes
Observations	202,578	203,626	202,578	203,626
F-test (P<0.001)	0.0000	0.0000	0.0000	0.0000
R-squared			0.437	0.474

*Note: Robust standard errors omitted. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is log real monthly income*

Source: Authors

5.2. Pooled quantile regression

Next, we test the uniform distribution of earnings, estimating not only the mean earnings as in the Mincer earning function, but with respect to quantiles, focusing on wage differentials according to intervals and studying each interval separately. We apply the conditional quantile regression (Koenker & Bassett, 1978):

$$Q_k(\ln Income_{it}|x_{it}) = \alpha_j^{(k)} + \beta_j^{(k)} Informal_{it} + \sum_r \gamma_t^{(k)} x_{it} + \delta_j^{(k)} Education_{it} + +\varepsilon_j^{(k)} Experience_{it} + u_{it},\ k \in (0,1) \quad [3]$$

Where Q_k (ln $Income_{it}$ | x_{it}) is the k^{th} per centile of the distribution of log real monthly income of the employee conditional on the covariate matrix x_{it}; α, β, γ, δ and ε are unknown coefficients; and u is a random disturbance and measurement error.

In Table 5, we run regressions separately for male and female employees.

The earnings distribution is not uniform along the quantiles. However the results of the conditional quantile regression suggest that there is a wage penalty for participation in informal employment for both male and female employees, being the highest at the bottom decile of income distribution (-0.25 for male employees and -0.28 for female employees). For males, the lowest wage penalty is estimated at the level of (-0.19) and represents the highest decile. For females, the lowest wage penalty is at the second lowest quantile and reaches (-0.21); later it gradually decreases to (-0.24) at the highest income decile.

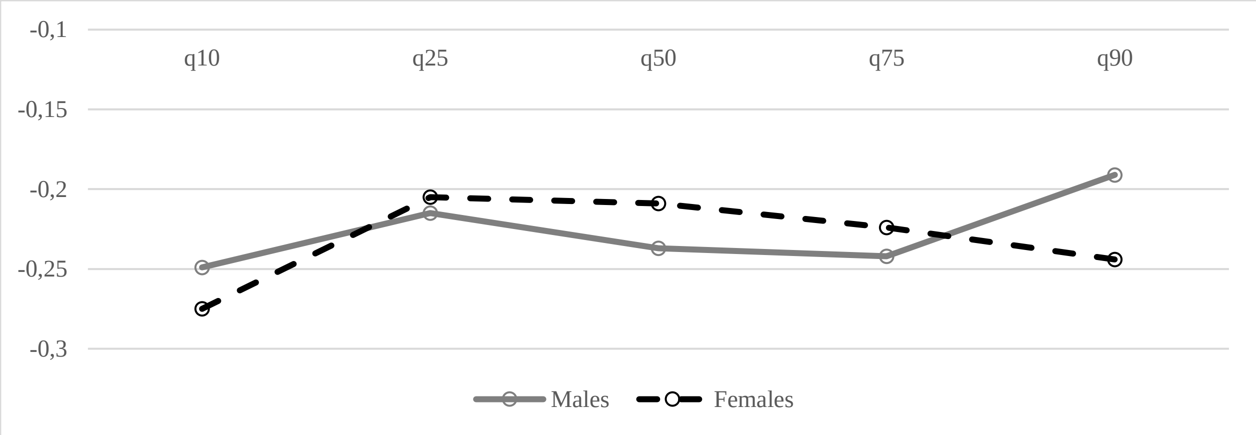
Table 5. Pooled quantile regression for male and female employees (2009-2016)

	Male					Female				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	**q10**	**q25**	**q50**	**q75**	**q90**	**q10**	**q25**	**q50**	**q75**	**q90**
Informal	-0.249***	-0.215***	-0.237***	-0.242***	-0.191***	-0.275***	-0.205***	-0.209***	-0.224***	-0.244***
Hrs_wu	0.013***	0.017***	0.019***	0.019***	0.018***	0.023***	0.024***	0.023***	0.020***	0.017***
Age_25-39	0.080***	0.045***	0.057***	0.074***	0.097***	0.068***	0.036***	0.040***	0.022***	0.005
Age_40-54	0.073***	0.033***	0.049***	0.055***	0.092***	0.097***	0.062***	0.067***	0.029***	0.009
Age_55-64	0.099***	0.078***	0.097***	0.086***	0.126***	0.135***	0.105***	0.111***	0.066***	0.050***
Age_65+	0.091***	0.108***	0.192***	0.243***	0.367***	0.065***	0.068***	0.120***	0.088***	0.096***
Experience	0.013***	0.017***	0.019***	0.021***	0.024***	0.011***	0.012***	0.013***	0.015***	0.017***
Experience2	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
Below second.edu	-0.219***	-0.212***	-0.219***	-0.171***	-0.116***	-0.148***	-0.134***	-0.142***	-0.148***	-0.144***
University education	0.057***	0.078***	0.079***	0.121***	0.163***	0.033***	0.053***	0.075***	0.116***	0.171***
Student	-0.022*	0.003	0.011	0.018*	0.037***	-0.042***	-0.019***	-0.011*	-0.001	-0.001
Married	0.050***	0.059***	0.063***	0.071***	0.070***	-0.035***	-0.039***	-0.036***	-0.038***	-0.045***
Agriculture	0.054***	0.040***	0.018*	0.020	0.014	0.026	0.040***	0.069***	0.117***	0.150***
Manufacturing	0.214***	0.206***	0.196***	0.151***	0.107***	0.150***	0.139***	0.120***	0.109***	0.066***
Construction	0.170***	0.162***	0.160***	0.152***	0.154***	0.108***	0.117***	0.135***	0.142***	0.124***
Trade	0.111***	0.107***	0.086***	0.076***	0.070***	0.044***	0.009	-0.049***	-0.075***	-0.071***
Transportation	0.202***	0.234***	0.239***	0.218***	0.200***	0.159***	0.157***	0.155***	0.146***	0.131***
Accommodation	0.096***	0.094***	0.070***	0.086***	0.059***	0.019	0.007	-0.027***	-0.039***	-0.021
Finances	0.084***	0.114***	0.146***	0.152***	0.154***	0.136***	0.157***	0.161***	0.179***	0.191***
Public administration	0.159***	0.147***	0.140***	0.111***	0.064***	0.153***	0.133***	0.109***	0.091***	0.063***
Education	0.087***	0.034***	-0.011	-0.055***	-0.096***	0.106***	0.058***	-0.004	-0.052***	-0.106***
Director	0.457***	0.536***	0.595***	0.610***	0.664***	0.571***	0.665***	0.753***	0.803***	0.831***
Professional	0.449***	0.487***	0.504***	0.472***	0.485***	0.507***	0.557***	0.605***	0.617***	0.608***
Technician	0.310***	0.338***	0.353***	0.307***	0.287***	0.376***	0.414***	0.456***	0.460***	0.443***
Semi-skilled	0.043***	0.028***	0.034***	0.017***	0.004	0.170***	0.199***	0.219***	0.235***	0.225***
Fulltime	0.215***	0.046***	-0.050***	-0.076***	-0.086***	0.071***	-0.007	-0.061***	-0.063***	-0.050***
Small firm	0.079***	0.077***	0.080***	0.074***	0.074***	0.126***	0.110***	0.101***	0.093***	0.088***
Medium-Large firr	0.238***	0.246***	0.238***	0.210***	0.203***	0.235***	0.228***	0.232***	0.217***	0.214***
Country	0.076***	0.056***	0.021***	-0.002***	-0.008***	0.080***	0.063***	0.032***	0.008***	0.001
Constant	4.074***	4.472***	4.944***	5.429***	5.770***	3.638***	4.054***	4.572***	5.072***	5.506***
Observations	228,558	228,558	228,558	228,558	228,558	228,817	228,817	228,817	228,817	228,817
Pseudo R-squared	0.100	0.121	0.143	0.161	0.173	0.100	0.121	0.143	0.161	0.173

*Note: Robust standard errors omitted. *** p<0.01, ** p<0.05, * p<0.1.*
Source: Authors

Figure 2 supports the previous paragraph documenting informal wage penalty for male and female employees.

Figure 2. Quantile regression: Informal wage penalty for male and female employees



Note: 2009-2016

Source: Authors based on EU-SILC

5.3. Panel fixed effects regression

We take advantage from panel data to detect changes in wage differentials over all waves from 2009 to 2016 and extract unobservable characteristics that may influence wages (such as abilities, etc.).

We expand our study for all available waves of EU-SILC (2009 to 2016) and apply fixed effects model to account for time-invariant unobserved individual characteristics:

$$\ln Income_{it} = \alpha_j + \beta_j Informal_{it} + \sum_r \gamma_t x_{it} + \delta_j Education_{it} + \varepsilon_j Experience_{it} + +Z_i + u_{it} \qquad [4]$$

Where ln $Income_{it}$ denotes the log real monthly income of the employee *i* at time *t;* the dummy variable *Informal* takes the value of one if individual is in informal employment and zero otherwise; *x* is the set of individual, household and job characteristics, *Education* and *Experience* are the main explanatory variables; *α*, *β*, *γ*, *δ* and *ε* are unknown coefficients, *Z* is the time-invariant factor that captures unobserved individual fixed effects; and *u* represents a random disturbance and measurement error that is normally distributed and IID.

We performed Hausman test to compare fixed effects and random effects models, whereby fixed effects estimates proved consistent. Table 6 records the results of this model separately for males and females. Although we account for unobservable characteristics, the earnings differentials associated with informal employment do not disappear. There is still a wage penalty for informal employment of 10.6 per cent for male employees and 23.1 per cent for female employees. Fixed effects model correlates with our previous findings, being positive and highly significant for higher educational attainment and experience. Gender proves to be as well significant, as is the married status for males (but not females).

Overall, the results of the panel fixed effects Mincer model application support our suggestion that for the set of eight transition countries (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland and Slovakia) over 2009-2016: wage differentials depend on personal characteristics (educational attainment, work experience, gender, age and marital status) and job characteristics (working hours, fulltime and firm size).

Table 6. Fixed effects regression (2009-2016)

	Male	Female
Variables	**(1)**	**(2)**
Informal	-0.106***	-0.231***
Working hours	0.011***	0.018***
Age_25-39	0.007	-0.036
Age_40-54	0.029	-0.003
Age_55-64	0.133***	-0.003
Age_65+	0.007	-0.036
Experience	0.022***	0.018***
Experience2	-0.000***	-0.000***
Below secondary education	-0.141***	-0.102***
University education	0.197***	0.194***
Student	0.017	-0.025
Married	0.059***	0.004
Industry	Yes	Yes
Occupation	Yes	Yes
Fulltime	0.070***	0.052***
Small firm	0.095***	0.109***
Medium-Large firm	0.242***	0.208***
Constant	5.264***	4.806***
Observations	201,816	203,300
R-squared	0.297	0.397
Number of id_ind	159,600	162,281

*Note: Standard errors are omitted. *** p<0.01, ** p<0.05, * p<0.1.*
Source: Authors

5.4. Oaxaca-Blinder decomposition

We design an Oaxaca-Blinder wages decomposition (Oaxaca, 1973; Blinder, 1973) in order to determine the share of explained *vs*. unexplained variables as regards the difference between formal and informal employees. As in the previous models, we explain ln *Income* by a vector of determinants, according to the following equation:

$$\ln Income_{it} = \begin{cases} \beta^{Informal} x_{it} + u_{it}^{Informal}, \ if \ Informal \\ \beta^{Formal} x_{it} + u_{it}^{Formal}, \ if \ Formal \end{cases} \quad [5]$$

Where x is the vector of determinants and β is the vector of parameters including an intercept.
The gap between formal and informal employees is calculated as follows:

$$\ln Income^{Formal} - \ln Income^{Informal} = \beta^{Formal} x^{Formal} - \beta^{Informal} x^{Informal} \quad [6]$$

Where x^{Formal} and $x^{Informal}$ are the vectors of explanatory variables of formal and informal employees, respectively. The income gap can be further decomposed into the explained (differences in x) and unexplained (differences in β) components (Jann, 2008). We can also produce decomposition into the endowments, coefficients and interaction components:

$$\ln Income^{Formal} - \ln Income^{Informal} = \beta^{Informal} \Delta x + \Delta\beta x^{Informal} + \Delta\beta\Delta x = E + C + I \quad [7]$$

Where $\Delta x = x^{Formal} - x^{Informal}$, $\Delta\beta = \beta^{Formal} - \beta^{Informal}$ E represents the endowments, C – the coefficients and I – the interaction between endowments and coefficients.

Endowments quantify the mean increase in the income of informal employees assuming they had the same characteristics as formal employees. Coefficients account for the change in the income of informal employees when applying the coefficients of formal employees to the characteristics of informal employees. Finally, interaction term measures simultaneous effect of both endowments and coefficients (Jann, 2008).

Table 7. Oaxaca-Blinder decomposition, formal vs. informal, male/female employees

	Male				Female			
Variables	**Overall**	**Endowments**	**Coefficients**	**Interaction**	**Overall**	**Endowments**	**Coefficients**	**Interaction**
Hrs_wu		0.001	0.268***	0.001		0.049***	0.067	0.005
Age_25-39		0.000	0.017	0.000		-0.004	-0.011	0.002
Age_40-54		0.002	0.004	0.002		0.019*	-0.015	-0.010
Age_55-64		0.004	-0.004	-0.001		0.004	-0.002	-0.001
Age_65+		0.000	0.000	0.000		0.001	0.002	-0.001
Experience		0.098***	-0.064	-0.013		0.041**	0.165**	0.045**
Experience2		-0.075***	0.067	0.016		-0.030**	-0.066	-0.019
Below second.		-0.000	-0.065***	0.000		-0.018***	-0.072***	0.007***
University		0.090***	-0.026***	-0.034***		0.066***	-0.043***	-0.022***
Student		0.003**	0.005*	-0.003*		0.003	0.002	-0.001
Married		0.016***	-0.004	-0.001		0.005*	-0.035***	-0.010***
Agriculture		0.009***	0.006	-0.003		0.010***	0.009**	-0.007**
Manufacturing		0.004	0.006	0.004		0.001	-0.012	-0.001
Construction		-0.016**	-0.024*	0.014*		0.000	-0.000	-0.000
Trade		0.000	-0.005	-0.000		0.001	-0.029***	0.007***
Transportation		0.006***	-0.007**	-0.004**		-0.000	0.001	0.001
Accommodation		-0.000	-0.003	0.001		0.001	-0.011***	0.005***
Finances		-0.000	0.006	0.000		-0.001	0.001	-0.000
Public admin.		-0.005	0.000	0.001		0.004	-0.018***	-0.019***
Education		0.000	-0.001	0.000		0.004	-0.003	0.002
Director		0.014***	0.004***	0.015***		0.018***	0.002***	0.009***
Professional		0.035***	0.004	0.007		0.066***	0.014***	0.024***
Technician		0.015***	0.006***	0.008***		0.020***	0.019***	0.021***
Semi-skilled		-0.001	0.010***	0.001*		-0.012***	0.051***	-0.014***
Fulltime		0.016***	-0.208***	-0.021***		0.012**	-0.108***	-0.024***
Small firm		-0.002*	0.008	-0.001		0.001	-0.002	-0.000
Med-Large firm		0.053***	-0.012*	-0.009*		0.032***	-0.008	-0.004
Formal	6.448***				6.242***			
Informal	6.049***				5.797***			
Difference	0.399***				0.446***			
Endowments	0.267***				0.293***			
Coefficients	0.153***				0.159***			
Interaction	-0.021**				-0.006			
Constant			0.164**				0.261***	
Observations	201,814	201,814	201,814	201,814	203,297	203,297	203,297	203,297

*Note: Standard errors omitted. *** p<0.01, ** p<0.05, * p<0.1. 2009-2016.*
Source: Authors

According to Table 7, there is no substantial difference in as much as overall explained variables (endowments and interaction) account for about two thirds of the difference (0.246 out of 0.399 for males, and 0.287 out of 0.446 for females), whereas unexplained variables (coefficients) account for about one third of the difference. There is also not much difference between the male and female samples as regards the decomposition output. The difference between formal and informal employees is higher for females (0.446 compared to 0.399 of males).

In the samples for female and male employees, variables are consistent with both descriptive data and model estimates.

For males, the mean increase in the income of informal employees assuming they had the characteristics of formal employees would be 0.267. The variables that account for the wage gap (0.399) between formal and informal male employees are working hours, work experience, being a professional or a director, working in a medium or a large firm and university educational.

For females, the mean increase in the income of informal employees assuming they had the characteristics of formal employees would be 0.293, one fifth higher than males. The variables that account for the wage gap (0.446) between formal and informal female employees are working experience, being a professional or a technician, working hours, educational attainment, working in a medium or a large firm, and being a director.

Summing up, the difference between formal and informal employees seems to be better explained on the demand side by characteristics of the firms (occupation, firm size and working hours) than on the supply-side by the workers characteristics (age, education and experience). The difference is explained at around 62 per cent with the selected variables for males and at 65 per cent for females. The mean increase in the income of informal male employees if they had the characteristics of formal employees would be 27 per cent. The mean increase in the income of informal female employees if they had the characteristics of formal employees would be 29 per cent. Hence, females face a higher wage penalty.

6. Conclusions

We defined informal employment, according to the ILO (2013) as employment without receiving employer's social insurance contribution and at the same time with no permanent contract at the main job. We demonstrate that the share of informal employees in our post transition countries sample is increasing over time, with the exception of Bulgaria and Latvia. Informal employees earn significantly less (between 25-30%) in real terms (€ 398-490 per month) compared to € 580-662 for formal employees); they are on average six years less experienced than formal employees. There are about 10 per cent more employees with a university degree in formal employment. In addition, more married individuals are present among formal employees. Most of informal employees have low-skilled occupations.

Application of a pooled OLS Mincer model supports human capital theory in as much as education, skills and experience prove to be highly significant in wages determination, whereas males and married individuals tend to have higher income. A large share of wage penalty for informal employment, about 69 per cent for male employees and 63 per cent for female employees, is explained by both individual and job characteristics. However, 31 per cent of wage penalty remain unexplained for male and 37 per cent for female employees. When correction for selection bias is taken into account, wage penalty declines to 11 per cent for males and to 16 per cent for females. The conditional quantile regressions show that both male and female employees experience wage penalty for informality, being the highest at the bottom decile (-0.25 for male employees and -0.28

for female employees) and the lowest at the highest decile for males (-0.19) and at the second lowest quantile for females (-0.21).

Fixed effects regression demonstrates that even when accounting for unobservable characteristics, wage penalty for informality does not disappear, reaching 22 per cent for female employees and 7 per cent for male employees.

According to an Oaxaca-Blinder wages decomposition, the difference between formal and informal employees is explained by 62 per cent with the selected variables for males and at 65 per cent for females. The characteristics of the firms (occupation, firm size and working hours) on the demand side explain this difference better than the workers characteristics (age, education and experience) on the supply-side, confirming labour market segmentation theory. In addition, wage penalty proves higher for female employees, who face double penalty, one for gender and the other one from labour demand.

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Appendix

Table A1. Dictionary of variables

Variable	Description
Informal	1 if informal employee, 0 otherwise
Working hours	Number of hours usually worked per week by an employee in the main job
Age cohorts	1 – from 16 to 24 2 – from 25 to 39 3 – from 40 to 54 4 – from 55 to 64 5 – above 65
Experience	Number of years spent in paid work (as employee or self-employed)
Gender	1 if male, 0 if female
Education level categories	1 – below secondary education (no education and lower secondary education) 2 – completed secondary education 3 – vocational training and university degree
Student	1 if enrolled as a student, 0 otherwise
Married	1 if married, 0 otherwise
Industry (NACE)	1 – Agriculture 2 – Manufacturing and utilities 3 – Construction 4 – Trade 5 – Transportation 6 – Accommodation and food 7 – Finances and real estate 8 – Public administration 9 – Education and health 10 – Other services
Occupation (ISCO)	1 – Director, manager or CEO 2 – High level professional 3 – Technician 4 – Semi-skilled white collar (sales, clerks) worker 5 – Low-skilled and low-unskilled (elementary professions, domestic) worker
Fulltime	1 if full time worker, 0 otherwise
Firm size categories	1 – Micro, 1-9 workers 2 – Small, 10-49 workers 3 – Medium and large, above 50 workers
Log real monthly income	Log of full time equivalent real monthly income. Calculated as the sum of “gross employee cash or near cash income” and “gross non-cash employee income” adjusted for a full-time equivalent and a CPI (World Bank, 2017a, 2017b), with 2010 as a base year.

Source: Authors

Table A2. Summary statistics, formal employees (2009, 2013, 2016)

	2009			2013			2016		
Variables	Mean	SD	N obs	Mean	SD	N obs	Mean	SD	N obs
Real month. income	730	(629.41)	57321	658.5	(498.47)	53247	724.8	(578.19)	52262
Working hours	40.5	(6.61)	51051	40.3	(6.5)	48844	40.2	(6.22)	48383
Age	40.9	(11.53)	57321	42	(11.53)	53247	42.5	(11.67)	52262
Experience	21.8	(11.9)	57301	22.6	(12.04)	53228	23	(12.15)	52258
Male	0.5	(0.5)	57321	0.5	(0.5)	53247	0.5	(0.5)	52262
No second. educat.	0.1	(0.27)	57321	0.1	(0.25)	53247	0.1	(0.25)	52262
Second. educat.	0.6	(0.49)	57321	0.6	(0.49)	53247	0.6	(0.49)	52262
Univers. education	0.3	(0.46)	57321	0.3	(0.47)	53247	0.4	(0.48)	52262
Student	0	(0.21)	57321	0	(0.18)	53247	0	(0.16)	52262
Married	0.6	(0.48)	57320	0.6	(0.48)	53247	0.6	(0.49)	52261
Agriculture	0	(0.16)	57321	0	(0.16)	53247	0	(0.16)	52262
Manufacturing	0.2	(0.43)	57321	0.3	(0.43)	53247	0.3	(0.44)	52262
Construction	0.1	(0.26)	57321	0.1	(0.24)	53247	0.1	(0.24)	52262
Trade	0.1	(0.33)	57321	0.1	(0.33)	53247	0.1	(0.33)	52262
Transportation	0.1	(0.24)	57321	0.1	(0.24)	53247	0.1	(0.24)	52262
Accommodation	0	(0.17)	57321	0	(0.16)	53247	0	(0.17)	52262
Finances	0.1	(0.3)	57321	0.1	(0.31)	53247	0.1	(0.31)	52262
Public administ.	0.1	(0.27)	57321	0.1	(0.28)	53247	0.1	(0.28)	52262
Education	0.1	(0.35)	57321	0.1	(0.36)	53247	0.2	(0.36)	52262
Other services	0.1	(0.32)	57321	0.1	(0.31)	53247	0.1	(0.29)	52262
Director	0.1	(0.22)	56965	0	(0.21)	52927	0.1	(0.24)	52181
Professional	0.2	(0.36)	56965	0.2	(0.39)	52927	0.2	(0.39)	52181
Technician	0.2	(0.36)	56965	0.1	(0.35)	52927	0.1	(0.34)	52181
Semi-skilled	0.2	(0.42)	56965	0.2	(0.43)	52927	0.2	(0.42)	52181
Low-skilled	0.4	(0.49)	56965	0.4	(0.49)	52927	0.4	(0.49)	52181
Fulltime	0.8	(0.4)	57321	0.8	(0.38)	53247	0.9	(0.3)	48383
Micro firm	0.2	(0.39)	57321	0.2	(0.38)	53247	0.2	(0.36)	52262
Small firm	0.4	(0.48)	57321	0.4	(0.48)	53247	0.4	(0.48)	52262
Medium-Large firm	0.4	(0.48)	57321	0.4	(0.49)	53247	0.4	(0.49)	52262

Note: weighted descriptive statistics

Source: Authors

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Table A3. Summary statistics, informal employees (2009, 2013, 2016)

	2009			**2013**			**2016**		
Variables	Mean	SD	N obs	Mean	SD	N obs	Mean	SD	N obs
Real month. income	512.9	(464.19)	2625	449.8	(317.46)	2014	510	(399.4)	1633
Working hours	38.6	(10.78)	1947	38.8	(10.54)	1592	39.1	(10.57)	1327
Age	36.3	(12.79)	2625	36.4	(12.72)	2014	37.3	(13.08)	1633
Experience	18.1	(13.25)	2616	18.2	(13.33)	2014	19	(13.69)	1633
Male	0.6	(0.5)	2625	0.6	(0.5)	2014	0.5	(0.5)	1633
No second. educat.	0.2	(0.41)	2625	0.2	(0.39)	2014	0.2	(0.38)	1633
Second.education	0.6	(0.49)	2625	0.6	(0.48)	2014	0.6	(0.49)	1633
Univers. education	0.2	(0.38)	2625	0.2	(0.4)	2014	0.2	(0.4)	1633
Student	0.1	(0.33)	2625	0.1	(0.28)	2014	0.1	(0.27)	1633
Married	0.5	(0.5)	2625	0.5	(0.5)	2014	0.4	(0.5)	1633
Agriculture	0	(0.21)	2625	0.1	(0.26)	2014	0.1	(0.26)	1633
Manufacturing	0.1	(0.35)	2625	0.2	(0.36)	2014	0.2	(0.38)	1633
Construction	0.1	(0.35)	2625	0.1	(0.35)	2014	0.1	(0.33)	1633
Trade	0.1	(0.32)	2625	0.1	(0.33)	2014	0.1	(0.32)	1633
Transportation	0	(0.18)	2625	0	(0.18)	2014	0	(0.16)	1633
Accommodation	0	(0.2)	2625	0	(0.19)	2014	0.1	(0.22)	1633
Finances	0.1	(0.28)	2625	0.1	(0.29)	2014	0.1	(0.31)	1633
Public administrat.	0	(0.2)	2625	0	(0.19)	2014	0	(0.21)	1633
Education	0.1	(0.25)	2625	0.1	(0.26)	2014	0.1	(0.23)	1633
Other services	0.3	(0.45)	2625	0.2	(0.42)	2014	0.2	(0.42)	1633
Director	0	(0.09)	2617	0	(0.09)	2006	0	(0.13)	1630
Professional	0.1	(0.25)	2617	0.1	(0.22)	2006	0.1	(0.24)	1630
Technician	0.1	(0.26)	2617	0.1	(0.24)	2006	0.1	(0.23)	1630
Semi-skilled	0.3	(0.45)	2617	0.3	(0.44)	2006	0.3	(0.45)	1630
Low-skilled	0.6	(0.49)	2617	0.6	(0.49)	2006	0.6	(0.49)	1630
Fulltime	0.6	(0.49)	2625	0.6	(0.49)	2014	0.8	(0.41)	1327
Micro firm	0.3	(0.44)	2625	0.3	(0.43)	2014	0.2	(0.43)	1633
Small firm	0.3	(0.46)	2625	0.3	(0.47)	2014	0.4	(0.48)	1633
Medium-Large firm	0.2	(0.4)	2625	0.2	(0.41)	2014	0.2	(0.4)	1633

Note: weighted descriptive statistics
Source: Authors