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Wage inequality and structural change

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Abstract

Income inequality in the context of large structural change has received a lot of attention in the literature, but most studies relied on household post-transfer inequality measures. This study utilizes a novel and fairly comprehensive collection of micro datasets between 1980s and 2010 for both advanced market economies and economies undergoing transition from central planning to market based system. We show that earned income inequality was initially lower in transition economies and immediately upon the change of the economic system surpassed the levels observed in advanced economies. We decompose changes in wage inequality into parts that can be attributed to changes in characteristics (mainly education) and changes in rewards, but did not find any leading factor. Finally, in the context of skill-biased technological change literature we find a very weak link between structural changes and wages in both advanced and post-transition economies. %This holds regardless of whether an economy has underwent a large structural shock or not.

Keywords:

wage inequality, structural change, transition, skill biased technological change

JEL Classification

E24, D31, N34, O57, P36, P51

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1 Introduction

There is a number of theoretical reasons why a structural shock may matter for the relationship between wage compression and normatively understood inequality. First, shocks usually ocurr with adjustment frictions, which typically implies a larger role for the unexplained component than for the adjustment in characteristics of the labor force. Second, prices typically adjust faster than quantities. In the context of a Mincerian wage regression $w = \beta X + \epsilon$ this implies that the changes in β will exhibit in changes of w, given X. For these two reasons, changes in wage dispersion will signify changes in inequality, until quantities fully adjust. Third, since eventually shocks trigger adjustment in X, the question is if immediate reaction in β drives the incentives for these adjustments in the way which restores initial decompression or leads to a reshuffling of the social structures.

Installing a market based system in the place of central planning created room for unprecedented and rapid wage decompression in the so-called transition economies of Central and Eastern Europe (CEE, see e.g. Milanovic, 1999; Brainerd, 2000). Highly centralized wage-setting mechanisms were replaced by market, while high inflation along with large shocks to employment levels and employment structure along with high churning made it essentially impossible to "preserve" wages from either a firm-level or an individual-level perspective. Compelling evidence shows that this structural shock has triggered an increase of income inequality (Milanovic, 1998). However, the typical indicators of income inequality measure post-redistribution household income inequality. Moreover, there is substantial dispersion across countries in terms of inequality prevalence, increase and persistence of this increase (Milanovic and Ersado, 2012; Aristei and Perugini, 2012; Ott and Wagner, 2013; Aristei and Perugini, 2014).

Importantly, the earnings (de)compression and the household income (in)equality need not be directly related. The difference between the two is not only statistical (gross for an individual vs. net of taxes and subsidies for a household) but also conceptual. Namely, with high dispersion of individual characteristics, one would expect low compression of wages which need not imply inequality in the normative understanding of the term (Salverda and Checchi, 2014). Consider a frictionless wage process $w = X\beta + \epsilon$, where the random noise to wage process ($\epsilon \sim i.i.d$) is negligible and there are no biases/constraints in choosing the relevant characteristics X. With diverse X, the distribution of w is likely to be dispersed as well, given β. The opposite holds if X is homogenous. However, if a process is characterized by a large ϵ component, for a given dispersion of X, wage dispersion would be amplified relative to characteristics, thus implying inequality.

Transition from a centrally planned to a market economy experienced by Central and Eastern European countries could constitute an interesting case study for at least two reasons. First, the region comprises relatively large set of disperse economies, while these countries have also followed somewhat different policies, also in terms of labor market equality and access. Suffice it to say that forming one country prior to 1989, Czech Republic has one of the lowest and Slovak Republic one of the highest unemployment rates in Europe. Second, the transition has started nearly three decades ago yielding a sufficiently long period to observe the wage compression processes. However, due to limitations in data availability, there was little comparative research so far into wage (de)compression in the course of a large structural shock. For example, Milanovic (1999); Milanovic and Ersado (2012) analyze household survey data and provide evidence that increase in inequality stems mostly from disappearing middle of the wage distribution (unfortunately, these analyses comprise only few selected transition countries and over a relatively short horizon). By contrast, Pryor (2014) argues that despite transition, around the year 2000

CEECs are characterized by lesser income inequality than would have been expected given their economic development. One of the reasons behind this result may be the institutional inertia. Indeed, institutional setting seems to matter for wage compression, as shown in a recent comprehensive comparative study by Salverda and Checchi (2014). Building on earlier insights by Bertola et al. (2001) they argue that what matters most for the inequality is the wage compression "from below".[1] Unfortunately, both Pryor (2014) and Salverda and Checchi (2014) analyze data from a decade or two past the transition, they pay only a lip service to the structural change from a centrally planned to a market economy.

Comparative studies of transition processes *per se* are rare due to limited data availability. In most transition economies, household surveys do not permit direct identification in wage incomes by person, while not all labor force surveys collect information on wages. Also, one needs a sufficiently long horizon. For example, Gernandt and Pfeiffer (2009) analyze wage convergence between East and West Germany showing that even after 15 years this process is not complete, with substantial differences in wages of workers in East and West Germany who are observationally identical.[2] In this study we utilize a large collection of micro-economic data from as many as 31 countries of which 14 are transition economies. Our earliest samples come from 1984 and in some cases coverage continues to 2014, with over 42 million individuals observed. Hence, for each country we are able to produce indicators of wage distribution as well as provide a variety of counter-factual exercises.

Given the main interests of the earlier literature as well as policy relevance, we formulate the following three research objectives. First we provide a description of the trends in the wage compression across time in the process of transition from a centrally planned to a market economy. We utilize the data from non-transition countries to provide a baseline scenario, as every country experienced skill-biased technological change and globalization over this horizon. Our findings show that the initial shock to wage distribution was essentially instantaneous, whereas countries experiencing a rapid structural change effectively do not return to the initial levels of wage compression.

Second, we provide a series of counter-factual analyses, which help to understand if the changes in wage distribution reflect prices or quantities. Namely, earlier literature seems to suggest that economic processes affect the returns to individual characteristics and thus influence the wage distribution. However, an important feature in all transition economies has been an educational boom as well as massive reallocation of the labor force coupled with relatively high non-employment in some of these countries. We construct counter-factual distributions of wages to assess how much of the change in the wage structure occurred due to change in labor force structure as opposed to the changing evaluation of the individual characteristics in the course of transition. Given its strong foundation in the economic theory, we pay particular attention to the skill biased technological change. We show that most of the decompression stems from diverging wages, because the labor force remains substantially more homogeneous in terms of productive characteristics than in the advanced market economies.

Third, the earlier literature argues that the role of the institutional framework is decisive for determining wage compression, particularly "from below". Given the richness of our data, we are able to develop a series of counter-factual scenarios to gauge the role of human capital in the in the course of a large structural shock. While these estimates do not aspire to be causal in terms of the relationship

[1] This notion is also consistent with theoretical implications from the skill-biased technical change: it creates a rise in income inequality and deteriorates the position of the low tail of the wage distribution in developed countries (e.g. DiNardo and Card, 2002; Autor et al., 2008).

[2] Germany is a compelling case where a household panel survey is collected with direct individual information on wages, this panel comprises data on Eastern Germany from 1992 onwards.

between a given institution and a level of wage compression, they are informative about the effects of shock – such as transition – on the distribution of wages given the institutional design. We show that more structural change is actually associated with lower extent of wage decompression.

Our study is structured as follows. In the next section we provide an overview of the existing literature, showing how our paper contributes to the existing body of research. We also discuss how is wage compression measured in the literature so far. Given the diversity of data sources and its heterogeneity, we discuss at large the characteristics of the acquired datasets and limits to their usefulness from the perspective of our main research question in section 4. The methodology for constructing the counter-factual distributions is discussed in section 4.2, whereas the estimates for the original data and the counter-factual scenarios are presented in section 5. In concluding remarks we emphasize the policy implications of our study along with directions for future research.

2 Literature review

Analyzing the case of the US over 1980s and 1990s DiNardo and Card (2002) provide a list of possible explanations for changes in wage distribution. In addition to the usual suspect of the skill-biased technical change (SBTC) they also point to gender gaps, racial gaps and cohort gaps within educational groups.[3] SBTC hypothesis postulates that the demand for 'more-skilled' workers combined with the relative abundance of skilled workers determine jointly the dynamics of the wages disaggregated by educational groups increasing the dispersion between high earners and low earners due to technology-skill complementarities. Indeed, as argued by Autor et al. (2008), there have been substantial price adjustments in the bottom of the earnings distribution in the US, but their effect on total wage inequality has been moderated (or effectively wiped out) by the downward quantitative adjustment in workers with low earnings potential.

While role of SBTC seems to have been corroborated empirically, the trends in gender, racial and other gaps are less systematic. For example, in the US the gender wage gaps appear to drop (Blau and Kahn, 2016), but this trend is not universal around the world (Polachek and Xiang, 2014; Rendall, 2013). Racial gaps tend to be remarkably stable in the US (Heywood and Parent, 2012; Kreisman and Rangel, 2015) and other countries (Longhi et al., 2012; Lang et al., 2012). College premium have first exhibited a stark increase (Grogger and Eide, 1995; Dinardo et al., 1996), but in many countries it was followed by a substantial decline (Walker and Zhu, 2008; Acemoglu and Autor, 2011) with increasing dispersion of returns to higher education (Reimer et al., 2008; Green and Zhu, 2010). Overall, in the advanced economies, the changes in the wage distribution clearly do not follow one single pattern, with multiple processes interacting (Checchi et al., 2016).

There is also natural limitations to this strand of the literature. First, since SBTC and equalization of opportunities are slow moving processes, analyzing the effects of these structural changes on wage compression is very data intensive both in terms of length of comparable micro-level data and in terms of data quality. Short periods of observation make it impossible to notice substantial changes in wage distribution, but only few countries can offer comparable micro-level datasets for a few decades. Second, it is also relatively rare in most countries that wage data is systematically collected in labor force surveys

[3]In addition to the structural change literature, there is also an extensive literature which analyzes the effects of trade unions and minimum wages on the distribution of wages (eg. Blau and Kahn, 1996a; Gosling and Machin, 1995; Lee, 1999; Card et al., 2004; Töngür and Elveren, 2014). These, however, are institutional rather than structural changes and we abstract from this strand of the literature in the reminder of our paper.

(or analogous studies). Hence, most of the analyses concern few countries for which data is readily available: the US (eg. Lee, 1999; Acemoglu and Autor, 2011), with some evidence for Canada (Lemieux, 2006), Japan (Kawaguchi and Mori, 2008) and Germany (Beaudry and Green, 2003; Dustmann et al., 2009).

Given these high data requirements, there has been substantially less research into changes of wage distribution in countries undergoing a *sudden* structural change of replacing centrally planned with a market based system. This rather unique case of shock to the economic system involved both types of processes expected to drive SBTC: opening of the transition economies to global trade and immediate installation of direct price incentives where there were substantially compressed direct rewards to individual skills and characteristics. This process is modeled in a general equilibrium simulation framework by Aghion and Commander (1999), who show that indeed technological and organizational change may drive wage decompression if asymmetrically affected groups cannot smoothly adjust skills. However, in their setup, majority of the effect comes from differentiated employment opportunities for various groups and not directly from changing distribution of wages for the respective groups. This stylized framework is useful for interpreting the empirical findings in the (scarce) literature. For example, Milanovic (1999) argues that the decompression of wages stems from dismantling of the state sector with compressed wage structure, and its replacement by the newly-emerging private sector with much broader wage distribution. Similar insights stem from study by Keane and Prasad (2006), who argue that the reallocation of workers from the state owned sector to private sector translated to replacing a compressed distribution of wages with a more dispersed one. These micro-level studies were complemented by multiple cross-country comparisons utilizing more or less standardized measures of income inequality (e.g. Milanovic and Ersado, 2012; Aristei and Perugini, 2012, 2014), and which mostly focus on household income inequality rather than worker earnings dispersion. Gernandt and Pfeiffer (2009) rely on data from Germany and analyzes the convergence between the average in the East and the West. However, this study does not address the dispersion of wages in the two regions. Unfortunately, majority of other empirical studies focuses on issues such as poverty incidence and utilize household after-transfer income inequality rather than worker earnings dispersion (Ott and Wagner, 2013, provide an overview of earlier literature in the field).

The literature referring to the sudden structural change of transition so far has not addressed a number of issues relevant for the literature on structural change and wage compression.[4] First, studies tend to attribute increased income inequality to increased earnings dispersion due to the flow of workers from state owned firms to the emerging private sector with more decompressed wage distribution. However, later studies show that there was in fact little reallocation of workers *per se*, rather premature exits to retirement and entry of young cohorts drove the overall change in employment structure (Tyrowicz and van der Velde, 2016). There is also substantial evidence that privatizations rather than worker flows explain the change in ownership structure of employment. Hence, although there has possibly been different wage dispersion patterns between the emerging private sector and the state owned sector, the actual flows of workers appear to have been smaller than initially expected. Moreover, these studies do not explain *why* the wage distribution in the private sector should be more dispersed – in other words, due to which processes and how much more dispersed should one expect it to be.

Second, there has been little insights into the role the changing composition of the labor force in

[4]In the interest of brevity, we are abstracting here from substantial literature about gender inequality over transition (eg. Polachek and Xiang, 2014; Rendall, 2013).

changing the distribution of wages. Namely, well documented phenomenon of the educational boom, growth in service sector employment and relatively fast aging of the population all may contribute to changing the dispersion of wages, even if returns to individual characteristics do not change. Analyses of the SBTC and wage compression show that ‘prices’ matter substantially for the changes in the distributions of wages, because they react to the changes in the (relative) abundance of demanded skills. However, with SBTC, because all these changes are gradual, there can be adjustments in both prices and quantities. With changes as sharp as transition from a centrally planned to a market economy one should expect prices to play a bigger role in changing wage distribution, at least in the short and medium run. These are the issues our analysis will help to address.

3 Measuring wage inequality

Literature provides several concepts that describe wage distribution. The main differences between inequality measures and dispersion/compression measures is the fact that inequality indices take into account the whole distribution of income, while measures of dispersion and/or compression are typically concerned with the range between specific points in the distribution. Wage inequality seems to have a broader meaning as well as it takes into account observable characteristics, especially occupation and education.[5]

To express the properties of a distribution in single indicator, both in terms of inequality and in terms of compression/dispersion, studies rely on various statistical measures. In principle, one would expect measures to fulfill some basic properties: mean independence, size independence, symmetry, transfer sensitivity as well as decomposability (Shorrocks, 1980). For example, Gini satisfies the first four, but not the last of these five properties, whereas most generalized entropy measures satisfy them all (e.g. mean log deviation, Theil index). None of these indicators, however, nor the positional dispersion measures from the distribution (e.g. ratios between percentiles) allows for statistical comparisons. First, none of them has theoretical confidence intervals, so the only feasible alternative is bootstrapping. Second, most of the studies rely on survey data and thus are bounded with survey error if they are to be treated as approximation for the entire underlying population.

Empirical literature so far has considered numerous measures of wage compression / dispersion. Most frequently used are positional measures of dispersion, i.e. log difference between 90th, 50th and 10th percentiles as well as 75th and 25th (e.g. Blau and Kahn, 1996b; Koeniger et al., 2007; Koeniger and Leonardi, 2007; Autor et al., 2008). This popularity is well reasoned. First, 90th and 10th percentiles combined with the median allow to distinguish within the whole distribution the dispersion from above and the dispersion from below. Both are likely to be driven by other processes, not necessarily occurring under the same circumstances (see also Beaudry and Green, 2003; Milanovic and Ersado, 2012). The measures focused on the quartiles of the distribution capture the non-extreme majority of the labor market and thus complement the picture.

Due to wider availability, the literature has also frequently relied on synthetic indicators, such as Gini or Theil index as well as measures based on distribution moments (e.g. coefficient of variation, mean log deviation, etc. Card et al., 2004; Töngür and Elveren, 2014; Checchi et al., 2016). However, these indicators may exhibit the same dynamics whether the compression of wages changes from below or from

[5]Salverda and Checchi (2014) highlight conceptual difference between dispersion and inequality. In their view, dispersion is just a mathematical difference, which does not have to be always an inequality – e.g. dispersion does not have to include differences in efforts or characteristics.

above. Hence, while these indicators are intuitive for discussion of inequality, they are less informative from the perspective of the research question in this study.[6]

While the literature is rich in synthetic measures of wage distribution, each of the measures has specific strength and weaknesses in representing the whole distribution in a form of one number. Because of the core interest in this paper, we exclude measures which focus on a specific segment of the wage distribution (e.g. in-work poverty, or top 1% share in income), as they are less relevant in analyzing the the processes of the wage compression. However, there is also a pragmatic reason for which these measures may be less relevant in our study. First, it is well documented that top earners are weakly represented in surveys studies, such as the majority of data sources utilized here. Second, structure of earnings survey do not report the earnings of individuals below the legal limits such as minimum wage (that would be self-incrimination in many legal systems, which firms naturally attempt to avoid even if they violate the minimum wage regulations). In sum, some sources of data particularly poorly capture high earners, whereas others particularly poorly capture low earners. Hence, focusing on the top or the bottom of the wage distribution may be relatively more biased than measures from other segments.

Given the nature of the analyzed processes – large structural change and skill biased technological change – one would expect the patterns to differ between the rich, the poor and middle class workers. Rather than choosing one specific measure we thus provide analyses for several measures as indicators of changes to the wage compression: ratio p10 to p50, ratio p50 to p90, complementary ratio p10 to p90 and the synthetic Gini coefficient.

4 Data and empirical strategy

It is our objective in this paper to address the patterns in wage dispersion in the context of the large structural shock such as economic transition with special emphasis on the role of human capital and skill biased technical change. This section describes the data collected and the empirical strategy followed. First, we describe data sources. Then we show how the wide array of micro data sets was used to compute measures of wage dispersion comparative across time and between countries. We also show how our measures fare against the widely accessible indicators from OECD Statistics on wages. Finally, we show the main advantage of using the microeconomic data, i.e. we describe the counter-factual scenarios.

4.1 Data

In order to address the question at hand we utilize a large collection of micro-level data sets. Already in 1990s, International Social Survey Program (ISSP) made individual data on wages available for some selected countries (compare Blau and Kahn, 1992; Polachek and Xiang, 2014; Blau and Kahn, 2003). However, ISSP often changes the way wage data is collected between nominal and categorical, which makes it rare that data for a given country could be analyzed continuously over time. Montenegro and Hirn (2009) develop The World Bank micro-database with data from 120 countries, in total app. 600 surveys (utilized by Ñopo et al., 2012; Rendall, 2013; Gindling et al., 2016, among others)[7]. However,

[6]Some of the literature formulates measures dedicated to poverty and exclusion, such as low pay incidence (Meulders et al., 2004), in-work poverty (Bennett, 2014), share of income accruing to the top 1%, etc. We abstract from these measures in the reminder of this paper due to definitional issues: poverty lines definitions differ across countries and usually refer to household level, whereas top 1% share of income cannot be adequately measured in survey data as these are often censored (by design or as a consequence of survey sampling).

[7]Currently, this collection of datasets is only available internally at The World Bank.

the focus of The World Bank is on the most recent years and on developing countries, which results in relatively poorer coverage of 1980s and 1990s as well as Europe. Luxembourg Income Study operates an initiative to standardize data from European countries, LISSY (utilized by Polachek and Xiang, 2014; Pryor, 2014, among others). However, LISSY comprises mostly data from European Household Community Panel and EU Survey of Income and Living Conditions (EU-SILC). The former covers EU member states from 1984, with poor coverage of CEECs. In the latter coverage of CEECs starts usually in late 1990s. Moreover, for many countries and years EU-SILC collects detailed data on annual salaries, but not on hours and months worked. Hence, meaningful comparisons are only possible between full-time full-year salaried workers.

Given these constraints, we created a collection of micro-datasets from transition countries. We addressed all statistical offices in the CEE region and acquired labor force surveys (LFS) and household budget surveys (HBS) data as early as they are available, which is typically 1993-1995 for most CEECs. Data for benchmark countries were acquired if available online. Standardized EU data sources such as ECHP and EU-SILC as well as Structure of Earnings Survey (SES) were acquired from the Eurostat (in the case of Hungary and Poland we also acquired SES data from statistical offices, which gave us access to a larger number of years for these countries). We also utilize data from the ISSP as well as other sources available, as we discuss the details in Appendix A.

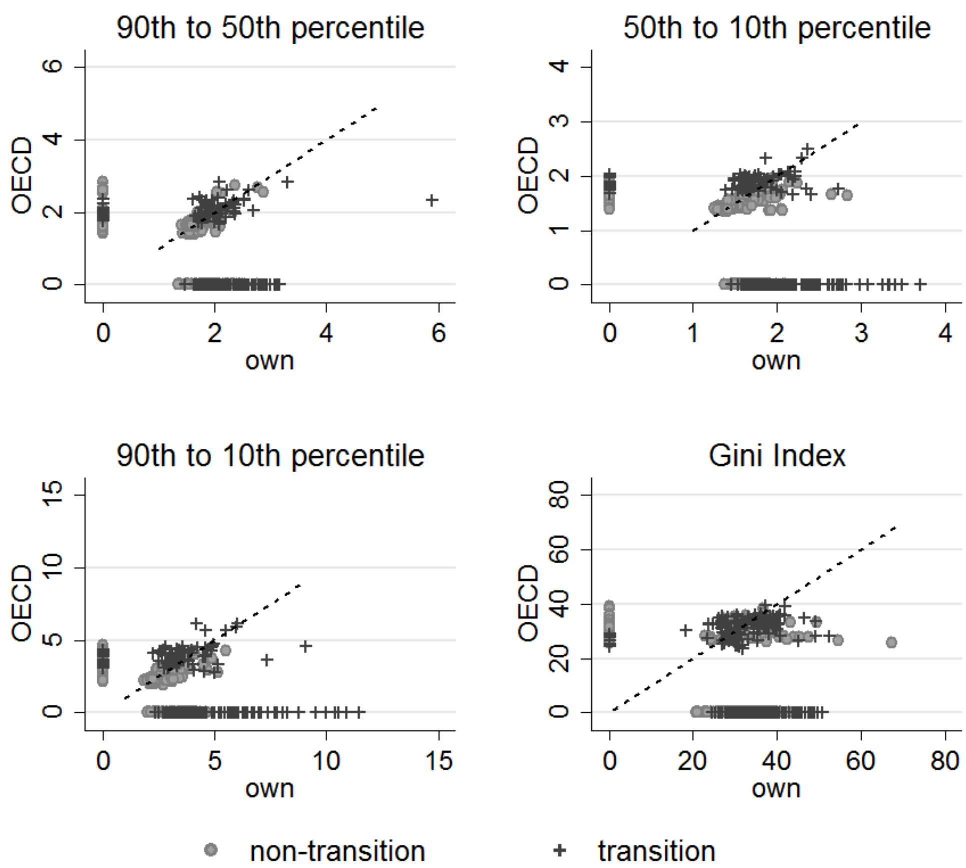
Compared to these earlier efforts, our database is rich and comprehensive. We can track labor markets of 31 countries (from which 14 are post-transition economies) in longer and shorter time spans between 1984 and 2014. The data sources and country coverage is summarized in the Table A.1. While the number of countries covered is lower than in The World Bank study, regional coverage of the transition economies is more comprehensive (14 countries in our database vs. 7 in the World Bank analysis). Also our coverage of 1990s is richer than in earlier literature. For example, compared to Milanovic (1999) we have weaker coverage of the pre-transition years, but we are able to comprise many transition economies from 1992/1993 onwards. In total, we collected information on over 40 million individuals: wages, hours worked, education, age, gender, occupation, etc. As the data for each country (and often each source) has differentiated variable definitions, we harmonize all the variables to signify the same concepts. Wages are expressed in local currency units and per hour worked. For example, if a given dataset contained data on monthly wage and weekly hours, we recoded wages to reflect hourly compensation, assuming four weeks per month. Since hours are not available in each dataset, we also utilize average monthly wages for full time workers. This harmonization of data sources is typically not controversial, but narrows the number of categories to be considered for each variable. For example, in the case of education, after comparing all the sources, we had to utilize three levels only: primary or below, secondary and tertiary or above. As in some sources the age has been aggregated in age groups, we follow this classification for all the sources (below 19, 20-29, 30-39, 40-49, 50-59 and 60+).

4.2 Measures of wage inequality

All measures are derived for hourly wages, but some datasets do not contain information on hours. Hence, we also develop these indicators for monthly reported wage income and present these results in the Appendix. All the indicators are computed in the same manner across all the datasets, which makes them methodologically comparable.

Not all indicators we derive are identical to measures reported in various data sources on *income* inequality. For example, comparing to the OECD database reveals relatively strong correlation where our selection of countries and OECD data coverage overlaps for the income percentile ratios, but not for Gini, see Figure 1. This comparison reveals how numerous assumptions are taken to compute the OECD indicators and how sometimes they need not reflect the actual wage compression patterns. The highest correlation – app. 50% – is found for the p90/p10 ratio. We also find roughly similar figures for the the upper half of the wage distribution. Much lower correlation concerns the bottom half of the wage distribution – correlation between our indicators and those reported by the OECD falls to 24%. The reasons behind this lower correlation stem from the data shortages discussed earlier (e.g. in EU-SILC). Since indicators for the lower half of the wage distribution differs between OECD and our data, one should expect Gini to be an accumulation of these discrepancies, which indeed is the case.

Figure 1: Comparison of the inequality measures derived from micro-datasets and OECD indicators



Source: total monthly wages of full time workers in OECD, total monthly wages in own measures. Data coverage from OECD is smaller than reported in Table A.1. Overall, correlations computed for the following countries: Czech Republic, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden. If the indicator is available only for one source, it is shown on the figure with zero imputed for the other source. Transition countries coverage in the OECD data starts usually in 2000s. Detailed comparative statistics reported in Table B.2 in the Appendix.

However, knowing the methodological choices in constructing the OECD indicators, one should expect exactly these discrepancies. First, OECD only uses wages of full-time employees. Hence, own measures show substantially more dispersion than the OECD data. Second, OECD relies mostly on household level data (such as the EU-SILC for example), which makes it less comparable to studies focusing on labor issues (such as the labor force surveys) and studies focusing on other issues, which also inquire about self-reported wages. For example, measures of wage compression for one selected country – Poland – derived from EU-SILC and from Polish LFS differ substantially, with household level data revealing much lower wage compression at the bottom half of incomes. On the other hand, some of the outcomes differ also because the data collection used in this study are sometimes not fully representative surveys. For example, data from the ISSP show systematically higher measures of dispersion. While this data source has been used extensively in labor market research (cfr. Blau and Kahn, 1992, 1996b, 2003), one needs to recognize smaller sample size than in representative surveys as well as the fact that in self-administered surveys responders tend to report more rounded numbers when reporting wages.

Overall, the comparison reported in Figure 1 reveals the advantages of the methodological approach taken in this study. First, unlike studies utilizing wage compression measures compiled by other sources, we may obtain measures which reflect the general population of workers, not a systematically selected subsample (e.g. full-time workers). Second, we may obtain these indicators for years and countries for which standard data sources such as OECD, World Income Inequality Database or Transmonee are short in coverage. Finally, we are specific to utilize worker earned income rather than household income measures. Naturally, not all data sources are characterized by the same reliability of the indicators. To address this issue, all the estimations will comprise data source fixed effects. Having discussed the data characteristics, in the remainder of this study we pursue with the empirical analysis.

4.3 Empirical strategy

We analyze actual reported wages to measure the changes in (hourly) wage inequality. However, change in wages may stem from two distinct processes: structural change of the underlying labor force characteristics (e.g. increase in tertiary attainment) and the change in rewards to these characteristics. To isolate the first effect we provide counter-factual scenarios utilizing estimated structure of rewards from a benchmark dataset. Given the richness of this data, we rely on American Community Survey. For the sake of robustness, we obtain three sets of benchmark rewards: from ACS wave of 1990, wave of 2000 and wave of 2010. Using these estimates we provide counter-factual structures of wages for each micro-data set in our sample, independently. Then, changes across time reflect only changes in labor force structure – not how it is being rewarded. The models to obtain the counter-factual structure of wages are highly saturated, with two-way interactions of education (3 levels), age (5 groups), gender and occupation (9 levels).

The parametric approach to wage structure is appealing, but may be susceptible to several methodological hazards. Thus, we also utilize Dinardo et al. (1996) semi-parametric approach (henceforth, interchangeably DFL). Using the ACS data from 1990 wave we estimate the likelihood function that a given person from a given country and data source in a given year has the same characteristics as an average American worker.

$$weight_{i,j} = \frac{1 - Pr_{i,j}(ACS = 1|x)}{Pr_{i,j}(ACS = 1|x)} \cdot \frac{Pr_{i,j}(ACS = 1)}{1 - Pr_{i,j}(ACS = 1)} \tag{1}$$

where ACS is equal to 1 if the worker is from the US ACS sample and zero otherwise, x are the characteristics of the worker and conditional probabilities are obtained from probit models. Characteristics used in the probit model are the same as in the case of parametric approach, with models run separately for every analyzed sample. These weights are then used to obtain counter-factual distribution of wages as if a given country and data source had identical employment structure as the US from a given wave. On these semi-parametric counter-factual distributions we also obtain measures of wage compression.

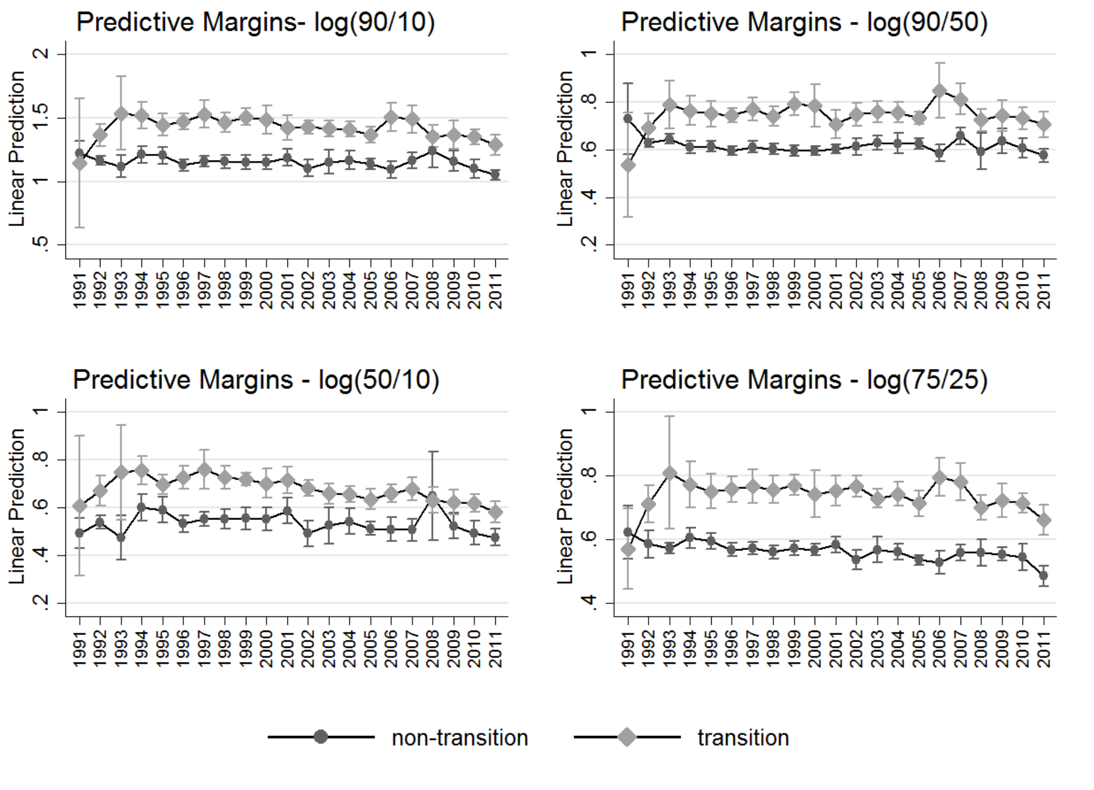
This approach has an additional advantage that it allows to partially account for differentiated selectivity patterns. Admittedly, the US labor market has a higher employment rate than most of the transition countries, especially in early transition. Similar approach was employed by Campos and Jolliffe (2007). By the means of Dinardo et al. (1996) correction, we replicate the weights in the population as if employment was as likely, given age, gender, education and other relevant characteristics. For majority of the distribution, the two counter-factual distributions are expected to correlate relatively well. However, the parametric approach cannot recover dispersion in the top of the earnings distribution. By contrast, DFL reflects it relatively well. This difference stems from the fact that probably high earned incomes are associated not only with highly rewarded characteristics, but also unusually high compensation for them. Hence, although the parametric model is highly saturated (interactions of all the involved characteristics), this part of compensation must be residual in parametric approach and hence cannot be recovered in fitted wages. DFL, meanwhile, only reweighs distributions to replicate the structure of individual characteristics, but takes wages as given. Hence, what is residual and thus omitted in parametric approach, remains on the distribution in the semi-parametric approach of Dinardo et al. (1996). We portray these considerations using example of transition country and one advanced economy in Figure B.1. This comparison yields two important insights for the interpretations of the counter-factual wage compression measures, as pursued in the subsequent section. First, it appears that especially in the top, counter-factuals from DFL may reflect actual distributions closer than the parametric ones. Hence, for the p90/p50 ratio one should consider estimates on counter-factuals from DFL as more reliable. Second, the estimates concerning p50/p10 are expected to produce similar outcomes.

The exercise with the counter-factual scenarios reveals that in fact the changes in the wage structures had a relatively big importance. When cleared of the rewards effect in parametric approach, the time variation in the indicators of wage compression are substantially larger, but in DFL counter-factual scenario the result is the opposite - especially in the case of p50/p10 ratio, see Table B.3. This is especially pronounced in the “from the top” compression. These might suggest that the counter-factual scenarios show slightly different stories on changes in workers characteristic and rewards with DFL taking into account more variation caused by other then time trend effects.

The results are reported in three substantive parts. First, we provide the overview of the time patterns as well as cross-sectional heterogeneity. Second we analyze time trends of wage compression measures based on counter-factual wage distributions. This way we show the contribution of changes in characteristics of workers (mainly connected to educational boom and occupational structure changes) in wage compression processes. In some cases we actually find that if wage structure would follow only changes in characteristics - distribution of salaries would change in opposite direction than we observe in actual data. Third, we provide analyses on the relationship between selected specific structural changes and wage compression measures. We pay special attention to, separately, inequity on the top and on the bottom of the distribution. Differences between transition and non-transition countries are highlighted.

In the first step we present the estimators of the year effects from a regression with country and source fixed effects for all four indicators of wage compression. These predictive margins report both the magnitude of the effect and the size of the estimated confidence interval and thus permit fairly reliable comparisons across time. Since we control for time and data source fixed effects, the changing country availability in the sample has as small bearing on the results as possible. For the sake of comparison, there were separate estimations for the transition countries and the benchmark countries. The results are reported in Figure 2.

Figure 2: Wage compression - time trends



Source: hourly wages from data sources described in Table A.1, results for the total (monthly) wages available in Figure B.2 in the Appendix. Marginal effects of years obtain from regressions on wage compression measures and country, source, year and interaction of year and transition dummies as independent variables. Robust type of variance estimator was used.

Even this relatively simple descriptive statistic reveals several important observations. First, the adjustment in wage compression were almost immediate, occurring in the first few years of transition. Second, while wages were substantially more compressed, especially in the upper half of the distribution in the transition economies, this is where the adjustment took place – from levels below the benchmark countries, the indicators of compression jump almost instantaneously to the much higher levels and this initial differential continuous for the reminder of the sample. Third, there appears to be a very slow, negative trend indicating more wage compression in both transition and benchmark countries, especially in the years post the global financial crisis. Fourth, beyond this initial jump in the upper half of the wage distribution, there were not much changes in the subsequent 20 years of transition. Especially this last conclusion is potentially puzzling – adjustments such as skill biased technical change, plugging into global value chains, etc – involve substantial adjustments by firms and henceforth by the workers.

4.4 Variation of wage compression across time

Time variation provides for only a small share of changes in inequality. Table B.4 reports the estimates of the level effect between transition countries and the benchmark countries along with the estimates of the time trend. We interact the time trend and transition to observe if there are statistically significant differences between the two groups of countries. The results reveal a level effect of transition countries – from 0.6 for the p90/p10 ratio and 0.2-0.3 for p50/p10 and p90/p50 ratios. These differences are persistent over time, but not very large: with the current rate of change, it would take the transition countries approximately 10 years to close down the gap. Recall Figure 2, the gap emerged in the first 2-3 years of early transition. There is no catching-up effect when it comes to a top-down inequality (p90/p10).

We complement these estimates with a similar analysis but for the counter-factual distributions. Using the "prices" of individual characteristics from the US, we reestimate the distributions of wages based on individual characteristics in both transition and benchmark countries. We find striking results. First, the counter-factual wage distributions are in fact *more* compressed in transition countries than in the advanced economies. The negative estimate of the transition dummy is consistent across all indicators of wage compression (sometimes insignificant, but never positive). These are not the characteristics of workers that stay behind decompression of wages subsequent the introduction of the market economy, but swiftly adjusting prices of individual characteristics increase the dispersion of wages.

Second, the speed of convergence between the two groups of countries appears much faster, in the parametric counter-factuals and much slower or even inexistent in semi-parametric counter-factuals. Hence, it appears that any divergence between the two groups of countries stems from prices, whereas any convergence between the two groups of countries comes from characteristics of the labor force becoming more similar. Lack of convergence revealed by the DFL counter-factuals suggests that the abnormally high wages for some individuals, beyond their characteristics, stand behind relatively higher dispersion of wages in transition countries. On the other hand, the top down comparisons (p90/p10 and p90/p50) reveal relatively high convergence, requiring approximately 10 years for the transition countries to catch up with the advanced market economies.

Third, the disparities in wage dispersion between the two groups of countries are particularly pronounced at the bottom half of the wage distribution. This is especially relevant from a policy perspective – most of the transition countries kept the institutional features such as minimum wages and centralized wage bargaining. Despite these institutional arrangements, wage distribution decompressed rapidly and remained as decompressed ever since. Comparison of the parametric and semi-parametric counter-factuals reveals that this process was stronger for the unexplained part of the variation in wages, even controlling for prices.

5 Results

The analysis of time trends alone is not satisfactory. To address the economics behind the time trends we follow the vast literature on the structural change. We collected several standard indicators: share of trade in GDP (to reflect globalization), share of services in employment (to reflect the transition between industrial and service based society), high-technology share in exports and high-skill share in employment (to reflect the role an economy plays in the global value chain). Each of these indicators measures a secular, global trend. However, countries absorb these changes at varied pace. Our objective is to test if and to which extent the differences in absorbing these global trends explains the variaiton in wage compression.[8] Each of these indicators is correlated with the obtained measures of wage compression with the intention to verify if their variations are in any way correlated. We include country (and data source) fixed effects, so mostly the variation over time is exploited. To account for possible differences between the countries undergoing a rapid structural change and countries experiencing it gradually, we provide also estimates of the interaction term for the dummy denoting transition countries. These correlations are computed for original measures of the wage compression and for the counter-factual ones. Results are reported in Table B.9.

Table 1: Wage compression and the indicators of structural change

	5th-to-1st			9th-to-5th		
	Raw	Parametric	DFL	Raw	Parametric	DFL
Trade	-0.001***	0.0002	-0.0002	-0.0005*	-0.0002	0.0001
	(0.0003)	(0.0002)	(0.0006)	(0.0002)	(0.000315)	(0.000147)
#Transition	-0.0003	0.0001	-0.0006***	-0.0005	0.0007**	-0.00001
	(0.0004)	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.00001)
Obs.	488	416	416	416	488	416
Countries	31	30	30	30	31	30
Employment	-0.005***	0.003***	-0.004***	-0.004***	0.0002	-0.003***
in services	(0.001)	(0.0005)	(0.001)	(0.001)	(0.0002)	(0.001)
#Transition	0.0004	0.0008**	-0.001*	-.002**	-0.0004	0.001**
	(0.0008)	(0.0003)	(0.0007)	(0.0008)	(0.0003)	(0.0006)
Obs.	470	403	403	403	470	403
Countries	31	30	30	30	31	30
High-tech export	-0.0008	-0.0004	0.001*	-.00049	-0.003**	-0.0002
	(0.001)	(0.0003)	(0.0005)	.00096	(0.001)	(0.0006)
#Transition	-0.004*	-0.0006	-0.003***	-.0035	0.005**	0.0006
	(0.002)	(0.001)	(0.0008)	.0014	(0.002)	(0.0007)
Obs.	458	399	399	399	458	399
Countries	31	30	30	30	31	30
R&D	-0.06***	-0.006	-0.05***	-0.046***	-0.072***	-0.006
	(0.019)	(0.007)	(0.011)	(0.016)	(0.016)	(0.007)
#Transition	-0.061**	-0.004	-0.060***	-0.134***	0.020	0.013
	(0.0298)	(0.019)	(0.008)	(0.033)	(0.029)	(0.014)
Obs.	387	344	344	344	387	344
Countries	31	30	30	30	31	30
High-skilled	-0.684***	-0.012	-0.515***	-0.313***	-0.316*	-0.240*
workers	(0.176)	(0.102)	(0.182)	(0.118)	(0.175)	(0.126)
#Transition	0.230	-0.044	-0.355*	-0.757**	0.667***	0.086
	(0.201)	(0.114)	(0.199)	(0.166)	(0.185)	(0.072)
Obs.	330	289	289	289	330	289
Countries	26	25	25	25	26	25

Notes: see notes under Table B.4, wage compression measures based on hourly wages, results for the monthly wages and other counter-factual measures available in Table B.7 in the Appendix. Variance in regressions on counter-factual measures is bootstraped.

The indicators of the structural change correlate mostly with the decompression in the lower half of the wage distribution. Most indicators of structural change exhibit negative correlation, which implies that more compressed wage distributions and more structural change coexist, not the vice versa. Since some changes have been more rapid in the transition economies, some of the interaction terms provide significant estimates, but usually making the negative correlations larger not weaker. In particular, technology intensity of exports is only significant for the transition countries whereas the compression is twice as strong for R&D expenditure share in GDP. For the top of the distribution, most correlations

[8]Table B.6 reports the time patterns of these secular trends.

become insignificant once we isolate away the effects of the prices. The only exception is the share of high-skilled workers in the economy, which too is associated with lower wage compression. Hence, these results suggest that structural shocks correlate mostly with changes in prices, but not changes of individual characteristics.

Clearly, there correlations discussed above cannot be indicative of causality and were not intended so. Rather, they document that despite controlling for country-level heterogeneity, there seems to be relatively strong correlation between the speed of structural change and changes in the wage compression. This correlation is driven predominantly by changing prices.

6 Conclusions

In explaining wage inequality, existing literature has focused on skill-biased technical change (SBTC, e.g. DiNardo and Card, 2002; Acemoglu and Autor, 2011), related notion of college premium (e.g. Grogger and Eide, 1995; Walker and Zhu, 2008) as well as unionization (e.g. Gosling and Machin, 1995; Hibbs and Locking, 1996; Card et al., 2004). The notion of institutional or structural change is crucial in all these strands of the literature in explaining the changes in the wage distribution. However, most of the analyzed countries experienced gradual, slow-moving changes, which makes the identification troublesome. The exceptional event of rapid economic transition from a centrally planned to market economies is a great example of a rapid change, where identification may be clearer. Using a novel, unique collection of micro-datasets on wages in this paper we provide consistent estimates of unconditional and conditional wage distribution to analyze the sources of changes in the wage compression.

We show that indeed wage dispersion increased rapidly in early transition, but this adjustment was immediate. Since then a slow, negative trend is visible. While wages were more compressed than in the benchmark group of advanced market economies, the rapid increase made wages persistently more dispersed. This effect lasts despite being driven mostly by adjustment in prices – when the variation in prices is eliminated in the counter-factual scenarios, the wages continue to be more compressed in the transition countries. This implies that despite massive labor reallocation and unprecedented educational boom, characteristics of the salaried workers still remain more similar in transition countries than in advanced market economies.

To understand the sources of the observed time trends in wage dispersion, we sought to identify to what extent they may be attributed to globalization and skill-biased technical change. We correlate the measures of wage compression – both raw and counter-factual – on the indicators of globalization and structural change. We find that if anything, these processes correlate with more compressed wage distributions. This result partly disappears when we fix the prices of individual characteristics, which implies that adjustment in prices go in the opposite direction as the adjustments in characteristics, reducing the incentives to invest in skills. In fact, adjustment in prices must outpace on average the adjustment in characteristics. However, these effects are contained to the bottom half of the wage distribution. There is substantially less compelling evidence for the top of the wage distribution that globalization and skill-biased technical change affect the distribution of wages.

Usually in one country setting, earlier studies argue that changing returns to skills influence the observed inequality indicators. This evidence was consistent for the US, but less so for Germany and Japan. Our study is not to argue against these earlier findings. We focus on the alternative measures of wage dispersion to emphasize the differences in the 'from below' and 'from above' inequality. We find that indeed most of the effects occur in the bottom half of the distribution, especially if changes happen rapidly, as was the case of transition economies. However, the initial shock in demand appears to have been relatively swiftly absorbed.

References

Acemoglu, Daron and David Autor, "Skills, tasks and technologies: Implications for employment and earnings," in David Card and Orley Ashenfelter, eds., *Handbook of labor economics*, Vol. 4B 2011, pp. 1043–1171.

Aghion, Philippe and Simon Commander, "On the dynamics of inequality in the transition," *Economics of Transition*, 1999, *7* (2), 275–298.

Aristei, David and Cristiano Perugini, "Inequality and reforms in transition countries," *Economic Systems*, 2012, *36* (1), 2 – 10.

_ **and** _ , "Speed and Sequencing of Transition Reforms and Income Inequality: A Panel Data Analysis," *Review of Income and Wealth*, 2014, *60* (3), 542–570.

Autor, David H, Lawrence F Katz, and Melissa S Kearney, "Trends in US wage inequality: Revising the revisionists," *The Review of Economics and Statistics*, 2008, *90* (2), 300–323.

Beaudry, Paul and David A Green, "Wages and employment in the United States and Germany: What explains the differences?," *The American Economic Review*, 2003, *93* (3), 573–602.

Bennett, Fran, "The 'living wage', low pay and in work poverty: Rethinking the relationships," *Critical Social Policy*, 2014, *34* (1), 46–65.

Bertola, Giuseppe, Francine D Blau, and Lawrence M Kahn, "Comparative analysis of labor market outcomes: lessons for the US from international long-run evidence," Working Paper 8526, National Bureau of Economic Research 2001.

Blau, Francine D and Lawrence M Kahn, "The gender earnings gap: learning from international comparisons," *The American Economic Review*, 1992, *82* (2), 533–538.

_ **and** _ , "International Differences in Male Wage Inequality: Institutions versus Market Forces," *Journal of Political Economy*, 1996, *104* (4), 791–837.

_ **and** _ , "Wage structure and gender earnings differentials: an international comparison," *Economica*, 1996, pp. S29–S62.

_ **and** _ , "Understanding International Differences in the Gender Pay Gap," *Journal of Labor Economics*, 2003, *21* (1).

_ **and** _ , "The Gender Wage Gap: Extent, Trends, and Explanations," NBER Working Paper 21913 2016.

Brainerd, Elizabeth, "Women in transition: Changes in gender wage differentials in Eastern Europe and the former Soviet Union," *Industrial & Labor Relations Review*, 2000, *54* (1), 138–162.

Campos, Nauro and Dean Jolliffe, "Earnings, schooling, and economic reform: econometric evidence from Hungary (1986–2004)," *The World Bank Economic Review*, 2007, *21* (3), 509–526.

Card, David, Thomas Lemieux, and W Craig Riddell, "Unions and wage inequality," *Journal of Labor Research*, 2004, *25* (4), 519–559.

Checchi, Daniele, Cecilia García-Peñalosa, and Lara Vivian, "Are changes in the dispersion of hours worked a cause of increased earnings inequality?," *IZA Journal of European Labor Studies*, 2016, *5* (1), 15.

Dinardo, J, NM Fortin, and T Lemieux, "Labor market institutions and the distribution of Wages, 1973-1992: A semiparametric approach," *Econometrica*, 1996, *64* (5), 1001–1044.

DiNardo, John and David Card, "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles," *Journal of Labor Economics*, 2002, *20* (4), 733–783.

Dustmann, C, J Ludsteck, and U Schonberg, "Revisiting the German wage structure," *Quarterly Journal of Economics*, 2009, *124* (2), 843–881.

Gernandt, Johannes and Friedhelm Pfeiffer, "19. Wage convergence and inequality after unification: (East) Germany in transition," in Ravi Kanbur, ed., *Labour Markets and Economic Development*, Vol. 73, Taylor & Francis, 2009, p. 387.

Gindling, TH, Nadwa Mossaad, and David Locke Newhouse, "Earnings premiums and penalties for self-employment and informal employees around the world," World Bank Policy Research Working Paper 7530, The World Bank 2016.

Gosling, Amanda and Stephen Machin, "Trade Unions and the Dispersion of Earnings in British Establishments, 1980-1990," *Oxford Bulletin of Economics and Statistics*, 1995, *57* (2), 167–184.

Green, Francis and Yu Zhu, "Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education," *Oxford Economic Papers*, 2010, *62* (4), 740–763.

Grogger, Jeff and Eric Eide, "Changes in college skills and the rise in the college wage premium," *Journal of Human Resources*, 1995, pp. 280–310.

Heywood, John S and Daniel Parent, "Performance pay and the white-black wage gap," *Journal of Labor Economics*, 2012, *30* (2), 249–290.

Hibbs, Douglas A and Håkan Locking, "Wage compression, wage drift and wage inflation in Sweden," *Labour Economics*, 1996, *3* (2), 109–141.

Kawaguchi, Daiji and Yuko Mori, "Stable Wage Distribution in Japan, 1982-2002: A Counter Example for SBTC?," Working Paper 20, RIETI 2008.

Keane, Michael P and Eswar S Prasad, "Changes in the structure of earnings during the Polish transition," *Journal of Development Economics*, 2006, *80* (2), 389–427.

Koeniger, Winfried and Marco Leonardi, "Capital deepening and wage differentials: Germany versus US," *Economic Policy*, 2007, *22* (49), 72–116.

_ , _ , and Luca Nunziata, "Labor market institutions and wage inequality," *Industrial & Labor Relations Review*, 2007, *60* (3), 340–356.

Kreisman, Daniel and Marcos A Rangel, "On the blurring of the color line: Wages and employment for Black males of different skin tones," *Review of Economics and Statistics*, 2015, *97* (1), 1–13.

Lang, Kevin, Jee Lehmann, and K Yeon, "Racial discrimination in the labor market: Theory and empirics," *Journal of Economic Literature*, 2012, *50* (4), 959–1006.

Lee, David S, "Wage inequality in the United States during the 1980s: Rising dispersion or falling minimum wage?," *Quarterly Journal of Economics*, 1999, *114* (3), 977–1023.

Lemieux, Thomas, "Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill?," *The American Economic Review*, 2006, *96* (3), 461–498.

Longhi, Simonetta, Cheti Nicoletti, and Lucinda Platt, "Explained and unexplained wage gaps across the main ethno-religious groups in Great Britain," *Oxford economic papers*, 2012, p. gps025.

Meulders, D., R. Plasman, and F. Rycx, *Minimum Wages, Low Pay and Unemployment* Applied Econometrics Association Series, Palgrave Macmillan UK, 2004.

Milanovic, Branko, *Income, inequality, and poverty during the transition from planned to market economy* 1998.

_ , "Explaining the increase in inequality during transition," *Economics of Transition*, 1999, *7* (2), 299–341.

_ **and Lire Ersado**, "Reform and Inequality during the Transition: An Analysis Using Panel Household Survey Data, 1990–2005," in Gérard Roland, ed., *Economies in Transition: The Long-Run View*, London: Palgrave Macmillan UK, 2012, pp. 84–108.

Montenegro, Claudio E and Maximilian Hirn, "A new disaggregated set of labor market indicators using standardized household surveys from around the world," Background paper prepared for World Development Report, The World Bank 2009.

Ñopo, Hugo, Nancy Daza, and Johanna Ramos, "Gender earning gaps around the world: a study of 64 countries," *International Journal of Manpower*, 2012, *33* (5), 464–513.

Ott, Notburga and Gert G Wagner, *Income inequality and poverty in Eastern and Western Europe*, Springer Science & Business Media, 2013.

Polachek, Solomon W and Jeff Xiang, "The gender pay gap across countries: A human capital approach," IZA Discussion Paper 8603, Institute for the Study of Labor (IZA) 2014.

Pryor, L. Frederic, "A Note on Income Inequality in East and Central Europe," *Comparative Economic Studies*, 2014, *56* (1), 42–51.

Reimer, David, Clemens Noelke, and Aleksander Kucel, "Labor market effects of field of study in comparative perspective an analysis of 22 European countries," *International Journal of Comparative Sociology*, 2008, *49* (4-5), 233–256.

Rendall, Michelle, "Structural change in developing countries: has it decreased gender inequality?," *World Development*, 2013, *45*, 1–16.

Salverda, Wiemer and Daniele Checchi, "Labour-Market Institutions and the Dispersion of Wage Earnings," IZA Discussion Paper 8220, Institute for the Study of Labor (IZA) 2014.

Shorrocks, Anthony F, "The class of additively decomposable inequality measures," *Econometrica: Journal of the Econometric Society*, 1980, pp. 613–625.

Töngür, Ünal and Adem Yavuz Elveren, "Deunionization and pay inequality in OECD Countries: A panel Granger causality approach," *Economic Modelling*, 2014, *38*, 417–425.

Tyrowicz, Joanna and Lucas van der Velde, "Demographics and Labor Reallocation," 2016, (forthcoming).

Walker, Ian and Yu Zhu, "The college wage premium and the expansion of higher education in the UK," *The Scandinavian Journal of Economics*, 2008, *110* (4), 695–709.

A Data sources

Labor Force Surveys (LFS) Many of the LFS samples do not contain information on wages (or information on wages is not disclosed due to national legislative implementation of the statistical secrecy clauses; in some cases wages are reported as deciles, which may be used for some studies, but not in wage compression analyses). Hence, in this study we could utilize the data for Croatia, Poland, Serbia as well as France and the UK.

LFS data are self-reported worker data and contain information individual labor market status. LFS are standardized in terms of sample design and general definitions, but not variables. Coding for education, labor market status, occupation and industry differed and were harmonized (ISCO for occupations, NACE for industries). Hourly wages were calculated based on the self-reported monthly net wage and averaged hours of worked per week. The only exception if LFS Croatia where hours information is missing.

Household Budget Surveys (HBS) Many of HBS do not comprise individual incomes, rather household incomes by source. In household with two wage earners, individual earnings may only be attributed if the head of the household is a wage earner. This feature makes the wage data not comparable across countries and years. Given these constraints, we only utilize HBS data where individual earnings are reported (along with individual characteristics). This limits the choice of countries to Belarus and Latvia. Another constraint of HBS is that it often lacks data about hours worked. Hence, we can only utilize monthly earnings. Similar to LFS, HBS data is self-reported, typically in net terms.

Structure of Earnings Survey (SES) Employers with more than 9 employees, FTE, participate in this large survey program in most European biennially. This data comprises detailed information on earnings, hours and worker as well as employer characteristics. As of 2002 it is standardized within the EU and the data are distributed by the Eurostat. Some of the countries collected their own SES data and thus we were able to extend the data coverage for Hungary and Poland to 1990s. SES data is typically very detailed, with two digit NACE and four digit ISCO. However, this level of data disaggregation is typically missing in other sources. Hence, we resort to one digit aggregation.

European Community Household Panel (ECHP) and EU-Study of Income and Living Conditions (EU-SILC) Developed by the Eurostat, ECHP was a European level analog of the household budget surveys in Member States. In principle it contains high quality data on both household structure and earnings, but some relevant data are missing (e.g. coding for urban/rural residence in some countries). This study was done among the EU Member States between 1994 and 2001 and was subsequently replaced by EU Study of Income and Living Conditions. EU-SILC initially comprised only six Member States, with other countries joining in later years. ECHP did not cover any of the transition countries, but it is a great source of data for early years in benchmark countries. EU-SILC only covers transition countries from 2005 onwards and thus is less useful for the analysis of the wage compression *in transition.*

Living Standards Measurement Survey (LSMS) Recognizing data shortage, The World Bank initiated standardized survey program with a number of developing countries, including the transition economies. It is a household budget survey with a number of modules in the questionnaire relating labor market status and wages. While LSMS is coordinated by The World Bank, it is usually implemented by statistical offices from the beneficiary countries. This implies that the wage module was not implemented in each country. Moreover, there can be some doubts concerning both the quality of the data (e.g. many missing values) and representativeness of the sample. LSMS sample sizes for comprise between app. 10 000 observations for smaller countries up to 30 000 individuals for larger countries. Data availability makes LSMS from three transition countries useful in our study: Albania, Armenia, Azerbaijan, Bulgaria, Bosnia and Herzegovina, Kazakhstan, Kyrgystan, Romania, Serbia and Tajikistan. Notably, for most of the countries there is no data on hours worked.

Russian Longitudinal Monitoring Survey (RLMS) Prepared and conducted together by Carolina Population Center and Demoscope team, this is a unique project designed to track changes and effects of post-transition reforms on households and individuals in the Russian Federation. Currently data are available for years from 1994 to 2011. RLMS respondents report monthly net wage and hours worked.

Ukrainian Longitudinal Monitoring Survey (ULMS) Ukrainian Monitoring Survey is an irregular study conducted by Insititue for the Study of Labor, IZA together with Kiev International Institute of Sociology. So far, three waves were conducted - in 2003, 2004 and 2007. ULMS was created to provide detailed information on households and labor force in Ukraine. It is nationally representative for working-age population. It includes both information on monthly wages and usual hours worked per week.

International Social Survey Programme (ISSP) The International Social Survey Programme is one of the longest and most comprehensive dataset used in the study. In total program that started in 1984, includes now about 50 countries from all over the world. Unfortunately, national surveys are inconsistent both between years and within one country. Thus, we carefully selected countries and years for which question on monthly (or yearly) wages was asked. We excluded countries for which salaries were presented in categories, keeping only those with continous wage structure. For some countries, there are missing information on hours worked, so they are excluded from the analysis on the counterfactual wage distribution. Finally, excluding countries from outside of Europe, we were able to collect indicators for 19 countries.

Table A.1: Countries and periods covered with data sources

Country	LFS	HBS	SES	ECHP	LSMS	ISSP
				Transition countries		
Albania					2002-2005	
Armenia					1996	
Azerbaijan					1995	
Belarus		2008, 2011				
Bulgaria			2002/06/10		1995/97/2001/03	1992/93/95/
						97-98/00/02-05/
						2007/09-12
Bosnia & Herz.					2001-2004	
Croatia	1996-2008					2006-2012
Czech Rep.			2002/06/10			1992/95-00/10
Estonia			2002/06/10			2009
Hungary			1995-2012			1986-99/01-09
Latvia	1995-2014	2011-2013	2002/06/10			1995-96/98-10/12
Lithuania			2002/06/10			
Poland	1995-2014	1993-2013	2002/06/08/10			1987/91-99/
						2001-04/06/
						2009/11-12
Romania			2002/06/10		1994-1995	
Russia	1994-2011[a]					1991-97/99/
						2001/03/
						2005-12
Serbia	1995-2002				2002/03/07	
	2008-2011					
Slovakia			2002/06/10			1991/02-04
Slovenia						1991-2012
Ukraine	2003/04/07[b]					2008-2009
				Benchmark countries		
Austria				1995-2001		
Cyprus			2002/06/10			1997
Denmark				1994-2001		
Finland			2002/06/10	1996-2001		2001-10/12
France	1984-2012		2002/06/10	1994-2001		2011/12
Germany		1984-2008[c]	2006/10	1994-2001		1986-94/96-00
						02-10/12
Greece			2002/06/10	1994-2001		
Ireland				1994-2001		
Italy			2002/06/10	1994-2001		1986-87/94/
						97-98/08
Luxembourg			2002/06/10	1994-2001		
Netherlands			2002/06/10	1994-2001		
Norway			2002/06/10			1989/96-12
Portugal			2002/06/10	1994-2001		2008
Spain			2002/06/10	1994-2001		
Sweden			2002/06/10	1997-2001		1991/94/
						1997-00/02-12
Switzerland						1996-96/01/08-09
UK	1992-2007		2002/06/10	1994-2001		

[a] Russian Longitudinal Monitoring Survey
[b] Ukrainian Longitudinal Monitoring Survey
[c] German Socio-Economic Panel

B Tables

Table B.2: Correlation between our and OECD measures of wage compression

	OECD measure			
Our measure	9th-to-1st	5th-to-1st	9th-to-5th	Gini Index
9th-to-1st	0.625***			
	(.048)			
5th-to-1st		0.574***		
		(0.046)		
9th-to-5th			0.409***	
			(0.048)	
Gini Index				0.114***
				(0.038)

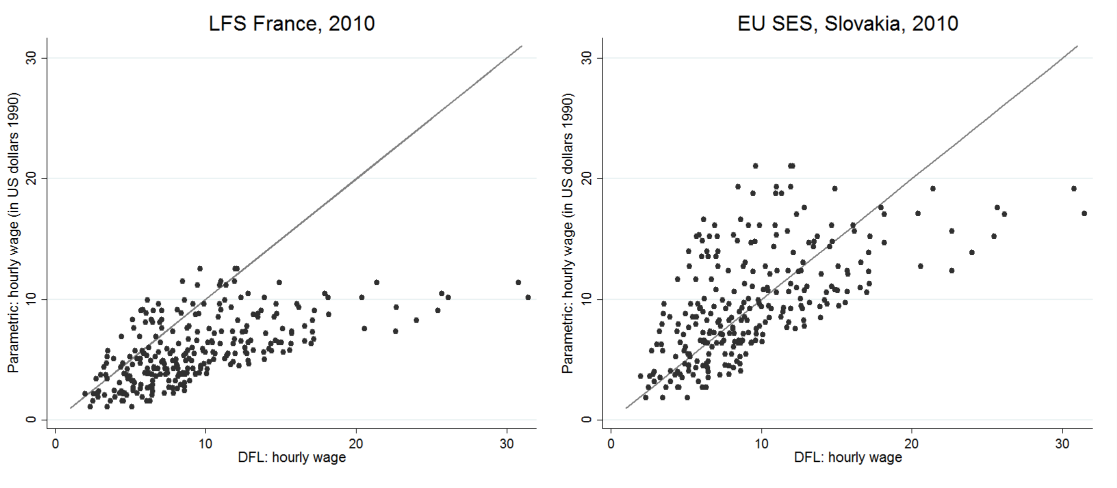
Notes: Correlation parameters from linear regression with fixed effects of country, year and source from our dataset.

Table B.3: Share of the variation of wage compression measures attributed to time

		counter-factual scenarios			
percentile	raw	Parametric			DFL
ratios	data	ACS 1990	ACS 2000	ACS 2010	ACS 1990
p 90/ p10	54,8%	58,1%	54,9%	55,6%	51,41%
p 50/ p10	72,7%	70,4%	61,5%	62,6%	58,75%
p 90/ p50	42,8%	57,8%	59,1%	68,4%	40,96%
p 75/ p25	42,8%	67,1%	58,5%	54,1%	40,57%

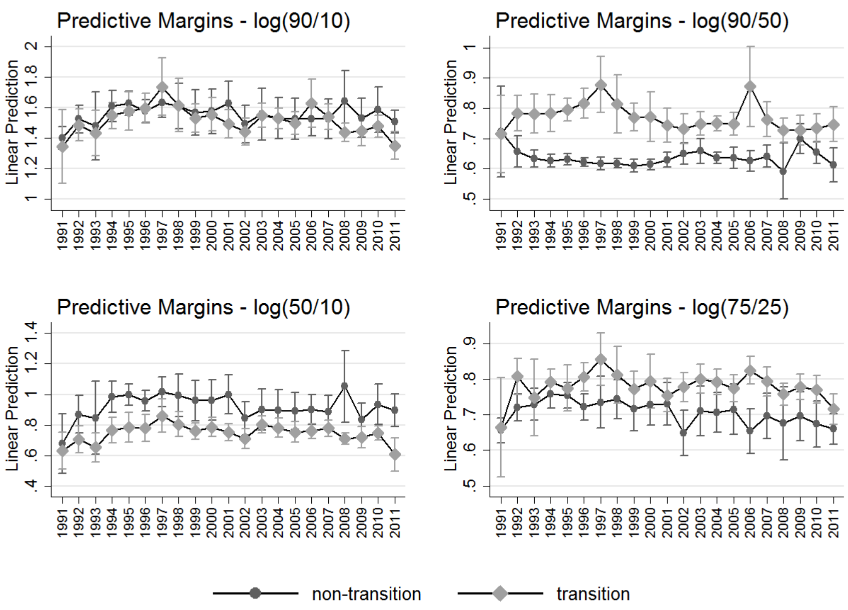
Note: measures of wage compression based on hourly wages, shares of the variation obtained from panel regressions including only country, time and source fixed effects

Figure B.1: Comparison: individual hourly wages from parametric and DFL approach



Source: counter-factual hourly wages of workers in two selected sources, countries and years - LFS France and in Slovakia from EU SES in 2010. Parametric counter-factual wages are obtained as fitted values from probit regression on sample of US population in ACS 1990 dataset and assigned to European workers based on gender, age group, education level and occupation. DFL counter-fatual wages are weighted averages of hourly wages in US in 1990 in gender, age, education level and occupational groups.

Figure B.2: Wage compression - predictive margins of year effects - monthly wage



Source: monthly wages from data sources described in Table A.1. Marginal effects of years obtain from regressions on wage compression measures and country, source, year and interaction of year and transition dummies as independent variables. Robust type of variance estimator was used.

Table B.4: Time trends in wage compression

	Hourly wage - raw data			Hourly wage - parametric (ACS1990)		Hourly wage - DFL (ACS 1990)	
	OLS	RE	FE	RE	FE	RE	FE
	9th-to-1st						
Transition	0.61***	0.34***		-0.16***		-0.20***	
	(0.12)	(0.08)		(0.04)		(0.05)	
Time x10	-0.01	-0.04*	-0.04**	-0.005	-0.02	-0.06***	-0.05***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Transition#Time x10	-0.08**	-0.04*	-0.04*	0.06***	0.07***	0.03*	0.03*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	5th-to-1st						
Transition	0.27***	0.21***		-0.04		-0.12***	
	(0.08)	(0.05)		(0.03)		(0.04)	
Time x10	-0.03**	-0.02**	-0.02**	0.02	0.002	-0.05***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Transition#Time x10	-0.05**	-0.05***	-0.05***	0.02*	0.04**	0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
	9th-to-5th						
Transition	0.34***	0.13***		-0.12***		-0.08***	
	(0.07)	(0.05)		(0.02)		(0.02)	
Time x10	0.01	-0.01	-0.01	-0.02***	-0.02**	-0.01**	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Transition #Time x10	-0.03	0.002	0.006	0.04***	0.03***	0.02***	0.02***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
	75th-to-25th						
Transition	0.43***	0.19***		-0.06		-0.07***	
	(0.06)	(0.04)		(0.04)		(0.02)	
Time x10	-0.01	-0.02**	-0.03***	-0.005	-0.03**	-0.01**	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Transition #Time x10	-0.03*	-0.001	-0.001	0.03**	0.06***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
	Gini Index						
Transition	0.13***	0.11***		-0.03***		tbc	tbc
	(0.041)	(0.020)		(0.008)		tbc	tbc
Time x10	0.008	0.009*	0.008	0.001	0.001	tbc	tbc
	(0.006)	(0.005)	(0.005)	(0.002)	(0.003)	tbc	tbc
Transition #Time x10	-0.020***	-0.025***	-0.024***	0.010***	0.011***	tbc	tbc
	(0.008)	(0.007)	(0.007)	(0.003)	(0.003)	tbc	tbc
Obs.	491	491	491	418	418	418	418
Countries	31	31	31	30	30	30	30

Notes: measures of wage compression based on hourly wages, results for the monthly wages, ACS 2000 and ACS 2010 specifications available in Table B.5 in the Appendix. The results are from the panel regressions including time, country and source fixed effects. In parametric approach wage compression measures obtained on distribution of fitted values from Mincerian regression on ACS 1990 sample assigned to workers from Europe based on gender, education level, occupation and age group. In DFL approach distribution on wages in ACS 1990 sample was reweighed by distribution of characteristics (gender, education level, occupation and age group) from European samples. Bootstrapped standard errors (with 1000 replications) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.5: Time trends in wage compression

	Monthly wage - original			Hourly wage - Parametric ACS2000		Hourly wage - Parametric ACS2010	
	OLS	RE	FE	RE	FE	RE	FE
	9th-to-1st						
Transition	0.243	0.006		-0.183***		-0.188***	
	(0.167)	(0.111)		(0.048)		(0.055)	
Time x 10	0.005	0.004	0.005	-0.006	-0.012	-0.004	-0.008
	(0.030)	(0.023)	(0.023)	(0.014)	(0.015)	(0.016)	(0.017)
Transition#Time x 10	-0.065	-0.052*	-0.052*	0.075***	0.078***	0.071***	0.071***
	(0.042)	(0.031)	(0.031)	(0.020)	(0.020)	(0.022)	(0.023)
	5th-to-1st						
Transition	-0.020	-0.168*		-0.051		-0.037	
	(0.137)	(0.095)		(0.036)		(0.043)	
Time x 10	-0.023	0.002	0.004	0.014	0.007	0.015	0.011
	(0.024)	(0.016)	(0.016)	(0.011)	(0.011)	(0.013)	(0.013)
Transition#Time x 10	-0.008	-0.026	-0.027	0.025*	0.031**	0.008	0.008
	(0.034)	(0.022)	(0.022)	(0.015)	(0.015)	(0.017)	(0.018)
	9th-to-5th						
Transition	0.263***	0.185***		-0.134***		-0.152***	
	(0.072)	(0.045)		(0.027)		(0.028)	
Time x 10	0.028**	0.007	0.001	-0.020**	-0.019**	-0.019**	-0.019**
	(0.013)	(0.013)	(0.013)	(0.008)	(0.009)	(0.009)	(0.010)
Transition#Time x 10	-0.057***	-0.032*	-0.025	0.050***	0.050***	0.064***	0.063***
	(0.018)	(0.018)	(0.018)	(0.011)	(0.012)	(0.012)	(0.013)
	75th-to-25th						
Transition	0.015	0.091		-0.193***		-0.213***	
	(0.079)	(0.056)		(0.042)		(0.037)	
Time x 10	0.008	0.001	0.002	-0.025**	-0.039***	-0.039***	-0.046***
	(0.014)	(0.010)	(0.011)	(0.012)	(0.013)	(0.010)	(0.011)
Transition#Time x 10	-0.014	-0.016	-0.017	0.084***	0.096***	0.094***	0.100***
	(0.020)	(0.014)	(0.014)	(0.016)	(0.017)	(0.014)	(0.014)
	Gini Index						
Transition	0.130***	0.065***		-0.033***		-0.033***	
	(0.040)	(0.017)		(0.008)		(0.008)	
Time x 10	0.015***	0.014***	0.012**	-0.0002	-0.0008	-0.001	-0.001
	(0.005)	(0.005)	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)
Transition#Time x 10	-0.0242***	-0.0254***	-0.0242***	0.012***	0.012***	0.012***	0.012***
	(0.007)	(0.006)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)
Obs.	548	548	548	418	418	418	418
Countries	31	31	31	30	30	30	30

Notes: measures of wage compression based on monthly (first three columnd) and hourly wages. The results are from the panel regressions including time, country and source fixed effects. In parametric approach wage compression measures obtained on distribution of fitted values from Mincerian regression on ACS 2000 or 2010 sample asigned to workers from Europe based on gender, education level, occupation and age group. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.6: Time trend and structural changes

	Trade	Employment in services	High-tech exports	R&D	High-skilled workers
Time	1.728***	0.657***	0.220***	0.180***	0.007***
	(0.108)	(0.016)	(0.002)	(0.002)	(0.0002)
Observations	488	470	458	387	330
Beetwen R-sqaured	0.017	0.0005	0.003	0.042	0.086
Within R-squared	0.376	0.807	0.086	0.227	0.736

Notes: panel regressions with country, source and year fixed effects. Time is the only independent variable. Measures of dependent variables described in Table B.8.

Table B.7: Wage compression and structural change

	5th-to-1st			9th-to-5th		
	Monthly wage	Parametric ACS2000	Parametric ACS2010	Monthly wage	Parametric ACS2000	Parametric ACS2010
Trade	0.0003	0.0003	0.0003***	-0.0002	0.0001***	0.0003
	(0.0006)	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0003)
# Transition	-0.0009	0.0001	-0.0001	0.0004	0.0001	0.0002**
	(0.0007)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Obs.	538	416	416	538	416	416
Countries	31	30	30	31	30	30
Employment in services	0.003**	0.003*	0.002	-0.002**	0.001***	0.002**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.0004)	(0.0009)
# Transition	-0.002	0.001**	0.0006	0.001**	0.0005***	0.0007**
	(0.002)	(0.0005)	(0.0005)	(0.0006)	(0.0002)	(0.0003)
Obs.	524	403	403	524	403	403
Countries		30	30		30	30
High-tech export	0.003	0.0005	0.0008	-0.003**	-0.00001	-0.0003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.0009)	(0.001)
# Transition	-0.006*	0.001***	-0.0006	0.003	0.001	0.002***
	(0.003)	(0.0004)	(0.0009)	(0.002)	(0.001)	(0.0007)
Obs.	507	399	399	507	399	399
Countries	31	30	30	31	30	30
R&D	0.083**	-0.012**	-0.019***	-0.057***	-0.011**	-0.012
	(0.036)	(0.005)	(0.007)	(0.017)	(0.005)	(0.011)
# Transition	-0.166***	0.005	-0.018	0.013	0.023	0.024
	(0.051)	(0.011)	(0.015)	(0.032)	(0.025)	(0.028)
Obs.	421	344	344	421	344	344
Countries	31	30	30	31	30	30
High-skilled workers	-0.362	0.025	-0.012	-0.227	-0.260	-0.241***
	(0.313	(0.150)	(0.101)	(0.190)	(0.176)	(0.084)
# Transitions	0.270	0.013	-0.105	0.438**	0.121	0.189***
	(0.370)	(0.080)	(0.097)	(0.195)	(0.137)	(0.058)
Obs.	351	289	289	351	289	289
Countries	26	25	25	26	25	25

Notes: wage compression measures based on monthly and counter-factual hourly wages from ACS 2000 and 2010. Coefficients from panel regressions with random effects (country-source and time) and source effects included. In parametric approach wage compression measures obtained on distribution of fitted values from Mincerian regression on ACS 2000 and 2010 sample and assigned to workers from Europe based on gender, education level, occupation and age group. In DFL approach distribution on wages in ACS 2000 and 2010 sample was reweighed by distribution of characteristics (gender, education level, occupation and age group) from European samples. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.8: Indicators of structural changes - descriptive statistics

Name	Indicator	Mean	Std. Dev.	Min	Max	Coverage (Countries)	Source
Trade	Total national trade as a percentage of GDP	81.2%	39.7%	23.2%	326.1%	488 (31)	World Bank
Employment in services	Share of employment in services in total employment	62.8%	8.7%	35.5%	81.3%	470 (31)	World Bank
High-technology exports	Share of high-technology exports in total manufactured exports	13.9%	9.3%	1.8%	47.8%	458 (31)	World Bank
R&D expenditure	Expenditure on research and development as a percentage of GDP	1.4%	0.9%	0.3%	3.9%	387 (31)	World Bank
High-skilled workers	Share in total hours of hours worked by high-skilled persons engaged	20.2%	7.2%	5.9%	38.2%	330 (26)	WIOD SEA

Table B.9: Wage compression and the indicators of structural change - 9th-to-1st

	9th-to-1st		
	Raw	Parametric	DFL
Trade	-0.00110**	0.0002291	-0.000268
	(0.000534)	(0.0004547)	(0.000551)
#Transition	0.000438	-0.0001107	-0.000760
	(0.000583)	(0.0003)	(0.000528)
Observations	488	416	416
Countries	31	30	30
Employment	-0.00774***	0.00353	-0.00366**
in services	(0.00169)	(0.00217)	(0.00153)
#Transition	0.00185*	0.000848	-0.00157**
	(0.00111)	(0.000711)	(0.000617)
Observations	470	403	403
Countries	64	60	60
High-tech export	-0.00373*	-0.000573	0.00222
	(0.00216)	(0.00140)	(0.00198)
#Transition	0.000910	5.14e-05	-0.00533**
	(0.00316)	(0.00117)	(0.00267)
Observations	458	399	399
Countries	65	61	61
R&D	-0.121***	-0.00890	-0.0545**
	(0.0287)	(0.0135)	(0.0215)
#Transition	-0.0265	0.0133	-0.0755*
	(0.0472)	(0.0277)	(0.0390)
Observations	387	344	344
Countries	64	60	60
High-skilled workers	-0.920***	-0.250	-0.500**
	(0.279)	(0.178)	(0.235)
#Transition	0.932***	0.0194	-0.414**
	(0.307)	(0.157)	(0.204)
Observations	330	289	289
Countries	56	52	52

Notes: see notes under Table B.4, wage compression measures based on hourly wages, Variance in regressions on counter-factual measures in bootstraped.