Job Tasks and the Comparative Structure of Income and Employment: Routine Task Intensity and Offshorability for the LIS*

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Abstract

Comparative sociologists have long considered occupations to be a key source of inequality. However, data constraints make comparative research on two of the more important contemporary drivers of occupational stratification—globalization and technological change—relatively scarce. This article introduces a new dataset on occupational "routine task intensity" (RTI) and "offshorability" (OFFS) for use with the Luxembourg Income Study (LIS). To produce these data, we recoded 23 country-specific occupational schemes (74 LIS country-years) to the two-digit ISCO-88 scheme. When combined with the handful of LIS countries already reporting their occupations in ISCO-88, we produce individual level RTI and OFFS scores for 38 LIS countries and 160 LIS country-years. To assess the validity of these recodes, we compare average labor-income ratios predicted by recoded ISCO-88 occupational categories to those predicted by reported ISCO-88 occupational categories within countries that transitioned from country-specific to ISCO-88 codes over time. To assess the utility of these RTI and OFFS scores and advance the literature on income polarization, we analyze their association with work hours and labor incomes in the global North and South. Both covariates correlate with work hours in ways that are consistent with previous research and additional theoretical considerations. Moreover, we show that both RTI and OFFS contribute to *income* polarization directly in the North, but not in the South. This article generates a public good data infrastructure that will be of use to a wide variety of social scientists, and brings new evidence to bear on the question of income polarization in rich democracies.

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Introduction

Comparative sociologists have long considered occupations a key determinant of income, employment, prestige and other markers of material and symbolic status (Stolzenberg 1975; Kim and Sakamoto 2008; Mouw and Kalleberg 2010). In the most contemporary period, two of the more prominent occupation-based dynamics are technological change and globalization, both of which are thought to differentially impact the demand for particular types of occupations. In particular, both technological change and globalization are thought to reduce the demand for "low-skill" occupations, and increase the demand for "high-skill" occupations, which has implications for the structure of income and employment, the prevalence of poverty and the shape of the income distribution. However, research taking place largely outside our discipline has advanced new conceptualizations of what it means to be "low-skill" and "high-skill," at least with respect to these two processes.

Early research in economics examining the role of skill-biased technological change (SBTC) (e.g. Katz and Autor 1999) operationalized skill with education or industrial characteristics. Recent research develops more nuanced conceptualizations by detaching "skill" from workers, and instead identifying characteristics of job tasks that require more or less of different *types* of skill. One is the "Routine Task Intensity" (RTI) approach, which suggests that job tasks vary on three dimensions: routine—non-routine, manual—analytic and personal—impersonal. Along these dimensions, tasks cluster into five particular types: routine-manual, non-routine manual, routine-cognitive, non-routine interactive and non-routine analytic (e.g. Autor, Levy and Murnane 2003). The most routine-intense tasks are those that are manual, repetitive and require little interpersonal interaction. At the other extreme, tasks with low routine intensity are those "demanding flexibility, creativity, generalized problem-solving, and complex communications" (Autor et al. 2003: 1284). What is key to the RTI framework is that routine-intensive tasks are easily automated, while non-routine tasks are not. Scholars developed the RTI framework to understand the role routine-biased technological change (RBTC) for changes in the wage, income and employment structure of advanced countries.

The second approach builds upon research linking globalization to the fate of occupations (e.g. Wood 1994). "Offshorability" (OFFS), conceptualized by Blinder (2009) and Blinder and Krueger (2013), is the degree to which a particular job "must be done at a particular…location (e.g. selling food at a sports arena, building a house) and (2) whether the work can be done at a remote…location …with little or no loss of quality" (Blinder and Krueger 2013: S103). That is, offshorable jobs are not "place bound," and can be done in the global South without a loss of quality. Whereas RTI focuses explicitly on the role of RBTC, OFFS focuses on the role of globalization.

Much of the RTI work focuses upon the American (Acemoglu and Autor 2011; Autor et al. 2003; Autor and Dorn 2013; Autor, Katz and Kearney 2006) or other individual economies (e.g. Goos and Manning 2007). Comparative work is newer, infrequent and absent outside of Europe (Goos, Manning and Salomons 2009; 2014). Likewise, research involving measures of offshorability focuses almost exclusively upon the US Economy (Blinder 2009; Blinder and Krueger 2013; Firpo, Fortin and Lemieux 2011). Comparative work is difficult for two reasons. The first is a dearth of cross-nationally comparable micro-datasets outside of the EU. The second is that measures of both RTI and OFFS are linked to occupations and have been operationalized using American occupational schemes, but such schemes vary both within and between countries. This lack of comparative work is unfortunate. It leaves unexamined the rich sociological processes that should matter for the wage and employment effects of RTI and

OFFS, and the degree to which RTI and OFFS can inform sociological theories of occupational stratification.

In this paper, we advance comparative work on RTI and OFFS by introducing measures of each into the LIS, widely regarded as the industry standard for maximizing both comparability and country/year coverage of micro data. To create these data, we recoded country-specific occupational schemes for 23 LIS countries into ISCO-88, and used cross-walks by Goos, Manning and Salomons 2014 to assign RTI and OFFS scores to two-digit ISCO-88 codes. After briefly discussing the measurement of RTI and OFFS, we present data to suggest that these recodes are sufficiently valid. To establish the scientific utility of these data, we examine partial associations between RTI and OFFS and both work-hours and labor incomes over a 39 year period (1974-2013). For both theoretical and technical reasons, we compare these associations across the global North and global South.

Our analysis suggests that these variables correlate with work hours and labor income in a manner consistent with previous work and existing theory. Occupations with high RTI and OFFS experience declining work hours, but only in the North and the RTI effects are stronger. Similarly, occupations with high RTI experience declining labor incomes, but only in the North. Occupations with high OFFS scores experience declining labor incomes in the North, but rising labor incomes in the South. Thus, in addition to replicating the work-hour findings of Goos et al. (2014), we also show that RTI and OFFS contribute to *income* polarization in rich democracies. We conclude by discussing how macro-comparative sociology can advance research on RTI and OFFS, and how a consideration of RTI and OFFS can enhance sociological models of income and employment.

The Data

RTI

We follow recommendations elsewhere that researchers use existing measures of the content of occupations as much as possible. Thus, we use RTI from Autor and Dorn (2013), mapped on to ISCO-88 according to Goos et al. (2014). Autor, Levy and Murnane's (2003) original operationalization began with the US' Dictionary of Occupational Titles (DOT), and selected five variables to quantify jobs as non-routine/cognitive, routine/cognitive, routine/manual, non-routine/manual and non-routine/interactive. The intuition here is that routine, manual, non-interactive (i.e. does not involve face-to-face interaction) job tasks are the most susceptible to automation. Conversely, non-routine/cognitive/interactive jobs are the least susceptible. Two variables capture non-routine cognitive tasks. The variable Direction, Control and Planning of Activities (DCP) captured the degree to which an occupation required interactive, communication and managerial skills. A second variable, GED-MATH, captured the quantitative reasoning requirements of US occupations. A third variable—Sets Limits, Tolerances or Standards (STS)—captures routine cognitive tasks. To measure routine manual activity, Autor et al. (2003) employed Finger Dexterity (FINGDEX). To measure non-routine manual occupations, they used Eye-Hand-Foot Coordination (EYEHAND).

Goos et al. (2014) follow previous work by Autor, Katz and Kearney (2006, 2008), Autor and Dorn (2012) and Autor, Dorn and Hanson (2013) by simplifying these into an overall measure of "routine task intensity." First, they convert the five variables above into three aggregate measures: **MANUAL** jobs demand high EYEHAND. **ROUTINE** jobs are high in STS or FINGDEX. **ABSTRACT** jobs require high DCP and GED-MATH. An overall **Routine Task**

Intensity (RTI) index is the difference between the log of ROUTINE and the sum of the log of ABSTRACT and the log of MANUAL (Goos et al. 2014: fn 3). That is, RTI jobs are high on either cognitive or manual routine tasks (DOT variables STS and FINGDEX), and low on either cognitive (DOT variables DCP or GDP-MATH), manual (DOT variable EYEHAND) or both types of non-routine tasks. The RTI index is 0/1 standardized.

OFFS

Also following Goos et al. (2014), we use one of the three measures of OFFS produced by Blinder and Krueger (2013). As we discuss above, OFFS depends upon both the “place boundedness” of a job, and on the degree to which the output can be produced with the same quality at an alternative location *in the global South*. Blinder and Krueger (2013) produced three measures of OFFS, the third of which was the product of expert coders. These coders examined a stratified random sample of the 2003 National Assessment of Adult Literacy. The answers to three questions were coded (Blinder and Krueger 2013: S104):

- For what kind of business or industry do you work?
- What is your occupation, that is, what is your job called?
- What are the most important activities or duties at this job?

With this information, the coders assigned an industry and Standard Occupational Classification (SOC) occupation to each job. In addition, they categorized each job on a scale of 1 to 5, where 1 is “not offshorable” and 5 is “easily offshorable with only minor (or no) difficulties or loss of quality.” To determine what value to assign to each job, the coders were given the following job characteristics as indicators of “not offshorable” (Blinder and Krueger 2013: S104):

- Need for face-to-face interaction with customers or suppliers

- Delivering/transporting products or materials that cannot be transported electronically (e.g., mail, meals, fruits, and vegetables).
- Public speaking
- Requires “cultural sensitivity” (e.g., newscaster, sports broadcaster).
- Providing supervision, training, or motivation to others working in the United States.
- Physical presence at site (or sites) in the United States is required
- Maintaining or repairing fixed structures that are in the United States (e.g., roofs, plumbing, gardens, yards).
- Maintaining or repairing large objects (e.g. cars, boats, washing machines).

Through this process, Blinder and Krueger’s expert coders created an offshorability score varying from 1-5 for each SOC occupation. Because this was their preferred measure, and because it predicts real degrees of task offshoring better than alternatives (Blinder and Krueger’s other two measures, and those of Firpo, Fortin and Lemieux 2011), we implement it as cross walked from SOC to ISCO 08 to ISCO-88 by Goos et al. (2014). This variable is also 0/1 standardized.

Recodes

Goos et al. (2014) report RTI and OFFS at the 2-digit ISCO-88 level. As of this writing, the LIS has micro data for 47 countries and 274 country years. Many countries report occupations to the LIS using country-specific occupational schemes, while others report occupations using ISCO-88. To maximize the country-year coverage of these data, we recoded as many country-specific occupational codes into ISCO-88 as possible. Most generally, our recoding procedure was to either locate an existing cross-walk between a country-specific code and ISCO-88 or create our own cross-walk. When we could not find an existing cross-walk, we obtained the list of occupations within country-specific occupational categories reported to the LIS, and mapped these onto the ISCO-88 category that houses them.

As we detail below in Appendix A, 62 of the country-year schemes we recoded included at least one country-specific category that contained a mix of jobs spanning multiple ISCO categories. This made it impossible to code these country-specific occupational categories into a single ISCO-88 category. In these cases, we create weighted RTI and OFFS measures equal to $\sum_{j=1}^{k} \theta_{isco88_i} * p_j$, where *j* indexes the subset of occupations in country-specific occupational code k (CSC_k) that belong in ISCO-88_i, p is the proportion of occupations in CSC_k that belong to ISCO-88_i, θ is the RTI or OFFS score from Goos et al. (2014) for ISCO-88_i, and p sums to 1 across the full set of jobs in CSC_k. Overall, only 16.5 percent of the individuals in these data have RTI and OFFS scores based on this weighting procedure. We provide dummy variables equal to 1 in cases where an individual has a weighted RTI or OFFS score to allow users to make judgements about these cases *vis* quality. [1]

Some country-specific codes were too incomparable to ISCO-88 to recode. Some countries reported their occupations to the LIS in ISCO-88, but did so at the 1 digit level. In other cases, it was impossible to identify a list of occupations within the aggregated country-specific occupational codes reported. In total, we recoded occupational schemes for 23 LIS countries and 76 LIS country-years. When combining our recoded cases with those that already reported in ISCO-88 at the 2 digit level or higher, we produced RTI and OFFS scores for 38 LIS countries and 160 LIS country-years. These country-years are reported in Table 1, along with detailed notes pertaining to each country. The full set of detailed cross-walks is available at http://matthewcm.ucr.edu/data.html.

[Table 1 about here]

Recode Validity

To assess the validity of these recodes, we identified all of the countries that transitioned from a country-specific occupational scheme to ISCO-88 within the LIS data. These countries are Finland (switching from country-specific to ISCO-88 between 1995 and 2000), Hungary (switching from specific to ISCO-88 from 1991-1994 and away from ISCO-88 to specific from 2005-2009), Netherlands (switching from specific to ISCO-88 between 1999 and 2004) and Spain (switching from specific to ISCO-88 between 1990 and 1995). We then used our recoded ISCO-88 categories to predict occupation-specific labor income ratios, [2] and compared these predicted values to those predicted by ISCO-88 categories as reported by the same country in the closest year to the recode. Because this necessarily involved comparing predicted income ratios across time, and one would expect to observe some change over time for both stochastic (e.g. sampling) and structural (e.g. socio-economic change) reasons, we also compared income ratios predicted by country-reported ISCO-88 categories across the closest two years of similar distance to those in our recode comparison. This second set of comparisons give us a baseline rate at which occupation-specific mean labor incomes change over time. We use these baselines to assess the degree to which any difference we observe between a reported and recoded ISCO-88 categorical mean labor income ratio is larger than one might expect by chance.

We conduct our validation analysis by testing two types of null hypotheses. In both cases, *the null hypothesis is consistent with recode validity*. The first null hypothesis is “macro.” Here, we correlate the mean labor income ratios for each ISCO-88 occupational category predicted by a reported ISCO-88 year with those predicted by a recode year. We then compare this correlation to one obtained by correlating the mean labor income ratios for each ISCO-88 occupational category as predicted by the closest two (in time) reported ISCO-88 years. The “macro” null hypothesis test is that difference between these two correlations is equal to zero.

We also test two "meso" hypotheses. Here, we first pool LIS individuals across the reported and comparison year and then regress labor income ratios on ISCO-88 scores and an interaction between ISCO-88 categories and a dummy variable equal to 1 in a recode year. The interaction term tests the null hypothesis $\bar{X}_{kt} = \bar{X}'_{kt}$, where k indexes the occupational categories in ISCO-88 and $'$ refers to the mean labor income ratio as predicted by a recoded year. We then test the same null hypothesis across two recoded years (e.g. $\bar{X}_{kt1} = \bar{X}_{kt2}$) and compare this to the previous result. This second comparison tests the cross-model null hypothesis that $abs[\bar{X}_k - \bar{X}'_k] = abs[\bar{X}_{kt1} - \bar{X}_{kt2}]$. These "meso" tests address the degree to which (a) recoded ISCO-88 category *k* produces a comparable estimate of a labor income ratio to a reported ISCO-88 category *k* and (b) any differences observed in (a) are greater than the difference between estimated mean labor income ratios for ISCO-88 category k predicted by two reported years. Each $\bar{X}$ is estimated with OLS after adjusting coefficients and standard errors for the sampling design (via the LIS' popwgt sampling weight) and standard errors for heteroskedasticity (via robust standard errors).

We take two additional steps to reduce the likelihood of a type II error (i.e. a finding of valid recodes when in fact they are invalid). First, as we describe in Appendix A, we used either an 80 percent exclusion rule (i.e. a country code was cross-walked to an ISCO 88 code if at least 80 percent of the country code jobs were listed in the focal ISCO 88 code) or the weighting scheme described above for the RTI and OFFS measures. The weighting procedure limited data loss on the RTI and OFFS measures. However, we could not use this weighting procedure to assign jobs to 2-digit ISCO-88 occupations because these designations are categorical, whereas RTI and OFFS are continuous. Thus, to preserve a greater number of cases, we used a looser restriction rule. In this validation analysis, a country-specific occupational code *i* is recoded to

ISCO-88 *j* if at least fifty-one percent of the occupations in *i* belong to *j*. This leads to more measurement error in the ISCO-88 categorical recodes used below than in our RTI and OFFS measures. Because measurement error in a recoded year should promote dissimilar labor incomes *vis-à-vis* a reported year, this decision should make it easier to reject the null hypothesis of no difference between reported and recoded ISCO-88 years (i.e. to conclude the recodes are invalid). Second, when conducting the second step of the "meso" test, we pool the variance estimate across the recode = reported and reported = reported regression models before conducting the cross-model hypothesis test $abs[\bar{X}_k - \overline{X'}_k] = abs[\bar{X}_{kt1} - \bar{X}_{kt2}]$ with seemingly unrelated regression (Zellner 1962). The greater level of information thus obtained makes it easier to reject the null hypotheses we test, and therefore more likely conclude the recodes are not valid. In short, our validation tests are quite conservative *vis-à-vis* evidence for validity.

[Table 2 about here]

For brevity, Table 2 provides the labels corresponding to each ISCO-88 occupational category; we only mention the numerical values for these categories below. Beginning with the conclusion, both our "macro" and "meso" validation tests suggest our recodes are valid. At the macro level, the correlation between predicted and recoded occupation-specific labor incomes is no different than that between two temporally proximate ISCO-88 years. At the meso level, there are only three cases (out of 111) in which there is a significant difference between an occupational mean predicted by a recode year and the temporally proximate ISCO year, but only one of these is differences is significantly different from the baseline comparison difference.

[Figure 1 about here]

The results yielding this conclusion are recorded in Figure 1 and Tables 3a and 3b. The top left pane in Figure 1 plots two correlations for Finland. The dashed line represents the association between the labor income-ratios predicted by our recode of Finland's country-specific occupational scheme in 1995, and the labor income-ratios predicted by the ISCO-88 categories Finland reported in 2000. The solid line represents the association between labor income ratios as predicted by two years that Finland reported their occupations to LIS in ISCO-88—2004 and 2010. The association between the two ISCO years is about 17 percent larger than that between the ISCO and recoded year. Some of this variance is driven by the difference in the predicted labor income ratio between our recoded and the ISCO category 22, which is relatively large. Category 92 appears to vary significantly between the two ISCO years. However, the quantity in the lower right corner is the p-value on the null hypothesis that the difference between the two correlations is equal to zero; the difference is not significantly different from zero by conventional standards.

[Table 3a about here]

The analysis in Figure 1 compares the correlation between the entire set of predicted income ratios across a recode and reported ISCO-88 year, but cannot yield evidence on the degree to which predicted income ratios for *individual ISCO categories* vary more across recoded and ISCO years than they do between ISCO years. Thus, Table 3a and b report the results of a regression analysis in which we test the two "meso" null hypotheses described above. The first two columns under each country sub-heading test the null hypothesis that the difference between the labor income ratio predicted by the recoded and ISCO years is equal to zero, and the right two columns test the same hypothesis for the two baseline ISCO years. The rightmost "*Diff*" column reports rejections (asterisks only) of the null hypothesis that the absolute difference between these two differences is equal to zero. Thus, for example, and consistent with our discussion of Figure 1, the difference in the predicted labor income ratio for Finland's recoded and ISCO-88 category 22 (-.555) is significantly different from zero, but this difference is not significantly different from the difference between the two ISCO years (-.594). Similarly, the difference in labor income ratio for Finland's ISCO category 93 as predicted by the two ISCO years (-.571) is significantly different from zero, but this difference is not significantly different from that reported in the left-hand column. In short, the labor income ratios for individual recode categories do not vary more from a proximate ISCO year than do those predicted by two proximate ISCO years.

The middle pane on the top row of Figure 1 repeats this exercise for Hungary. We compare 1991, a recode year, to 1994, an ISCO year. The two ISCO comparisons are 1994 and 1999. The association is again (14%) larger for the two ISCO years, but this difference is not significant. Categories 34 and 11 appear to be outlying for the recoded and ISCO comparisons, respectively. However, the above described regression for this case reported in Table 3a shows that there are no significant differences in the categorical labor income ratio as predicted by the ISCO and recode year, and none of these differences are significantly different from those produced by the ISCO comparison.

The top right pane of Figure 1 displays the comparison for a later Hungarian period. 2009 is a recode year, and we compare it to an ISCO year in 2005. The baseline ISCO comparison is between 1999 and 2005. In this case, the correlation between the categorical labor income ratios predicted by our paired recode and ISCO years is (11%) *higher* than that between the two ISCO years, though this difference is not significant. Still, this slightly stronger association bears out in the regression reported in Table 3a. None of the recoded ISCO categories predict labor income ratios that are significantly different from those predicted by the comparison ISCO categories. However, the categorical labor income ratios predicted by the two ISCO years are significantly different in each case, and three of these differences are significantly larger than the comparison recode-ISCO difference owing to the large size of the former.

[Table 3b about here]

The Netherlands case in the left-most pane of the bottom row of Figure 1 compares 1999 (recode) to 2004 (ISCO), and the baseline ISCO years are 2004 and 2010. The correlation between the two ISCO years is roughly 7 percent larger than that between the recode and ISCO year, though this difference is not significant. The recoded ISCO category 82 is most outlying. This is corroborated by the significant difference between labor income ratio predicted by the ISCO and recoded ISCO category 82 in Table 3b. However, this difference is not significantly larger than the same difference for the two ISCO years.

Finally, Figure 1 reports two scatter plots for Spain in which the recode comparison is between 1990 (recode) and 1995, and the ISCO baseline comparison is 2004 to 2010. In the middle pane, the association involving the recode is 59 percent smaller than that between the ISCO years, and this difference is significant. Much of this variation between 1990 and 1995 is driven by categories 11 and 12. Category 11's average labor income ratio is estimated at .728 in the 1995 ISCO year, and 1.764 in the recode year. In the other two ISCO years, category 11's average labor income ratio is estimated at 1.890 (2004) and 2.430 (2010). Thus, this variance appears to be more a function of the ISCO 1995 year than our recoded year. Category 12's average labor income ratio is estimated at 1.943 in the 1995 ISCO year, but only .862 in the recode year. By comparison, its average labor income ratio is estimated at 1.827 (2004) and 2.058 (2010) in the two other ISCO years. Thus, the variance for category 12 appears to be more related to our recode than the ISCO 1995 year. This is the only average income ratio for which the difference between the recode and ISCO-88 years is significant. This difference is also significantly larger than the difference between category 12 from the two baseline ISCO-88 years (Table 3b). We believe this problematic case in the recode year is primarily a function of the looser restriction rule we applied to these categorical comparisons. [3]

Moreover, the rest of the recode-estimated categorical labor income ratios are closer to those estimated by the 2004 and 2010 ISCO years than are those predicted by the 1995 ISCO year. This is reflected in part by the finding that none of the other ISCO categories in the 1995 ISCO year (upper left-hand column of Table 3b) yield labor income ratios that are significantly different from that predicted by category 11, a pattern we observe only in the Spanish 1995 series (see Tables 2-5). The bottom right panel of Figure 1 displays the same correlations for Spain, excluding categories 11 and 12. The correlation involving the recoded year is only 11 percent smaller, and this difference is not significant (see Figure 1).

By way of summary, when we compare ISCO-88 categorical labor income ratios across recoded and reported ISCO years within countries that transition from a country-specific to the ISCO occupational scheme, we observe the following. At the macro (e.g. country-year) level, the correlation between labor income ratios predicted by our recoded ISCO categories and those predicted by a temporally proximate ISCO-88 year are comparable and differences we observe are not statistically significant. At the occupational-year level, there are only three cases in which an ISCO category-specific labor income ratio predicted by a recode year is significantly different from that predicted by a temporally proximate ISCO year (22 for Finland 1995; 82 for the Netherlands 1999; 12 for Spain 1990). Two of these differences are not significantly different from those produced by paired ISCO years with comparable temporal distance. The third is driven as much by measurement error in the Spanish ISCO year (1995) as it is by that in the recoded year (1990), and the rest of our recode-estimated labor income ratios are closer to the other two Spanish ISCO years (2004; 2010) than are those estimated by the 1995 ISCO year. Our recodes appear to provide useful additions to the ISCO years available in the LIS.

RTI, OFFS, and the Structure of Employment and Earnings

Having validated our recoding strategy, we now assess the substantive utility of RTI and OFFS. To begin, we first outline a replication of the Goos et al. (2014) analysis of work hours. Then, we outline an analysis of labor incomes. Both analyses point to the utility of RTI and OFFS for questions related to inequality and polarization.

Routine Task Intensity, Offshorability and Work Hours

Literature linking RTI to the structure of employment and earnings originates in older literatures on skill-biased technological change. In this literature, skill-biased technological change (SBTC) reduces the demand for unskilled labor; the jobs most easily made redundant by technological change. Simultaneously, SBTC increases the relative demand for highly skilled labor. Through both processes, SBTC increases the high-skill wage premium (see Katz and Autor 1999).

Likewise, routine-biased technological change (RBTC) recognizes that technological changes impact the relative demand of routine-intensive and non-routine-intensive tasks, both within and between industries. Routine-intensive tasks are made redundant through automation, and computerization “raises the demand for [non-routine] tasks such as responding to discrepancies, improving production processes, and coordinating and managing the activities of others” (Autor et al. 2003: 1285). Most work examining the RBTC thesis treats polarized labor markets as a critical explanandum. Here, RBTC decreases employment in routine-manual, and non-interactive jobs relative to both non-routine/cognitive/interactive (e.g. health professionals; high-skill) and routine-interactive (e.g. sales clerks; low-skill) jobs. Thus, a natural replication with which to evaluate these data is the finding of Goos et al. (2014), who show declining work hours for high RTI occupations over time. Our first hypothesis (**H_1**) is for an increasingly negative association between work hours and RTI over time.

Theory linking OFFS to the structure of employment originates in Heckscher–Ohlin (HO) trade theory, but resembles SBTC/RBTC with respect to the particular distributional mechanism involved (e.g. Wood 1994). Here, North-South trade exposes northern workers to price competition from Southern workers (and vice-versa). Because unskilled labor is relatively abundant in the South, and skilled labor is relatively abundant in the North, Northern countries shift to skill-intensive production, while Southern countries shift to unskilled- (or low-skilled) intensive production. That is, the demand for unskilled/low-skilled labor falls in the North and increases in the South, while the opposite is true for skilled-labor.

A newer literature on the offshorability of job tasks recognizes that just as some job *tasks* (as opposed to skill categories) are more easily automated, so too are some job tasks more easily offshored. As we discuss above, the two key criteria as originally established by Blinder (2009) are the "place boundedness" of a task, and the quality implications of offshoring that task. Globalization reduces the demand for job tasks that are highly offshorable, and increases the demand for those that are not. Thus, we follow Goos et al. (2014) to hypothesize that (**H_2**) offshorability has an increasingly negative association with work hours over time.

Routine Task Intensity, Offshorability and the Structure of Income

RBTC also has implications for the structure of earnings, though we are not aware of research that examines these implications empirically. As routine biased technological change makes routine-intense job tasks redundant, there are fewer jobs available for “routine-intense qualified” workers. Holding the supply of these workers fixed, falling demand should reduce the bargaining power, and thereby the earnings, of routine-intensive occupations. However, RBTC also suggests a second inequality generating mechanism, whereby technological change increases the relative labor income of non-routine tasks by increasing the marginal productivity of “non-routine qualified” workers. That is, non-routine workers are more productive when aided with better technology, which further boosts their relative labor income (Autor et al. 2003). Given the temporal coverage of our empirical context (1979-2013), this process suggests both a static and a dynamic relationship between RTI and labor incomes. Allowing for a cumulative effect of RBTC over this period, we hypothesize (**H_3**) a negative association between RTI and labor incomes. However, as the work of Goos et al. (2014) and others shows, RBTC also increases over time. Thus, we also hypothesize (**H_4**) that the negative association between RTI and labor incomes increases in size over time. [4]

Because of the mechanistic similarity between RBTC and HO theories—RBTC and offshoring reduce the demand for routine-intensive and offshorable tasks and increase the demand for non-routine, place-bound or high-quality demanding tasks—there is also an empirical symmetry with respect to their expectations for labor incomes. In the North, offshoring should boost the labor income of workers with place-bound and high-quality demanding jobs, and reduce the labor income for “offshorable-qualified” workers (*ceteris paribus*). That is, combining HO trade theory with this conceptualization of the offshorability of job tasks leads naturally to a fifth hypothesis (**H_5**) of a negative association between labor income and offshorability (e.g. Blinder 2009).

Counterintuitively, however, OFFS tends to have a weak positive association with education (Blinder and Krueger 2013).[5] Thus, empirical work tends to find less clear results, at least for the United States (Blinder and Krueger 2013) and Germany (Firpo, Fortin and Lemieux 2011). Here, "the least offshorable jobs…pay the lowest wages," but the overall relationship is "hill shaped: the highest wages are paid to workers in the…middle categories" (Blinder and Krueger 2013: S123-S124). Thus, we test a sixth (**H_6**) hypothesis of a curvilinear association between OFFS and labor incomes.

Offshorability should also have implications for the income polarization thesis (e.g. Firpo et al. 2011; Goos et al. 2014). First in manufacturing, and now increasingly in services, non-placed bound jobs with a skill match in the Global South experience declining demand. This falling demand creates a growing surplus of "offshorable qualified" workers in the North. As such, globalization should reduce the bargaining power of these workers, and thus the incomes of remaining offhorable occupations, over time. Therefore, our seventh (**H_7**) hypothesis is that OFFS has an increasingly negative association with labor incomes over time. Of course if **H_6** is correct, we should expect the association between labor incomes, OFFS and time should in turn vary across the vector of OFFS.

Additional Validity Tests

A strength of the LIS is the wide variation in economic development across represented countries. This variation allows us to compare the effects of RTI and OFFS across the North and the South, which has both technical and substantive advantages. There are strong theoretical reasons to expect that RTI and OFFS have different effects in developed and less developed countries. RBTC effects clearly depend on the level of technology: if technology has not advanced enough such that automation is possible, then job tasks with high RTI scores should not experience redundancy or downward wage pressure. Similarly, the downward pressure of OFFS should depend on the "offshoring demand" in a focal country. Where firms are not engaged in offshoring, or where firms are in fact absorbing offshorable job tasks from abroad, we should expect a weaker (or more positive) association between OFFS work hours/earnings. Thus, our eighth (**$\mathbf{H_8}$**) hypothesis is that both RTI and OFFS have larger effects in the North than the South. And given this rather straightforward intuition, finding a significant difference in the effect of RTI and OFFS across the North and the South would provide an additional source of content validity; it would be consistent with our claim that our ISCO recodes (and ISCO categories more generally) allow for meaningful cross-national comparisons of the tasks-content of occupations.

Analysis

Sample

To examine the association between RTI, OFFS and the labor income structure, we regress the LIS' labor income variable on both covariates, along with common correlates of labor income. We restrict our analysis to individuals who were employed at the time of the survey. We also excluded individuals whose primary occupation was in the armed forces. After accounting for missing data on the left and right hand side of our equations, our analysis includes the country-year surveys listed in Table 4 (Northern countries italicized). We excluded the post-socialist transition countries, which do not fit neatly in either category for obvious reasons (e.g. Curwin and Mahutga 2014). In total, 20 countries, 62 country-years and 2,077,590 individuals appear in the work hour models. 21 countries, 77 country-years, and 2,318,870 individuals appear in the labor income models.

[Table 4 about here]

Labor income

We measure labor income with the LIS' Labor Income variable (*pil*), which includes "monetary payments and value of non-monetary goods and services received from dependent employment," as well as "profits/losses and value of goods for own consumption from self-employment." These are annual figures. Importantly, these data exclude capital income and transfer income. Following LIS recommendations, we trimmed labor income for each country year by deleting all of the zero and negative values, and then trimming off the 1st and 99th percentile. To make valid comparisons across countries (currencies and price structures) and time (inflation), we transform these trimmed labor incomes with $\log 10\left(LI_{ijt}/\widetilde{LI}_{jt}\right)$, where *i* indexes individuals, *j* indexes countries and *t* indexes periods. Each individual enters the model with labor income expressed as the logged ratio of his/her income to the median income in his/her country-year.

Work Hours

We measure work hours with the LIS' work hours variable (*hours*), measured as regular hours worked in a typical week. Weekly hours are top-coded at 99 hours.

Baseline Work Hour and Labor Income Correlates

We control for several common labor market correlates. The first is *education*. The LIS has a cross-nationally harmonized measure of education with four categories: low, medium, high and unknown. Low corresponds to less than secondary (ISCED levels 0, 1 or 2) education completed; medium corresponds to secondary (ISCED levels 3 or 4) education completed; high corresponds to tertiary (ISCED levels 5 or 6) education completed. An individual is coded as unknown if their level of education was unreported or otherwise unknowable. The second is *age*, which has been widely documented as having a curvilinear association with labor income. Thus, we include *age* (in years) and *age squared*. Finally, we also include *sex*, which equals one for women and zero for men.

In addition, we also include industry dummies. These are the primary sector (ISIC categories A-C), manufacturing (ISIC category D), other industry (ISIC E-F), retail, entertainment and transport services (ISIC G-I), finance, insurance and real estate (FIRE) (ISIC J-K), public services and health (IISIC L-N), community and personal services (ISIC O-Q) and an "other" category including all of the cases for which the industry could not be coded in the LIS data. [6]

We also include GDP per capita as a country-year level covariate.

<u>Regression Models</u>

In the following tables, we report unstandardized coefficients from two-way (country and year) fixed effects regressions. To accommodate the sampling designs, our regressions include LIS probability weights (PPOPWGT) such that coefficients and standard errors reflect the experience of the average person in the sample given differences in sampling design and population size across countries. We also adjust the variance-covariance matrices for heteroscedasticity and serial correlation.

Results

[Table 5 about here]

Table 5 reports the results of the regressions of work hours on RTI, OFFS and their interaction with time. For brevity, we do not report coefficients on the baseline controls, but they perform as expected: relative work hours are highest for secondary graduates in the South, and college graduates in the North. Labor incomes increase linearly with education in the North and South. Both work hours and labor incomes increase and then fall with age, and are lower among women than men in both the North and the South. GDP per capita is only weakly correlated with labor incomes.

Model 1 introduces RTI and its interaction with time. Consistent with literature linking declining work hours in routine-intense occupations with RBTC, the interaction term is negative and significant, but only in the North. In the South, where RBTC should be lower, we see a slight increase in routine-intensive work hours over time. Model 2 introduces OFFS. The interaction between OFFS and time is also significantly negative in the North, and positive but just marginally significant in the South. These results are largely in keeping with the literatures on offshorability and globalization, which anticipate declining work hours to offshorable jobs in the North (from where jobs are offshored), and rising work hours to offshorable jobs in the South (to which jobs are offshored).

Model 3 introduces both concepts simultaneously. In an identical fashion to the findings of Goos et al. (2014), the interaction involving OFFS becomes non-significant in the North: OFFS "loses a 'horse race' against RTI" (Goos et al. 2014: 2518). In the South, both interaction terms remain positively signed but only the interaction with RTI remains even marginally significant. Jobs with high RTI and OFFS experience declining work hours in the North, and rising work hours in the South. Overall, RTI is a better predictor of job polarization than OFFS in the North, and neither are terribly important for work hours in the global South.

[Table 6 about here]

Table 6 reports the results from our regressions of labor incomes on RTI, OFFS and the interaction of each with time. In model 1, we see that RTI is negatively correlated with labor incomes in the North and null in the South. In model 2, OFFS is positively associated with labor incomes in the North, and null in the South. Model 3 examines the "hill-shaped" relationship described in hypothesis 6. In both the North and the South, OFFS appears to have a convex curvilinear association with labor incomes, though the quadratic is much more strongly correlated in the North. Model 4 introduces RTI and the OFFS quadratic simultaneously, and yields significantly negative coefficients for RTI and a significant convex quadratic for OFFS in both the North and the South. The apex of the parabola—the point at which the association between OFFS and labor incomes switches from positive to negative—is roughly 1.08 in the North, and .93 in the South.

Model 5 introduces the interaction between RTI and time. Here we observe an increasing labor income penalty in the global North, but no significant trend in the global South. Given the quadratic association in models 3 and 4, model 6 reports the results of the three-way interaction: OFFS X OFFS X Year. In the South, there is a declining labor income penalty (or rising incomes) for high OFFS occupations over time (i.e. the three-way interaction is positive). In the North, there is an increasing labor income penalty (or declining incomes) for high OFFS occupations over time (i.e. the three-way interaction is negative). Model 6 includes all of these simultaneously, and produces identical results: RTI produces an increasingly large labor income penalty in the North but not the South. High OFFS occupations experience declining incomes in the North, and increasing incomes in the South.

[Figure 2 about here]

To better facilitate the interpretation of the three-way interaction involving OFFS, Figure 2 reports the marginal effects of OFFS over time at five different levels of OFFS: the minimum, ½ of the distance from the minimum to the parabola, the parabola, ½ the distance from the parabola to the maximum, and the maximum. A declining slope indicates that the labor income penalty(below zero)/premium (above zero) is getting larger/smaller over time, and a rising slope indicates the opposite. In the South, we see that both income premium to low OFFS jobs, and the income penalty to high OFFS jobs, are declining. That is, the correlation between OFFS and labor incomes is converging toward zero over time in the global South. Contrarily in the North, both the income *premium* to low OFFS jobs, and the income *penalty* to high OFFS jobs, are increasing. In short, offshorability is equalizing labor incomes in the South, and polarizing labor incomes in the North. Both outcomes are consistent with theories of globalization and income inequality in the North and South (e.g. Alderson 1999; Alderson and Nielsen 2002; Mahutga, Roberts and Kwon 2017; Wood 1994).

Discussion

In this article, we present two new individual level covariates available for the LIS. RTI captures the "routine task intensity" of occupations following the work of Autor, et al. (2003) as operationalized by Goos, Manning and Salomons (2014). OFFS captures the "offshorability" of occupations following Blinder and Krueger (2013) as operationalized by Goos, Manning and Salomons (2014). Both are mapped onto 2-digit ISCO-88 occupational categories, and are available only because of our recode of country-specific occupational schemes for 23 LIS countries and 76 LIS country-years. These recodes produce ISCO-88 categorical labor income ratios that are comparable to, and not significantly different from, those produced by reported ISCO-88 schemes. Our addition of RTI and OFFS to the LIS dataset should enhance interdisciplinary research on both processes by allowing researches to use the same variables across studies, and include much broader samples of countries and historical periods. To our knowledge, current research on these concepts using LIS data operationalize them in much cruder ways on limited samples (e.g. Mueller, Ouimet and Simintzi 2015; Parteka and Wolszczak-Derlacz 2016).

Both RTI and OFFS are correlated with work hours and labor incomes in ways that are consistent with existing theory. They have an increasingly negative association with work hours in the global North, but not in the global South. However, the association between RTI and work hours is stronger than the association between OFFS and work hours. RTI has a negative association with labor incomes in the North and South. Consistent with previous findings on the US case (Blinder and Krueger 2013), OFFS has a curvilinear association with labor incomes in the North and South. However, these associations trend very differently in the North and South. RTI has an increasingly large labor income penalty over time in the North, but no trend in the South. In the North, the income premium to low OFFS jobs gets larger over time, as does the income penalty to high OFFS jobs. We observe the opposite trend in the South, where the income premium to low OFFS jobs gets smaller over time, as does the penalty for high OFFS jobs. The divergent trends in the associations between RTI, OFFS, work hours and labor incomes between the North and South are in keeping with theories of RBTC and globalization, which should have different effects in the North and South.

In the remaining pages, we would like to discuss how macro-comparative sociology can contribute to research on RTI and OFFS, and vice versa. In terms of the former, a key contribution for macro-comparative sociologists involves examinations of the degree to which national and world-level phenomena moderate the impacts of RTI and OFFS on incomes and employment. For example, comparative sociologists recognize that macro-level phenomena operating at the global and national levels impact the degree to which occupations promote or constrain the material and symbolic achievement of individuals. At the global level, the past several decades witnessed a fairly dramatic change in the way that production (particularly manufacturing) is organized, as firms increasingly extend their boundaries across nations states through either formal (e.g. FDI) or informal (sub-contracting) relationships (Bair 2009; Gereffi, Humphrey and Sturgeon 2005). Sociologists argue that this greater worldwide entrenchment of globalized production networks matters for economic and socio-economic outcomes at the national level. Recent work includes the structure of the manufacturing sector (Mahutga 2014), the relationship between industrialization and economic growth in poor countries (Pandian 2016), income inequality in rich countries (Mahutga, Roberts and Kwon 2017), and so on. That is, the employment and income effects of OFFS should vary by how a country connects to the global economy, and with the entrenchment of global production networks worldwide.

Comparative sociologists also identify a growing list of institutional factors that should constrain or enhance the supply and demand mechanisms impacting occupations differentially (Neckerman and Torche 2007). The size and content of the welfare state (Rosenfeld and Kalleberg 1990; Mandel and Shalev 2009), the strength of organized labor (Western and Rosenfeld 2011), the character of the relationships between business, labor and the state (Alderson and Nielsen 2002; Gustafsson and Johansson 1999; Hicks and Kenworthy 1998), regionalization (Beckfield 2006), labor market flexibility (Mahutga and Jorgenson 2016), and so on, should matter for the degree to which RTI and OFFS impact individual incomes and employment, and therefore, for the structure of wages and employment. That is, various types of national level institutions could work to both constrain and enhance the employment and income effects of RTI and OFFS. This line of research seems all the more important in light of the fact that current research on RTI and OFFS ignore these sociological perspectives entirely, and may thus suffer from a significant degree of unmeasured parameter heterogeneity.

In terms of the degree to which RTI and OFFS provide additional explanatory power to sociological models of income and employment, we contend that RTI and OFFS could illuminate *any theory for which income or employment are the key explananda*, since occupations are central determinants of those outcomes. Moreover, we suggest that RTI and OFFS could have fairly dramatic implications for these sociological models because they impact both the composition and pattern of remuneration in national labor markets. We use one seminal LIS study by Bardasi and Gornick (2008) to illustrate our point. Bardasi and Gornick (2008) analyze the female part-time/full-time wage gap using LIS data. A key finding is that as much as 57.6 percent of the observed full-time wage premium for women can be explained by the sorting of full- and part-time women into occupations. This occupational effect is driven by the concentration of women in sales/clerical/service sector occupations. Thus, income dynamics in these occupations are critical to the female full-time wage premium.

Our addition of RTI, OFFS and expanded set of ISCO-88 categories to the LIS can advance this line of research. For one, Bardasi and Gornick (2008) acknowledge that more disaggregated data would probably allow them to “explain an even higher fraction of the part-time/full-time wage gap” (55). Our data would allow for an expanded set of occupations (from 3 to 27 ISCO-88 categories). Moreover, it would also allow for an assessment of the degree to which RBTC and globalization explain any of the wage gap explicable by occupations. Indeed, theories of RBTC and globalization have much to say about the changing fortunes of workers in the heterogeneous sales/clerical/service occupations. As the contemporary “Amazon revolution” lays bare, there is a large swath of sales jobs that are neither interactive nor place-bound. Similarly, much clerical work is both routine intensive and offshorable. Jobs in the residual service sector category are more heterogeneous. Thus, RBTC and globalization likely reduce female work hours all three categories. This would increase the prevalence of part-time work in this sector, as more job tracks become automated or offshored. It should also increase the full-time wage premium, as remaining full-time jobs involve more non-routine, cognitive and place-bound job tasks than remaining part-time jobs. The combined effect on the overall female full-time wage premium should thus depend on both the rising premium in this sector, and the declining proportion of female work-hours residing in this sector. The overall effect is thus hard to predict *a-priori*, suggesting in turn that the potential contribution of RTI and OFFS to the sociology of income and employment is very much an open empirical question.

End Notes

1 The cross-walks from SOC to ISCO-08 and, to a lesser degree, ISCO-88 to ISCO-08 are in and of themselves non-trivial. Thus, converting our ISCO-88 cross-walked country-specific codes to RTI/OFFS scores actually entails a train of cross-walks: Country-Specific→ISCO-88→RTI/OFFS←ISCO-88←ISCO-08←SOC. Measurement error is thus the sum of the errors from SOC to ISCO-08 to ISCO-88 and from the country-specific codes to ISCO-88.

2 Labor income ratios are constructed by trimming the outlying observations in the local currency at each extreme, and then dividing by the country-year median and taking the base-10 logarithm. See below for greater detail.

3 Our 50% rule excluded three occupational categories that would reside partially in ISCO-88 category 12. Spain categories 40 (directors and managers of enterprises and shops) and 41(managing director of enterprises and shops) were split 50%/50% with ISCO-88 categories 12 and 13. Spain category 60 was split 12(50%)/ 13(25%)/ 61(25%). While we could use our weighting procedure for the RTI and OFFS scores below, our 50% rule leads to the omission of these Spanish categories in our estimate of the Spanish ISCO-88 wage ratio displayed in Figure 1.

4 We thank an anonymous *IJCS* reviewer for this insight.

5 The top four most offshorable 2-digit ISCO codes (73, 74, 81, 82) require little formal education. But, workers in the fifth most offshorable code—21, Physical, Mathematical and Engineering Science Professionals—are exceedingly educated, and those in the sixth to ninth most offshorable categories (41, 24, 34, 31) would be a mix of high to very highly educated. With our data, OFFS is positively associated with the LIS' three-level education dummies.

6 These ISIC categories translate as follows: **A**-agriculture, hunting and forestry, **B**-fishing , **C**-mining and quarrying, **D**-manufacturing, **E**-electricity, gas and water supply, **F**-construction, **G**-wholesale and retail trade; repair, **H**-hotels and restaurants, **I**-transport, storage and communication, **J**-financial intermediation, **K**-real estate, renting and business, **L**-public administration and defense, **M**-education **N**-health and social work, **O**-other community, social and personal services, **P**-activities of private households as employers, **Q**-extra-territorial organizations and bodies.

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Table 1: Country-Years with RTI and OFFS Scores.

Country	ISCO-88 Survey Years	Recoded Survey Years	Unable to Recode Survey Years	Notes
Australia		1981	1985, 1989, 1995, 2001, 2003, 2008, 2010	CCLO Scheme – crosswalk created from list of occupations
Austria	1995, 2004		1987, 1994, 1997, 2000	
Belgium	1995, 1997, 2000		1985, 1988, 1992	
Brazil		2006, 2009, 2011, 2013		CBO-DOMICILIAR Scheme – crosswalk created from list of occupations
Canada		1994, 1997, 1998, 2000, 2004, 2007, 2010	1971, 1975, 1981, 1987, 1991	SOC-80 (1994-1997) and SOC-90 (1998-2010) Schemes – crosswalks created from list of occupations
Colombia		2004, 2007, 2010, 2013		ISCO-68 Scheme – crosswalk from Ganzeboom and Treiman (2012)
Czech Republic	1992, 1996, 2002, 2004, 2007, 2010			
Denmark	1992, 2004, 2007	2010	1987, 1995, 2000	ISCO-08 Scheme – crosswalk from International Labour Organization (2012)
Dominican Republic	2007			
Egypt	2012			
Estonia	2000, 2007, 2010		2004	
Finland	2000, 2004, 2007, 2010	1987, 1991, 1995, 2013		TLN Scheme (1987-1995) – crosswalk created from list of occupations and ISCO-08 Scheme (2013) – crosswalk from International Labour Organization (2012)
France		1978, 1984, 1989, 1994, 2000, 2005, 2010		PCS (1978), PCS-82 (1984-2005), and PCS-03 (2010) Schemes – crosswalks from Ganzeboom and Treiman (2012)
Germany	1984, 1989, 1994, 2000, 2004, 2007, 2010		1973, 1978, 1981, 1983	
Georgia		2010, 2013		
Greece	2004, 2007, 2010		1995, 2000	
Guatemala	2006			
Hungary	1994, 1999, 2005	1991, 2007, 2009, 2012		ISCO-68 (1991) Scheme – crosswalk from Ganzeboom and Treiman (2012) and FEOR-93 (2007-2009) and FEOR-08 (2012) Schemes – crosswalks from Hungarian Central Statistics Office (1999; 2011)
Iceland	2004, 2007, 2010			
India		2004, 2011		NCO-68 Scheme – crosswalk from International Household Survey Network

Table 1, continued

Country	ISCO-88 Survey Years	Recoded Survey Years	Unable to Recode Survey Years	Notes
Ireland	1994, 1995, 1996, 2000, 2004, 2007	1987, 2010		CSO-86 (1987) Scheme – crosswalk created from list of occupations and ISCO-08 (2010) – crosswalk from International Labour Organization (2012)
Israel		2007, 2010, 2012	1979, 1986, 1992, 1997, 2001, 2005	Standard Classification of Occupations 1994 (2007-2012) – crosswalk from Israel Central Bureau of Statistics (1994)
Luxembourg	1997, 2000, 2004, 2007, 2010	2013	1985, 1991, 1994	ISCO-08 Scheme – crosswalk from International Labour Organization (2012)
Mexico		2008, 2010, 2012	1984, 1989, 1992, 1994, 1996, 1998, 2000, 2002, 2004	CMO (2008) and SINCO-2011 (2010-2012) Schemes – crosswalk from INEGI (2012)
Netherlands	2004, 2007, 2010	1990, 1993, 1999	1987, 1983	CBS-90 (1990-1993) and SBC-1992 (1999) Schemes – crosswalks from Ganzeboom and Treiman (2012)
Panama		2007, 2010, 2013		CNO 2000 (2007-2010) and CNO 2010 (2013) – crosswalks created from list of occupations
Peru		2004, 2007, 2010, 2013		INEI Occupational Scheme – crosswalk created from list of occupations
Poland	1999, 2004, 2007, 2010	2013	1986, 1992, 1995	ISCO-08 Scheme – crosswalk from International Labour Organization (2012)
Romania	1995		1997	
Russia	2000, 2004, 2007, 2010, 2013			
Serbia	2006, 2010, 2013			
Slovak Rep.	1992, 2004, 2007, 2010		1996	
Slovenia	1997, 1999, 2004, 2007, 2010	2012		ISCO-08 Scheme – crosswalk from International Labour Organization (2012)
Spain	1995, 2000, 2004, 2007, 2010	1980, 1990, 2013	1985	CNO-79 (1980-1990) – crosswalk created from list of occupations and ISCO-08 Scheme (2013) – crosswalk from International Labour Organization (2012)
Switzerland	2000, 2002	1992	1982, 2004	PBER Scheme – crosswalk from Lambert and Prandy (2012)
United Kingdom		1991	1969, 1974, 1979, 1986, 1994, 1995, 1999, 2004, 2007, 2010, 2013	UK SOC-90 Scheme – crosswalk from Lambert and Prandy (2012)

Table 1, continued

Country	ISCO-88 Survey Years	Recoded Survey Years	Unable to Recode Survey Years	Notes
United States		1974, 1979, 1986, 1991, 1994, 1997, 2000, 2004, 2007, 2010, 2013		SOC-70 (1974-1979) – crosswalk created from work based on Lambert and Prandy (2012), SOC-80 (1986) – crosswalk from Lambert and Prandy (2012), SOC-90 (1991-2000) – crosswalk from Lambert and Prandy (2012), Census 2002 (2004-2007) – crosswalk created from list of occupations and crosswalk from Analyst Resource Center (2016), and Census 2010 (2010-2013) – crosswalk created from list of occupations and crosswalk from Analyst Resource Center (2016)
Uruguay	2004	2007, 2010, 2013		CNUO-95 (2007-2010) Scheme – crosswalk created from list of occupations, ISCO-08 Scheme – crosswalk from International Labour Organization (2012)

Note: We did not recode any country years for China, Italy, Japan, Norway, Paraguay, South Africa, South Korea, Sweden, and Taiwan.

Table 2: ISCO-88 Category Labels.

Number	Label	Number	Label
11	Legislators, Senior Officials and Managers	52	Models, salespersons and demonstrators
12	Corporate managers	61	Market-Oriented Skilled Agricultural and Fishery Workers
13	Managers of small enterprises	62	Subsistence Agricultural and Fishery Workers
21	Physical, mathematical and engineering professionals	71	Extraction and building trades workers
22	Life science and health professionals	72	Metal, machinery and related trade work
23	Teaching Professionals	73	Precision, handicraft, craft printing and related trade workers
24	Other professionals	74	Other craft and related trade workers
31	Physical, mathematical and engineering associate professionals	81	Stationary plant and related operators
32	Life science and health associate professionals	82	Machine operators and assemblers
33	Teaching Associate Professionals	83	Drivers and mobile plant operators
34	Other associate professionals	91	Sales and service elementary occupations
41	Office clerks	92	Agricultural, Fishery and Related Labourers
42	Customer service clerks	93	Laborers in mining, construction, manufacturing and transport
51	Personal and protective service workers		

Table 3a: Tests of Meso Null Hypotheses.

	Finland 1995							Hungary 1991							Hungary 2009						
	Recode vs Reported			Baseline			*Diff*	Recode vs Reported			Baseline			*Diff*	Recode vs Reported			Baseline			*Diff*
ISCO 88	b	se	sig	b	Se	sig	sig	b	se	sig	B	se	sig	sig	b	se	Sig	b	se	sig	sig
12	-0.240	0.237		-0.599	0.353			0.294	0.681		-0.635	0.603			0.133	0.615		1.070	0.399	**	
13	---	---		-0.519	0.354			0.039	0.700		-0.574	0.613			-0.185	0.619		1.311	0.403	**	
21	-0.085	0.232		-0.617	0.352			-0.141	0.698		-0.702	0.620			0.529	0.622		0.985	0.407	*	
22	-0.555	0.252	*	-0.594	0.365			0.152	0.700		-0.625	0.638			0.541	0.728		1.505	0.462	**	
23	0.103	0.231		-0.545	0.352			0.620	0.667		-0.464	0.572			-0.066	0.592		1.591	0.374	***	*
24	0.055	0.234		-0.525	0.353			0.092	0.707		-0.401	0.608			0.038	0.608		0.834	0.392	*	
31	0.431	0.252		-0.552	0.353			0.795	0.729		-0.123	0.596			0.129	0.600		1.202	0.408	**	
32	-0.209	0.235		-0.549	0.351			0.677	0.665		-0.498	0.571			0.152	0.593		1.501	0.373	***	
33	---	---		-0.687	0.456			0.401	0.731		-0.532	0.602			-0.522	0.717		2.237	0.507	***	*
34	0.247	0.233		-0.551	0.351			0.806	0.682		-0.456	0.592			0.156	0.592		1.256	0.382	**	
41	0.079	0.229		-0.543	0.351			0.723	0.664		-0.282	0.574			0.274	0.589		1.247	0.376	**	
42	---	---		-0.504	0.352			0.535	0.693		-0.529	0.581			0.028	0.599		1.332	0.382	**	
51	-0.013	0.240		-0.539	0.351			0.499	0.666		-0.390	0.574			0.160	0.588		1.409	0.372	***	
52	---	---		-0.617	0.351			0.551	0.665		-0.432	0.574			0.241	0.589		1.426	0.375	***	
61	-0.112	0.234		-0.473	0.351			0.502	0.705		-0.824	0.587			0.094	0.591		1.606	0.375	***	*
71	-0.134	0.233		-0.558	0.351			0.889	0.665		-0.329	0.572			0.184	0.590		1.315	0.374	***	
72	0.038	0.230		-0.629	0.351			0.808	0.664		-0.235	0.571			0.326	0.589		1.162	0.370	**	
73	0.084	0.235		-0.369	0.358			0.815	0.683		-0.296	0.604			0.443	0.631		1.189	0.421	**	
74	0.077	0.233		-0.617	0.356			0.648	0.665		-0.336	0.573			0.219	0.588		1.288	0.372	**	
81	0.149	0.237		-0.543	0.356			0.837	0.674		-0.243	0.588			-0.152	0.650		1.535	0.413	***	
82	0.071	0.233		-0.604	0.352			0.739	0.673		-0.355	0.581			0.231	0.593		1.291	0.381	**	
83	-0.056	0.231		-0.546	0.352			0.748	0.669		-0.398	0.580			0.258	0.590		1.249	0.378	**	
91	0.068	0.230		-0.574	0.351			0.786	0.662		-0.309	0.569			0.161	0.587		1.443	0.369	***	
92	---	---		-0.797	0.369	*		0.868	0.673		-0.478	0.602			0.036	0.598		1.345	0.411	**	
93	0.097	0.232		-0.571	0.355			0.874	0.667		-0.460	0.575	***		0.180	0.589		1.450	0.376	***	

Notes: Unstandardized coefficients from OLS; heteroscedasticity consistent standard errors in parentheses. "Diff" reports significant rejections of the null hypothesis that the cross-model difference between the absolute value of the focal interaction terms is equal to zero, and employs the pooled variance estimate in seemingly unrelated regression. * p<.05; **p<.01; ***p<.001 (two-tailed tests). Finland 1995 compares 1995 (Recode) to 2000 (ISCO 88). Finland's baseline compares 2004 to 2010. Hungary 1991 compares 1991 (Recode) to 1994 (ISCO 88). Hungarian baseline compares 1994 to 1999. Hungary 2009 compares 2005 (ISCO 88) to 2009 (Recode). Hungary's 2009 baseline compares 1999 to 2005.

Table 3b: Tests of Meso Null Hypotheses.

	Netherlands 1999							Spain 2009						
	Recode vs Reported			Baseline			*Diff*	Recode vs Reported			Baseline			*Diff*
ISCO 88	b	se	Sig	b	se	sig	sig	b	se	sig	b	se	sig	sig
12	0.131	0.169		0.174	0.227			-1.738	0.586	**	-0.420	0.213	*	*
13	-0.280	0.409		0.038	0.231			-0.621	0.501		-0.529	0.194	**	
21	0.003	0.181		0.127	0.229			-0.238	0.539		-0.623	0.196	***	
22	-0.143	0.268		-0.151	0.244			0.077	0.460		-0.676	0.196	***	
23	0.098	0.165		0.090	0.225			-0.163	0.457		-0.681	0.188	***	
24	-0.016	0.178		0.072	0.227			-0.250	0.483		-0.398	0.198	*	
31	0.181	0.170		0.171	0.228			-0.533	0.473		-0.583	0.192	**	
32	0.150	0.181		0.030	0.224			-0.257	0.449		-0.679	0.196	***	
33	0.020	0.259		0.105	0.297			---	---		-0.639	0.283	*	
34	0.076	0.167		0.128	0.224			-0.256	0.451		-0.654	0.189	***	
41	0.139	0.158		0.121	0.223			-0.312	0.443		-0.557	0.185	**	
42	---	---		0.070	0.226			---	---		-0.577	0.187	**	
51	0.111	0.159		0.099	0.224			-0.629	0.441		-0.561	0.185	**	
52	-0.155	0.161		0.089	0.225			-0.385	0.443		-0.552	0.186	**	
61	0.073	0.171		0.042	0.229			-0.585	0.445		-0.578	0.188	**	
71	0.092	0.164		0.191	0.225			-0.561	0.441		-0.570	0.186	**	
72	0.016	0.167		0.109	0.225			-0.438	0.442		-0.490	0.186	**	
73	---	---		-0.064	0.294			-0.530	0.453		-0.650	0.204	***	
74	-0.284	0.169		-0.012	0.245			-0.478	0.443		-0.613	0.187	***	
81	---	---		0.235	0.239			-0.399	0.467		-0.745	0.193	***	
82	-0.421	0.163	*	0.107	0.227			-0.513	0.446		-0.506	0.189	**	
83	0.047	0.165		0.104	0.226			-0.468	0.445		-0.591	0.187	**	
91	-0.035	0.170		-0.009	0.226			-0.342	0.440		-0.625	0.184	***	
92	---	---		-0.007	0.324			---	---		-0.648	0.193	***	
93	---	---		0.066	0.228			---	---		-0.677	0.185	***	

Notes: Unstandardized coefficients from OLS; heteroscedasticity consistent standard errors in parentheses. “Diff” reports significant rejections of the null hypothesis that the cross-model difference between the absolute value of the focal interaction terms is equal to zero, and employs the pooled variance estimate in seemingly unrelated regression. * p<.05; **p<.01; ***p<.001 (two-tailed tests). Netherland’s recode comparison is 1999 (Recode) to 2004 (ISCO 88). Netherland’s baseline compares 2004 to 2010. Spain’s recode comparison is 1990 (Recode) to 1995. Spain’s baseline compares 2004 to 2010.

Table 4: Country-Years and Individuals Included in Work Hour and Labor Income Analysis.

Country	Work Hours	Labor Income
Austria	1995, 2004	2005
Belgium	1995, 2004	1995, 2000
Brazil	2006, 2009, 2011, 2013	2006, 2009, 2011, 2013
Colombia	2004, 2007, 2010, 2013	2004, 2007, 2010, 2013
Denmark		1992, 2004, 2007
Dom. Republic	2007	2007
Finland	1991, 2007	1987, 1991, 1995, 2000, 2004, 2007
France	2005	1984, 1989, 1994, 2005, 2010
Germany	1989, 1994, 2000, 2004, 2006, 2007	1984, 1989, 1994, 2000, 2004, 2007, 2010
Greece	2004, 2007	2004, 2007
Guatemala	2006	2006
India		2004, 2011
Ireland	1994-1996, 2000, 2004, 2007, 2010	1994-1996, 2000, 2004, 2007, 2010
Luxembourg	1997, 2000, 2004, 2007	1997, 2000, 2004, 2007
Mexico	2008, 2010, 2012	2008, 2010, 2012
Netherlands	1999	1990, 1999
Panama	2007, 2010	2007, 2010
Peru	2007, 2010, 2013	2004, 2007, 2010, 2013
Spain	1995, 2000, 2007	1995, 2000, 2007
Uruguay	2004, 2007, 2010	2004, 2007, 2010
USA	1974, 1979, 1986, 1991, 1994, 1997, 2000, 2004, 2007, 2010, 2013	1974, 1979, 1986, 1991, 1994, 1997, 2000, 2004, 2007, 2010, 2013

Notes: Global North italicized.

Table 5: Work Hour Regressions

	(1)		(2)		(3)	
	South	North	South	North	South	North
RTI	-134.895*	41.935**			-75.54	38.968*
	(42.86)	(10.89)			(33.74)	(12.73)
RTI X Year	0.067*	-0.021**			0.037†	-0.020*
	(0.021)	(0.005)			(0.017)	(0.006)
OFFS			-164.299	23.606***	-135.317	1.498
			(77.00)	(3.048)	(78.66)	(8.730)
OFFS X Year			0.081†	-0.012***	0.067	-0.0003
			(0.038)	(0.002)	(0.039)	(0.004)
Year	-1.681*	-0.123	-1.644*	-0.12	-1.631*	-0.124
	(0.702)	(0.069)	(0.678)	(0.073)	(0.680)	(0.067)
R^2	0.106	0.141	0.105	0.137	0.106	0.143

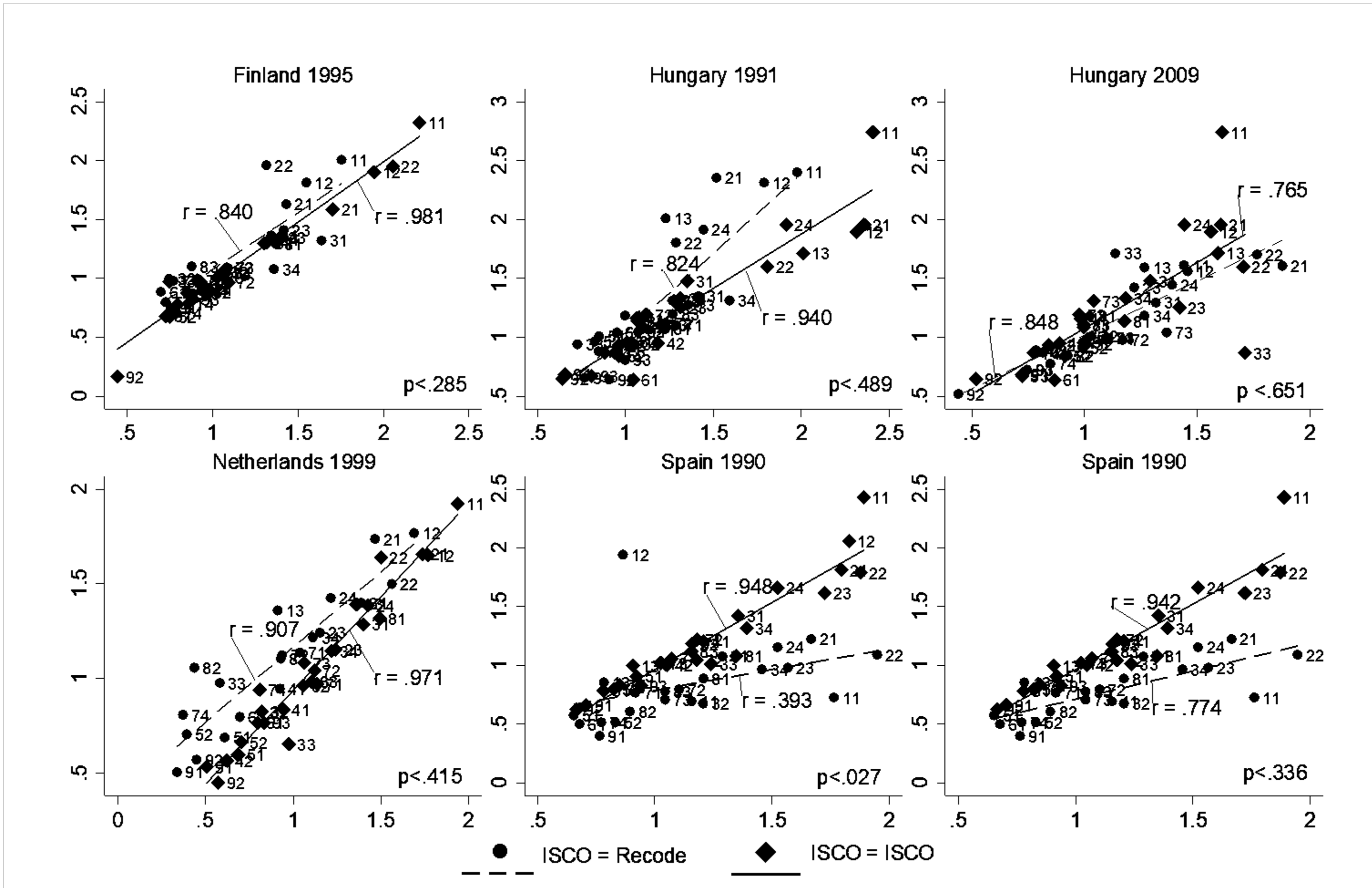
Notes: N = 1,127, 908 in the South and 949,682 in the North. Two-way FE results. Heteroscedasticity and serial correlation consistent standard errors in parentheses. †p<.10; *p<.05; **p<.01; ***p<.001. Controls include country, year and industry fixed effects, education, gender, age, age squared and GDP per capita.

Table 6: Labor Income Regressions

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	LEVELS								TRENDS					
	South	North	South	North	South	North	South	North	South	North	South	North	South	North
RTI	**-0.011**	**-0.015*** **					**-0.040*** **	**-0.032*** **	0.692	0.781***			-0.508	0.918***
	(0.009)	**(0.001)**					**(0.007)**	**(0.002)**	(1.311)	(0.087)			(2.375)	(0.918)
RTI X Year									**.0003**	**-0.0005*** **			**.0002**	**-0.0005*** **
									(0.001)	**(0.000)**			**(0.001)**	**(0.00005)**
OFFS			0.015	0.008***	0.056*	0.034***	0.093***	0.065***			8.575***	-0.718***	8.043**	-0.969***
			(0.007)	(0.001)	(0.021)	(0.001)	(0.014)	(0.004)			(1.357)	(0.115)	(1.793)	(0.130)
OFFS X OFFS					**-0.036***	**-0.020*** **	**-0.050** **	**-0.032*** **			-7.428***	0.681***	-7.062***	0.707***
					(0.015)	**(-30.618)**	**(0.012)**	**(0.001)**			(0.823)	(0.066)	(0.774)	(0.073)
OFFS X Year											-0.004***	0.0004***	-0.004**	0.001***
											(0.001)	(0.000)	(0.001)	(0.000)
OFFS X OFFS X Year											**0.004*** **	**-0.0004*** **	**0.003*** **	**-0.0004*** **
											(0.000)	**(0.000)**	**(0.000)**	**(0.00004)**
Year									-0.032***	0.0005	-0.035***	0.001	-0.034***	0.001
									(0.004)	(0.001)	(0.003)	(0.891)	(0.003)	(0.001)
R^2	0.398	0.348	0.399	0.341	0.411	0.353	0.423	0.38	0.398	0.348	0.412	0.354	0.424	0.381

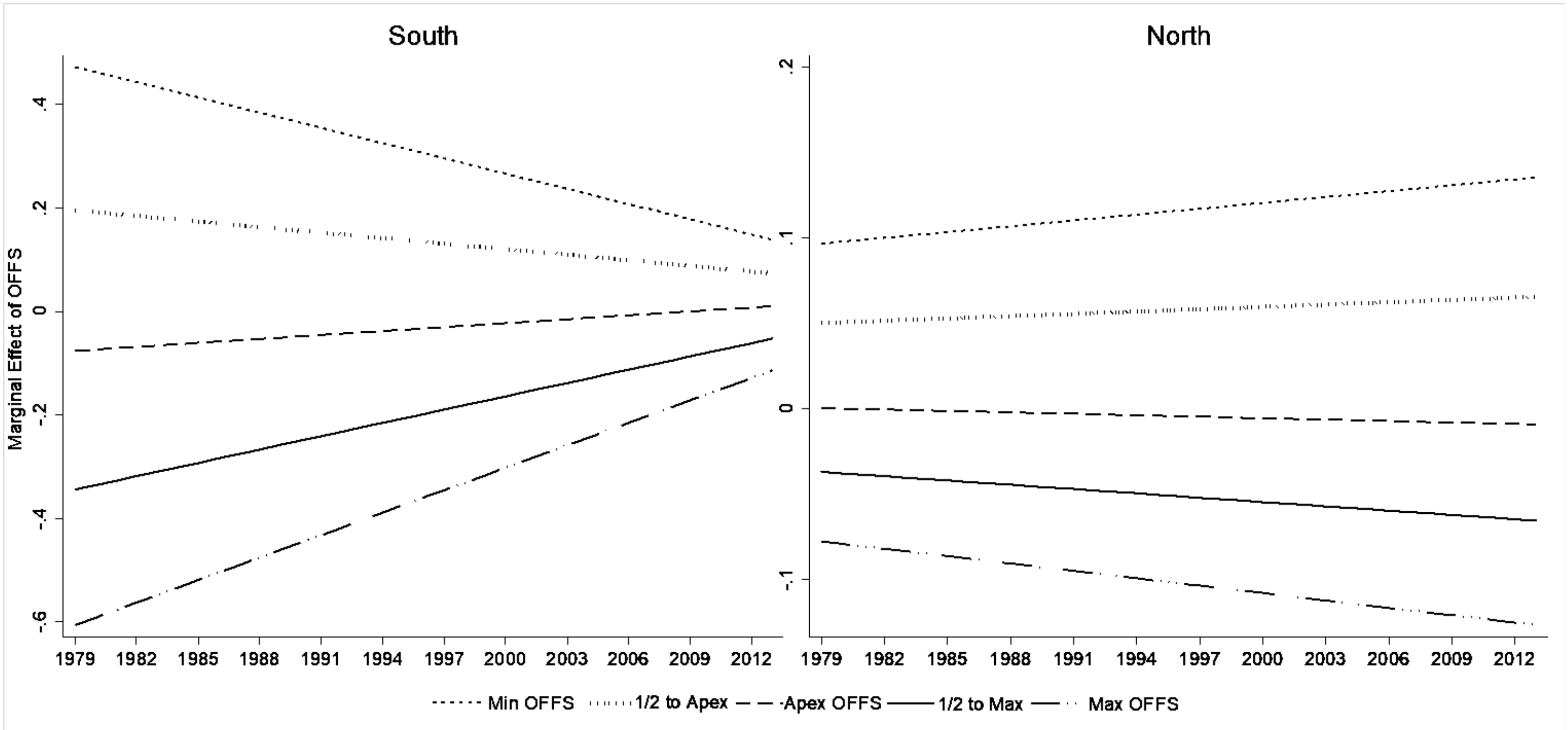
Notes: N = 1,163,160 in the South and 1,155,710 in the North. Two-way FE results. Heteroscedasticity and serial correlation consistent standard errors in parentheses. *p<.05; **p<.01; ***p<.001. Controls include country, year and industry fixed effects, education, gender, age, age squared and GDP per capita.

Figure 1: Macro-level Correlation of Mean Labor Income Ratios between Recoded and Reported ISCO Categories.



Notes: Smoothers fit with least squares; r is the zero-order correlation between predicted ISCO categorical mean labor income ratios for paired years. p values refer to the null hypothesis that the difference between the two correlations is equal to zero. **Finland 1995**: ISCO (2000) = Recode (1995); ISCO (2004) = ISCO (2010). **Hungary 1991**: ISCO (1994) = Recode (1991); ISCO (1994) = ISCO (1999). **Hungary 2009**: ISCO (2005) = Recode (2009); ISCO (1999) = ISCO (2005). **Netherlands 1999**: ISCO (2004) = Recode (1999); ISCO (2010) = ISCO (2004). **Spain 1990**: ISCO (1995) = Recode (1990); ISCO (2010) = ISCO (2004). Second graph excludes ISCO category 11 and 12, which are outliers in the ISCO = Recode comparison.

Figure 2: Marginal Effect of OFFS by OFFS and Year



Appendix A: Recoding Procedures

Our recoding procedure proceeded in three primary steps as described below.

(1) Searched for an existing cross-walk from occ1_c to ISCO-88 that yielded a one to one mapping
    a. We utilized two national occupational crosswalk repositories, the CAMSIS project and International Stratification and Mobility File (ISMF) project
    b. Contacted national statistical offices
    c. Other web searches.
(2) If no existing cross-walk could be found and the LIS data reported occ1_c at a level of aggregation at or below the two-digit ISCO-88 categories, or if a cross-walk was found but it did not yield a one to one mapping, we cross-walked the scheme ourselves as follows:
    a. From the reported occ1_c codes by LIS, we located the source (country) specific coding scheme (CSC) listing specific occupations within the source codes, with as much disaggregation as possible.
    b. We then matched the occupations in the CSC to occupations in the ISCO-88 scheme, using the following procedures:
        i. If the LIS codes described a respondent's occupation at a level of CSC aggregation below the equivalent ISCO-88 two-digit level, it was generally possible to match the occupation to one of the ISCO-88 unit groups at the two-digit level without ambiguity.
        ii. If the LIS codes described a respondent's occupation at an equivalent level of CSC aggregation, but the mix of occupations in this higher level of aggregation was nearly equivalent to that in a single two-digit ISCO-88 unit group because the CSC was modeled after ISCO-88, we coded this CSC aggregation to its most similar ISCO-88 equivalent.
        iii. If the LIS codes described a respondent's occupation at a high level of aggregation in the CSC, the CSC was not modeled closely on ISCO-88 but we were able to identify a two-digit ISCO-88 code that did not differ substantially from the CSC code, we coded this CSC aggregation to this ISCO-88 code.[†]
            1. A determination of "substantially differ" was based on the following criteria:
                a. The numerical dominance rule, according to which judgement were made concerning the relative importance of the occupations classified in the CSC group. If approximately 80 per cent or more of the Jobs classified in the CSC group belong to a particular ISCO-88 group, then the whole CSC group was classified in this ISCO-88 group.
                    i. In determining the "80%" rule, we considered both the skill content and production rule of occupations, as follows:
                        1. If the occupational mix of the CSC group was ambiguously skilled, the mapping onto

an ISCO-88 group was carried out on the basis of the occupations found to be the most skilled.

2. If the CSC category included production, sales and managerial occupations we used the production rule, according to which the occupational mix of a CSC group production occupations took priority over sales or managerial occupations.

iv. If the 80% rule did not obtain, but it was possible to categorize all of the occupations in the CSC to a mix of ISCO-88 codes, then we applied a weighting procedure whereby the weighted score (see 4aii) equal to $\sum_{j=1}^{k} \theta_{isco88_i} * p_j$, where j indexes the subset of occupations in country-specific occupational code k (CSC_k) that belong in ISCO-88$_i$, p is the proportion of occupations in CSC_k that belong to ISCO-88$_i$, θ is the RTI or OFFS score from Goos et al. (2014) for ISCO-88$_i$, and p sums to 1 across the full set of jobs in CSC_k.*

v. If the way of grouping certain CSC occupations is so different from ISCO-88 that an existing CSC group cannot validly be mapped onto any two-digit ISCO-88 groups (e.g. there is no numerical dominance and it was impossible to recode all of the occupations in CSC_i into ISCO-88 groups), then no new cross-walk was created.

The cross walks we report can thus be categorized as either 1 (based on a pre-existing cross-walk), 2bi, 2bii, 2biii and 2biv.

Notes

†In some instances, the LIS recoded the occupations from the CSC. These LIS-specific occupational codes were matched up with the CSC headings based upon the labels and/or numeric codes and then the rules above were applied.

*Certain country occupational schemes use "not elsewhere classified" or "other" categories that serve as a catch-all for potential leftover occupations. Some countries place managers and supervisors into a separate category rather than mapping them thematically. We developed a procedure for classifying these categories appropriately. This process is as follows:

(1) If the entire set of occupations in a CSC occupational category could not be mapped to an ISCO-88 category, we recoded it to missing.
(2) If the CSC occupational category was weighted but the unknown portion was greater than 20%, we recoded the entire category to missing.
(3) If the unknown portion of the CSC occupational category was weighted less than 20%, we used the following criteria to recode the unknown portion into ISCO-88:
    a. We first looked at the surrounding (i.e., in the same or a nearby category) occupational headings in the country-specific scheme or crosswalk.
        i. If the group appears to refer to high skill occupations, the unknown portion was recoded to the modal ISCO-88 category. If more than one category is modal, the unknown portion was split amongst them.

ii. If the group appears to refer to low skill occupations, the unknown portion was recoded to the modal ISCO-88 category. If more than one category is modal, the unknown portion was split amongst them.

iii. If the group appears to refer to mixed skill or ambiguous skill level occupations, we assigned the missing portion based on the following rules:

1. First, we checked to see if there is separate low skill (e.g., labourers, technicals, etc.) category elsewhere in the scheme.
    a. If there was a separate low skill category, we opted to recode to a higher-skilled ISCO-88 code based upon proximal categories' codes and face validity.
    b. If there was not a separate low skill category, we opted to recode to a lower-skilled ISCO-88 code based upon proximal categories' codes and face validity.

b. In a fraction of cases where we utilized an external crosswalk with a weighting procedure that had an unknown portion because it was assigned at higher level of aggregation than ISCO-88 level two, we used the one digit ISCO-88 code as a guide to recode. For example, if the crosswalk assigned a portion of the category to ISCO-88 heading 3, we recoded the unknown portion into the represented ISCO-88 two digit heading 3 categories (e.g., 31, 32, etc.). If no heading 3 categories were represented in the rest of the weighed codes, we divided it amongst all possible two digit heading 3 categories or assigned the code based upon face validity.

Appendix B: Accessing the Data

Users can access these data in one of two ways. Users who wish to make use of assembled RTI and OFFS scores used above, as well as new ISCO-88, occ1a and occ1b covariates that result from our recode (plus a few country-waves added after the writing of this text), can find them on the LIS website (http://www.lisdatacenter.org/resources/other-databases/) and here http://matthewcm.ucr.edu/data.html. We also provide user guide and codebook for the variables included in these data, as well as a very large document detailing the recoding particulars for each country-year recoded.

Users who wish to work with (or augment) our original script may find it on http://matthewcm.ucr.edu/data.html or by emailing the lead author. This script can be used to recode additional datasets as they come online in the LIS. The user guide includes instructions on how to use our cross-walks to generate weighted RTI and OFFS scores.