Informal Pay Gaps in Good and Bad Times: Evidence from Russia

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Abstract

Informal work is traditionally large in Russia and has further increased in the recent years. We explore the implications of this shift in terms of wage dynamics. Our characterization is based on the estimation of informal pay gaps at the mean and along the wage distribution, relying on the Russian Longitudinal Monitoring Survey for 2003-2017. Our approach comprises three original features: we rely on *unconditional* quantile effects of informality, we incorporate quantile-specific fixed effects using a tractable approach, and we suggest a treatment of the incidental parameter bias. Over the whole period, informal wage penalties are relatively small and do not suggest heavily segmented labor markets, even at low wage levels. Yet, in the past decade, a substantial negative selection into informal employment and self-employment has taken place, on average and especially at low earnings. Economic downturns and labor market policies have likely contributed to the shakeout of less productive workers in the formal sector, making the low-tier informal sector more of a last resort.

Key Words: Russia, informal employment, wage gap, unconditional quantile regression, fixed effects, incidental parameter bias, jackknife.

JEL Classification: J31, C14

1 Introduction

The Russian economy, which had been growing by an average of more than 7% a year in the previous decade, has suffered from the Great Recession, with a fall in GDP of 7.9% in 2009. Some years later, economic sanctions and low oil prices have led to a new episode of recession (the GDP went down by 3.7% in 2015 and real disposable income fell by 10%). These events hardly show up in terms of unemployment: unemployment rates have experienced a long-term decline from 10.6% in 2000 to a 5-6% since 2012, with only short and moderate increases in the wake of the crisis (7-8% in 2009-10). In addition to adjustments in wages and hours of work, these trends are explained by the role of informal work as a buffer to a deteriorated economic situation (Gimpelson and Kapeliushnikov, 2015). For the standards of industrialized countries, informality in Russia was already high before the crisis: the country counted more than 15 million informal workers in a labor force oscillating between 70 and 76 million workers over the past two decades(Russian Federal Service for State Statistics, Rosstat).

These recent trends therefore raise questions about the evolution of the informal sector and its composition. From a positive point of view, one can imagine that this is an expansion of small -informal- businesses following the 2008-09 crisis, generating additional employment and growth (even if not contributing to fiscal revenues, by definition). A less rosy picture is a possible negative selection into the informal sector, with the least productive workers pushed into precarious forms of informal activity. Despite the attention devoted to recent trends in wage inequality (e.g. Calvo et al., 2015, Dang et al., 2018), little is known about the wage dynamics associated with changes in the sectoral composition of the Russian labor market. Against this background, we suggest an extensive analysis of the informal-formal earnings gap.

We rely on the Russian Longitudinal Monitoring Survey (RLMS-HSE) and its informal employment module for the period 2003-2017. Estimations at the mean may conceal a great variety of situations due to the very heterogeneous nature of the informal sector (and the possible accentuation of this heterogeneity). Estimations at different points of the earnings distribution seem useful and we rely on quantile estimation approaches. We explore additional dimensions of heterogeneity: gender differences in wage gaps, the type of informal work (wage gaps between formal work and informal employment or informal self-employment) as well as time changes (using time-heterogeneous quantile estimates). We address three main limitations that characterize the bulk of the literature on sector wage gaps.

First, omitted variables may affect both earnings levels and selection into a particular sector. Panel estimations in distributional analyses have emerged as an interesting way to reduce this bias (see for instance Hospido and Moral-Benito, 2016, on public-private sector wage gaps). We follow this path using the panel dimension of the RLMS-HSE. It allows controlling for individual fixed effects, which capture workers' unobserved characteristics and skills. Our estimator of the informal premia/penalties is also more flexible than usual – our fixed effects are quantile-specific – and tractable at the same time.

Then, a common issue found in the literature is that nonlinear estimators with fixed effects potentially suffer from the incidental parameter bias, especially when panels are short. This bias smoothes the true quantile effects, concealing part of the effect heterogeneity and giving the impression that unobserved heterogeneity is explaining most of the earnings variation along the distribution. We avail of 15 years of RLMS-HSE data but this issue may still affect our estimates substantially (see Bargain et al., 2018). While there is hardly any study correcting for the incidental parameter bias in the context of fixed effect quantile estimations, we suggest a simple jackknife correction for our estimator, inspired from Dhaene and Jochmans (2015).

Finally, a contribution of our work is the use of *unconditional* quantile effects. Most of the literature relies on conditional quantile estimations, which lead to a very specific interpretation of the wage gap when panels are used. Indeed, wage penalties or premia at different quantiles are to be understood as pay differentials conditional on the workers' (time-invariant) fixed effects. These pay differentials then essentially reflect time variation, which is not very informative. Several contributions have suggested ways to estimate unconditional quantiles (Firpo et al., 2009, Chernozukhov et al., 2013) and rare applications have used them to also account for fixed effects in panel estimations (Hospido and Moral-Benito, 2016).

The present contribution suggests the estimation of unconditional quantile effects following Chernozukhov et al. (2013) while accounting for fixed effects and, importantly, without changing the interpretation of the informal wage premia/penalties. In this way, it becomes possible to assess how the informal wage gap varies, at each point of the unconditional wage distribution, when unobserved characteristics are taken into account or not. In other words, the difference between pooled estimations and fixed effect estimations allows us to characterize the extent of negative or positive selection into the informal sector. This can be done all along the (unconditional) distribution as well as at different points in time, for instance before and after the Great Recession.

Results are as follows. We first characterize the complexity of the informal sector by use of quantile estimations of the informal pay gap over the whole period. We distinguish informal salary workers and informal self-employed, eliciting in each case the earning gap relative to formal salary workers. Small informal wage penalties exist among the least productive salary workers (less than 10%), for both men and women, but do not suggest heavily segmented labor markets. The informal self-employment earning gap is basically zero except at the top of the distribution for men, with a modest earning premium in self-employment.

We then address time changes and provide an extensive robustness analysis. Informal pay gaps gradually decline over the period but show only small variation around zero. They turn negative for informal salary work in the recent years. Earnings premia in informal self-employment are observed at the beginning of the period but quickly disappear. Most interestingly, comparisons of estimations with and without individual fixed effects point to a negative selection into informal work in the years 2010s. This trend is especially pronounced in informal salary work and for men, at low and median wage levels. We further characterize the fact that among low-wage workers, there is an acceleration of the transitions from formal to informal work in the last decade for those with below-average individual fixed effects.

These results tend to reflect the shakeout of less productive workers in the formal sector and possibly the role of some of the labor market reforms following the crisis. We discuss the implications of these findings. With a growing share of the labor force in unregulated, less productive activities, the labor reallocation that followed the crisis may contribute to reduce growth and overall productivity. Our results are also consistent with a heterogeneous, two-tiered view of the informal sector in Russia (Gimpelson and Kapeliushnikov, 2015). This picture seems to aggravate: with the low-tier informal sector becoming more of a last resort option, the Russian labor market is increasingly susceptible to exacerbate inequalities in living standards.

2 Background

2.1 Informal Employment and Wage Gaps: A Brief Survey

Average Pay Gaps and Selection. The debate on whether informal work is a bad form of employment – and whether it is involuntary by nature – is not new. In the traditional paradigm (Harris and Todaro, 1970), labor markets are segmented so that the traditional, unregulated sector is a free-entry market while the modern sector benefits from minimum wages and job protection/amenities that create entry barriers. Models have been suggested (Fields, 1975) and tested (Dickens and Lang, 1985) that allow the coexistence of multiple sectors and unemployment. Empirically, many studies have attempted to check whether traces of segmentation are observable in the form of large wage changes when workers transit across sectors (Gong and Van Soest 2002, Funkhouser, 1997). More recently, some authors have described the informal sector as a desirable and voluntary-entry segment of the labor market, often taking Mexico as an interesting case study (e.g. Marcouiller et al., 1997, Maloney, 1999, 2004, Bosch and Maloney, 2007). However, this statement mainly concerned the self-employed rather than salary workers. Hence, it seems important to focus on each employment type separately, when comparing earnings gaps with the formal sector, as we do hereafter. For salary workers, more recent empirical studies have shown that large wage gaps between sectors tend to disappear when unobserved heterogeneity between workers is taken into account, which would indicate that markets are more competitive than earlier thought (Gong et al., 2004, Pratap and Quintin, 2006, Badaoui et al., 2008, Cichello et al., 2005). A few studies even report the fact that labor market regulations in place in the formal sector sometimes pervade informal employment, notably the effect of minimum wages (Gindling and Terrell 2005, Khamis, 2013).

Heterogeneity and Distributional Analyses. The reality of labor markets in emerging or transition economies probably lies beyond the mere divide between segmentation and competition views. For one thing, other aspects have rarely been considered like the possibly large differences in bargaining power across sectors or sub-groups of workers (Carneiro and Henley, 1998). Also, the informal sector is possibly greatly heterogeneous. We have mentioned the necessity to distinguish salary workers and the self-employed, especially due to fact that self-employment is more often a voluntary choice motivated by independence and flexibility (Maloney, 2004). More generally, even within each of these groups, there must be a coexistence of unchosen informality and desired, upper-tier informal work. This reconciliation of the traditional and competition paradigms has emerged in the policy-oriented literature (Fields 1990, 2005, Perry et al. 2007). Empirical studies also illustrate this diversity. Recent investigations have used quantile estimations and point to informal wage penalties of varying size at the bottom of the conditional wage distribution and smaller or zero penalties at the top (Tannuri-Pianto and Pianto, 2008, Bargain and Kwenda, 2013). These analyses also find – for a significant segment of the labor force – substantial self-employment premia at the top of the distribution.

Evidence from Middle-Income and Transition Countries. It turns out that most of the empirical evidence stems from Latin American countries, possibly due to the prevalence of informal sectors in this region. There are some exceptions: a few studies cover African countries (for instance Kingdon and Knight 2004, 2007, Gunther and Launov, 2012) or Asia (e.g. Vietnam in Nguyen et al., 2013, or China, in Appleton et al, 2002, Long et al, 2014, or Liang et al., 2016). There is also a protean literature on transition countries. Some studies use sector transitions to reveal potential signs of segmentation, for instance in Georgia (Bernabe and Stampini, 2008), Bulgaria (Dimova et al., 2005) or Russia (Slonimczyk and Gimpelson, 2015, Gimpelson and Kapeliushnikov, 2015). Other studies rely on suggestive evidence based on wage gaps, pointing to heterogeneous informal sectors in Ukraine (Lehmann and Pignatti, 2008) and Serbia (Blunch, 2011). A branch of the literature addresses undeclared work as a form of tax evasion, sometimes focusing on secondary activities because they are most often unregistered (Guariglia and Kim, 2004) or showing how moves to flat tax system may affect informal employment (Slonimczyk, 2012). More generally, the relatively disenfranchised groups are most likely to evade payroll tax and work informally (for instance in Estonia, see Kriz et al., 2008). The informal sector hence tends to function as a last resort for marginalized groups (see Kim, 2005, for Romania). Using data from Ukraine, Akay and Khamis (2012) provide one of the most convincing piece of evidence about the persistence of poverty through informality, pointing to the possibly long-lasting perception that social security benefits are not worth contributing to by workers in the informal sector. Finally, an interesting comparison between Latin American and transition countries (Albania, Georgia and Ukraine) is established by Pages and Stampini (2007), who find smaller informal wage penalties in the latter group.[1]

Note that our interpretations will be drawn from a more advanced empirical strategy than currently used in the literature on transition countries (or even that on Latin America). Indeed, none of the aforementioned studies on informal wage gaps do provide unconditional quantile effects of informality while controlling for unobserved heterogeneity and the incidental parameter bias. Also, while several studies address the extent of a gender wage gap in transition countries (e.g. Atencio and Posadas, 2015) – notably across the formal-informal divide – there is little focus on how the informal sector wage gap may vary across gender, something that we investigate hereafter. Finally, we provide one of the rare exploration of the sectoral wage dynamics for Russia.

2.2 The Russian (Informal) Labor Market

Transition Process and Labor Market Regulation. As noticed by Slonimczyk (2014), transition to a market economy may lead to a shift from state enterprises to the private sector, from large firms to smaller firms and from industry to services – hence a potential move towards the typical characteristics of informal firms. Russia seems to follow this pattern but only to some extent. Admittedly, transition has resulted in the development of informal entrepreneurial activities, yet not to the level observed in

[1]Our own results support this finding if we compare the estimates of the present paper with those for Brazil or Mexico for instance, in Bargain and Kwenda (2013).

emerging economies (like Mexico, for instance). The industrial base of the economy has remained large despite the growing role of the service sector. Several factors may have encouraged informal employment also in large firms and traditional sectors. The shadow economy entails the non-registration of entire (rather small) firms but also the presence of some workforce without formal contracts (and double book-keeping) within large firms.

Note that stringent labor market regulations are often blamed for the existence of a relatively large informal sector in Russia, despite the partial liberalization of labor laws in 2002. Yet there is some discussion on their real effectiveness given the poor enforcement of employment protection legislation and the unbinding nature of the minimum wage. While informal work relationships can stem from firms' intention to escape formal costs (social contribution payment, labor market rigidity, etc.), some of it may also be on account of workers who avail of very low unemployment benefits and show a growing distrust toward the state's ability to deliver on social obligations (Gimpelson and Kapeliushnikov, 2015). For the years under study, overall mobility between formal and informal employment does not seem to indicate much of entry barriers to the formal sector (Slonimczyk and Gimpelson, 2015). The results in the present study will corroborate this point by showing relatively modest informal pay gaps but also the rise of a low-tier informal sector.

Informality in Russia and Trends. It is difficult to precisely estimate the size of informality in transition countries. In the middle of the period under study, which corresponds to the onset of the Great Recession, informal work in Russia represented between 13% and 35% of total labor depending on the definition at use (Gimpelson and Zudina, 2012). Despite such a broad confidence interval, there is no doubt that a substantial part of economic activities are not registered and that many workers enter employment relationships that provide no (or only partial) social security and unemployment protection (Slonimczyk, 2012). Using RLMS-HSE data (described in the next section) and combining both undeclared salary work and informal self-employment in the main job, we find an average informality rate of 15% in 2009, which is about the same as the average over 2003-2017.[2]

[2]Larger rates of informality tend to be found when unregistered secondary occupations are included. Guariglia and Kim (2004, 2006) address the role of moonlighting in informal second job activities as a stepping stone towards job changes and moves towards self-employment. We do not consider moonlighting in this study (represent a marginal fraction of our sample) but only the main activity. We will nonetheless consider the impact of adding casual workers who are not officially working otherwise.

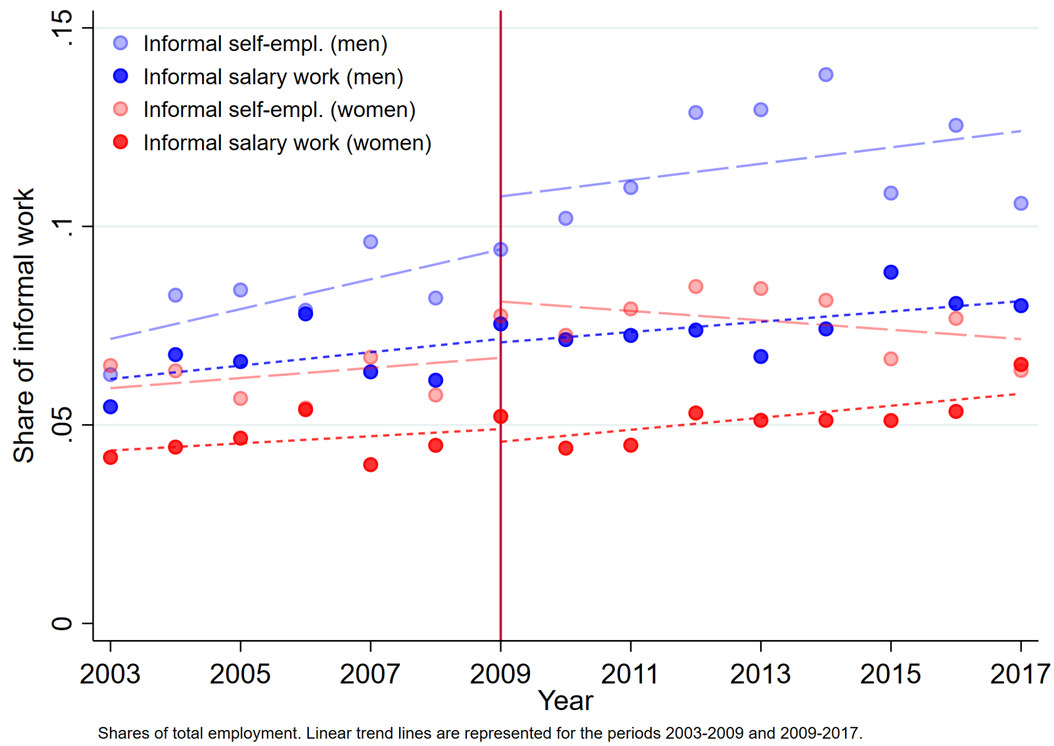


Figure 1: Trend in Informal Employment Share (Russia, 2003-17)

We investigate how the structure of the Russian labor market has evolved in the recent period. Based on RLMS-HSE data, Figure 1 presents the shares of informal employment and informal self-employment in percent of total labor (they are complement to 1 of formal salary work), for each year and separately for men and women. We also show linear trends separately before and after 2009. We see an overall increase in the share of informal work for both men and women after this point. The only exception is a slightly decline in the share of self-employment for women. An overall increase of informal work, i.e. a compression of formal employment, is robust to alternative definitions of informal work (Lehmann and Zaiceva, 2015). These general trends hide contrasted patterns across wage groups, as discussed in the next section.

Recent Downturns and Policy Reforms. In Russia, employment levels tend to be relatively resilient to shocks. The very low sensitivity of unemployment to fluctuations in output is described as “a major trade mark of the Russian labor markets” (Gimpelson and Kapeliushnikov, 2013). It seems to be explained by flexible wages, flexible work hours (hour losses being possibly compensated by moonlighting) and transitions to low-productivity informal employment during downturns. One of the characteristics of the 2008-09 crisis and the subsequent shocks experienced by the Russian economy is the greater reliance on informal work. The compression of formal employment may also be explained by subsequent institutional changes, initiated in 2008 and put in effect in 2009. While these policies have been justified by the crisis, they may have had their own effects on labor market performance. In particular, minimum wages nearly doubled in 2009 (see Kapelyuk, 2015), i.e. increasing from 13% to 23% of the average wage. Other measures might have had more ambiguous effects on informality.[3]

A central question is whether this upward trend in informality is worrying. It may correspond to the creation of new activities, for instance a dynamic employment growth in micro-entrepreneurship that could have contributed to the rapid recovery of Russian employment in 2010 (see Gimpelson and Kapeliushnikov, 2015). Yet, it is also a source of concern if a larger share of informal workers put further pressure on tax revenue and public deficits while moving to vulnerable unregistered salary work or precarious own-account work. Our analysis aims to shed some light on this question.

3 Empirical Approach

3.1 Data and Selection

We make use of the Russian Longitudinal Monitoring Survey (RLMS-HSE).[4] This is a relatively long panel dataset covering the period 1994-2019 with the exception of years 1997 and 1999. We focus on the years 2003-2017, i.e. a period surrounding the Great Recession.[5] We restrict the sample to 15-64 years old, and drop those who are on military duties or do not receive labor income. The final sample contains 85,471 person-year observations corresponding to 21,745 individuals (observed between 2 and 15 times). A specific module on the employment status allows defining informal types of activity as follows. Salary workers are identified using information on whether they work at an enterprise or organization as well as information on their primary occupation. They are deemed informal salary workers if they answer negatively to the question “Are you employed in this job officially, in other words, by labor book, labor agreement or contract?”.[6] Informal

[3]Another measure is the increase in the maximum value of unemployment benefit in 2009. Yet it did not impact the replacement ratio, which had gradually declined for years, reached a low 10% before continuing its downward slide the following years. Other measures include an extensive support to firms in order to allow them to keep their labor force and, at the same time, administrative pressure on firms to keep dismissals on hold.

[4]It is collected by a consortium of organizations with the financial support from the Higher School of Economics (HSE), see https://www.hse.ru/en/rlms/

[5]Note that the key variable used to define informal salary work is not always available before 2003.

[6]A question “Why aren’t you officially registered at this job?” might also be used to elicit whether informality is freely chosen (when the answer is “I do not want to register”) or is more of an ‘involuntary’

self-employed are defined as individuals who declare “working at other than an enterprise, organization, collective farm, state form or cooperative” but who report labor income and are involved in entrepreneurial activity or individual labor activity. In sensitivity checks, we will also include paid workers without a primary activity but who provide casual work for a pay. They are most likely informal own-account workers and will be treated as informal self-employed. Overall, we focus on three categories of workers including formal employees, informal employees and the informal self-employed. Hourly earnings are calculated using declared earnings, taken net of tax for those in formal activities, and usual working time. Hourly wage gaps are then measured as the log hourly earnings difference between the informal employees (or self-employed) and formal salary workers.

3.2 Descriptive statistics

While we have already commented on the increased share of informal activity, Figure 2 takes a closer look at employment trends by sector detailed at extreme points of the earnings distribution, namely top and bottom quintiles. It reveals that most of the action observed in Figure 1 comes from the lower part of the wage distribution. The graph on the left focuses on informal salary work. Its share in total employment actually declines for male top earners. For the lowest quantile, on the contrary, there is a gradual increase for men, which tends to accelerate in the recent years when women's informal employment also takes off. Between 2010 and 2017, the increase in informal salary work in the bottom wage quintile is twofold for men (a shift from 10% to 20%) and almost threefold for women (from 5% to 14% of total employment). On the right side of Figure 2, we observe a similar pattern for the self-employed. During 2010-2017, informal self-employment increases a lot for men (from 6% to 17%) and more modestly for women (.from 6% to 12.5%). Contrasted wage dynamics at different points of the unconditional wage distribution justify the use of quantile regression techniques as suggested hereafter.

nature (with the answer being “The employer does not want to register”). Yet, we have refrained from using this information given the very subjective nature of the question and the fact both answers are not mutually exclusive (but are recorded as such).

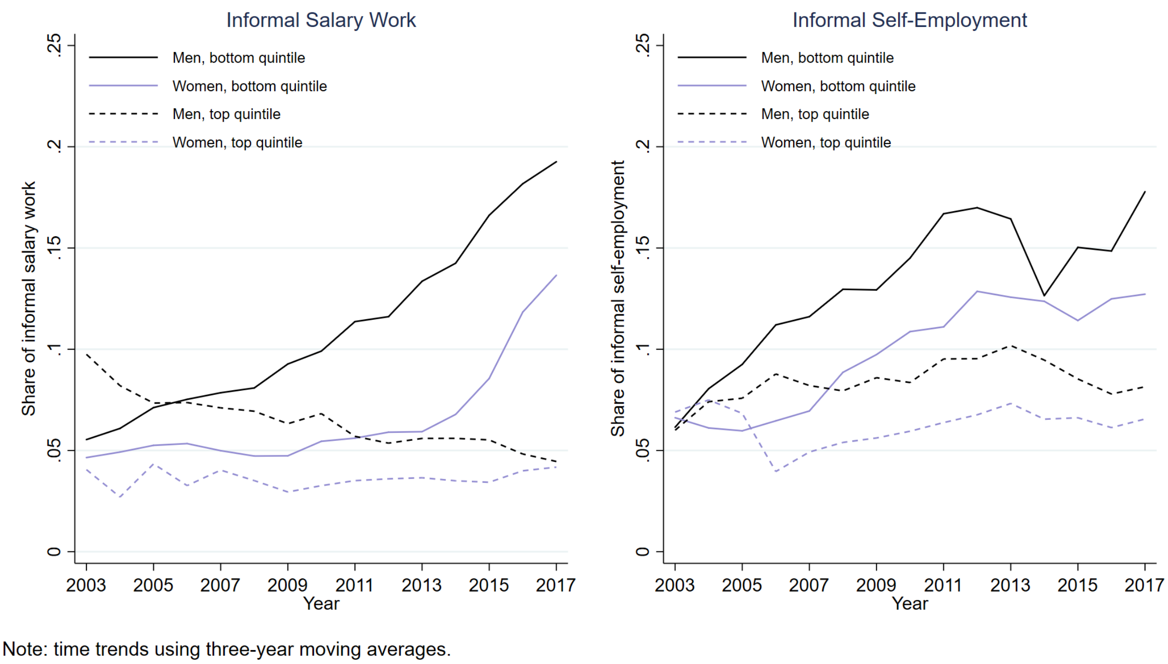


Figure 2: Trends in Informality Share for Extreme Wage Deciles (Russia, 2003-17)

A further inspection of the data reveals that the distribution of hourly earnings is not very different across types of employment. The left hand side of Figure 3 indeed shows similar distributions, over the whole period, for formal salary, informal salary and self-employed workers. On the right, we represent the time change in mean hourly earnings for each employment type. Again, their trends are not very different. Nonetheless, for both men and women, wage dynamics diverge in the 2010s as a gap emerges between formal and informal earnings. This relative stall in informal salaries can be related to the previous employment trends and the hypothesis of job destructions in the formal sector, compensated by a transition of dismissed workers to the informal sector. Our sectoral wage gap estimations will characterize these transformations in the Russian labor market more precisely – with like-for-like comparisons of workers across sectors – to ultimately shed light on the changing nature of informality in this country.

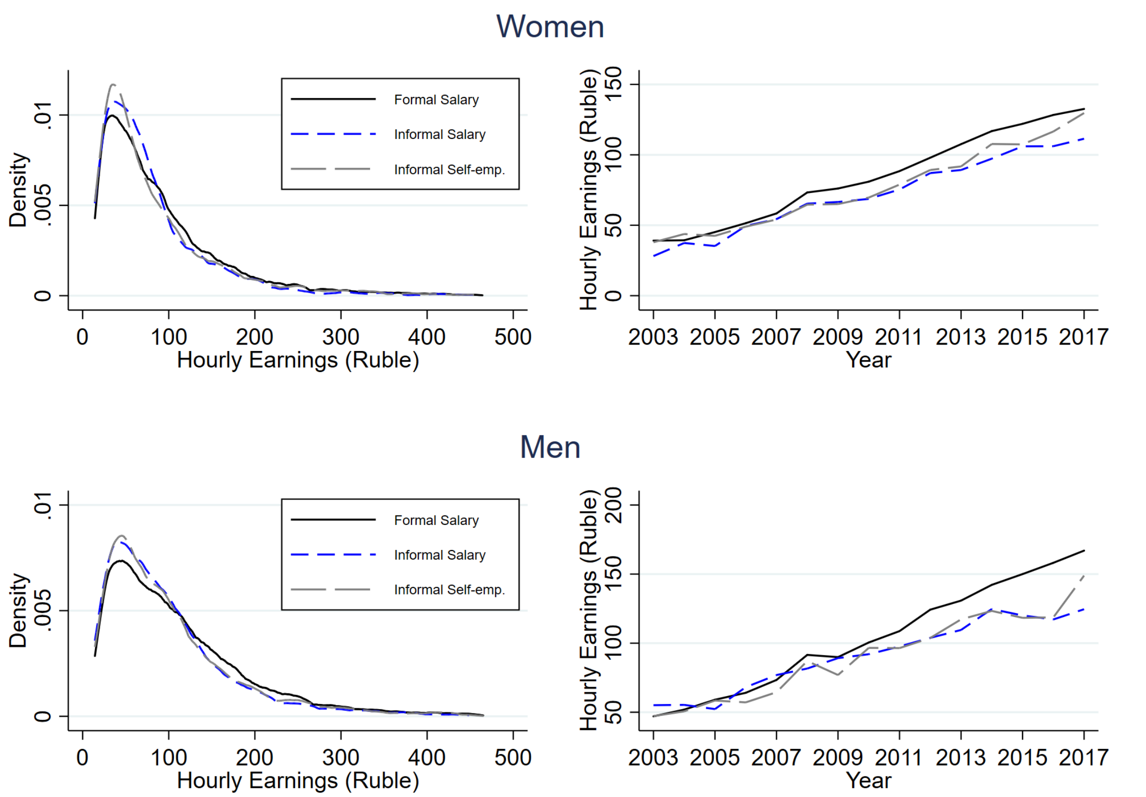


Figure 3: Trend in Hourly Earnings (Russia, pooled years 2003-17)

Table 1 reports broad statistics for each employment type. As expected, informal workers have lower education achievement than their formal counterparts. However, informality in transition countries is characterized by higher education levels than, say, in emerging economies (like Mexico). A majority of the Russian population has secondary or tertiary education: 90% in formal jobs, 82% in self-employment and 78% in informal salary work. There is a relatively small gap across sectors in terms of potential experience, as proxied by average ages. Informal work is composed by a majority of men. There are limited differences across sectors in terms of geographical allocation. We also report the main sectors where informal workers are to be found: trade and small-scale services, construction, transportation and industry. More than half of informal employment – 59% of salary work and 63% of self-employment – operates in the trade and construction sectors, while the latter represent only around a quarter of the formal activity. These statistics are in line with other description of informal work in Russia using slightly different definitions of informality.[7]

[7] For instance, according to Gimpelson and Zudina (2012), a higher probability to be informal concerns

	Formal Salary Work			Informal Salary Work			Informal Self-Employment		
Variables	All	Male	Female	All	Male	Female	All	Male	Female
Age	39.8	39	40.5	36.3	35.1	37.9	37.8	36.9	38.9
Male (%)	0.45	1.00	0.00	0.57	1.00	0.00	0.57	1.00	0.00
Married (%)	0.73	0.81	0.65	0.65	0.72	0.56	0.72	0.78	0.63
Second Educ. (%)	0.58	0.60	0.56	0.65	0.63	0.68	0.67	0.65	0.71
High Educ. (%)	0.32	0.25	0.37	0.13	0.11	0.14	0.15	0.14	0.17
Rural (%)	0.26	0.27	0.25	0.20	0.21	0.19	0.36	0.37	0.34
Regions (%)									
Moscow, St. Peterburg	0.18	0.18	0.18	0.20	0.19	0.22	0.09	0.09	0.10
Northwestern Federal District	0.07	0.07	0.08	0.05	0.05	0.05	0.05	0.04	0.06
Eastern Siberian and Far Eastern	0.24	0.23	0.24	0.32	0.30	0.34	0.23	0.23	0.24
Central and Volga	0.38	0.39	0.38	0.32	0.35	0.29	0.36	0.36	0.36
South	0.13	0.13	0.12	0.11	0.12	0.11	0.27	0.28	0.26
Hourly earnings	99.5	110.6	90.3	89.9	97.9	79.5	93.4	101	83.5
Weekly working hours	39.1	41.2	37.3	42	44.6	38.5	43.4	46.1	39.8
Occupation (%)*									
Trade and small services	0.16	0.12	0.18	0.42	0.25	0.63	0.46	0.27	0.72
Construction	0.07	0.12	0.03	0.17	0.28	0.03	0.17	0.29	0.02
Transportation	0.09	0.13	0.06	0.11	0.15	0.04	0.10	0.17	0.02
Industry	0.06	0.07	0.06	0.09	0.08	0.11	0.04	0.03	0.05
Others	0.03	0.04	0.03	0.03	0.03	0.03	0.02	0.02	0.03
# observations	72,744	33,007	39,737	5,174	2,922	2,252	7,553	3,265	4,288

Note: own calculation using RMLS over 2003-2017 on a sample of 15-64 years old, not on military duties.

* Reported occupation types are selected as the main occupations held by informal salary workers, for a comparison with other employment groups.

Table 1: Descriptive Statistics

Finally, Table 2 presents statistics about panel information. Around 44% of the workers are observed between 4 and 8 times. The average number of panel observations per individual, 6.1, hides some dispersion across individuals but, reassuringly, the proportion of people observed only once, and hence dropped from panel estimations, is relatively small (8%). The lower part of the table shows the percentage of movers across sectors. This latter statistics is important for the identification of the informal pay gaps in our approach. As in difference-in-difference estimations, we implicitly compare, for instance, a worker staying in the formal sector (stayer) to a similar worker transitioning from the formal to the informal sector (mover) to elicit the informal pay gap. This approach assumes that, conditional on individual fixed effects, moves are random (see Bargain and Kwenda, 2013). Since we estimate quantile effects, sufficient movers are required at different points of the

men, workers with lower education and employed in construction, retail trade and services (hotel and restaurant) especially. At the regional level, the share of informal employment is positively correlated with local unemployment rates. Informal salary work is more concentrated in the Eastern Siberian and the Far Eastern Regions than formal work.

wage distribution to capture an effect. Table 2 shows a relatively satisfying frequency of movers at all four quartiles of the distribution. For instance, 15% of the male workers in the first quarter of the wage distribution have experienced a transition between formal and informal salary work (this way or the opposite) over the period. As expected, this frequency is lower – but remains substantial – at higher quartiles. These conclusions apply both to transitions between informal and formal salary work and to those between formal work and informal self-employment.

Panel Observations					
People observed :		1 time	2-3 times	4-8 times	9-13 times
	#	6,247	15,376	34,137	21,103
	%	0.08	0.20	0.44	0.27
Average # of panel obs. per individual:		6.1			
Proportion of Movers, all					
between formal salary work and...	All	Quartiles of Earnings Distribution			
		Q1	Q2	Q3	Q4
...informal salary work	.09	.13	.10	.08	.07
...informal self-employment	.09	.13	.11	.09	.07
Proportion of Movers, males					
between formal salary work and...	All	Quartiles of Earnings Distribution			
		Q1	Q2	Q3	Q4
...informal salary work	0.10	0.15	0.11	0.10	0.08
...informal self-employment	0.11	0.16	0.13	0.10	0.08
Proportion of Movers, females					
between formal salary work and...	All	Quartiles of Earnings Distribution			
		Q1	Q2	Q3	Q4
...informal salary work	0.07	0.12	0.09	0.07	0.06
...informal self-employment	0.08	0.12	0.09	0.07	0.07

Note: own calculation using RMLS over 2003-2017 on a sample of 15-64 years old, not on military duties.

Table 2: Panel Structure and Sector Movers

3.3 Estimation methods

Tractable Quantile Estimations with Fixed Effects. When estimating informal sector wage gaps, the usual difficulty pertains to the potential presence of unobserved factors that may influence wage or productivity and, at the same time, selection in a particular sector. There has been an active literature suggesting the incorporation of fixed effects in quantile models in order to reduce this bias. We propose a version of some of the most recent estimators that combines both tractability and flexibility.

Let Y_{it} denote the outcome (log wage) for observations $i \in \{1, 2, ..., n\}$ in period $t \in \{1, 2, ..., T\}$. We also observe a vector of regressors X_{it} and the informal sector indicator variable S_{it}. The first fixed effects quantile estimator model that has been suggested assumes that the individual fixed effects α_i only shift the conditional distribution of the outcome without changing its shape (Koenker, 2004). Contrary to the other regressors X_{it}, the fixed effects are constrained to be the same at all quantiles, which seems unnatural in a setting where the goal is precisely to analyze the heterogeneity of the effects. While the approach consists in estimating jointly several quantile regressions, Canay (2011) suggests a more tractable 2-step estimator. In the first step, the traditional within-estimate of the fixed effects, $\hat{\alpha}_i$, is obtained by standard linear fixed effect estimations. In the second step, this component is introduced in separate quantile regressions at each point of the distribution. Kato et al. (2012) and Kato and Galvao (2016) consider more general quantile regression models whereby individual effects $\alpha_i(\theta)$ are quantile-specific. While this approach is very flexible, it requires the estimation of the whole quantile function for each individual. This may not be computationally feasible, especially (i) when using large samples and (ii) given the large number of quantile regressions needed to obtain the precise unconditional effects (as explained below) and (iii) the large number of bootstrap replications needed to estimate the variance.

For this reason, we suggest an intermediate and more tractable model with interacted fixed effects (see also Bargain et al., 2018):

$$Q_{Y_{it}}\left(\theta | X_{i1}, ..., X_{iT}, S_{i1}, ..., S_{iT}, \alpha_i\right) = X_{it}'\beta\left(\theta\right) + S_{it} \cdot \gamma\left(\theta\right) + \alpha_i \cdot \delta\left(\theta\right). \quad (1)$$

This model treats the observed (X_{it} and S_{it}) and unobserved (α_i) regressors symmetrically by keeping them constant over the distribution but allowing them to have a different effect at each quantile. Similarly to Canay (2011), we first compute the within-estimate of the fixed effects $\hat{\alpha}_i$, then we regress Y_{it} on X_{it}, S_{it}, and $\hat{\alpha}_i$ via traditional quantile regression. This approach shares a common characteristic with all the other estimators in the literature that we have mentioned: it is inconsistent with a finite number of periods because $\hat{\alpha}_i$ suffers from the incidental parameter bias. Indeed, $\hat{\alpha}_i$ is consistent for α_i only at the $\sqrt{T}$ rate. We suggest reducing the bias using a half-panel jackknife correction adapted from Dhaene and Jochmans (2015), fully described in Appendix A2.

Unconditional Quantile Effects. Conditional quantile regression models – as used in the bulk of the literature on wage gaps, as previously summarized – bear a particular interpretation. In the present context, we may see the effect of being informal at low quantiles as the effect for low earners (and the effect at high quantiles as the effect for high earners). This is correct but only conditionally on observed covariates and individual fixed effects. Thus, for high (low) values of θ, $\gamma(\theta)$ provides the effect of being employed in the informal sector during the periods with high (low) wages. In other words, the inter-personal differences are captured by the fixed effects while the variation of γ over the distribution captures the differences over time.

This problem of a very specific interpretation is rarely acknowledged in the literature.[8] Most importantly, it is probably more useful – notably for policy analyses – to know the informal sector effect on the *unconditional* wage distribution. Analyses of income inequality, for instance, are always stated in absolute terms and not conditionally on an individual's ability. For this reason, we shall estimate the informal sector effect on the unconditional wage distribution following the procedure suggested by Chernozhukov et al. (2013). In our setting, we will allow one of the regressor to be the individual fixed effect, which has been estimated in a first step (as in Canay, 2011). The approach consists in (i) retrieving (a precise approximation of) the conditional quantile function by estimating quantile regressions of Y_{it} on X_{it}, S_{it} and $\hat{\alpha}_i$ on a regular and thin grid of quantiles (we use 100 values of τ from 0 to 100); (ii) integrating the conditional distributions over the distribution of the covariates, including the estimated fixed effects, to obtain unconditional distributions. The unconditional quantile informal sector effect is obtained by differentiating, at each quantile of the grid, the counterfactual unconditional distributions of the informal and formal sectors. In other words, the estimated parameter is the difference between the τ quantile of the unconditional distribution that we would observe if everybody was employed in the informal sector and the τ quantile of the distribution that we would observe if everyone was employed in the formal sector. The algorithm adapted from Chernozhukov et al. (2013) is exposed in detail in Appendix A.1 (see also Bargain et al., 2018).

4 Results

We first report estimates of the informal sector effect at unconditional quantiles for the whole period 2003-2017. We then investigate the evolution of the average informal wage gap over time, in order to characterize the potential role of the 2008-09 crisis and of subsequent policy changes, providing several robustness checks. Lastly, we describe the time changes at different points of the unconditional wage distribution to refine this picture. Results are presented in graphical form hereafter and the main estimates are also gathered in Table A.1 in the Appendix.

[8] It was not clearly understood in the many articles studying sectoral wage gaps using conditional quantile (for instance in Bargain and Kwenda, 2013, on informal wage gaps in Latin America).

4.1 Quantile Informal Effects on Pooled Years

In this section, we analyze the heterogeneity of the Russian labor market on pooled years. Figure 4 reports the informal earnings gap along the unconditional wage distribution, by gender. We consider the quantile effects of being in informal salary work or in informal self-employment, in both cases relative to being in formal salary employment. Estimates are unconditional quantile effects (UQE hereafter) or fixed effects UQE corrected from the incidental parameter bias (FE-UQE hereafter).

For both women and men, the FE-UQE (in light blue) are slightly negative: precisely, the informal wage penalty for salary workers is in a 95% confidence interval between -10% and 0 along the wage distribution. These wage gaps in informal employment are not large enough to suggest labor market segmentation. Penalties are slightly larger at low wage levels, a pattern that resemble previous findings in transition and emerging economies (e.g. in Bargain and Kwenda, 2013), but not significantly so. Small wage gaps may well correspond to compensating differentials, i.e. typically the choice of informal jobs as a stepping-stone for young workers, as a temporary activity in time of crisis, or as a more flexible job (for instance in terms of work hours). Similar conclusions are reached for self-employment, although the earnings gap level is slightly higher, from no difference at low earnings to small premia at the top (less than 10%), which are again reminiscent of results obtained for Latin America and notably Mexico.[9] Note that we present here an average picture over 2003-17 while things change quite substantially over the period, as investigated hereafter.

Let us now consider UQE (dark blue), i.e. the apparent earnings gaps when ignoring time-invariant individual characteristics. In most cases, there is no significant difference with FE-UQE at the top, or just traces of positive selection into informal self-employment for women. However, concerning the bottom of the wage distribution for men, we see large differences that convey the presence of an overall negative selection into informal work, both for informal employment and self-employment. Unobserved skills account for up to 20% of the apparent hourly wage differences between informal and formal salary workers. However, there seem to exist no such negative selection in informal work for women. We will see that such a negative selection for men has not been a constant feature of the Russian labor market and has emerged in the 2010s.

[9] Note that additional (unreported) estimations without jackknife correction indicate that these differences across quantiles are attenuated by the incidental parameter bias, which tends to overstate the role of individual effects in panel quantile estimations (see also Bargain et al., 2018).

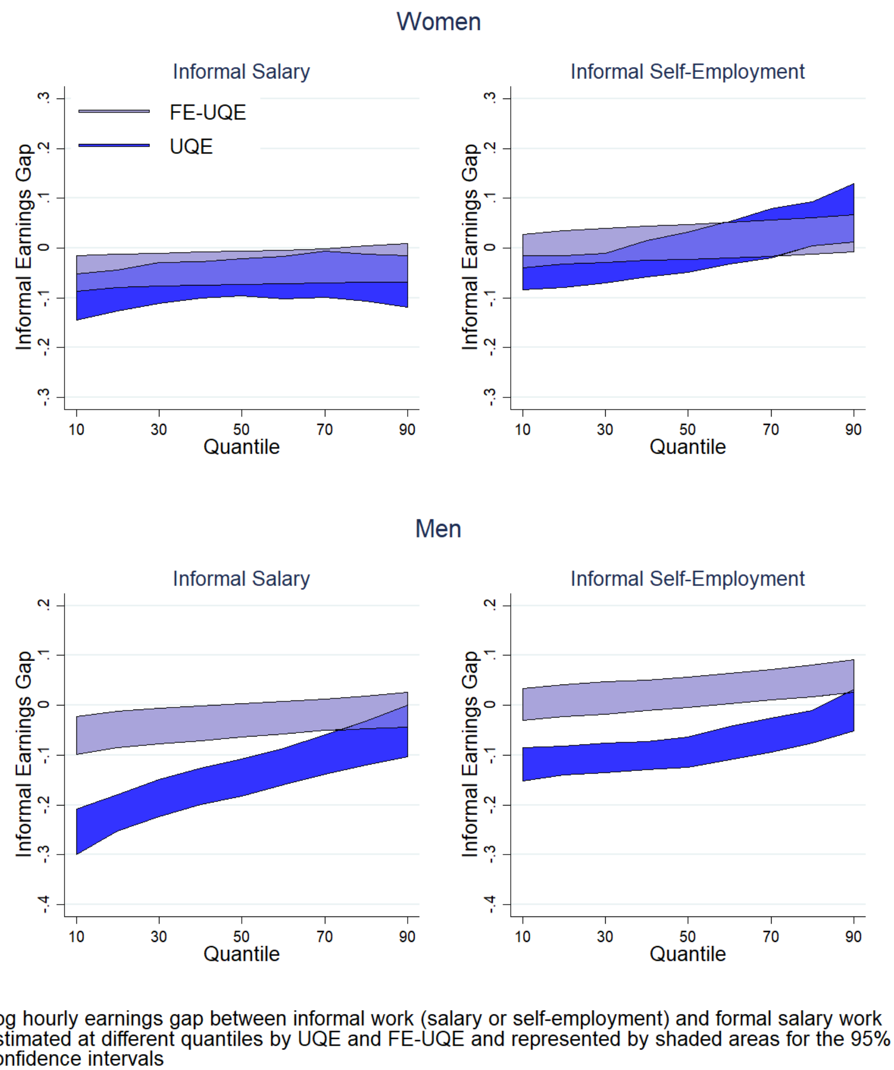
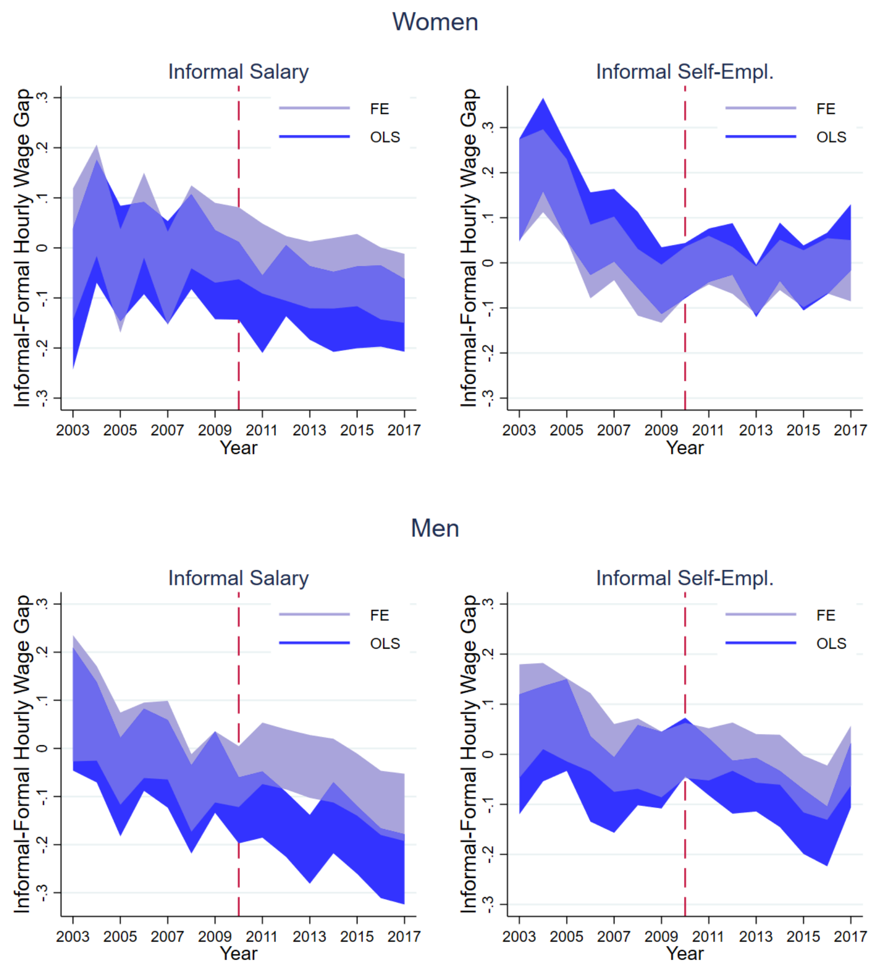


Figure 4: Quantile Informality Effects

4.2 Time Changes: Mean Effects

Baseline Results. We now turn to the average time change in informal pay gaps. As recalled above, employment levels have remained quite stable in Russia after the 2008-09 crisis, pointing to the cushioning role of the informal sector following job destruction in the formal sector (Gimpelson and Kapeliushnikov, 2015; Lehman et al, 2014). However, little has been said about the changing composition of these sectors and the potential role of selection effects. To investigate this question, we run OLS and FE estimations whereby the informality dummy is interacted with the years 2003 to 2017. Heterogeneous coefficients are reported with 95% confidence bounds in Figure 5. Estimations with (without) FE are represented in light (dark) blue.



Log hourly earnings gap between informal work (salary or self-employment) and formal salary work estimated over time by OLS and FE estimations and represented by shaded areas for the 95% confidence intervals

Figure 5: Informal Hourly Wage Gap over Time: OLS and FE

FE estimates point to an overall declining time trend in informal pay gaps for both men and women among salary workers. For them, the informal wage gap oscillates between zero and a small penalty (around -10%) in the recent years. Regarding informal self-employment, there was an interesting premium in the early 2000s, as unveiled by FE estimations. This sector of activity was desirable, as extensively discussed in other contexts (e.g., Maloney, 1999). This advantage has rapidly disappeared during our period of investigation. This shift takes place before the Great Recession and reflects more secular trends in the nature of informal self-employment in Russia than consequences of the crisis.

We move to the difference between FE and OLS estimates, which characterizes unobserved skill gaps. Both estimates broadly overlap before the Great Recession, which indicates the absence of skill-based selection into informality on average in the early period. Yet, a divergence appears around 2009. The actual decline in informal earnings gap, as measured by FE estimations, seems to be a slow gradual process throughout the whole period. In contrast, ignoring unobserved characteristics yields a stronger apparent decline in pay gaps as measured by OLS. This growing difference between the two curves corresponds to the emergence of a negative selection into informal work after 2009/2010, i.e. unobserved skills tend to deteriorate among workers who joint the informal sector. This pattern is particularly visible for male employees but there are also trace of it for employed women and self-employed men. There is no such effect for women in self-employment, which is consistent with Figure 4 and the overall absence of selection in this group. We verify these results formally. We test the equality of OLS and FE coefficients for 2009-2017 (or 2010-2017) using a joint F-test of all the post-crisis coefficients. The p-value is close to zero for informal salary work (both men and women) and informal self-employment (men).

Discussion. These results must be interpreted in the context of a compressed formal sector, as illustrated by the increasing share of informal salary and self-employed activities in Figure 1. We have recalled that total employment is traditionally not very sensitive to macroeconomic shocks in Russia, mainly because of wages and working time flexibility and, to a lesser extent, the presence of the informal sector. In fact, the buffering effect of informal jobs seems to have played a larger role than usual in the wake of the 2008-09 crisis, also inducing a noticeable transformation of the informal sector. Our FE estimates of the earnings gaps confirm that there is no sign of informal activity becoming relatively more attractive,[10] while our results also suggest a relative decline in the unobserved productivity of this sector.[11] The unobserved skill gap visible after 2009 is consistent with the fact that those transiting to informal activities at that time were the least productive workers of the formal sector, shaken out of formal jobs following the crisis or rationed out due to the surge in the minimum wage.[12] Despite the evidence of relatively competitive labor markets in Russia, these recent trends point to the emergence of some constrained informal employment in Russia. Its involuntary nature is relative: workers possibly accept low-paid

[10] On the contrary, Dang et al. (2015) find that moving from the informal to the formal sector had a statistical positive effect on earnings from 2009 onwards.

[11] Macroeconomic evidence confirms the declining productivity of the informal sector: its employment share has increased by almost 10 percentage points while its GDP share has decreased from 15% to 7% over the same period (cf. Gimpelson and Kapeliushnikov, 2015, using System of National Accounts data).

[12] Newcomers into informality may have been superior to informality incumbents (for instance if the latter have experienced a degradation of their skills relative to formal sector requirements). Yet their difference must be smaller than that between the former and formal workers, otherwise we would not observed unobserved skill gaps following the transition.

informal jobs, or start marginalized self-employment, rather than being left with very low unemployment benefits.

Gender Differences. We further explore the few gender differences observed in the previous results. First, we check if any gender difference may be due to different occupation choices in terms of industries (for instance if men were employed in sectors that are more hit by the crisis). Figure A.1 reports estimates of a model with 18 industry dummies as additional control variables. We see hardly any difference with the baseline. Second, to the extent that observed skills (e.g. education) and unobserved skills (captured by fixed effects) are positively correlated, a larger negative selection effect among men is consistent with the fact that informal male workers are those with the lowest education levels (lower rates of secondary and tertiary education than women's, as shown in Table 1). Third, we focus on the main gender difference pertaining to informal self-employed. Notice that transition from formal employment to informal self-employment (relative to any other transitions) is consistent with our results: between pre and post crisis periods, it has been multiplied by 2.6 for men but diminished by 44% for women. Finally, it is possible that informal work act in Russia similarly to unemployment in Western countries. That is to say, when married women are out of the labor force, it might be seen as intra-household specialization whereby women are allocated to childcare and domestic work, while in contrast, men out of the labor market reflect more some form of involuntary rationing due to a combination of low productivity and restrictive labor market regulations. We replicate estimations of the gap for self-employed workers by family status: results in Figure A.2 confirm that negative selection appears for single individuals and for married men but not for married women.

Sensitivity Checks: Casual Workers. We have mentioned above the case of casual workers. They are defined using a variable about additional work such as "sewing someone a dress, giving someone a ride in a car, assisting someone with apartment or car repairs", etc. This group represents around 12,000 people in our sample, but a quarter already declares a primary activity and are recorded as formal or informal workers according to the nature of their activity. For the others, only half of them declare to be paid for the casual work and effectively report earnings. We add them to the group of informal self-employed in alternative estimations presented in Figure A.3. The patterns are not essentially different from the baseline results. The informal earnings gaps for the self-employed are slightly larger overall and, most interestingly, the negative selection of men in informal self-employment appears even more clearly than in Figure 5.

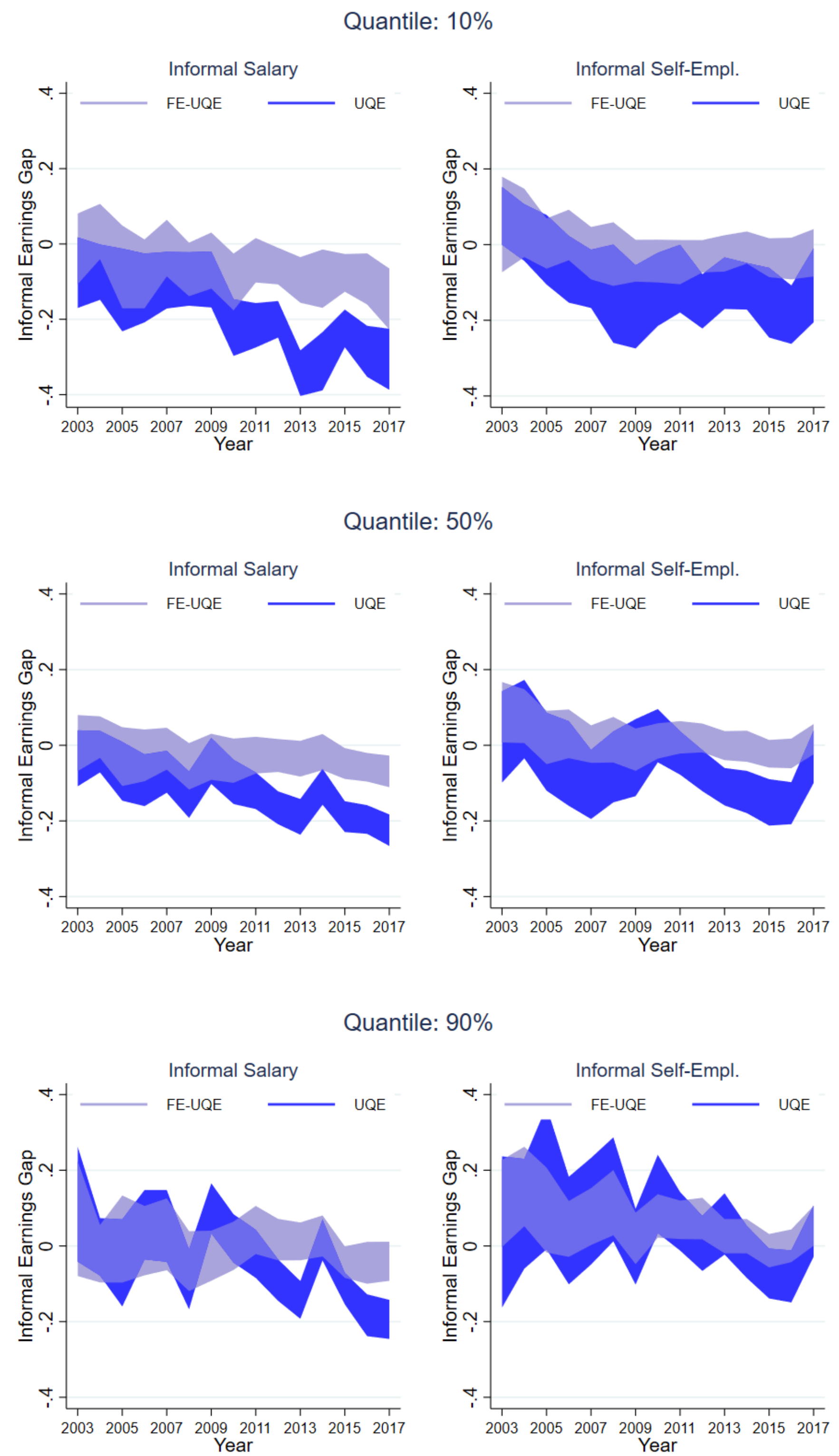
Sensitivity Checks: Hours and Earnings Gaps. We have followed common practice by estimating hourly wage gaps: it allows measuring differences in pay or productivity across workers of different sectors while neutralizing their differences in terms of working time and contract types. However, monthly earnings are important from welfare and policy points of view. Thus, we check the difference in working time across formal and informal sectors. It is likely that formal sector workers have more rigid work contracts set by regulation, while informal workers may have more flexibility in how much they work. In Figure A.4, we report hour distributions by sector. We see no major differences between informal salary work and informal self-employment. Compared to formal salary work, both types of informal activities show longer work durations, with hour distributions slightly shifted to the right and less concentrated.[13] Then we estimate the hour gap between informal and formal workers: as seen in Figure A.5, the hour gap tends to oscillate around zero throughout the period of investigation. As a result, we expect labor earnings to show similar patterns as hourly wages. This is verified with the estimations of monthly earnings gaps, reported in Figure A.6. It turns out that our conclusions – based on hourly pay gaps – can be extended to total earnings gaps.

4.3 Time Changes: Quantile Effects

We now interact the informality dummy with detailed years in both UQE and FE-UQE estimations, reporting results in Figures 6 and 7 for men and women respectively. Patterns are necessarily more noisy but we observe similar trends as discussed above, which now characterize more specifically certain segments of the wage distribution. In particular, the slow decline in informal pay gaps appears mainly for low-wage workers (FE-UQE estimates in light blue).

The other important result is the difference between estimates with and without FE. They characterize negative selection into salary work, which is expected to take place at lower wage levels. We have indeed conjectured that job destruction in the formal sector following the economic downturn and/or rising minimum wages was first targeted at workers in the lower part of the wage distribution. These workers had less options to remain inactive given the very low levels of unemployment benefits in Russia. This is one of the likely phenomena at play in Figure 2, whereby the share of informal employment (for both men and women) and of informal self-employment (mainly men) increases for low-wage workers.

[13] There are similarities across all sectors, for instance a small concentration at overtime around 55 hours/week (more marked for men).



Log hourly earnings gap between informal work (salary or self-employment) and formal salary work estimated over time by UQE and FE-UQE estimations and represented by shaded areas for the 95% confidence intervals

Figure 6: Men's Informal Hourly Wage Gaps: UQE and FE-UQE over Time

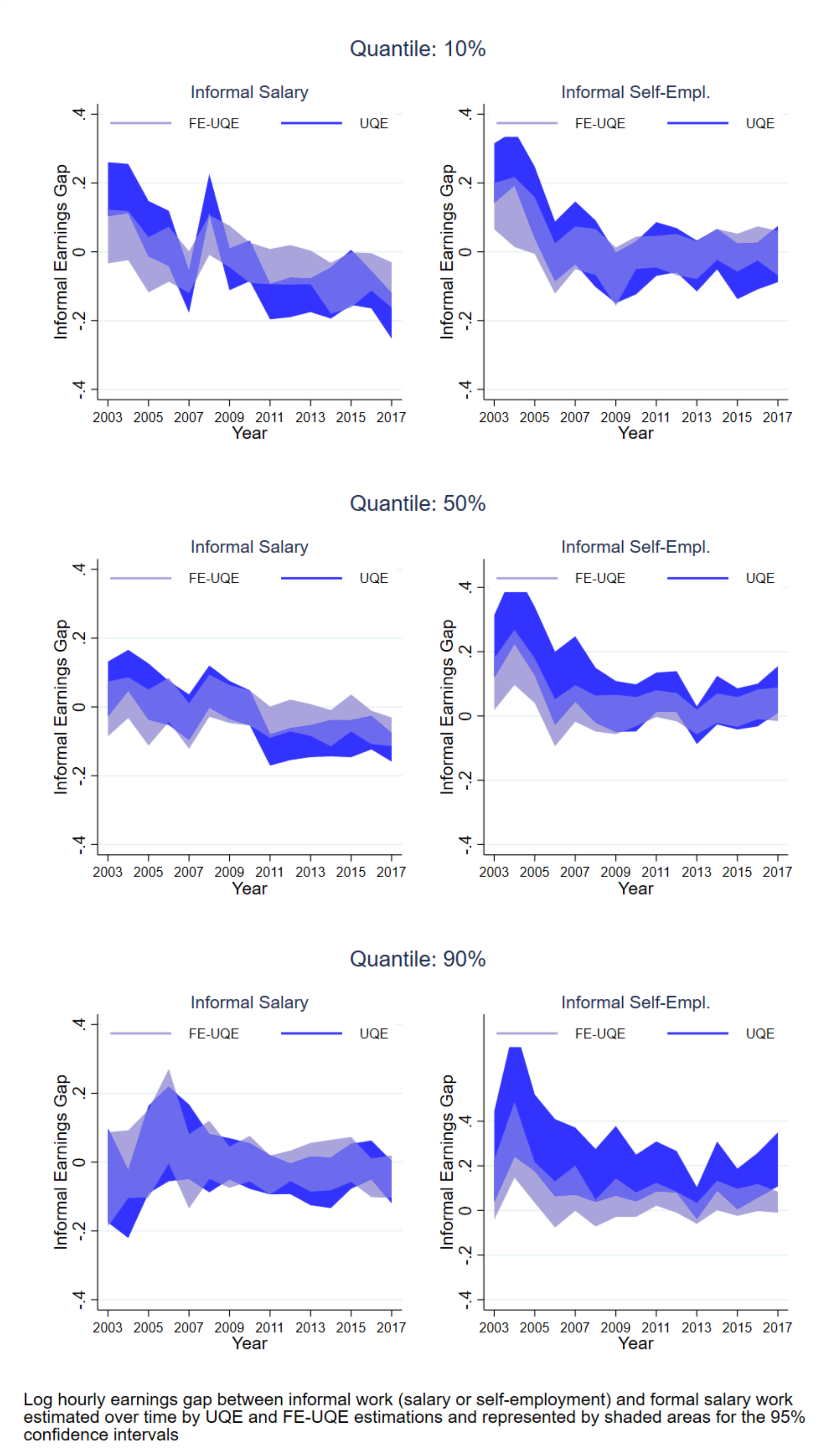


Figure 7: Women's Informal Hourly Wage Gaps: UQE and FE-UQE over Time

In Figure 6, we verify that, consistently, the relative skill deterioration in informal work for men has mainly taken place in the lower part of the distribution. As before for time variation at the mean (Figure 5), the effect is more marked in salary work but also visible in self-employment. Also consistent with the quantile effects over the whole period (Figure 4), the negative selection tends to disappear at top quantiles. A similar pattern can be seen for women in salary work in Figure 7, even if less pronounced. Yet, as in characterizations at the mean, we see no trace of negative selection into informal self-employment for women.

To better document this negative selection and how it has increased after the crisis, we characterize transitions across sectors at different levels of unobserved skills (see also Hospido, 2012, and Hospido and Moral-Benito, 2016). Focusing on the bottom 10% of the male wage distribution, we recover estimated FE for each worker and characterize high/low unobserved skills as those above/below mean FE (within the low earning group). Results are reported in Table A.2. We can see little action for those *above* mean FE: transitions towards (from) informal work in blue (in brown) represent 1.6% (1%) of all the pre-crisis transitions. After the crisis, these rates of transition increase a little (1.9% and 2% respectively). If we now focus on those *below* mean FE, we observe similar transition frequencies prior to the crisis (2.1% and 1% respectively) but an acceleration in the wake of the Great Recession and especially from formal to informal work (5.7% versus 3.6% for informal-to-formal).

5 Conclusion

This paper suggests a detailed analysis of pay gaps between formal and informal sectors in Russia around the time of the Great Recession. Using RLMS-HSE data for 2003-2017, we estimate unconditional earnings gaps between sectors at the mean and at different quantiles of the distribution while controlling for individual effects. We confirm that informal pay gaps are small for both salary work and self-employment, i.e. informal earning penalties are below 10%. This is consistent with a competitive functioning of the Russian labor market where workers are allocated across sectors according to their skills and preferences (and the presence of compensating differentials). Yet, it is possible that low-paid informal jobs and low levels of unemployment benefit put a downward pressure on formal wages and contribute to explain a structurally small informal-formal pay gap. Moreover, we also show noticeable changes since the 2008-09 economic crisis.

First, we report a sharp increase in the share of informal employment (for both men and women) and self-employment (for men) at low wage levels following the crisis. The compression of formal sector activities induces a change in the composition of both formal and informal sectors. While the Russian labor market used to attract workers with similar unobserved skills in both sectors, a negative selection into informal work arises after 2009, especially in the lower part of the wage distribution. Methodologically, this pattern is unveiled by unconditional quantile estimation methods with fixed effects. Our results are consistent with the hypothesis of a reallocation of the least productive formal sector employees to the informal sector. Complementary analyses based on transition patterns corroborate this point: we confirm that among low-wage workers, transitions towards informal jobs have accelerated in the wake of the Great Recession for those with below-average fixed effects.

These results may be interpreted as the consequence of the formal sector shakeout or the implication of some of the policy measures that have followed the crisis, notably a possible rationing out of formal employment due to the doubling of the minimum wage. The picture of a competitive labor market in Russia is somewhat altered if the informal sector has indeed become a last resort option for many low-skill salary workers who could not afford to live on unemployment benefits. When we control for observed skill differences (potential experience, education, region), but before accounting for fixed effects, informal wage penalties can reach 20%. It is unclear which type of unobserved characteristics or skills can justify such a loss. Another important question for future research is the contribution of these recent labor market dynamics to overall inequality in Russia, especially in a country characterized by a high incidence of low-paying jobs in the long run (Gimpelson, 2019).

Finally, while self-employment is not much developed in Russia, its informal segment does not appear to be a desirable sector, contrary to what is sometimes found in other countries (e.g., in Mexico). It might have been different in the past: our analysis with time heterogeneous effects actually points to earnings premia at the beginning of the period, which have quickly disappeared in the mid-2000s. Since then, earnings gap patterns are very similar to those found for informal salary workers. The expansion of the informal sector occurred mostly in activities like trade, construction and transportation, which may have attracted both informal employees and own-account workers in undeclared services micro-businesses. A growing unobserved skill gap also appears between formal employment and informal micro-entrepreneurs.

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A Appendix: Additional Methodological Inputs and Results

A.1 Algorithm for Unconditional Quantile Effects

In this section, we describe the algorithm that we use to estimate unconditional quantile effects (UQE). The unconditional distributions are obtained by integrating the conditional distributions over the distribution of the covariates, including the estimated fixed effects. The conditional distribution functions are approximated using 100 quantile regressions as defined in equation (1) in the main text. The algorithm goes precisely as follows.

Algorithm 1 *1. Using a standard fixed effects estimators for the mean, we obtain the estimated individual fixed effects* $\hat{\alpha}_i$*.*

2. We estimate 100 quantile regression of Y_{it} *on* X_{it}*,* S_{it} *and* $\hat{\alpha}_i$ *on a regular grid of 100* θ_q *quantiles. For* $q = 1, ..., 100$ *we obtain the estimates* $\hat{\beta}(\theta_q)$ *,* $\hat{\gamma}(\theta_q)$ *and* $\hat{\delta}(\theta_q)$*.*

3. *The estimate of the counterfactual unconditional distribution in the private and public sector take respectively the following forms:*

$$\begin{aligned}\hat{F}_{Y(0)}(y) &= \frac{1}{100\cdot n}\sum_{i=1}^{n}\sum_{q=1}^{100} 1\left(X_{iT}'\hat{\beta}(\theta_q) + \hat{\alpha}_i \cdot \hat{\delta}(\theta_q) \leq y\right)\\ \hat{F}_{Y(1)}(y) &= \frac{1}{100\cdot n}\sum_{i=1}^{n}\sum_{q=1}^{100} 1\left(X_{iT}'\hat{\beta}(\theta_q) + \hat{\gamma}(\theta_q) + \hat{\alpha}_i \cdot \hat{\delta}(\theta_q) \leq y\right)\end{aligned}$$

4. *We report the unconditional quantile public sector effects*

   $$\hat{\Delta}(\tau) = \hat{F}_{Y(1)}^{-1}(\tau) - \hat{F}_{Y(0)}^{-1}(\tau)$$

   for a grid of quantiles τ.

A.2 Incidental Parameter Bias Correction

All the estimators discussed in section 3.3 suffer from the incidental parameter bias. Even if the number of individuals is very large, these estimator will be biased when the number of periods is finite. Arellano and Weidner (2015) characterize the bias of the estimator of kato et al. (2012). They show that when the number of periods is moderate, the fixed effects estimators will underestimate the heterogeneity along the distribution by averaging the quantile coefficients around the quantile of interest. In the extreme case when $T = 2$, the estimated coefficients will be constant as a function of the quantile index θ. Thus, applying fixed effects quantile regression to short panels may give the impression that unobserved heterogeneity is explaining the variation along the distribution while this is only the consequence of the incidental parameter bias.

We apply the half-panel jackknife correction suggested by Dhaene and Jochmans (2015). Suppose that the number of periods T is even. Let $\hat{\gamma}(\theta)$ be the estimate based on the whole panel. We also compute the estimates based on the first $T/2$ periods and the last $T/2$ periods, which we respectively denote by $\hat{\gamma}_1(\theta)$ and $\hat{\gamma}_2(\theta)$. The bias corrected estimator is given by

$$\begin{aligned}\hat{\gamma}_{BC}(\theta) &= \hat{\gamma}(\theta) - [0.5\cdot(\hat{\gamma}_1(\theta) + \hat{\gamma}_2(\theta)) - \hat{\gamma}(\theta)]\\ &= 2\cdot\hat{\gamma}(\theta) - 0.5\cdot(\hat{\gamma}_1(\theta) + \hat{\gamma}_2(\theta)).\end{aligned}$$

The intuition is very simple: Since the incidental parameter bias is proportional to $\frac{1}{T}$, the bias of $0.5\cdot(\hat{\gamma}_1(\theta) + \hat{\gamma}_2(\theta))$ is twice as large as the bias of $\hat{\gamma}(\theta)$. Thus, the difference between these estimates provides an estimate of the bias. We substract this estimated bias from the original estimate.

Monte Carlo simulations confirm the theoretical results and show a very significant reduction of the bias, yet at the price of seriously increasing the variance of the estimator. We could reduce the variance of the jackknife bias correction by incorporating the information about the mean coefficients. We know that the traditional fixed effect estimator, denoted by $\hat{\gamma}$, is unbiased even when T is as low as 2. Also, model (1) for all $\theta \in (0,1)$ implies that $\gamma = \int_0^1 \gamma(\theta)\, d\theta$. Hence, our final estimator of $\gamma(\theta)$ is the recentered bias corrected estimator

$$\hat{\gamma}_{RBC}(\theta) = \hat{\gamma}_{BC}(\theta) + \hat{\gamma} - \int_0^1 \hat{\gamma}_{BC}(\theta)\, d\theta.$$

In simulations, the variance of this estimator is much lower than the variance of $\hat{\gamma}_{BC}(\theta)$ and only marginally larger than the variance of the uncorrected estimator $\hat{\gamma}(\theta)$. We also use the half-panel bias correction for the estimator of the unconditional effects. We correct both the first-stage quantile regression coefficients $\hat{\beta}(\theta), \hat{\gamma}(\theta)$ and $\hat{\delta}(\theta)$ and the second stage counterfactual quantile functions $\hat{F}^{-1}_{Y(1)}(\tau)$ and $\hat{F}^{-1}_{Y(0)}(\tau)$.

A.3 Additional Empirical Results

Informal Pay Gap	Informal Employment				Informal Self-Employment			
	Mean	10%	50%	90%	Mean	10%	50%	90%
Women								
OLS/UQE	-0.08	-0.03	-0.02	0.00	0.02	-0.07	0.00	0.11
FE/FE-UQE	-0.03	-0.02	-0.01	0.01	0.00	0.03	0.05	0.07
Men								
OLS/UQE	-0.13	-0.19	-0.12	-0.03	-0.06	-0.09	-0.05	0.05
FE/FE-UQE	-0.04	-0.06	-0.03	0.00	0.00	-0.01	0.02	0.06

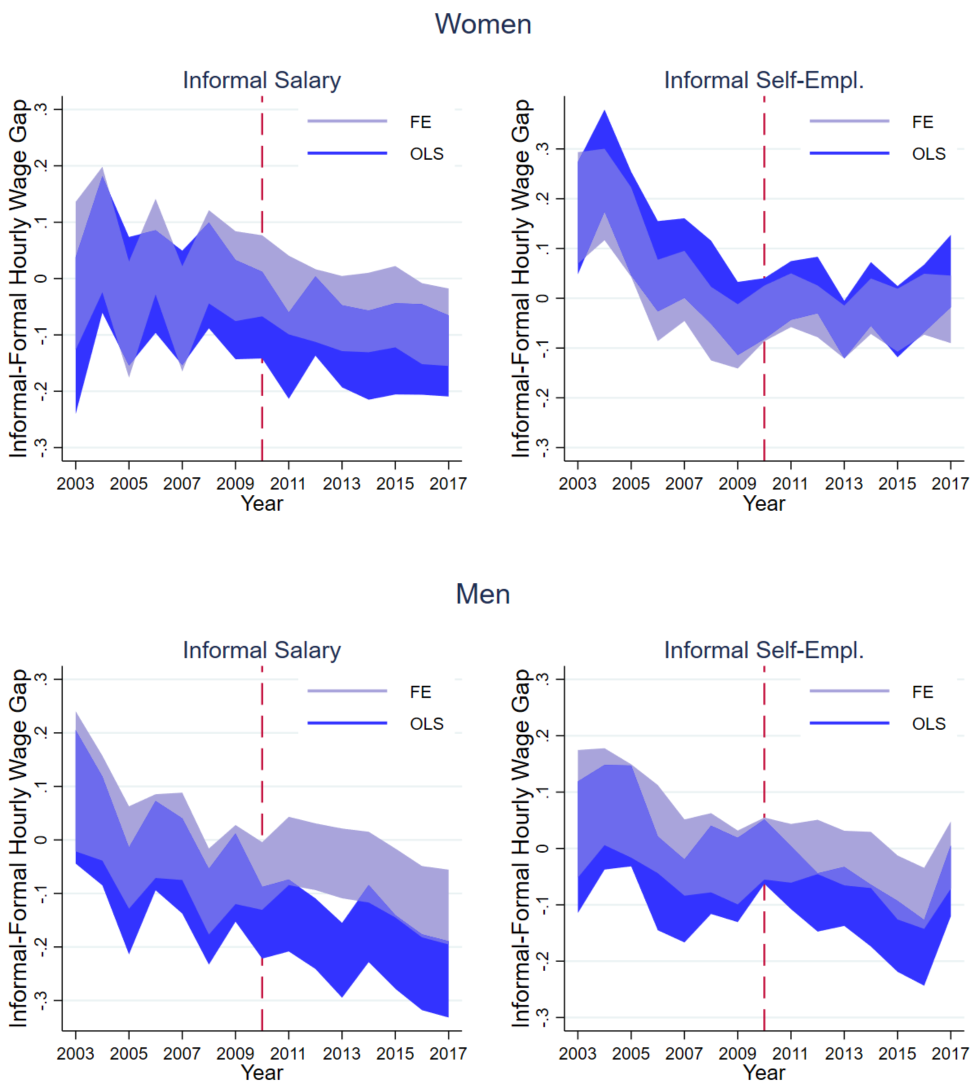
Estimates from linear estimations (OLS or with fixed effects FE) and unconditional quantile effects (UQE or FE-UQE, i.e. UQE with fixed effects and jackknife correction for incidental parameter bias), using RLMS 2003-2017.

Table A.1: Informal Earnings Gap: All Estimates

Heterogeneity	Before crisis		After crisis		Change	
Above mean FE						
From / To	Formal	Informal	Formal	Inf. Sal.	Formal	Inf. Sal.
Formal	21.8	**1.4**	19.5	**1.4**	-2.4	**0.0**
Informal	**1.6**	2.3	**1.2**	3.9	**-0.4**	1.7
Below mean FE						
From / To	Formal	Inf. Sal.	Formal	Inf. Sal.	Formal	Inf. Sal.
Formal	62.2	**2.5**	57.3	**3.2**	-4.9	**0.8**
Informal Sal.	**2.0**	6.1	**3.2**	10.3	**1.1**	4.2

Note: This table reports transitions between sectors (in %). We focus on the bottom 10% of the hourly earnings distribution and drop workers exiting or entering unemployment or inactivity. We distinguish between transitions that take place before the Great Recession (i.e. between any pairs of years during 2003-2007, in columns 1-2) and those that take place afterwards (i.e. between any pair of years over 2009-2017, in columns 3-4). Transitions are shown for individuals with a wage fixed effect (FE) above versus below the mean, so that all transitions (including stayers) for a given period (before or after crisis) sum to 1 when adding above and below mean FE workers. For instance, on average before the crisis, 3.9% of all transitions were between formal and informal work (1.4% by those above mean FE and 2.5% by those below).

Table A.2: Pre vs Post Crisis Transitions: FE Heterogeneity



Log hourly earnings gap between informal work (salary or self-employment) and formal salary work estimated over time by OLS and FE estimations and represented by shaded areas for the 95% confidence intervals

Figure A.1: Informal Hourly Wage Gaps over Time with Controls for Industries

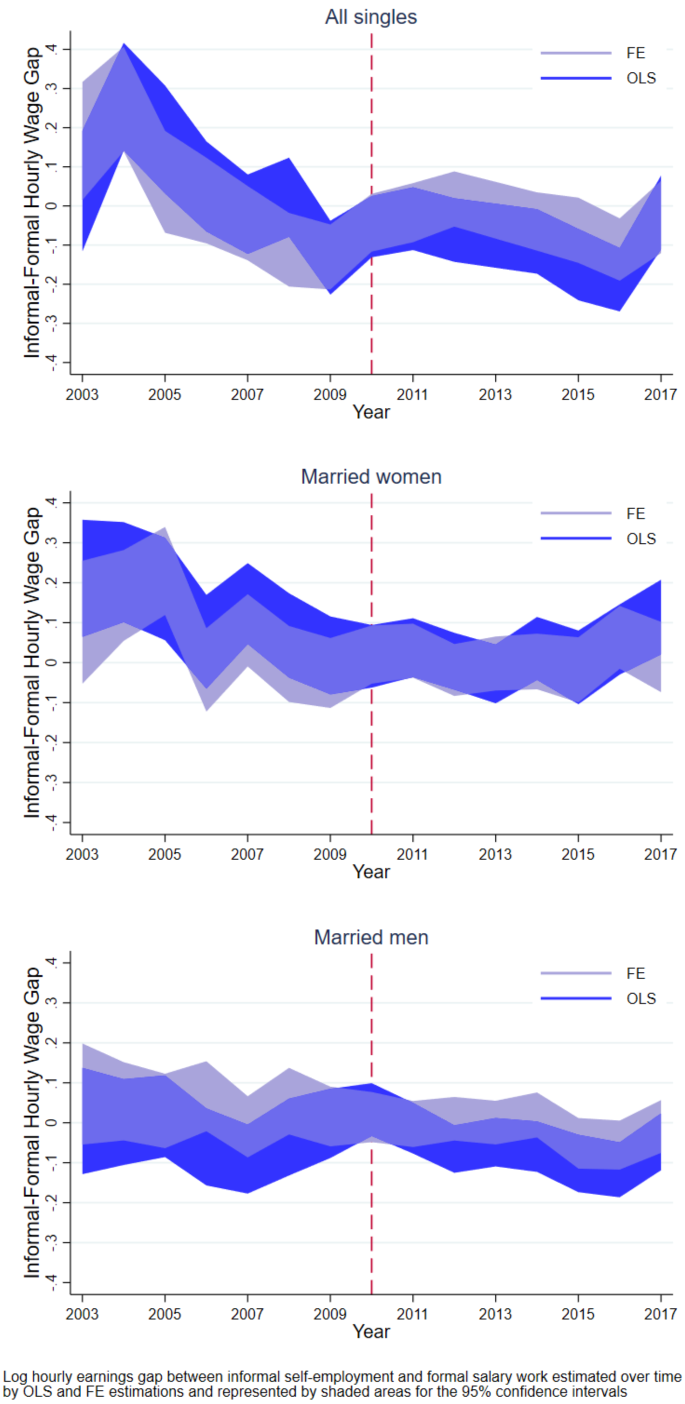
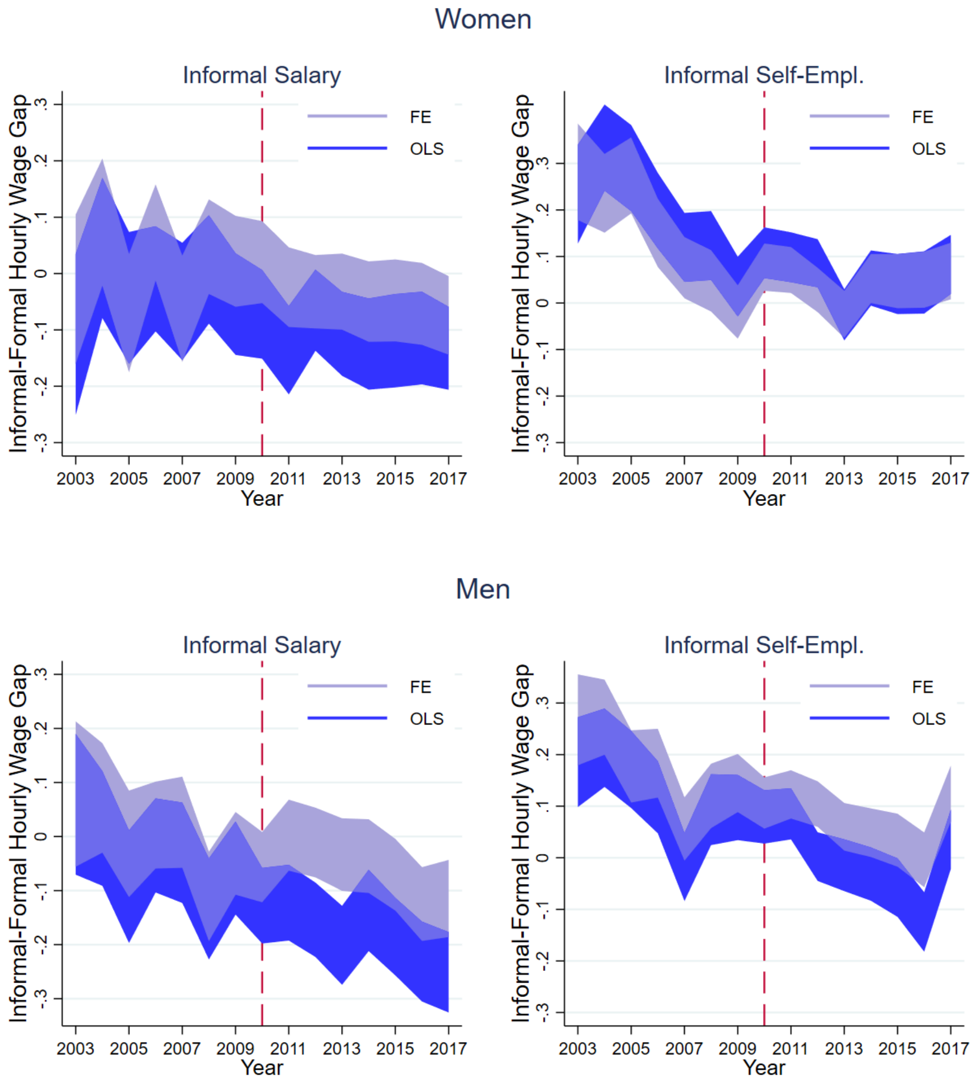


Figure A.2: Informal Hourly Wage Gaps over Time by Gender and Marital Status



Log hourly earnings gap between informal work (salary or self-employment) and formal salary work estimated over time by OLS and FE estimations and represented by shaded areas for the 95% confidence intervals

Figure A.3: Informal Hourly Wage Gaps over Time accounting for Casual Workers

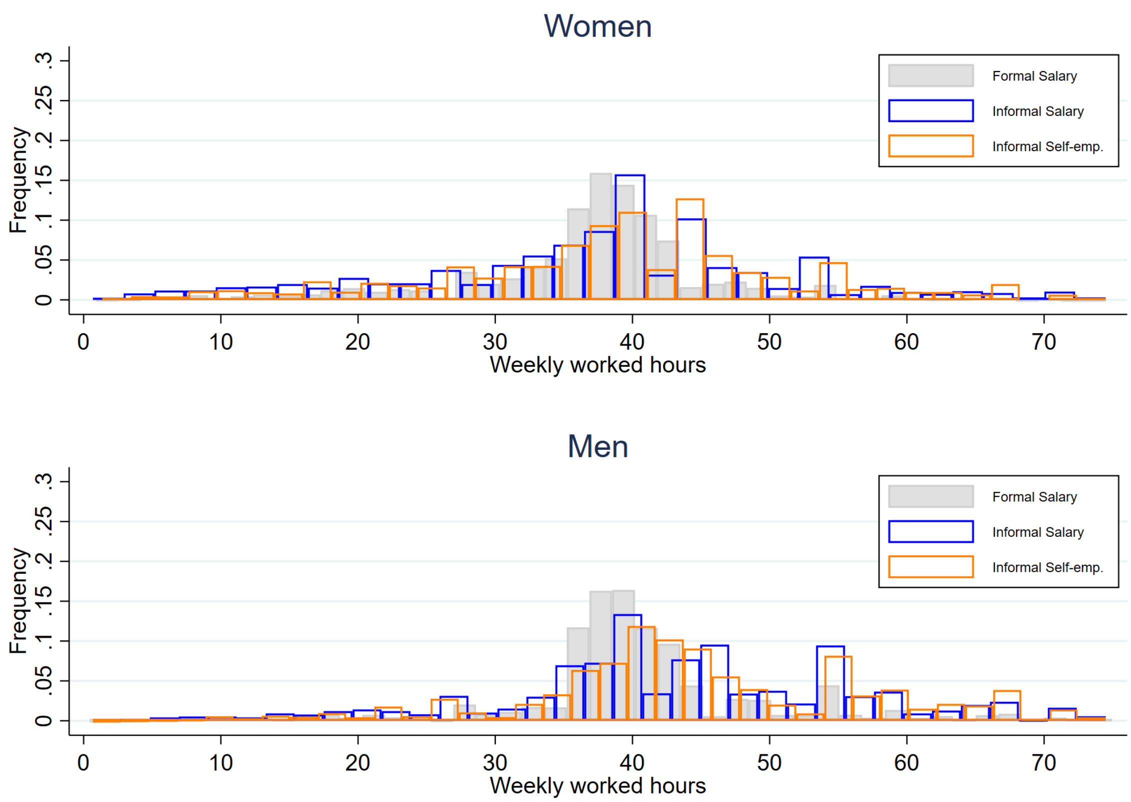
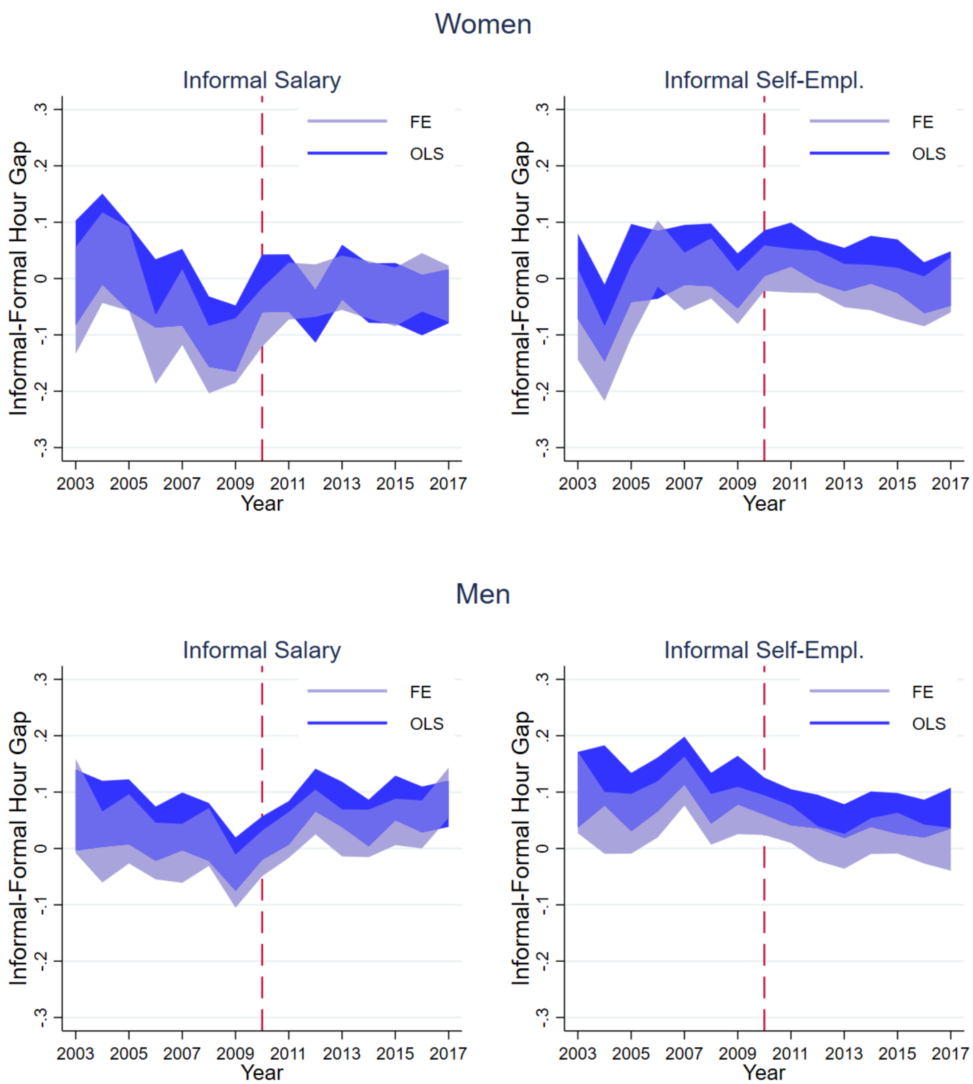
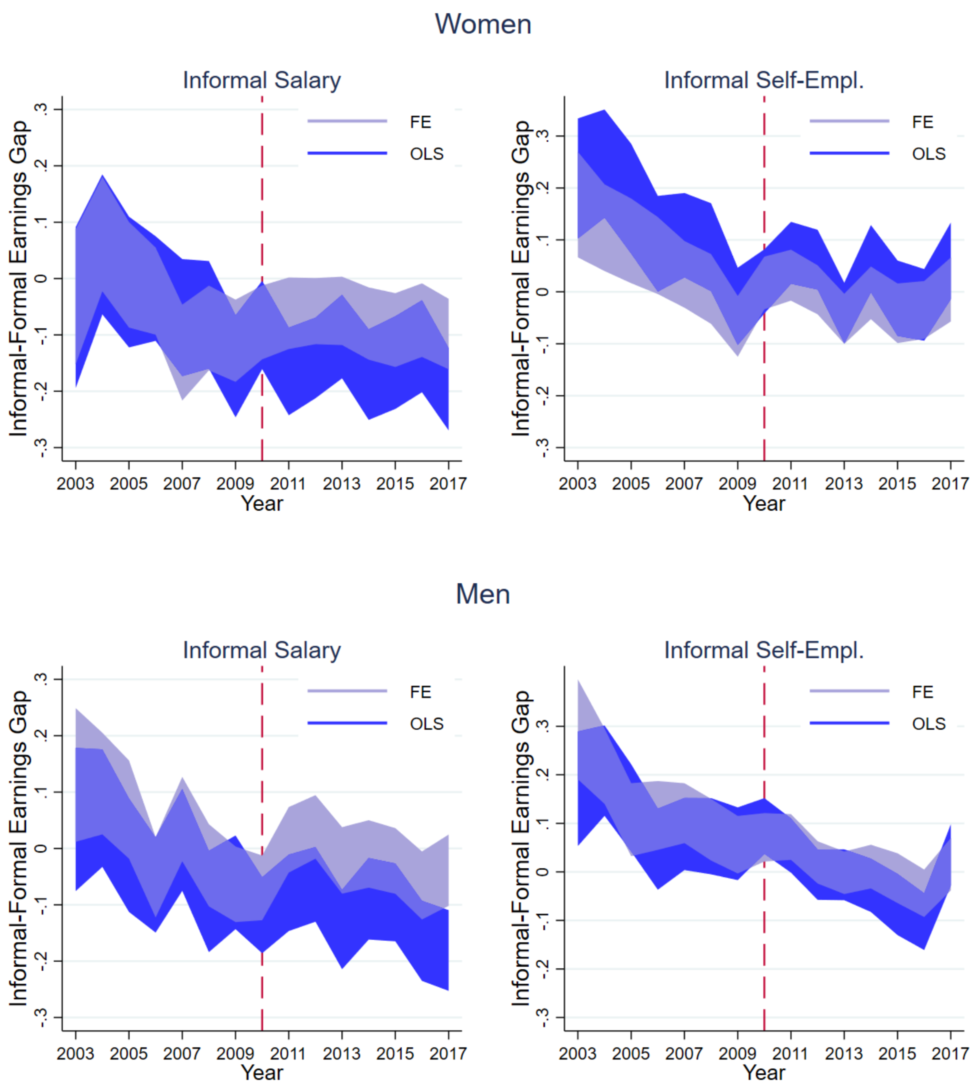


Figure A.4: Distribution of Worked Hours by Sector (Russia, pooled years 2003-17)



Log hourly earnings gap between informal work (salary or self-employment) and formal salary work estimated over time by OLS and FE estimations and represented by shaded areas for the 95% confidence intervals

Figure A.5: Informal Hours Gap over Time



Log hourly earnings gap between informal work (salary or self-employment) and formal salary work estimated over time by OLS and FE estimations and represented by shaded areas for the 95% confidence intervals

Figure A.6: Informal Earnings Gap over Time