TI 2021-068/V
Tinbergen Institute Discussion Paper

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Revision November 2021

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Returns to Routine Job Tasks in the German Labour Market: An Instrumental Variables Approach

Emil Mihaylov*

26 November 2021

This paper studies the impact of routine job tasks on workers wages in the German labour market. Using nationally representative data from the German Employment Survey, the paper finds that routine job tasks are negatively and significantly associated with workers hourly wages; the negative effect of routine tasks is most pronounced in high-skilled non-routine occupations where routine tasks are found to carry a substantial wage penalty. In order to account for the endogeneity of routine job tasks, the analysis employs an instrumental variable approach. The individual routine task-intensity of German workers in 2012 is instrumented with the routine task-intensity of the father's occupation in 1979 and the routine task-intensity of the workers' own occupation in 1979. The estimation procedure rests on the assumption that the two instruments are uncorrelated with the error term in the wage equation, conditional on a detailed set of individual, job, firm, industry and occupation-specific variables. Although the exogeneity of the instruments cannot be tested formally, the paper provides an extensive discussion of the instruments' validity and shows that the estimated negative effect is not sensitive to different model specifications, different definitions of the endogenous and instrumental variables, and different sample selection rules.

JEL Classification: J01, J24, J30
Keywords: job tasks, wages, instrumental variables, parents' occupation, Germany

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I would like to thank Frank den Butter, Daniela Rohrbach-Schmidt, Britta Matthes, and numerous participants at the 30th Annual Conference of the Italian Association of Labour Economists, the 4th SOLE-EALE World Meeting, the 4th International BIBB/IAB/ZEW Conference (TASKS IV), the EEA Congress in Mannheim, and the CPB Netherlands Bureau for Economic Policy Analysis seminars for valuable comments and suggestions. An earlier version of this paper was circulated under the title "Returns to Routine and Non-routine Job Tasks: Evidence from Germany". I gratefully acknowledge financial support from the Netherlands Organization for Scientific Research (NWO).

1 Introduction

This paper studies the returns to performing routine job tasks in the German labour market. From econometric perspective, there are numerous challenges associated with the estimation of the returns to tasks. First, the assignment of workers to occupations and tasks is not random but is systematically related to observable individual characteristics such as gender, race, education (Autor and Handel, 2013), cognitive skills (Agasisti, Johnes and Paccagnella, 2021; Deming, 2017), and unobservable individual characteristics such as innate ability (Cortes, 2016) and preferences[2]. Failing to account for such observable and unobservable factors, especially when these are correlated with individual wages, will produce biased estimates of the returns to tasks. This is likely to be the case in most observational studies that rely on cross-section data and OLS estimation methods, because in such studies it is inherently difficult to control for all relevant factors that simultaneously affect the assignment of workers to job tasks and their wages. Second, job tasks, different than education and skills, are not fixed or semi-fixed workers attributes that are determined prior to labour market entry (see Autor and Handel, 2013), but rather are a flexible attribute of jobs that can be modified at any time by the worker based on the expected wage. Rational workers will maximize their income by self-selecting into occupations and tasks that provide the highest expected earnings, given their abilities and skills. This means that the workers job tasks are themselves a function of wages (Autor, 2013), and a simple OLS regression of wages on tasks will not recover the average returns to jobs tasks. Third, the construction of job tasks measures is prone to error. The error stems from the fact that job tasks are typically extracted from a handful of data sources – e.g., the U.S. DOT and O*NET occupational databases, the German Employment Surveys, the British Skill Survey, the PIAAC survey – that are not designed to measure the routine task content of jobs (see Rohrbach-Schmidt and Tiemann, 2013 for an excellent discussion of the German surveys). This, in combination with the fact that there are no established procedures for how to construct job tasks measures, makes it likely that the development of such measures will be subject to error[3]. The possible measurement error in the job tasks variable, however, could have implications for the estimated returns to tasks – it could bias them towards zero.

[2] Autor and Handel (2013) show, for example, that post-college education is positively associated with performance of abstract tasks and negatively associated with performance of routine and manual tasks, while the opposite holds true for Spanish-language primacy. Agasisti, Johnes and Paccagnella (2021) find that literacy skills are positively associated with abstract and routine tasks, and negatively associated with manual tasks. Deming (2017) shows that people with higher social skills are more likely to work in non-routine and social skill-intensive occupations. Cortes (2016) finds that high-ability routine workers are more likely to switch to non-routine cognitive occupations, while low-ability routine workers are more likely to switch to non-routine manual occupations.

[3] Acemoglu and Autor (2011) point out, for example, that both the DOT and O*NET databases contain "numerous potential task scales, and it is rarely obvious which measure (if any) best represents a given task construct" (p. 1078). Also Autor (2013, p.191) notes that "researchers who wish to use these databases as sources for task measures are essentially required to pick and choose among the plethora of scales available" (p.191).

With these considerations in mind, the present paper employs an instrumental variables (IV) approach and estimates the returns to routine job tasks in the German labour market. The IV approach takes into account the endogeneity of the job tasks variable and provides (under certain conditions) an unbiased estimate of the returns to routine tasks. The analysis is based on the 1979 and 2012 waves of the German Employment Survey. We examine the relationship between routine tasks and wages by regressing the log hourly wages of German workers in 2012 on a measure of their individual routine task-intensity (RTI) in 2012 and a detailed set of individual, firm, industry and occupation-specific variables. The individual RTI measure in 2012 is instrumented with the RTI of the father's occupation in 1979 and the RTI of the worker's own occupation in 1979. In order to prevent our instruments from being correlated with omitted variables in the error term, we include in the regressions controls for education, experience, tenure, previous unemployment, duration of unemployment, number of employers since first job, computer use at work, complexity of the job, supervisory position, irregular working hours, working on the weekends, being on a stand-by duty, firm size, firm location, sector of economic activity, family status, children, health condition, migration background, and average RTI of the worker's own occupation in 2012. Although the exogeneity of the instruments cannot be tested formally (beyond the possibilities of the Hansen test), we go to great lengths to show that our instruments are not correlated with omitted variables and are also not directly related to individual wages in 2012. To this end: first, we control for a large number of explanatory variables in the model – this limits the possibility that a potentially relevant explanator (that is correlated either with the instruments or any of the explanatory variables) is left out of the model. Second, we run multiple regressions in which we gradually increase the number of explanatory variables in the model – if our instruments are correlated with omitted variables, then we might expect to see jumps in the size and/or the sign of the estimated coefficients as we add more explanatory variables to the model. Third, given that our model is overidentified (i.e., we have two instruments and one endogenous variable), we are able to test the excludability of our instruments directly by including each of them in turn as an additional explanatory variable in the second-stage model, while using the other variable as an instrument for the individual RTI in 2012. By doing this, we can not only directly test the excludability restriction (which postulates that the instruments should be excludable from the second-stage model), but we can also limit the possibility that the instruments are correlated with omitted variables in the error term[4]. Based on the results of all these informal tests, we show that our instruments are likely to be exogenous and excludable from the second-stage model. Also the results of the formal Hansen J test point in the same direction – the test statistic can never reject its joint null hypothesis of instrument validity.

The results of the IV regressions show that routine tasks have a negative and significant impact on wages - a one unit increase in the RTI measure is associated with about 35 percent decrease in workers hourly wages. To put this estimate into perspective, consider that roughly one unit is the difference between the RTI indices of the Professionals and the Clerical Support Workers. This means that if the Professionals were to perform the same type of tasks

[4] Because now we have one additional 'explanatory' variable (i.e., instrument turned into explanatory variable) from 1979.

as the Clerical Support Workers, they would earn on average 35 percent lower wages, ceteris paribus. This is a plausible result, and it is also comparable to the estimates of Stinebrickner, Stinebrickner and Sullivan (2019) who find that moving just half of the worktime from low-skilled object tasks to high-skilled information or high-skilled people tasks is associated with an increase in earnings of about 55 and 32 percent, respectively. Furthermore, the sensitivity analysis reveals that the estimated negative effect is not sensitive to different model specifications, different definitions of the endogenous and instrumental variables, and different sample selection rules. The analysis finds also that the impact of routine tasks on wages is not uniform across all occupations, and that the negative effect of routine tasks is stronger in high-skilled non-routine occupations.

The paper makes several contributions to the literature. First, to the best of our knowledge, this is the first study to use an instrumental variables approach to estimate the causal effects of routine job tasks on workers wages in the German labour market. While there are few other papers that use this technique to examine the returns to tasks in the United States and Britain, the vast majority of the existing studies rely on different econometric strategies for dealing with endogeneity when estimating the returns to tasks. These strategies range form exploratory OLS analyses to fixed effects and structural approach estimations, and are further discussed in the next section[5]. Second, the paper utilizes an innovative instrumental variable, based on the occupation of the father, that has only recently become available. In 2012, for the first time, the German Employment Survey included information about the occupation of the workers' fathers, and to the best of our knowledge, this information has not been used yet to construct instrumental variables that are used to study the impact of routine tasks on wages. Third, the paper employs three different versions of the endogenous variable and two versions of the instrumental variables, which allows us to rigorously examine the robustness of the main empirical results to alternative definitions of these key variables.

The rest of the paper is organized as follows. The next section provides an overview of the empirical literature on the wage returns to tasks. Section 3 presents the empirical model and discuses the validity of the instruments. Section 4 describes the data and details the construction of the endogenous and instrumental variables. Section 5 presents the main empirical results. Section 6 and 7 examine the robustness of the main empirical results with respect to sample selection (Section 6) and different definitions of the endogenous and instrumental variables (Section 7). Section 8 provides a comparison of the IV and OLS estimates, and explores the heterogenous effects of routine tasks across occupations. Section 9 concludes.

[5] It is important here to make a distinction between skills and tasks. As Autor and Handel (2013) point out, the first are attributes of workers, while the latter are attributes of occupations and jobs. Workers use their (inborn and acquired) skills to perform different tasks. The present analysis focuses thus on the returns to tasks. There is a large body of literature that studies the returns to skills (see e.g., Hanushek et al, 2015; Deming, 2017; Falck, Heimisch-Roecker and Wiederhold, forthcoming).

2 Alternative methods for estimating the impact of job tasks on wages

This section provides an overview of the empirical literature on the returns to tasks. The presented studies are organized into four categories and are discussed in relation to the empirical approach they use.

Cross-section data and OLS methods: To build intuition about how job tasks "should" be related to wages, Autor and Handel (2013) develop a simple conceptual framework that formalizes the causal links between human capital endowments, occupational choice, job tasks and wages. The framework is based on the Roy's (1951) model of self-selection and is motivated by the observation that occupational assignment of workers is not random, but rather determined by comparative advantage. The model makes several predictions for the relationship between job tasks and wages, and some of these predictions are empirically tested in Autor and Handel (2013), Agasisti, Johnes and Paccagnella (2021), Saltiel (2019) and Rohrbach-Schmidt (2019). To study the relationship between job tasks and wages, the authors of these papers typically estimate Mincerian-like wage equations augmented with task measures and interaction terms between worker-level and occupation-level task measures. The analyses are based on cross-section survey data and OLS methods, and the provided empirical evidence is descriptive in nature. A general conclusion that emerges from these papers is that abstract tasks are positively correlated with wages both across and within occupations, while manual tasks are negative correlated with wages. Some of the studies find also a negative relationship between routine tasks and wages (see e.g., Autor and Handel, 2013; Saltiel, 2019). The authors acknowledge that their results cannot be interpreted as causalities. Nevertheless, these papers provide valuable descriptive evidence on the relationship between job tasks and wages and the sorting pattern of workers across occupations[6].

Panel data and fixed effects methods: To identify the impact of job tasks on wages in the presence of endogenous sorting of workers into occupations, a number of studies use fixed effects panel data methods. One advantage of the fixed effects is that they can successfully remove unobserved heterogeneity across units (workers, occupations) that is constant over

[6] Other studies that use OLS methods to study the relationship between task and wages are De La Rica, Gortazar, Lewandowski (2020), Cassidy (2017) and Storm (2020). Rohrbach-Schmidt (2019) is the only study in this part of the literature review that accounts for endogeneity and estimates both OLS and Hausman-Taylor regressions (both methods yield nearly identical results). The consistency of the Hausman-Taylor estimator, however, hinges on the assumption that all covariates in the model are level-1 exogenous, that is, they are uncorrelated with the error term in the wage equation (e.g., the worker-level task measures are assumed to be level-1 exogenous variables). The assumed level-1 exogeneity would be violated, however, if there are omitted worker-level variables that affect workers wages and are correlated with the covariates included in the model. The Hausman-Taylor method focuses only on the presence of level-2 endogeneity, which, in the context of the discussed paper, is defined as "a correlation of covariates with the unobserved occupation effect" (Rohrbach-Schmidt, 2019, p.128). This makes the method somewhat less powerful, as compared to the IV approach, when it comes to dealing with endogenous variables. See Castellano, Rabe-Hesketh and Skrondal (2014) for a discussion of the Hausman-Taylor method.

time. If one believes that there are unobserved time-invariant factors that simultaneously affect the assignment of workers into occupations and workers wages, then one can use fixed effects regressions. The fixed effects exploit within-group variation over time and remove omitted variables bias (as long as the omitted variables are constant over time). This is the approach taken by Stinebrickner, Stinebrickner and Sullivan (2019), Cortes (2016) and Cavaglia and Etheridge (2020).

Using individual-level data from the Berea Panel Study and fixed effects methods, Stinebrickner, Stinebrickner and Sullivan (2019) study the relationship between job tasks and wages. They distinguish between low and high-skilled people, information and object tasks and examine the role these tasks play in the formation of wages. The paper finds that high-skilled tasks are paid substantially more than low-skilled tasks, and also information tasks are paid more than object and people tasks at both low and high-skill levels. A comparison of OLS and fixed effects estimates reveals that the fixed effects estimates are somewhat smaller in size, but the big picture takeaway from both methods is quite similar. The returns to tasks are estimated under the assumptions of (i) exogenous mobility of workers across jobs, (ii) constant task efficiencies (i.e., constant abilities of workers to perform tasks), and (iii) perfect information about tasks efficiencies of workers. The first assumption essentially implies that the occupational and task choices of workers are exogenous, conditional on the workers fixed effects and observable time-varying characteristics. The paper is unique in that it is the first study to use longitudinal task data at the worker-level.

Also Cortes (2016) and Cavaglia and Etheridge (2020) exploit the features of their panel datasets and estimate changes in occupational wage premia over time for routine, manual and abstract task-intensive occupations. The changes in wage premia (or task prices) are identified from the wage growth of workers within occupation spells, and are captured through time-varying occupation fixed effects[7]. A key identifying assumption in both papers is that occupational choice is exogenous, conditional on a set of observable characteristics and unobservable individual and occupation fixed effects. The fixed effects are assumed to capture time-invariant workers' skills and occupation-specific factors that determine the selection of workers into occupations. These are necessary assumptions for the fixed effects model to produce unbiased estimates. However, if these assumptions are not met (e.g., because workers acquire new skills over time), then the fixed effects would not be able to fully capture the unobserved workers' skills, and any time-varying parts of the workers' skills would end up as omitted variables in the error term of the wage regression.

In sum, the fixed effects estimator is a powerful tool for dealing with omitted variables bias, as long as the omitted variables are time-invariant, or at least, do not vary over the course of the studied period. However, the fixed effects cannot resolve the whole endogeneity problem. Other sources of endogeneity (e.g., time-varying omitted variables, simultaneity and measurement error) can still be present and can cause correlation between the explanatory variables and the error term, which then can cause the fixed effects to be inconsistent (see

[7] The authors include occupation spell fixed effects (an interaction between individual and occupation-fixed effects) in the regressions and, therefore, all variation in wage premia over time comes from within occupation spells.

Wooldridge, 2002, chapters 10 and 11). The fixed effects can namely exacerbate measurement error bias (Wooldridge, 2002, chapter 11).

Propensity regression, bounding and other approaches: In a recent study, Böhm (2020) employs a propensity method to estimate changing task prices in the U.S. He distinguishes between abstract, manual and routine intensive occupations and estimates the changing prices paid for a unit of labour in these occupations. His identification strategy relies on early measures of workers talents that are determined pre-entry into the labour market. In a first-stage, Böhm models the selection of workers into the three occupational groups and estimates the probability of choosing an abstract, manual or routine intensive occupation as a function of worker early talents (measured by mathematical, verbal and mechanical test scores) and risky behaviour. Then he uses the constructed probabilities to estimate changes in task prices during the 1990s and 2000s in the U.S. The changing task prices are identified from the wage growth of workers associated with the propensity to work in abstract, manual and routine intensive occupations[8].

A different approach is taken by Gottschalk, Green and Sand (2015), who use a combination of bounding and reweighting techniques to study the trends in occupational task prices in the U.S. over the period 1984 to 2013. The core idea behind these techniques, roughly speaking, is to generate an occupational wage series that is adjusted for changes in the composition and ability distribution of workers within occupations. Having such a series provides the opportunity to study developments in occupational wages over time that are free from composition and selection effects, and to draw inference about movements in occupational task prices. In order to obtain an ability constant sample, the authors first identify the workers who are stayers in each occupation (people who would not change occupations between two periods when relative task prices change) and focus on them. This is achieved by comparing the employment sizes of each occupation in two periods, making some extreme assumptions about the ability distribution of stayers (as compared to movers), and trimming a certain portion of workers from either the top or bottom of the wage distribution in the period with an excess employment[9]. The ultimate goal is to obtain an

[8] As Böhm (2020) points out, the estimated changes in task prices are in fact changes in prices paid for a unit of labour in three broad occupational groups. The three occupational groups are dominated by abstract, routine and manual tasks, respectively, and for this reason they are often labelled as abstract, routine and manual intensive occupations. However, they are comprised by many detailed occupations and contain a variety of different tasks.

[9] Consider, for example, that total employment in a given occupation has increased from 100 to 120 workers between period t and t+1. According to the logic of the model, this means that 100 workers are stayers in both periods and 20 workers are movers in the second period. The paper aims to identify the 20 workers who are movers and drop them from the sample, such that only the 100 workers who are stayers remain. To achieve this, the authors make some assumptions about the ability of movers (as compared to the median stayer) and trim 20 observations from the top or bottom of the wage distribution in the second period. Under the assumption that the movers are of lower (higher) ability than the median stayer, the authors trim from the bottom (top) of the wage distribution in the second period. The remaining sample of 100 observations constitute an ability constant sample of

ability constant set of workers (the stayers) and follow their observed median wages over time. Similarly, in order to obtain a composition constant set of workers, the authors divide the sample into cells based on observables and perform the described trimming procedure for each cell separately. The composition constant cells are then combined into a weighted average sample for which the median wage is calculated for each year and occupation group (routine, manual and cognitive occupation groups). By making different assumptions about the ability distribution of workers across occupations, the paper estimates different upper and lower bounds on the movements in occupational task prices. Overall, the paper finds that routine, manual and cognitive task prices have all increased in the 1990s and have fallen after 2000s.

Böhm, Von Gaudecker and Schran (2019) develop a model for estimating the occupation-specific prices paid for a constant unit of labour. The model is based on the Roy (1951) framework and incorporates endogenous switching across occupations and occupation-specific skill accumulation over the life-cycle. The model explicitly distinguishes between prices and skills, and decomposes the wage growth of workers into an occupation-specific price paid for a constant unit of labour and accumulated workers skills. The evolution of the occupation-specific prices of labour is captured through an interaction term between year dummies and an average occupational choice indicator, which is equal to 1 for workers who remain in their occupation between two periods, 1/2 for workers who enter or leave an occupation between two periods, and 0 for all other workers. The authors estimate the evolution of prices for 120 detailed occupations and find that the price changes are positively related to occupational employment changes and to the analytic and interactive task content of occupations, and negatively related to the routine and manual task content of occupations[10]. The authors recognize that the average occupational choice indicator might be correlated with the error term in the wage growth equation, and instrument this variable with the workers occupational choice in period t-1. The empirical analysis is based on German administrative panel data over the period 1975-2010.

In sum, two points can be made based on the literature review so far. First, the existing literature has presented a large variety of methods to estimate the returns to tasks and the evolution of occupational wage premia. The different methods aim to correct for the non-random assignment of workers into occupations and tasks, and the changing composition of workers within occupations over time. Second, the discussed studies can be roughly divided into works that estimate the level of returns to tasks (e.g., Stinebrickner, Stinebrickner and Sullivan, 2019; Autor and Handel, 2013; De La Rica, Gortazar, Lewandowski, 2020), and works that estimate the evolution of occupational wage premia over time (e.g., Cortes, 2016; Cavaglia and Etheridge, 2020; Gottschalk, Green and Sand, 2015; Böhm, Von Gaudecker and

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workers for whom the median wages are calculated in both periods. Analogously, when employment decreases between period t and t+1, then the trimming is done on the sample in period t.

[10] Note that the paper does not estimate returns to analytic, interactive, routine and manual tasks, but only relates the estimated price changes to the analytic, interactive, routine and manual task content of the 120 occupations.

Schran, 2019)[11]. The present paper examines the level of returns to tasks and fits thus within the first group of studies.

Instrumental variables and related approaches: The method of instrumental variables, which is one of the most commonly used methods in empirical economic research (see Wooldridge, 2002, Chapter 5), has not found many applications in the existing literature on the returns to tasks. The reason for this lies probably in the fact that it is difficult to find credible instruments that are correlated with job tasks assignments, but uncorrelated with individual wages. We are aware of only few papers that employ this technique to examine the returns to tasks (in the United States, Britain and Brazil, respectively).

An early example of using instrumental variables in the current context is the work of Borghans, Ter Weel and Weinberg (2008). The authors develop a theoretical framework to study the relationships between interpersonal styles, occupational choices and labour market outcomes. In the basis of this framework is the observation that people differ with regard to their interpersonal styles (e.g., some people are more caring, while others are more direct), and jobs require different mixes of interpersonal styles (e.g., directness is more important for managers than for nurses). Accordingly, the model predicts that people with different styles will be assigned into different types of jobs. The authors employ British and German survey data to study the implications of the model, and show among many others that interpersonal tasks (measured as the ratio of the importance of directness relative to caring in an occupation) are positively associated with wages. The latter relationship is of particular interest for the present discussion, because it is estimated using instrumental variables. Namely, the authors utilize two instrumental variables for interpersonal tasks. The first variable measures the change in the importance of interpersonal tasks among men, and serves as an instrument for the overall change in the importance of interpersonal tasks (1997-2001) in occupations. The second variable measures the change in interpersonal tasks between 1997 and 2001 in the workers' previous occupation (referring to the year 1997), and serves as an instrument for the difference between the workers' interpersonal tasks in 2001 and the mean interpersonal tasks in their previous occupation in 1997[12]. Both instruments are applied to the British data only, and provide results that are largely comparable to the OLS estimates in the paper.

Also Ross (2015) employs the instrumental variables approach (in combination with fixed effects) to examine the impact of occupational tasks on workers wages in the U.S. The paper is unique in that it combines panel data on individual workers with panel data on occupational task content (the latter is created from 14 versions of the O*NET database, released between 2003 and 2014)[13]. The big advantage of his panel data is that the task measures can vary both

[11] For example, Cortes (2016) and Cavaglia and Etheridge (2020) estimate the change in occupational wage premia over time relative to a base year and relative to the change in a base occupation category.

[12] Note that the authors create "synthetic" panel data on individuals by subtracting the workers' log wages and tasks measures in 2001 by the mean value of these variables in the workers' previous occupation.

[13] To our knowledge, this is the first study to generate a panel of occupational task content based on O*NET.

across and within occupations over time, and also the same workers are observed over multiple years and employment states. This allows the author to incorporate individual, occupation, and job-spell fixed effects in the model (each of which controls for a different level of unobserved heterogeneity), and still to be able to identify the effect of occupational tasks on workers wages. The inclusion of occupation/job-spell fixed effects implies furthermore that identification of the impact comes from within occupation/job-spell variation in task content over time. On the empirical side, the author constructs three instrumental variables for abstract, routine, and non-routine manual tasks and estimates a number of two-stage least squares and fixed effects wage equations. The instruments are created by interacting task measures in period t with the relative occupation-specific level of task measures in a base year (the year 2000); whereas the relative level of task measures is calculated by dividing the value of each task measure for a given occupation in 2000 by the mean value of that task measure across all occupations in 2000. The author employs the three instruments to study how changes in the abstract, routine, and non-routine manual task content of occupations affect the wages of U.S. workers. It should be noted, however, that the published version of the paper (Ross, 2017) does not contain instrumental variables estimation. The reason why we choose to discuss the 2015 paper here, is that it is one of the few works that use instrumental variables to examine the returns to tasks.

Another approach that is similar in spirit to the instrumental variables is the system GMM (see Roodman, 2009). Consoli, Vona and Rentocchini (2016) use system GMM and fixed effects regressions to study the impact of non-routine tasks on average hourly wages in 86 U.S. manufacturing industries between 1999 and 2010. The system GMM is a dynamic panel data estimation technique that is designed to deal with dynamic relationships between dependent and independent variables and models that include lagged dependent variables as regressors. An important aspect of the system GMM is that it exploits lagged values of the endogenous variables as instruments (see Roodman, 2009)[14]. Specifically, Consoli, Vona and Rentocchini (2016) estimate a series of dynamic wage equations where industry wages are regressed on past values of wages and lagged values of non-routine task-intensity, trade, and technology. The authors estimate the system GMM model for three different occupational groups (defined at the industry level), and find that non-routine tasks are positively and significantly associated with wages only for the group of high-skilled occupations, but not for the groups of medium-skilled and low-skilled occupations. Additional sensitivity analyses, based on standard fixed effects regressions (with industry fixed effects and without lagged dependent variables), show that non-routine tasks have a positive and significant effect on wages across all three occupational groups, and that the size of the effect is substantially higher for high-skilled and medium-skilled occupations than for low-skilled occupations.

Finally, before we conclude this section, it is worth referring also to the analysis of Ehrl and Monasterio (2021) who employ an instrumental variables approach to study how the spatial concentration of tasks in local labour markets affects the average wages in these labour

[14] "because the estimators [system and difference GMM] are designed for general use, they do not assume that good instruments are available outside the immediate dataset. In effect, it is assumed that the only available instruments are "internal"—based on lags of the instrumented variables" (Roodman, 2009, p.100, [own text]).

markets. The authors distinguish between five task types (non-routine analytic, non-routine interactive, routine cognitive, routine manual, and non-routine manual) and instrument the spatial concentration of these tasks by shift-share types of instruments in the spirit of Bartik (1991). Their empirical analysis is based on Brazilian micro data, and shows that a higher concentration of non-routine analytic tasks is associated with positive wage effects for all workers in the local labour market.

In sum, the instrumental variables approach is a powerful tool for estimating causal effects in the presence of endogenous regressors. Despite its many virtues, a key drawback of this technique is that its applicability in empirical research depends on the availability of valid instruments. And, as is often the case, finding valid instruments is easer said than done, and probably for this reason the IV method has not found many applications in the empirical literature on the returns to tasks. To the best of our knowledge, this is the first paper to use an instrumental variables approach to estimate the returns to routine job tasks in Germany, and it is also one of the few papers that use this method to study the returns to tasks in general.

Having said that, it should be noted that the above literature review is narrowly focused on returns to tasks, and does not cover other closely related areas of research that analyse the impact of routine tasks on computer adoption and employment growth (see e.g., Autor and Dorn, 2013), the effects of industrial robots on employment and wages (see e.g., Dauth et al., 2021; De Vries et al., 2020), the impact of immigration on the task content of native workers (see e.g., Akgündüz and Torun, 2020), the effects of occupational-mismatch/occupational intensity on individual wages (see e.g., Aepli, 2019; Bublitz, 2018), the wage impact of offshoring and how this varies with the task content of workers occupations (see e.g., Baumgarten, Geishecker and Görg, 2013), etcetera. In all these instances the authors use one or another form of instrumental variable estimation. This brings us to the conclusion that while the instrumental variables approach is rarely used in the literature on the returns to tasks, it is quite commonly used in the broader context of the task-based approach literature.

3 Empirical methods and validity of instrumental variables

This section is organized in two parts - Section 3.1 presents the empirical methods that are used to estimate the effect of routine task-intensity on wages, and Section 3.2 discusses the validity of the instruments.

3.1 Empirical methods

To examine the impact of routine tasks on wages, we regress the log hourly wages of German workers on a measure of their individual routine task-intensity and a detailed set of observable individual, job, firm and industry characteristics:

$$(1)\quad WAGE_{i,2012} = \delta_0 + \delta_1 RTI_{i,2012} + \delta_2 RTI_{occ} + \delta_3 DEM_{i,2012} + \delta_4 EDU_{i,2012} + \delta_5 EMPL_{i,2012} + \delta_6 JOB_{i,2012} + \delta_7 FIRM_{i,2012} + \delta_8 D_{i,2012} + u_{i,2012}$$

The outcome variable, WAGE, stands for the log hourly wage of survey respondent i in 2012. RTI_i is the main variable of interest and measures the individual routine task-intensity of respondent i in 2012. RTI_{occ} denotes the average routine task-intensity of worker i's occupation in that year[15]. *DEM* contains a set of standard socio-demographic characteristics such as marital status, children, health condition and migration background. *EDU* controls for level of education and measures the number of years of schooling of respondent i. *EMPL* stands for employment history and includes six variables – experience, experience squared, tenure, number of employers since first job, previous unemployment, and duration of unemployment. *JOB* controls for workplace characteristics such as job complexity, intensity of using computers at work, number of working hours, working irregular hours (outside the 7 a.m. to 7 p.m. range), working in the weekends, being on a stand-by-duty, and having a supervisory position. *FIRM* controls for firm size and includes six binary variables. *D* contains a set of location, sector and occupation-specific effects - 17 dummies for firm location, 21 dummies for sector of employment and 38 dummies for current occupation of respondents[16]. u is a random error term and δ_1- δ_8 are the parameters to be estimated. All regressions are weighted by the population weights provided in the data.

Endogeneity of RTI: One concern with the estimation of equation (1) is that RTI might be endogenous, i.e., correlated with the error term in equation (1). Endogeneity can arise as a result of omitted variables, simultaneity and measurement error and can lead to biased OLS estimates (Wooldridge, 2002)[17]. The first source of endogeneity may occur when there are unobservable factors that are related to both individual wages and RTI, and that are omitted from the model simply because they are not observable. The omission of such factors will put them into the error term of the wage equation and will cause a correlation between the error term and RTI variable. Two good examples of unobservable factors that are likely to affect both wages and RTI are workers ability and technology. Workers with higher abilities are more likely to self-select into jobs that are intensively using analytic and interactive cognitive tasks[18] (i.e., jobs with a lower RTI index), and also to earn higher wages. The same argument applies to unobserved technology. Technology affects the share of routine tasks in occupations and also the wages that individuals earn (via its effects on productivity)[19]. Failing to account for such unobservable factors can lead to (downward) biased OLS estimates[20].

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[15] RTI_{occ} is constructed at the three-digit occupation level, according to the ISCO-2008 classification system, and covers 130 occupation groups.

[16] Note that the occupation dummies are generated at the two-digit level, while RTI_{occ} is created at the three-digit ISCO-2008 level. The ISCO-2008 (International Standard Classification of Occupations, version 2008) classifies jobs into 10 major, 43 sub-major, 130 minor and 436 unit groups (see ILO, 2012b). The 38 occupation dummies in equation (1) represent the sub-major groups, which are commonly referred to as two-digit occupations because they are designated by a two-digit occupation code. We have fewer than 43 occupation dummies, because we exclude people with military occupations from the sample.

[17] The following discussion of endogeneity is based on Wooldridge (2002, Chapter 4).

[18] Cortes (2016) shows, for example, that high-ability routine workers who switch out of routine occupations are more likely to choose (non-routine) cognitive occupations, while low-ability routine workers are more likely to choose (non-routine) manual occupations.

[19] Spitz-Oener (2006) shows that between 1979 and 1999 there has been a pronounced shift from routine towards non-routine activities in German occupations. This change has been intensified by

The second source of endogeneity can arise when RTI is determined simultaneously with wages, and is partly a function of wages. One example of simultaneity is the situation where individuals choose which tasks to perform based on the expected earnings associated with different tasks. In such a case, not only will RTI affect wages, but also the wages will affect RTI through the decision of workers of whether to perform certain tasks; the causality will then run in both directions - from routine task-intensity to wages and from wages to routine task-intensity – and will cause a correlation between RTI and the error term.

Finally, endogeneity may arise also when RTI is not accurately measuring the 'true' routine task-intensity. This is a non-trivial concern given that RTI is constructed from individual survey data and is based on limited information. In this case our RTI variable can be expressed as a sum of the unobserved true routine task-intensity (RTI_{true}) and a measurement error: $RTI = RTI_{true}$ + measurement error. Because the measurement error is unobserved, it becomes part of the error term in equation (1). Whether mismeasurement will lead to endogeneity bias depends crucially on the assumptions that are made about the relationship between the measurement error, RTI and RTI_{true}. Under the classical errors-in-variables assumption, the measurement error is assumed to be independent of the unobserved true variable and correlated with the observed mismeasured variable, therefore leading to inconsistency of the OLS estimator (see Wooldridge, 2002). The other extreme assumption is that the measurement error is uncorrelated with the observed mismeasured variable (or any other variable in the model) and correlated with the unobserved true variable. Under this assumption, OLS remains a consistent estimator (see Wooldridge, 2002). Unfortunately, there is no way to tell whether and how exactly RTI and RTI_{true} are related to measurement error. Yet, it is plausible to assume that the measurement error is independent of RTI_{true}, because there are no reasons to believe that workers with certain true routine task-intensities, either low or high, are more likely to misreport their work demands (which are used to create the RTI variable). This necessarily implies that the measurement error must be correlated with the RTI variable in equation (1). Such correlations, however, are problematic for the OLS estimator. Under the classical errors-in-variables assumption, which is likely to hold in the present setting, the estimated effect of RTI on wages will be attenuated towards zero[21].

computerized technologies at the workplace, which according to Spitz-Oener, have acted as a substitute for routine and complement for non-routine tasks.

[20] The OLS estimates will be downward (negatively) biased under the assumption that the wages are positively correlated with ability and technology (Cov(Wage, Ability) > 0 and Cov(Wage, Technology) > 0) and RTI is negatively correlated with ability and technology (Cov(RTI, Ability) < 0 and Cov(RTI, Technology) < 0). However, other unobserved factors may lead to a different direction of the bias. The direction of the bias will dependent on the covariance of the omitted variables with the RTI and wages.

[21] The measurement error creates random noise around the unobserved true variable and weakens the true association between routine task-intensity and wages, therefore leading to attenuation of the RTI coefficient towards zero.

To address the above endogeneity concerns, equation (1) is estimated with OLS and instrumental variables (2SLS)[22]. The routine task-intensity of survey respondent *i* in 2012 ($RTI_{i,2012}$) is instrumented with the routine task-intensity of his father's occupation in 1979 and the routine task-intensity of his own occupation in 1979.

$$RTI_{i,2012} = \lambda_0 + \lambda_1 RTI_{j,1979} + \lambda_2 X_{i,\,2012} + \nu_{i,\,2012} \quad (2)$$

Where $RTI_{j,1979}$ denotes the two instrumental variables and X is the vector of explanatory variables included in equation (1).

The 2012 survey provides information about the occupation of the father at time when the respondents were 15 years old. Using this information, in combination with task data from the survey in 1979, we construct routine task-intensities for the fathers' occupations in 1979. The constructed instruments do not reflect actual tasks performed by the fathers or the workers, but the average routine task-intensity of their occupations in 1979.

3.2 Validity instrumental variables

To be a valid instrument, $RTI_{j,1979}$ is required to be correlated with $RTI_{i,2012}$ and uncorrelated with $u_{i,2012}$. The first condition can be easily tested – the partial correlation between the two instruments and the endogenous variable is high and statistically significant, which indicates that our instruments are relevant[23]. More complex is the second condition which requires $RTI_{j,1979}$ to be uncorrelated with $u_{i,2012}$. This is generally a non-testable condition, because it involves an error term that is unobserved. In what follows, we discuss different channels through which the validity of our instruments can be violated and provide strategies to work around them.

To fix ideas, it might be helpful to think of the error term in equation (1) as a composite variable containing worker, job, firm and macroeconomic factors that are unobserved. The exogeneity assumption will not be satisfied when there are unobserved worker characteristics that are relevant to worker i's wage in 2012 (e.g., innate ability, motivation, preferences) and these are correlated with the routine task-intensity of the father's occupation in 1979 or the routine task-intensity of the worker's own occupation in 1979. The relevant question being asked here is whether, and to what extent, the instruments might be correlated with worker *i*'s unobserved effects in 2012, once we control for a large number of individual characteristics such as education, experience, tenure, previous unemployment, duration of unemployment, number of employers since first job, family status, children, health condition and migration background. Although we cannot entirely rule out such possibility, it is reasonable to expect that such correlations would be limited. The instruments are constructed at the occupational

[22] For the 2SLS estimation we applied the user-written command "ivreg2" (Baum, Schaffer and Stillman, 2010). See Baum, Schaffer and Stillman (2007, 2003) for a discussion of the features of "ivreg2" and a comparison with "ivregress".

[23] The relevance of the instruments is not surprising; there is a large body of literature that studies the intergenerational transmission of occupations and finds that the occupational choices of children and parents are correlated (see e.g., Aina and Nicoletti, 2018; Lindquist, Sol and Van Praag, 2015; Scoppa, 2009).

level and do not reflect any actual tasks performed by the workers or the fathers in 1979[24]. This mitigates the possibility that the instruments are capturing any individual effects that might be associated with the fathers or the workers.

The second group of variables that are likely to enter the error term $u_{i,2012}$ (if not sufficiently observed in the data) are the job-related variables. Jobs are the most important determinants of the tasks that workers perform and the wages they earn[25]. To get such variables out of the error term, we include occupation fixed effects in the model (i.e., 38 occupation dummies and one occupation-specific index measuring the average routine task-intensity of worker i's occupation in 2012), as well as numerous other variables that capture the extent of computer use at work, the complexity of the job, the number of working hours per week, binary variables for having a supervisory position, working irregular hours, working on the weekends, and being on a stand-by duty. Once we control for all these job and occupation-specific factors, we assume that the routine task-intensity of the father's and the worker's occupation in 1979 are unrelated to omitted job-specific factors captured by $u_{i,2012}$.

The third group of variables that might enter $u_{i,2012}$ are the firm-related variables. Equation (1) controls for firm size, location and sector of economic activity in which the firm operates. Other factors that could influence individual wages, but are omitted from the model, are firm productivity and international trade[26]. The question being asked here again is whether these omitted variables could be correlated with our instruments. Firm productivity and foreign trade themselves are unlikely to be directly related to the routine task-intensity of the father's or the worker's occupation in 1979. Workers employed in more productive or trading firms might engage in different types of tasks than their counterparts employed in less productive domestic firms. However, such differences will be (partly) captured by the occupation fixed effects and the job-related variables in our model[27].

The final group of variables that potentially could threaten the validity of our instruments are the unobserved macroeconomic variables. Technology is the first factor that springs to mind in this respect. The link between technological change and occupations is well-established. New technologies are found to replace routine and complement non-routine

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[24] They merely reflect the 1979 level of routine task-intensity of the worker's and the father's occupations.

[25] Note that jobs and occupations are different concepts. A job is a set of tasks and duties which are performed by one worker for a particular employer or in self-employment, while an occupation is a set of jobs whose tasks and duties are highly similar (see ILO, 2012). An occupation is comprised by many jobs – two workers who have the same occupation may perform different types of tasks, depending on their jobs.

[26] There is a large body of literature on the link between firm productivity, international trade and wages (for an overview see Bernard, Jensen, Redding and Schott, 2012).

[27] To test the sensitivity of the results to omitted firm-specific variables, in Appendix D we control for four additional firm-specific variables (one variable measuring the economic situation of the firm, and three variables indicating whether the firm has relocated or outsourced firm units, merged with another firm, or strongly expanded in the past two years), and show that the estimated effect of RTI on wages is not sensitive to the inclusion of these variables in the model. The downside of this exercise, however, is that the four variables are a valid skip for some workers and their inclusion in the model leads to a significantly smaller sample size.

labour, leading to an overall decline in the share of routine tasks across and within occupations (Spitz-Oener, 2006). The question is whether past technology shocks that took place prior to 1979, and affected the task content of occupations in 1979, have long-persistent effects and are still related to current technology. If this is the case, then our instrumental variables might be correlated with (unobserved) current technology. The same argument applies to past positive shocks to wages that might have induced substitution of routine labour for machines. If such shocks tend to persist over long periods of time, then the instrumental variables will be correlated with the error term in the second-stage model.

The 33-year interval between the time when the instruments were realized and present time makes such threats to validity not very plausible. The instrumental variables go back to 1979, which is a time well before the widespread use of computers and Internet in the workplace[28]. It is, therefore, unlikely that our instruments will be related to current technology.

Even though we expect our instruments to be uncorrelated with unobserved current technology, we are sensitive to such concerns and take some further steps to limit possible links between the instruments and the error term. To this end, we include the routine task-intensity of worker i's occupation in 1979 (that is, our second instrument) as a right-hand side variable in the second-stage model, while using the routine task-intensity of the father's occupation in 1979 as an instrument. This new 'control' variable is shaped by the same technology as the father-based instrument and reflects the past impact of technology and wages on the task content of occupations in 1979. Hence, we believe that the routine task-intensity of the father's occupation in 1979 is uncorrelated with unobserved current technology, conditional on the routine task-intensity of worker i's occupation in 1979 and 2012, and the rest of the explanatory variables that we control for in the regressions[29].

Excludability instruments: The exogeneity condition implies that the instruments should not have a direct effect on wages, i.e., they must be excludable from the second-stage model. If, instead, the instruments have an independent effect on wages and are omitted from the model, then they will be absorbed into the error term and the error term will be correlated with the instruments (see Cameron and Trivedi, 2005, Sections 4.8). The most straightforward test of excludability is to include each of the instruments in turn as a right-hand-side covariate in the second-stage model, while using the other variable as an instrument. The question that we ask here is whether the routine task-intensity of the father's occupation in 1979 and the routine task-intensity of the worker's occupation in 1979 are directly and significantly related to individual wages in 2012, conditional on the rest of the explanatory variables in the model. The regression results (presented and discussed in Table 7 and A2) reveal that the two instruments are not related to individual wages in 2012 – the estimated coefficients and t-statistics are close to zero (which result holds true across different model specifications). Also

[28] As a reference, the first computers in the White House were installed in 1978 and the Internet was officially launched in 1983 (http://www.computerhistory.org/timeline). Retrieved on November 11, 2016.

[29] Analogously, we follow the same line of reasoning and repeat the same exercise also for the other instrument.

the Hansen J test of overidentifying restrictions point in the same direction – the test statistic can never reject its joint null hypothesis of instrument validity.

Overall, these exercises provide suggestive evidence that our instruments are likely to be excludable from the second-stage wage equation.

4 Data and descriptive statistics

The empirical analysis is based on data from two waves (1979 and 2012) of the German Employment Survey. It is a repeated cross-section survey administered by the Federal Institute for Vocational Education and Training (BIBB) in cooperation with the Institute for Employment Research (IAB) and the Federal Institute for Occupational Safety and Health (BAuA)[30]. The survey started in 1979 and since then it has been carried out several times (roughly once every six years). Section 4.1 describes the 2012 round of the survey, which is the primary data source for this analysis. Section 4.2 details the construction of the routine task-intensity measure. The 1979 survey, which is used for the construction of the two instruments, is discussed in Section 4.3 together with the description of the instruments.

4.1 German BIBB/BAuA Employment Survey 2012

The 2012 BIBB/BAuA Employment Survey (Hall, Siefer and Tiemann, 2015) is a representative cross-section survey among employed individuals who are 15 years or older and in paid employment for at least ten hours per week in Germany. The survey is organized around the thematic areas "work and occupation in transition" and "acquisition and utilisation of vocational qualifications" (Rohrbach-Schmidt and Hall, 2013, p.3) and provides rich information on employment status, occupational activity, job and workplace characteristics, general education and vocational qualifications, employment history, and socio-demographic characteristics. Of special interest for the present analysis is the collected data on work demands. The survey respondents are asked to indicate whether certain demands (e.g., repetitiveness of work, speed of work, pressure to perform) occur in their work and how often this happens. Section 4.2 describes further the work demands and the way we utilize them to create individual routine task-intensity scores. Of special interest for the current analysis is also the collected data on parental occupation. The survey respondents are asked about the title of the occupational activity pursued by their father (or mother, in case they did not live together with their father) at the time when they were 15 years old. Based on this information, we construct our first instrumental variable which measures the routine task-intensity of the father's occupation.

Table 1 provides summary statistics for the variables that are used in the empirical analysis (for a description of the variables, see Appendix B1). The sample is restricted to male workers who are between 18 and 65 years old, and who are in paid employment for at least 30 hours per week[31]. The sample excludes workers with military occupations, and all cases with

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[30] Until 1991 the survey was administered by BIBB and IAB, and afterwards by BIBB and BAuA (Rohrbach-Schmidt and Tiemann, 2013).

[31] This is our definition of full-time employment. Different working hours cut-offs, such as 35 or 40 hours per week, provide very similar results. The results are similar also when we restrict the

missing values on one of the variables included in the econometric model. This procedure significantly reduces the sample size, because we control for a very large number of explanatory variables. To ensure that the final sample remains representative, we weight all regressions by the population weights provided in the data. Later, in the sensitivity analysis section, we will examine the sensitivity of the results to sample selection; we will construct alternative samples with fewer explanatory variables and a much larger sample size, and will show that the estimated effects are not driven by sample selection.

sample to prime-age workers (ages 25-55). However, this comes at the cost of a smaller sample size (3,315 observations). Results are available upon request.

Table 1. Summary statistics

	Mean	**SD**
Log hourly wage	2.817241	.5136171
Years of schooling	14.67215	2.372645
Marital status (married)	.5645123	.495879
Children (yes/no)	.627262	.48359
Migration background	.0841363	.2776248
Health status (good)	.8841363	.320099
Age	45.76968	10.16403
Experience	25.33702	11.11874
Tenure	15.22914	11.32467
# employers since first job	3.516099	3.170913
Ever been unemployed (yes/no)	.2904818	.4540381
Duration unemployment (years)	.4038778	1.101425
Supervisory position (yes/no)	.4223267	.4939881
Share of time working on a computer (%)	41.0651	32.58893
Working hours per week	44.89589	8.496866
Regular working hours, 7 am - 7 pm (yes/no)	.7948296	.4038735
Working on weekends, even if occasionally (yes/no)	.7367803	.4404324
On stand-by duty (yes/no)	.2324324	.4224329
Longer working-in period required to perform activity	.8792009	.3259319
Firm size:		
1-9 persons	.1673325	.3733164
10-49 persons	.2176263	.4126804
50-99 persons	.1172738	.3217841
100-249 persons	.1410106	.3480734
250-499 persons	.1008226	.301129
500 or more persons	.2559342	.4364363
Firm location (17 dummies)		
Firm sector (21 dummies)		
Current occupation (38 dummies)		
N: 4,255 observations		

4.2 Constructing the routine task-intensity (RTI) measure

The routine task-intensity is the main explanatory variable of interest in this analysis. However, this variable is not readily available. For its construction, we select four questions from the survey that are informative about the workers' job demands and calculate individual RTI scores based on them. In our choice of questions, we are guided by the discussion of Rohrbach-Schmidt and Tiemann (2013) who provide an excellent analysis of the strengths and weaknesses of the survey when it comes to the creation of routine tasks indices. Table 2 presents the selected survey questions and shows how they are related to routine task-intensity. Survey respondents are asked to indicate whether each of the four demands occur in their work, and how frequently this happens (often, sometimes, rarely or never).

Table 2. Survey items used to construct RTI[32]

RTI	Work demands in 2012 survey
↑	Work is stipulated in minutest details (D_1)
↑	One and the same work cycle or process is repeated in minutest details (D_2)
↓	Worker facing new tasks which s/he has to think through and get familiar with (D_3)
↓	Worker has to improve existing procedures or try out something new (D_4)

Note: The work demands correspond to questions F411_02, F411_03, F411_04 and F411_05.

To calculate the individual RTI scores, first we recode the survey answers into yes (often, sometimes) and no (rarely, never) answers. We do this because the original answers (often, sometimes, rarely or never) represent an ordinal scale and do not have a numerical meaning. Then, we combine the four work requirements into a single measure of routine task-intensity. RTI increases when work is stipulated in the minutest details (D_1) and the same work is repeated in the minutest details (D_2), and decreases when workers face new tasks which they have to think through and get familiar with (D_3) and when they have to improve existing procedures or try out something new (D_4).

(3) $RTI_i = D_{1i} + D_{2i} - D_{3i} - D_{4i}$

whereas *i* stands for a survey respondent and *D* indicates the four requirements in Table 2. To assess the sensitivity of the results with respect to the definition of RTI, in the robustness analysis we generate two alternative RTI measures that are based on (i) a larger set of work requirements, and (ii) a different set of sixteen work activities.

The RTI scores range between -2 and 2, whereas a score of -2 indicates the absence of routine tasks in the work of an individual, and a score of 2 means the opposite. Figure 1

[32] Rohrbach-Schmidt and Tiemann (2013) use the same survey questions to create their measure of routine tasks.

shows the distribution of RTI for nine major occupation groups[33]. The routine scores are depicted on the x-axis, and the percentage of people associated with these scores is reported on the y-axis. The figure shows that around 70 percent of the Managers and Professionals and 50 percent of the Technicians and Associate Professionals have a negative score on RTI. This means that the people employed in these occupations perform on average more non-routine tasks than routine. On the other side, over 50 percent of the workers in Elementary Occupations and 40 percent of the Machine Operators and Assemblers are estimated to have a positive score on RTI, which may suggest that routine tasks constitute a substantial part of the tasks in these occupations. Finally, over 40 percent of the Clerical Support Workers, Services and Sales Workers, Craft and Related Trades Workers and Machine Operators and Assemblers have a 0 score on RTI – this means that the shares of routine and non-routine tasks are exactly balanced for 40 percent of the workers in these occupations.

Overall, Figure 1 shows that non-routine tasks are mostly performed by high-skilled workers, such as managers and professionals, while routine tasks are primarily done by low-skilled workers, such as those working in elementary occupations or plant and machine operation and assembly[34].

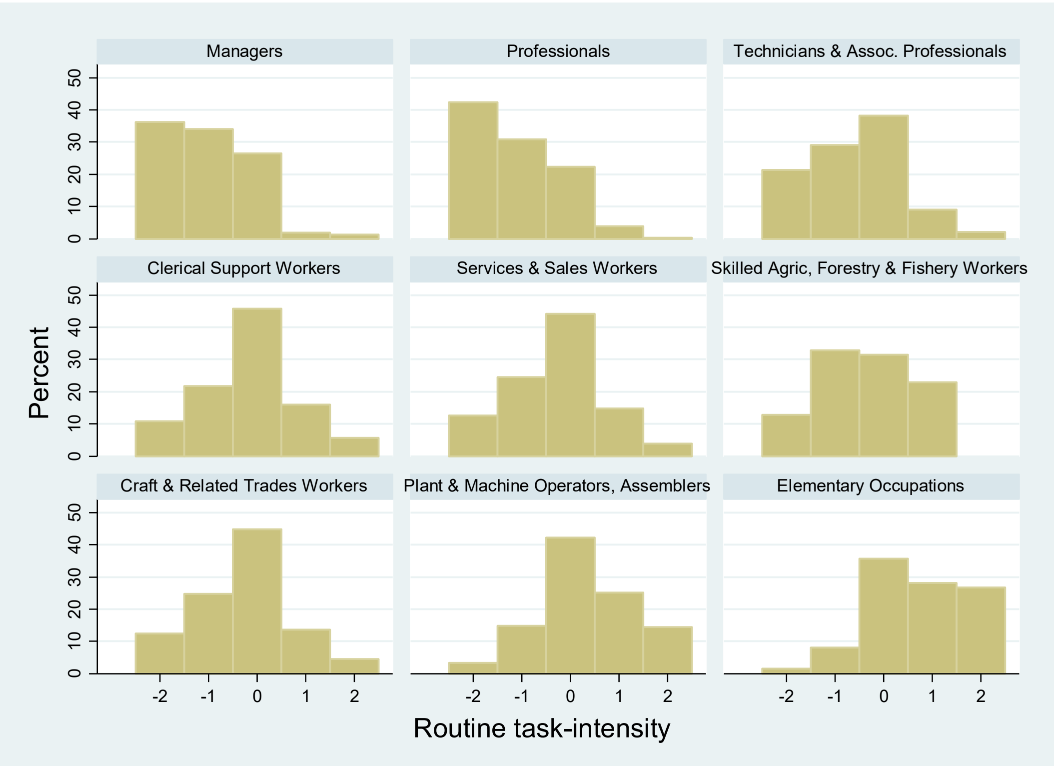

Figure 1. Distribution of RTI per major occupation group (4,255 observations)

[33] The nine major occupation groups are defined according to ISCO-2008. Military Occupations is the only major group that is not shown in the graph, because individuals with military occupations are not included in the sample.

[34] Figure A1 in the appendix depicts the mean routine task-intensity for the nine occupation groups.

Figure 2 plots the relationship between routine task-intensity and hourly wages. The five bars in the graph clearly show a negative correlation between RTI and wages - hourly wages are highest (23 euros) at the lowest level of routine task-intensity (a score of -2) and lowest (13 euros) at the highest level of routine task-intensity (a score of 2). Interestingly, Figure A2 in the appendix shows that the negative relationship between RTI and wages is also present within the nine major occupation groups – i.e., managers with lower routine task-intensities earn on average higher wages than managers who have higher routine task-intensities. The same holds true for professionals, technicians and associate professionals, clerical support workers, services and sales workers, and skilled agricultural, fishery and forestry workers. The negative correlation between wages and RTI is much weaker for craft and related trades workers, machinery operators and assemblers and elementary occupations (see Figure A2).

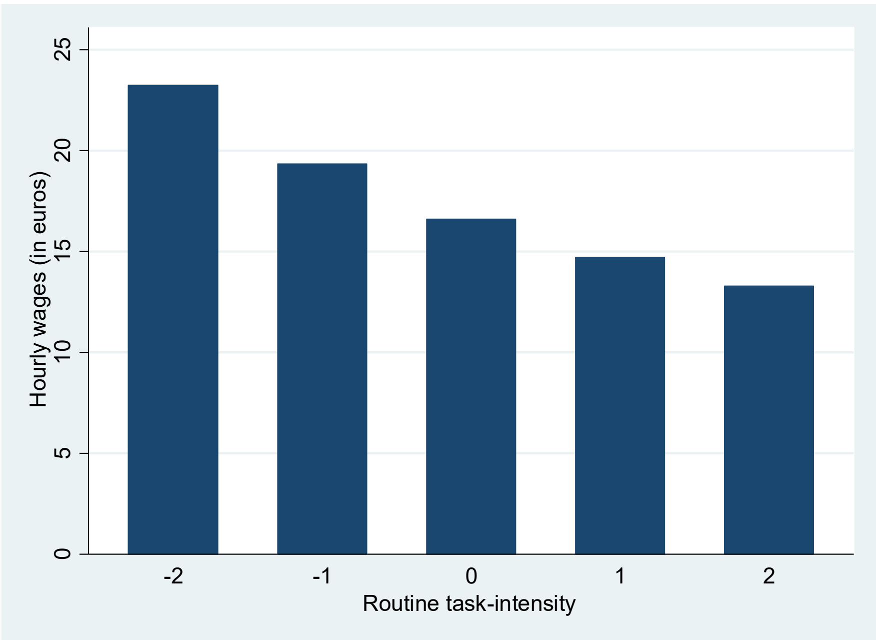

Figure 2. RTI and hourly wages (weighted, 4,255 observations)

4.3 Constructing the two instrumental variables

The 2012 survey provides information about the occupation of the fathers at the time when the workers were 15 years old. In order to construct routine task-intensity scores for the occupations of the fathers, we proceed as follows. First, based on the 1979 round of the survey (see Rohrbach-Schmidt, 2009 for a description of the survey) we calculate individual RTI scores for each participant in the survey:

(4) $RTI_{ijt} = D_{1ijt} + D_{2ijt} - D_{3ijt} - D_{4ijt}$

whereas D indicates the four requirements presented in Table 3, *i* stands for a survey respondent, *j* for occupation and *t* for the 1979 survey year. The individual RTI_{ijt} indices are then aggregated to a three-digit occupation level based on the KldB-1988 classification system, which results in 335 occupation-specific RTI measures:

(5) $RTI_{jt} = \sum_{j=1} (RTI_{ijt}) * w_{it}$

whereas RTI_{jt} stands for the average routine task-intensity of occupation *j* in 1979 and w_{it} denotes the weights given to each worker in the 1979 survey. Finally, the aggregated RTI_{jt} measures are merged with the occupation of the father in the 2012 survey[35]. The so constructed instrument reflects the routine task-intensity of the father's occupation in 1979.

To create the second instrument, we merged the occupation-specific RTI_{jt} measures from 1979 with the current occupation of survey respondents in 2012. The second instrument reflects thus the 1979 level of routine task-intensity of the current occupation of workers.

In sum, we construct two instrumental variables - one measuring the routine task-intensity of the workers' occupation in 1979 and another one measuring the routine task-intensity of the fathers' occupation in 1979[36].

Table 3. Survey items used to construct RTI_{jt} in 1979[37]

RTI	Work demands in 1979 survey
↑	Work is stipulated in minutest details (D_1)
↑	One and the same work cycle or process is repeated in minutest details (D_2)
↓	Work requires adapting to new situations (D_3)
↓	Worker has to improve existing procedures or try out something new (D_4)

Note: The work demands correspond to questions V276, V277, V269 and V262.

Figure 3 illustrates the relationship between the endogenous and instrumental variables – the first scatter plot shows the relationship between the individual RTI and the RTI of the father's occupation in 1979; the second one depicts the link between the individual RTI and the RTI of the worker's occupation in 1979; and the third one portraits the relationship between the two instruments. The fitted lines on the three scatter plots indicate that there is a positive correlation between the three variables – the pairwise correlation coefficients equal 0.18, 0.41 and 0.20, respectively.

[35] See Appendix B.2 for further details on the merging of the instrument with the occupation of the father.

[36] The instruments are calculated over a sample of workers who are between 18-65 years old, and without missing observations on occupational activity and work demands.

[37] The 1979 survey participants are asked to indicate how often each of these requirements occur in their work - always, often, sometimes, rarely or never. For the purposes of our calculation, we recode the provided answers into yes (always, often, sometimes) and no (rarely, never) answers.

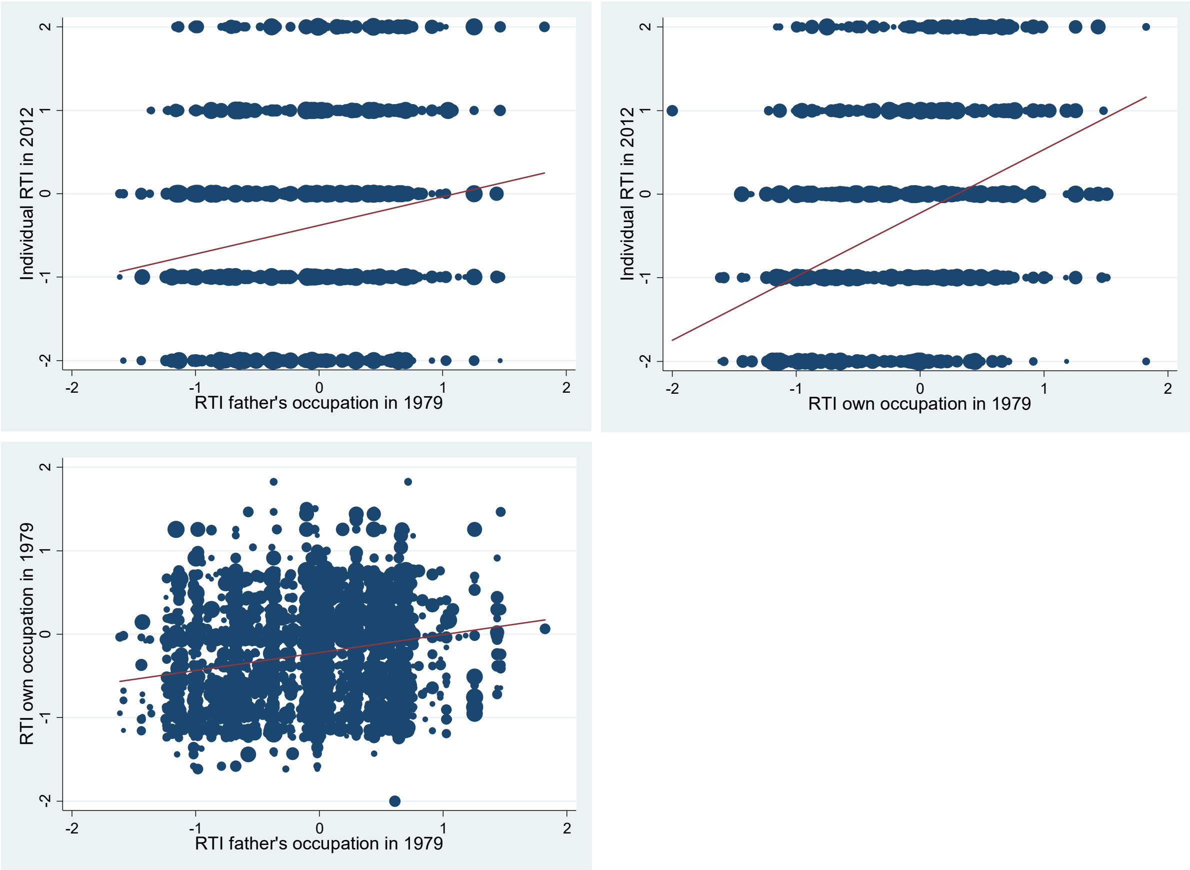

Figure 3. Correlation between endogenous and instrumental variables (weighted, 4,255 observations)

5 Empirical results[38]

This section presents the main results of the empirical analysis. Section 5.1 explores the relationship between RTI and wages using OLS regressions, while Section 5.2 and 5.3 report 2SLS estimates of the effect of RTI on wages based on the first and second instrument, respectively.

5.1 OLS estimates

Table 4 presents OLS estimates of the impact of routine task-intensity on individual log hourly wages. Each column in the table shows results from a different model specification. As a baseline, column (1) considers routine task-intensity as the only explanatory variable. The estimated coefficient is negative and highly statistically significant. However, as already discussed, the OLS estimates are likely to be plagued by endogeneity problems and therefore cannot be interpreted as causal effects. The estimated coefficient merely gives an idea about the existence of a negative correlation between routine tasks and hourly wages. The R-

[38] All Stata DO-files are available upon request from the author. Raw data is available from GESIS (Scientific Use Files: ZA5657, ZA1243). For more information on how to apply for data access see http://www.bibb.de/de/63182.htm.

squared in column (1) shows that the routine task-intensity alone explains around 8 percent of the variation in log hourly wages. Columns (2) to (5) add additional controls for demographic characteristics, level of education, employment history, job-related characteristics, as well as firm location, sector and size. The inclusion of these variables results in substantially lower estimates of the effect of RTI on wages – already in column (2) the coefficient of RTI drops to about -.05. The lower magnitude of the coefficient may suggest that omitted variables play an important role here, and that failing to account for such variables is likely to produce downward (negatively) biased OLS estimates. The explanatory variables in column (2) explain about 44 percent of the variation in log hourly wages. Column (4) presents regression results from the most extensive model specification, which controls additionally for occupation-specific effects. The regression includes 38 occupation dummies and one variable measuring the occupational routine task-intensity. The occupation dummies represent two-digit ISCO-2008 occupations, while the occupational RTI variable reflects the average routine task-intensity of 130 three-digit ISCO-2008 occupations[39]. A comparison of the coefficients and R-squared in columns (3) and (4) suggest that the occupational RTI variable has no additional explanatory power over the 38 occupation dummies – the estimates in both columns are roughly the same and the models explain approximately 50 percent of the variation in log hourly wages. The coefficient of RTI decreases slightly after the inclusion of the 38 occupation dummies in model (3) and (4), but it remains highly significant.

Table 4. OLS results log(hourly wages)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.137***	-.0518***	-.0370***	-.0370***	-.0461***
	(-16.50)	(-7.35)	(-5.47)	(-5.46)	(-6.59)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.08	0.44	0.50	0.50	0.45
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Dependent variable is log hourly wages.

Overall, the results in Table 4 show that workers with routine intensive jobs earn on average lower wages. The negative correlation between routine tasks and wages remains robustly significant across various model specifications. Remarkably, the results in columns

[39] Appendix B1 provides further details on the construction of the occupational RTI variable.

(3) and (4) find that the negative correlation is present also within the 38 two-digit occupations. Even though these results cannot be interpreted as causal effects, they suggest that there might be a causal relationship between routine tasks and wages. In the following section, we will examine further the causal effects of routine tasks on wages.

5.2 Two-stage least squares estimates first instrument

Table 5 reports the first-stage and second-stage results of the Two-Stage Least Squares (2SLS) regressions. In the second-stage, the dependent variable is the log hourly wage of German workers in 2012 and the endogenous variable is the individual routine task-intensity in 2012. The endogenous variable is instrumented with the routine task-intensity of the father's occupation in 1979. The upper panel of the table shows the first-stage results of the relationship between the instrument and the endogenous variable. The routine task-intensity of the father's occupation in 1979 is positively and significantly correlated with the individual routine task-intensity in 2012. The F-statistic on the excluded instruments is greater than 10 in three of the estimated models, which indicates that our instrument is sufficiently strong. As a rule-of-thumb, the F-statistic should be higher than 10 in order to reject the null-hypothesis of weak instruments (see Staiger and Stock, 1997)[40].

The lower panel of Table 5 presents the second-stage results for the main variable of interest, the RTI. Column (1) shows the results of the baseline model which includes routine task-intensity as the only explanatory variable. The estimated coefficient is negative and highly statistically significant, which means that routine tasks have a negative impact on individual hourly wages. Other things being equal, a one unit increase in routine task-intensity is associated with approximately 35 percent lower wages[41]. To put this estimate into perspective, consider that roughly one unit is the difference between the RTI indices of the Professionals and the Clerical support workers. The estimated coefficient of -.35 then means that if Professionals were to perform the same type of tasks as Clerical support workers, they would earn on average 35 percent lower wages, ceteris paribus[42].

Column (2) additionally controls for demographic characteristics, educational level, employment history, job-related characteristics, as well as firm location, sector and size. The included explanatory variables enter the wage equation with the expected signs. Notably, the coefficient of RTI remains largely unchanged and even increases slightly in magnitude to -.37. Column (3) explores further the role of occupations as determinants of wages and augments the model with 38 occupational dummy variables. The inclusion of the dummy variables allows us to study whether there is a negative effect of performing routine tasks on

[40] Cited in Baum, Schaffer and Stillman (2007).

[41] Strictly speaking, a one unit increase in routine task-intensity is associated with around 30 percent lower wages (exp(-0.357)-1)*100=-0.30). However, in order to keep the interpretation of the results simple and trackable we will stick to the coefficients values as shown in the table.

[42] Both occupations are quite different not only in terms of tasks, but also in terms of required skills and educational levels – e.g., for Professionals a second stage of tertiary education is required, while for Clerical support workers a secondary level of education is required (see ILO, 2012, tables 1 and 2, p.14). Also, in our sample, the Professionals have on average about 3.5 years more education than the Clerical support workers.

individual wages within occupations. The coefficient of RTI in column (3) confirms that routine tasks are negatively associated with hourly wages also within the 38 occupational groups. The size of the coefficient remains almost unchanged as compared to the previous column[43].

Table 5. Instrumental variables estimation results log(hourly wages)

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI					
RTI father's occupation 1979	.344***	.134***	.096**	.097**	.123***
	(9.68)	(4.00)	(2.96)	(2.98)	(3.72)
F-test excl. instr.	93.76	16.02	8.76	8.85	13.82
Hausman endogeneity [p]	[0.0000]	[0.0007]	[0.0073]	[0.0073]	[0.0015]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.357***	-.379**	-.376*	-.374*	-.380**
	(-6.57)	(-2.97)	(-2.18)	(-2.19)	(-2.71)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

Column (4) goes one step further and considers the occupational routine task-intensity as a potential predictor of individual wages. Differently from the 38 occupational dummies, which are aggregated at the level of two-digit occupations, the occupational RTI is constructed at the level of three-digit occupations and reflects the average routine task-intensity of 130 occupational groups. The correlation between the individual RTI and the occupational RTI is about .28. The results in column (4) show that the inclusion of the occupation-specific RTI variable in the model does not have any impact on the estimated effect of the individual RTI on wages – its coefficient remains unchanged in terms of size and significance. On the other side, the coefficient of the occupational RTI variable is close to zero and highly

[43] It might seem surprising that the negative effect of RTI on wages in model (3) is nearly as large as the effect in the rest of the models, which include no occupational dummies. However, it should be noted that RTI is constructed at the individual level and it has a high variation both within and across occupations.

insignificant[44]. To further examine the impact of the occupational RTI on individual wages, column (5) excludes the 38 occupation dummies from the model and retains the occupational RTI as the only occupation-specific variable. The estimated negative effect of RTI on wages in column (5) is very similar to the rest of the estimates in Table 5, and in particular to the estimate in column (2), which is based on a model without occupation-specific effects. As before, the coefficient of the occupational RTI is close to zero and highly statistically insignificant (results available upon request).

In sum, the results in Table 5 show that routine tasks have a negative and significant impact on individual hourly wages – on average, the more routine tasks people perform at work, the lower hourly wages they earn, other factors equal. The estimated negative effect is around 37 percent.

The validity of any instrument relies on the assumption of no correlation between instrument and error term. This essentially implies that the instrument should be excludable from the second-stage model. The excludability condition would be violated when the routine task-intensity of the father's occupation in 1979 has a direct effect on workers wages in 2012. Although such a direct connection might not seem very obvious at first glance, there is one channel through which this could happen, and this channel is the occupation of the father. The occupation of the father can potentially serve as a bridge between the instrument and the workers wages in 2012. On the one hand, fathers occupations are likely to be correlated with family income. Children who grow up in wealthy families could have better access to formal and informal education, spend more time on extracurricular activities, and eventually find jobs that better match their qualifications[45]. On the other hand, fathers occupations are also correlated with the instrument which measures the routine task-intensity of the father's occupation in 1979. The excludability condition could be violated even more so when fathers and children share the same or similar occupations, and the fathers decide to use their professional networks to help further the career of their children. Likewise, fathers with similar occupations could act as professional coaches for their children and could provide them with valuable occupational knowledge and expertise. To assure that the routine task-intensity of the father's occupation is not directly related to individual wages, we perform three specification tests. First, we generate a dummy variable that is equal to unity for workers who have the same or similar occupations as their fathers. If there are any positive effects of having the same occupation, then the coefficient of this dummy variable should be positive and statistically significant. Table 6 presents the regression results of this exercise. The coefficient of the dummy variable is not statistically significant, which indicates that workers are not benefiting from having the same occupation as their fathers[46]. The estimated effect of

[44] Results available upon request.

[45] For example, Akee et al (2010) find that a permanent increase in household income has a positive effect on children's educational attainment and criminal behavior; Maurin (2002) shows that parental income has a negative effect on the probability of being held back in elementary school; and Fletcher and Wolfe (2016) find that family income plays an important role in the formation and evolution of children's non-cognitive skills.

[46] We used the 3-digit KldB-1988 occupational codes of the workers' and the fathers' occupations to identify similar occupations. This is a natural strategy because the instruments are also constructed

RTI on wages remains very robust to the inclusion of the dummy variable – a one unit increase in individual routine task-intensity is associated with about 37 percent lower hourly wages. As a second exercise, we exclude all workers who have the same occupation as their fathers and re-estimate the model. Table A1 in the appendix reports the results – the five columns in the table, which correspond to five different model specifications, show that the coefficient of RTI is unaffected by the exclusion of these workers. Finally, we test the excludability of our instrument directly by including it as a right-hand-side variable in the wage equation. Given that we have two instruments, we are able to control for the routine task-intensity of the father's occupation in 1979 in the wage equation, while instrumenting the endogenous variable with our second instrument – that is, the routine task-intensity of the worker's own occupation in 1979. The results of this exercise are presented in Table A2 in the appendix and show that the routine task-intensity of the father's occupation in 1979 is not directly related to individual hourly wages in 2012. The coefficient of this variable is highly insignificant and close to zero, which may suggest that our instrument is excludable from the second-stage model.

Table 6. Instrumental variables estimation results log(hourly wages)

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
A. First-stage results: dependent variable is RTI					
RTI father's occupation 1979	.345***	.135***	.095**	.096**	.124***
	(9.67)	(4.01)	(2.92)	(2.94)	(3.72)
F-test excluded instruments	93.49	16.05	8.54	8.63	13.86
Hausman endogeneity [p]	[0.0000]	[0.0006]	[0.0068]	[0.0068]	[0.0014]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.361***	-.377**	-.379*	-.378*	-.379**
	(-6.67)	(-2.98)	(-2.18)	(-2.19)	(-2.73)
Same occupation as father	-0.0490	0.00833	-0.0165	-0.0166	0.00839
	(-1.00)	(0.19)	(-0.40)	(-0.40)	(0.19)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm

at the 3-digit KldB-1988 level. The results are not sensitive to using different classification systems and aggregation levels (e.g., 2-digit ISCO-2008 level) to identify similar occupations.

sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

Another concern about our instrument is that it might be affected by the available technology in 1979. If there are inter-temporal linkages between current technology and the technology in 1979, and current technology is not fully captured by the explanatory variables in the model, then the instrument might be correlated with unobserved current technology that is absorbed in the error term. To account for past technology, we include the routine task-intensity of the worker's own occupation in 1979 (i.e., our second instrument) as an explanatory variable in the model. The routine task-intensity of the worker's own occupation in 1979 is affected by the same technology that affects the instrument. By controlling for this variable, we are able to directly capture the effect of technology in 1979 on the task content of occupations in 1979 and, therefore, to reduce the possibility that our instrument is related to unobserved current technology. The results of the estimation are presented in Table 7. Overall, the table shows that the estimated RTI coefficients are robust to the inclusion of this variable. Other things equal, a one unit increase in routine task-intensity is estimated to result in about 32-39 percent lower wages. Furthermore, the results suggest that the routine task-intensity of the workers' own occupation in 1979 (our second instrument) is not directly related to individual hourly wages in 2012 – all the coefficients of this variable are statistically insignificant.

Table 7. Instrumental variables estimation results log(hourly wages)

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
A. First-stage results: dependent variable is RTI					
RTI father's occupation 1979	.189***	.114**	.097**	.097**	.111**
	(5.54)	(3.45)	(2.98)	(2.99)	(3.38)
F-test excluded instruments	30.75	11.93	8.87	8.95	11.45
Hausman endogeneity [p]	[0.0074]	[0.0017]	[0.0069]	[0.0069]	[0.0023]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.322***	-.394*	-.375*	-.374*	-.392*
	(-3.30)	(-2.56)	(-2.19)	(-2.20)	(-2.48)
RTI own occupation in 1979	-.0563	.0466	.0209	.0190	.0497
	(-0.74)	(0.61)	(0.41)	(0.38)	(0.71)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure,

number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

5.3 Two-stage least squares estimates second instrument

This section presents the regression results from our second instrument – that is, the routine task-intensity of the worker's own occupation in 1979. To add comparison and examine the robustness of the results, here we estimate the same model specifications as in Table 5. The results are reported in Table 8. The upper panel of the table shows that the second instrument is positively correlated with the endogenous variable – the estimated coefficients are all positive and highly statistically significant and the F-statistics are well above 10 in all models (and even above 500 in the first model), which indicates that we have a strong second instrument. The lower panel of the table shows that the individual RTI is negatively related to hourly wages. Other things being equal, an increase by one unit in routine task-intensity is associated with about 27-39 percent lower wages, depending on the model specification. The estimated coefficients in Table 8 are somewhat smaller in size than those in Table 5, but overall they show the same picture. When it comes to the differences, it seems that our first instrument provides more robust estimates than the second instrument. In Table 5 the coefficient of RTI remains remarkably stable across different model specifications, while in Table 8 the coefficient drops slightly (to about -.29) when we include additional control variables in the second column and onwards.

Taken together, the results in Table 5 and 8 suggest that there is a negative effect of performing routine tasks on wages and the size of the effect is largely robust to different definitions of the instrumental variable. The latter result can be seen as an indication that our instruments are not endogenous. If one or both of them were endogenous, then we would expect to find different estimates in both tables.

Table 8. Instrumental variables estimation results log(hourly wages)

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
A. First-stage results: dependent variable is RTI					
RTI own occupation in 1979	.761***	.467***	.226***	.222***	.416***
	(22.63)	(11.07)	(3.56)	(3.50)	(9.01)
F-test excluded instruments	512.08	122.46	12.70	12.25	81.18
Hausman endogeneity [p]	[0.0000]	[0.0000]	[0.0101]	[0.0099]	[0.0000]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.396***	-.294***	-.283*	-.288*	-.273***
	(-15.82)	(-7.31)	(-2.41)	(-2.41)	(-5.56)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

Another more formal test of the likely validity of our instruments is presented in Table 9. Given that our model is overidentified, i.e., we have two instruments and one endogenous variable, we are able to perform a test of overidentifying restrictions, also known as a Hansen J test. The Hansen J test tests the joint null hypothesis that both instruments are valid (uncorrelated with the error term) and correctly excluded from the estimated equation. Table 9 reports the results of the Hansen J test together with the estimated coefficients of the RTI[47]. The large p-values of the Hansen J statistic across the table indicate that the null hypothesis of joint instrument validity cannot be rejected. This gives us more confidence that our instruments are likely to be valid/exogenous. Unfortunately, the results of the Hansen J test cannot serve as a strong proof of instrument validity, because the test relies on the assumption that some of the instruments are valid and there are at least enough valid instruments to identify the equation exactly (see Murray, 2006). This assumption, however, may or may not be satisfied in practice. The test will be biased and inconsistent when too few of the instruments are valid (Murray, 2006). In our case this means that at least one of the two instruments should be valid in order for the Hansen J test to be valid and, thus, to be able to rightfully verify the joint validity of our instruments. Of course, we can never know for sure

[47] In Table 9 we use both instruments simultaneously and estimate the same model specifications as in Table 5 and 8.

whether one of our instruments is valid or not, and therefore we consider the results of Hansen J test as an indication of the likely validity of our instruments, rather than as a verification of validity.

Table 9. Instrumental variables estimation results log(hourly wages)

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI					
RTI own occupation 1979	.722***	.459***	.226***	.223***	.410***
	(20.94)	(10.82)	(3.58)	(3.51)	(8.84)
RTI father's occupation 1979	.189***	.114**	.097**	.097**	.111**
	(5.54)	(3.45)	(2.98)	(2.99)	(3.38)
F-test excluded instruments	287.59	72.63	12.21	12.02	49.90
Hausman endogeneity [p]	[0.0000]	[0.0000]	[0.0002]	[0.0002]	[0.0000]
Hansen J statistic [p]	[0.4851]	[0.4886]	[0.6539]	[0.6797]	[0.4140]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.392***	-.303***	-.317***	-.321***	-.287***
	(-16.11)	(-7.79)	(-3.34)	(-3.34)	(-6.04)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

In sum, the exogeneity of the instruments cannot be tested formally because it involves an error term that is unobserved. Even though, the above results provide some level of confidence that our instruments are likely to be valid, because: (i) the Hansen test of over-identifying restrictions never rejects its null hypothesis of instrument validity, (ii) the instruments are never significant when included as an explanatory variable in the second-stage model, and (iii) the instrumental variable estimates are robust to the inclusion of additional covariates in the model. If our instruments were endogenous, i.e., correlated with the error term, then the estimated effect would have changed every time when we took variables out of the error term and included them as explanatory variables in the model. The fact that the instrumental variable estimates of the effect of RTI on wages remained stable across different model specifications provides suggestive evidence that the instruments are not correlated with the error term.

6 Sample selection

The presented results so far are based on a sample of 4,255 full-time male workers, who (i) have no missing values for all the variables included in the econometric analysis, and (ii) have lived together with an employed father during their childhood. The first restriction is self-explanatory and aims to assure that we have the same number of observations across different model specifications, which facilitates the comparison of results. The second restriction aims to assure that we retain only cases with observed father's occupation. Our empirical strategy relies on the occupation of the father for the construction of the first instrument, and therefore we exclude all workers for whom the occupation of the father is unknown. These are workers who either did not grow up together with a father or workers whose father was unemployed. Both restrictions, however, can lead to a selective sample.

To examine the sensitivity of results to sample selection, in this section we relax both sample restrictions and create an alternative and larger sample of full-time male workers with non-missing data on wages, occupation and the four work requirements that are used to create the individual RTI measure[48]. This results in a new sample of 6,876 observations, which is around 38 percent higher than our original sample and which also includes individuals with unknown father's occupation.

Table 10 presents two-stage least squares estimates of the effect of RTI on wages based on the new sample. The individual routine task-intensity is instrumented with our second instrument – that is, the routine task-intensity of the worker's own occupation in 1979. This makes the results in Table 10 directly comparable to those in Table 8 – the only difference between both tables is the size of the sample. Furthermore, in our attempt to impose as little restrictions on the sample as possible, in Table 10 we allow the number of observations to vary per column, depending on the number of explanatory variables included in the model.

The estimates in Table 10 show that RTI has a negative and significant impact on individual hourly wages – a one unit increase in RTI is associated with approximately 30-39 percent lower wages. The coefficients in Table 10 are very similar (and even slightly higher in absolute terms) to those in Table 8, where the negative effect of RTI on wages is estimated to be around 27-39 percent. Overall, the results of the sensitivity analysis suggest that our baseline estimates are not driven by sample selection, either due to the inclusion of too many control variables and the resulting small sample size, or due to the exclusion of workers with unknown father's occupation.

[48] This is the minimum information that is required to estimate the effect of RTI on wages using instrumental variables.

Table 10. Instrumental variables estimation results log(hourly wages) – larger sample

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI					
RTI own occupation in 1979	.740***	.439***	.211***	.209***	.385***
	(27.81)	(12.93)	(4.09)	(4.04)	(10.30)
F-test excluded instruments	773.33	167.29	16.71	16.34	106.04
Hausman endogeneity [p]	[0.0000]	[0.0000]	[0.0038]	[0.0041]	[0.0000]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.394***	-.317***	-.303**	-.303*	-.301***
	(-18.44)	(-7.66)	(-2.58)	(-2.55)	(-5.91)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	6,876	6,194	6,141	6,141	6,141

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, tenure, number of employers since first job, previous unemployment and duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, stand-up duty, working with computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

A closer inspection of the data shows that individuals who lived together with an employed father have on average a higher level of education and income, and perform less routine tasks than those who grew up without a father or had an unemployed father (results available upon request). This suggests that there might be systematic differences between both groups. To examine the role of heterogeneity for the estimated results, in Table 11 we consider only those workers who did not live together with their father or who lived together with an unemployed father[49]. The results in columns (1), (2) and (5) of Table 11 confirm once again that the performance of routine tasks at work has a negative and significant impact on wages – an increase by one unit in RTI leads to approximately 28-31 percent lower wages for the workers who did not lived together with their father or whose father was unemployed. The estimates in columns (3) and (4), which additionally control for 38 occupational dummies, are not statistically significant. It is worth noting here that the F-statistic, which measures the strength of the instrument, is very low in these models and this makes the results in columns (3) and (4) less reliable.

[49] A further splitting of the sample is not meaningful due to the small number of workers with an unemployed father (71 observations or around 1 percent of the sample). This means that the results in Table 11 are practically driven by the workers who did not live together with their father.

In sum, the results of the sensitivity analyses show that the estimated negative effect of RTI on wages is largely robust to different definitions of the sample.

Table 11. Instrumental variables estimation results log(hourly wages) – workers did not live together with fathers or had unemployed fathers

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI					
RTI own occupation in 1979	.793***	.488***	.274*	.286*	.382***
	(13.56)	(6.54)	(2.25)	(2.38)	(4.55)
F-test excluded instruments	183.93	42.73	5.08	5.65	20.66
Hausman endogeneity [p]	[0.0000]	[0.0052]	[0.5504]	[0.6047]	[0.0392]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.314***	-.295**	-.139	-.123	-.287*
	(-6.56)	(-3.09)	(-0.72)	(-0.67)	(-2.18)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	1,206	1,066	1,052	1,052	1,052

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

7 Alternative definition routine task-intensity measure

This section examines the sensitivity of the estimated effect to alternative definitions of the routine task-intensity variable. Section 7.1 presents a broader version of the original RTI variable that is based on six work requirements instead of four, and Section 7.2 introduces an entirely different measure of routine task-intensity that is based on information about the frequency of performing sixteen work activities by survey respondents.

7.1 Alternative definition routine measure – RTI1

One potential criticism of the original RTI variable might be that it is created on the basis of a handful of work requirements. To address this concern, here we expand the set of work requirements from four to six and calculate the new routine task-intensity measure (RTI1) as follows:

(6) $RTI1_i = D_{1i} + D_{2i} - D_{3i} - D_{4i} - D_{5i} - D_{6i}$

As compared to the original RTI, RTI1 contains two additional work requirements - D_5 and D_6, whereas D_5 indicates whether the worker is expected to do things s/he has not learned and D_6 indicates whether the worker has to keep an eye on different work processes or sequences at the same time. As before, the work requirements are re-coded to take on values 0 (rarely, never) and 1 (often, sometimes). Hence, an affirmative answer to D_5 and D_6 by the survey respondents leads to a lower routine task-intensity index[50].

As for the construction of the instruments, we follow the same logic and select the same work requirements from the 1979 survey[51]. Furthermore, the instruments are computed as described in Section 4.2.

Table 12 reports two-stage least squares estimates of the effect of RTI1 on individual hourly wages based on the new instrument – that is, the routine task-intensity (RTI1) of the father's occupation in 1979. The coefficients in columns (1) to (5) show that RTI1 has a negative and significant impact on wages, and the size of the effect is quite robust across different model specifications – a one unit increase in routine task-intensity is estimated to result in about 28-29 percent lower wages, other things being equal. The coefficients in Table 12 are slightly smaller than those in Table 5, where the impact of RTI on wages is found to be around 35-37 percent, but overall they paint the same picture. This comes as no surprise, however, because RTI and RTI1 are highly correlated (the correlation coefficient is about .88) and so are the original and the new instrument (the correlation coefficient is about .98).

In the next section, we assess the sensitivity of the results to an entirely different definition of the routine task-intensity variable.

[50] RTI1 corresponds directly to the job complexity index of Antonczyk, Fitzenberger and Leuschner (2009), who utilize the same survey items for the construction of their index. Both measures represent two opposite concepts, however, and the work requirements carry opposite signs in the calculation of both indices.

[51] The 1979 survey does not have a comparable question to D_5, therefore we calculate the instruments from the answers to D_1, D_2, D_3, D_4 and D_6.

Table 12. Instrumental variables estimation results log(hourly wages)

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
A. First-stage results: dependent variable is RTI1					
RTI1 father's occupation 1979	.364***	.144***	.108**	.108**	.132***
	(9.38)	(3.93)	(3.05)	(3.06)	(3.65)
F-test excl. instr.	87.97	15.46	9.29	9.36	13.30
Hausman endogeneity [p]	[0.0000]	[0.0004]	[0.0058]	[0.0058]	[0.0010]
B. Second-stage results: dependent variable is log hourly wages					
RTI1	-.282***	-.295**	-.279*	-.277*	-.295**
	(-6.45)	(-2.93)	(-2.21)	(-2.22)	(-2.67)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

7.2 Alternative definition routine measure – RTI2

The original RTI measure is constructed from the answers of survey respondents about the frequency of (i) their work being stipulated in the minutest details, (ii) repeating the same work cycle in the minutest details, (iii) facing new tasks which they have to think through and get familiar with, and (iv) improving existing procedures or trying out something new. One potential concern with this definition of RTI is that it might not capture routine task-intensity, but rather some common features of low-paying jobs that are unrelated to routinization. Looking at Figure A1 in the appendix, it shows that RTI is highest for workers with Elementary Occupations and Plant and Machine Operators and Assemblers, which are also the occupations with the lowest levels of education in our sample. This raises the question of what exactly the RTI variable is measuring. To tackle these concerns, here we introduce an alternative measure of routine task-intensity (RTI2) that is based on the frequency of performing sixteen work activities by survey respondents. The sixteen work activities are characteristic for the BIBB/BAuA survey and have been widely used for the construction of routine task indices (see e.g., Spitz-Oener, 2006; Antonczyk, Fitzenberger and Leuschner, 2009; Gathmann and Schönberg, 2010).

We proceed as follows. Following Spitz-Oener (2006), we classify the sixteen work activities into five routine categories (non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual) and calculate the share of tasks performed by each worker in each category[52]. Then, we combine the five individual routine task indices into a single composite measure of routine task-intensity, RTI2:

(7) $RTI2_i = RC_i + RM_i - NRA_i - NRI_i - NRM_i$

where RC, RM, NRA, NRI and NRM stand for routine cognitive, routine manual, non-routine analytic, non-routine interactive and non-routine manual tasks, respectively, *i* denotes survey participants, and RTI2 indicates our new measure of routine task-intensity. The correlation between RTI2 and the original RTI variable is about 0.26.

Table 13 presents two-stage least squares regression results based on RTI2 and the two original instruments used in Section 5[53]. The estimates in column (1) are based on the first instrument (i.e., the routine task-intensity of the father's occupation in 1979) and those in columns (2) – (6) are based on the second instrument (i.e., the routine task-intensity of the worker's own occupation in 1979)[54]. The first-stage results in Table 13 show that the instruments are sufficiently correlated with RTI2 – the F-statistic on the excluded instruments is above 10 in all models. The second-stage results find that RTI2 is negatively and significantly associated with log hourly wages – for every one unit increase in RTI2, the hourly wages decrease by about 41-65 percent, other things equal. To put the size of the estimated effect into perspective, consider that approximately one unit is the difference between the RTI2 indices of Teaching Professionals and Refuse Workers and Other Elementary Workers, and between the RTI2 indices of Health Professionals and Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers. Furthermore, a comparison of the coefficients in column (1) and (2) shows that both instruments provide very similar results.

Taken together, the results in Table 13 confirm once again that the performance of routine tasks at work leads to lower hourly wages.

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[52] See Appendix A.2 for further details.

[53] We made an attempt to create an alternative instrument that is based on the work activities included in the 1979 survey. However, this turned out to be challenging, because there are more than 120 work activities in the 1979 survey and sometimes multiple activities are included in the same question, which complicates the classification of activities and the computation of the five routine indices (see Rohrbach-Schmidt and Tiemann, 2013 for an excellent discussion of the survey).

[54] The first instrument is sufficiently correlated with RTI2 only in column (1), which includes RTI2 as the only explanatory variable. However, when we add additional control variables to the model, the F-statistic on the excluded instrument drops to very low levels (results available on request), which makes the interpretation of the estimated effects not meaningful. For this reason, in columns (2) – (6) we report the results from the second instrument, which is sufficiently correlated with RTI2.

Table 13. Instrumental variables estimation results log(hourly wages)

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
A. First-stage results: dependent variable is RTI2						
RTI own occupation 1979	-	.484***	.251***	.152***	.157***	.188***
		(19.76)	(8.37)	(3.78)	(3.93)	(5.94)
RTI father's occupation 1979	.187***	-	-	-	-	-
	(7.37)	-	-	-	-	-
F-test excluded instruments	54.28	390.59	69.99	14.28	15.47	35.30
Hausman endogeneity [p]	[0.0000]	[0.0000]	[0.0000]	[0.0050]	[0.0051]	[0.0000]
B. Second-stage results: dependent variable is log hourly wages						
RTI2	-.658***	-.622***	-.548***	-.424*	-.411*	-.603***
	(-5.46)	(-13.29)	(-6.43)	(-2.49)	(-2.52)	(-4.59)
Control variables[1]	-	-	yes	yes	yes	yes
38 occupation dummies	-	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	-	yes	yes
N	4,236	4,236	4,236	4,236	4,236	4,236

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

8 Comparison of OLS and 2SLS estimates, and heterogenous effects of RTI

In this section, we briefly address two issues that have not been discussed yet – the first issue is the different size of the estimated negative effect produced by OLS and 2SLS (Section 8.1), and the second issue is the possible heterogenous effect of RTI on wages across different occupations (Section 8.2).

8.1 Why are the 2SLS estimates bigger than the OLS estimates?

Comparing the results in Table 5 and Table 4 shows that the 2SLS estimates are larger in magnitude than their OLS counterparts. Naturally, the question arises whether OLS underestimates or 2SLS overestimates the 'true' effect of RTI on wages. As discussed in Section 3, in the presence of random measurement errors the OLS coefficients will be attenuated towards zero. The fact that OLS produces smaller estimates than 2SLS might suggest that the attenuation bias induced by random measurement errors outweighs the downward bias induced by omitted variables and simultaneity. To get a rough idea about the importance of random measurement error, we aggregate the RTI variable to a three-digit occupation level (according to ISCO-2008) and re-estimate the five models in Table 4 with the aggregated RTI variable[55]. Aggregation is expected to reduce random measurement error because it averages out positive and negative errors within each occupation group. Table 14 presents the regression results and shows that aggregation yields much higher OLS estimates of the effect of routine task on wages. As compared to Table 4, the estimated effects in Table 14 are almost three times larger in magnitude in column (1) and nearly four times larger in magnitude in column (5), which brings them much closer to the 2SLS estimates. This provides speculative evidence that random measurement error indeed attenuates the OLS coefficients towards zero and that the latter bias possibly outweighs the downward biases due to omitted variables and simultaneity. Another possibility, which we have already examined in the previous sections, is that our instruments are endogenous and the 2SLS estimates are biased. As already argued, such endogeneity/bias is not very likely to occur in the present setting because we control for a large number of covariates in the 2SLS regressions and it can therefore be reasonably assumed that our instruments are at least conditionally exogenous. Also, the fact that the 2SLS estimates are robust to alternative model specifications can be seen as a support for the exogeneity of the instruments[56].

Table 14. OLS results log(hourly wages)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Aggregated RTI	-.364***	-.175***	-.0719	-.0725	-.155***
	(-20.48)	(-9.48)	(-1.93)	(-1.93)	(-7.82)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.15	0.45	0.50	0.50	0.46
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics

[55] The individual RTI is aggregated to a three-digit occupation level using population weights; and the aggerated variable is linked to the three-digit occupation code (ISCO-2008) of survey respondents. Please note that the aggregated RTI variable is different than RTI_{occ} which is used throughout the analyses and which is based on Acemoglu and Autor (2011). The aggregated variable here is used only in this section, and its sole purpose is to shed more light on how aggregation impacts the size of the OLS estimates. The aggregated RTI is calculated over the sample of 4,255 observations used in Table 4 and throughout the paper.

[56] A similar line of reasoning is followed by Acemoglu, Johnson and Robinson (2001, see footnote 24), who gradually add additional control variables to their model to assess the importance of omitted variables for the estimates of interest.

(job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Dependent variable is log hourly wages.

Finally, before we move on to the next section, it is also worth looking at whether the newly aggregated RTI variable has any effect on the 2SLS estimate of interest. To examine this, we include the aggregated RTI variable as an additional covariate in the 2SLS regression and re-estimate the five model specifications in Table 5. The regression results show that the inclusion of this variable does not lead to any significant change in the estimated effect of interest – the coefficient of the individual RTI variable remains largely unchanged in three of the estimated models (corresponding to column 1, 3 and 4 in Table 5) and increases slightly in magnitude in two of the models (corresponding to column 2 and 5 in Table 5). Results are available upon request.

8.2 Heterogenous effects of RTI on wages across occupations

Looking once again at Figure A2 in the appendix, it shows that the negative relationship between routine tasks and wages is most pronounced for the occupations of Managers, Professionals, Technicians and Associate Professionals, Clerical Support Workers and Skilled Agricultural, Forestry and Fishery Workers, and it is much less pronounced for the occupations of Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, and Elementary Occupations. This suggests that routine tasks might have a different impact on individual wages across different occupations, and that the law-of-one price might not apply to the returns to routine tasks[57]. To examine this possibility, here we depart from the implicit assumption of one constant price of tasks across all occupations, and allow the returns to tasks to vary by occupation.

Ideally, we would want to estimate the returns to routine tasks for each (major) occupation group separately using the method of 2SLS, but unfortunately this is not possible because the value of the F-statistic (which measures the strength of the instruments) drops to very low levels already in model (1), which includes RTI as the only covariate, and this makes the interpretation of the 2SLS results not meaningful. Therefore, we return once again to the method of OLS and estimate the returns to routine tasks for each occupation group separately using OLS. We distinguish between nine major ISCO-2008 occupation groups – Managers, Professionals, Technicians and Associate Professionals, Clerical Support Workers, Services and Sales Workers, Skilled Agricultural, Forestry and Fishery Workers, Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, and Elementary Occupations[58]. The regression results are presented in Tables C1-C9 in Appendix C.

[57] Autor and Handel (2013) argue, for example, that due to indivisible bundling of tasks within occupations, the productive value of tasks will not necessarily be equated across occupations, and the law-of-one price will not generally apply to the rewards to tasks.

[58] As already noted in Footnote 16, the ISCO-2008 system distinguishes between 10 major occupation groups – i.e., the nine occupation groups here plus Commissioned Armed Forces Officers.

Based on the results in the tables, two points can be made. First, the impact of routine tasks on individual wages is not uniform across occupations. The RTI measure is negatively and significantly related to individual wages in the occupations of Managers, Professionals, Skilled Agricultural, Forestry and Fishery Workers, and Plant and Machine Operators and Assemblers, while it is not significantly related to individual wages in the rest of the occupations. The estimated negative effect is remarkably robust across different model specifications (see Tables C1, C2, C6, C8). Second, looking at the value of the R-squared, it shows that there are big differences in the size of the R-squared across the nine tables. This indicates that RTI has different explanatory power, and explains different portions of the variation in wages in different occupations. For example, the RTI variable alone explains about 13 percent of the variation in wages of Skilled Agricultural, Forestry and Fishery Workers, 7 percent of the variation in wages of Managers, and 1 percent of the variation in wages of Professionals (see column (1) in Tables C6, C1, C2).

Taken together, the results in Tables C1-C9 indicate that routine tasks have heterogenous effects on wages across different occupations. The negative effects of routine tasks on wages seem to be stronger in high-skill occupations such as Managers, Professionals, and Skilled Agricultural, Forestry and Fishery Workers, and routine-intensive occupations such as Plant and Machine Operators and Assemblers.

To elaborate further on the heterogenous effects of RTI on wages, we proceed here by grouping the nine major occupations into various groups and estimating the returns to routine tasks for the various groups using 2SLS. To this end, we use the results in Figure A1 and A2 as a basis for assigning occupations into groups. First, based on Figure A1, we divide the nine major occupations into three groups of three occupations – the first group includes the least routine-intensive occupations (Managers, Professionals, Technicians and Associate Professionals), the second group includes the middle routine-intensive occupations (Services and Sales Workers, Skilled Agricultural, Forestry and Fishery Workers, Craft and Related Trades Workers), and the third group includes the most routine-intensive occupations (Clerical Support Workers, Plant and Machine Operators and Assemblers, Elementary Occupations)[59]. Second, based on Figure A2, we divide the nine major occupations into two groups – the first group contains high-skilled and clerical occupations for which the graph shows that there is a strong relationship between RTI and wages (Managers, Professionals, Technicians and Associate Professionals, Clerical Support Workers, Skilled Agricultural, Forestry and Fishery Workers), and the second group contains the rest of occupations for which the graph shows that there is no a strong relationship between RTI and wages (Services and Sales Workers, Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, Elementary Occupations)[60]. Tables C10-C13 present the regression results of this exercise – the results in Table C10 and C11 are based on the first instrument (i.e., RTI of the father's occupation in 1979), while those in Table C12 and C13 are based on the second instrument (i.e., RTI of the worker's own occupation in 1979).

[59] Assigning the Clerical Support Workers to the group of the middle routine-intensive occupations does not change the results.

[60] Moving the Skilled Agricultural, Forestry and Fishery Workers to the second group of occupations does not change the results.

A quick glimpse at the four tables reveals that the F-statistic on the excluded instruments is far below 10 in most of the columns, which makes the results in these columns not interpretable. Nevertheless, there are several columns in which the F-statistic is larger or close to 10, and based on the results in those columns we can make some inferences about the heterogenous effects of RTI on wages. The first finding that emerges from the tables is that routine tasks are negatively (and significantly) associated with individual wages in the group of Managers, Professionals, Technicians and Associate Professionals (see columns 1 and 2 of Table C10 and C12), and the group of Managers, Professionals, Technicians and Associate Professionals, Clerical Support Workers, Skilled Agricultural, Forestry and Fishery Workers (see columns 1 and 2 of Table C11 and C13). The second finding is that routine tasks are not significantly associated with individual wages in the group of Clerical Support Workers, Plant and Machine Operators and Assemblers, Elementary Occupations (see columns 5 and 6 of Table C10 and C12), and the group of Services and Sales Workers, Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, Elementary Occupations (see columns 3 and 4 of Table C11 and C13).

One conclusion that we can safely draw from these results is that routine tasks seem to have heterogenous effects on wages across different occupations, and that the negative effect of routine tasks on wages is found mostly in high-skilled non-routine occupations such as Managers, Professionals, and Technicians and Associate Professionals. Regarding the Clerical Support Workers and the Skilled Agricultural, Forestry and Fishery Workers, we cannot draw any clear conclusion about the impact of routine tasks on wages in these occupations, because we find different results for the different groups in which these occupations are included (e.g., for Clerical Support Workers see columns 5 and 6 of Table C10 and C12 versus columns 1 and 2 of Table C11 and C13; and for Skilled Agricultural, Forestry and Fishery Workers see columns 3 and 4 of Table C10 and C12 versus columns 1 and 2 of Table C11 and C13).

In sum, the results of both the OLS and 2SLS regression analyses show that there are heterogeneities in the impact of RTI on wages.

9 Conclusions and discussion

This paper builds on the task-based approach literature by studying the relationship between routine job tasks and workers wages. Using nationally representative survey data from Germany, the paper finds that routine job tasks are negatively and significantly associated with workers wages. For every one unit increase in routine task-intensity the workers wages are estimated to decrease by about 28-39 percent, other things being equal. The relationship between routine tasks and wages is examined using both ordinary least squares and instrumental variables. The instrumental variables approach takes into account the endogeneity of the routine job tasks variable and provides the conditions under which the effect of routine tasks on wages can be estimated consistently. Namely, that there should be an instrumental variable that is correlated with the endogenous variable and uncorrelated with the error term in the wage equation. Although finding such an instrument is quite challenging, the current analysis presented two variables that potentially meet the conditions for being valid instruments, and used them as instruments for the individual routine task-intensity of German workers in 2012. The two variables were the routine task-intensity of the father's occupation in 1979 and the routine task-intensity of the worker's own occupation in 1979. The analysis assumed that both instruments are exogenous and excludable from the second-stage wage equation, conditional on a very detailed set of individual, job, firm, industry and occupation-specific variables (the set of control variables included, among many others, occupational dummies and the average routine task-intensity of the worker's occupation in 2012). Even though we could not entirely rule out the possibility that our instruments are correlated with omitted variables in the error term of the wage equation, we presented suggestive evidence that such correlations, if they existed, would be limited. Part of this suggestive evidence was the observation that the estimated negative effect of routine tasks on wages is not sensitive to different model specifications, different definitions of the endogenous and instrumental variables, and also the fact that the Hansen J test never rejected its null hypothesis of instrument validity. Based on the results of the instrumental variable estimation, we concluded that there is a negative relationship between routine tasks and wages.

The most important contribution of this paper to the literature is that it uses instrumental variables to estimate the causal effects of routine tasks on wages in Germany. To our knowledge, this approach has not been used previously in the current context (that is, to examine the returns to tasks in Germany); the fact that this has not been done underscores the difficulty of finding "instruments which credibly affect task choices but not potential wages" (Böhm, 2020, p. 778).

When it comes to the limitations of the paper, it is important to note that the presented results here are based on instrumental variables estimation, and therefore hinge on the assumption of instrument validity. This is a hard to test assumption which may or may not hold. Furthermore, it is well-known that instruments that are based on family characteristics are far from perfect, as they can be correlated with various observable and unobservable characteristics of family members. Despite these limitations (of the instrumental variable approach in general, and our two instruments in particular), we believe that the current analysis provides a valuable insight into the impact of routine job tasks on workers wages. The ideal econometric setting for this analysis would be the situation where workers are randomly assigned into occupations and tasks, and there is no selection on observables or unobservables. However, such an experimental design is generally not feasible in the current context. This makes the method of instrumental variables the next best alternative for studying the returns to routine tasks. As Murray (2006) points out, "all instruments arrive on the scene with a dark cloud of invalidity hanging overhead. This cloud never goes entirely away, but researchers should chase away as much of the cloud as they can" (p.114). This is what we tried to do in this paper.

References

Acemoglu, D. and D. Autor (2011), Skill, Tasks and Technologies: Implications for Employment and Earnings, In: Ashenfelter, O., Card, D. (Eds.), *Handbook of Labor Economics*, vol. 4b, 1043-1171, Amsterdam: Elsevier.

Acemoglu, D., S. Johnson and J.A. Robinson (2001), The Colonial Origins of Comparative Development: An Empirical Investigation, *American Economic Review*, 91 (5), pp. 1369-1401.

Aepli, M. (2019), Technological change and occupation mobility: A task-based approach to horizontal mismatch, GLO Discussion Paper, No. 361, Global Labor Organization (GLO), Essen.

Agasisti, T., G. Johnes and M. Paccagnella (2021), Tasks, occupations and wages in OECD countries, *International Labour Review*, 160 (1), pp. 85-111.

Aina, C. and C. Nicoletti (2018), The intergenerational transmission of liberal professions, *Labour Economics*, 51, pp. 108–120.

Akee, R., W. Copeland, G. Keeler, A. Angold and E. Costello (2010), Parents' Incomes and Children's Outcomes: A Quasi-Experiment Using Transfer Payments from Casino Profits, *American Economic Journal: Applied Economics*, 2(1), pp. 86–115.

Akgündüz, Y. and H. Torun (2020), Two and a half million Syrian refugees, tasks and capital intensity, *Journal of Development Economics*, 145, pp. 1-16. https://doi.org/10.1016/j.jdeveco.2020.102470.

Antonczyk, D., B. Fitzenberger and U. Leuschner (2009), Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?, *Jahrbucher Fur Nationalokonomie Und Statistik*, 229(2+3), pp. 214–238.

Autor, D. (2013), The "task approach" to labor markets: an overview, *Journal of Labour Market Research*, 46 (3), pp. 185–199, DOI 10.1007/s12651-013-0128-z.

Autor, D. and D. Dorn (2013), The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market, *American Economic Review*, 103(5): 1553–1597.

Autor D. and M. Handel (2013), Putting Tasks to the Test: Human Capital, Job Tasks and Wages, *Journal of Labor Economics*, 31 (2), pp. S59-S96.

Bartik, T. J. (1991), Who benefits from state and local economic development policies?, Kalamazoo, MI: WE Upjohn Institute for Employment Research.

Baum, C.F., M.E. Schaffer and S. Stillman (2010), IVREG2: Stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class regression, Statistical Software Components S425401, Boston College Department of Economics, http://ideas.repec.org/c/boc/bocode/s425401.html.

Baum, C.F., M.E. Schaffer and S. Stillman (2007), Enhanced routines for instrumental variables/Generalized method of moments estimation and testing, *Stata Journal*, 7(4), pp. 465-506.

Baum, C.F., M.E. Schaffer and S. Stillman (2003), Instrumental variables and GMM: Estimation and testing, *Stata Journal*, 3(1), pp. 1-31.

Baumgarten, D., I. Geishecker and H. Görg (2013), Offshoring, tasks, and the skill-wage pattern, *European Economic Review*, 61, pp. 132–152.

Bernard, A., J. Jensen, S. Redding and P. Schott (2012), The Empirics of Firm Heterogeneity and International Trade, *Annual Review of Economics*, 4, pp.283-313.

Böhm, M. (2020), The price of polarization: Estimating task prices under routine-biased technical change, *Quantitative Economics*, 11 (2), pp. 761–799.

Böhm, M., H.M. von Gaudecker and F. Schran (2019), Occupation Growth, Skill Prices, and Wage Inequality, CESifo Working Paper 7877.

Borghans, L., B. ter Weel and B. A. Weinberg (2008), Interpersonal Styles and Labor Market Outcomes, *Journal of Human Resources*, 43 (4), pp. 815-858.

Bublitz, E. (2018), Matching skills of individuals and firms along the career path, *Oxford Economic Papers*, 70(2), pp. 509–537. doi: 10.1093/oep/gpx056.

Cameron, A.C. and P.K. Trivedi (2005), *Microeconometrics: Methods and Applications*, Cambridge University Press, New York.

Cassidy, H. (2017), Task Variation Within Occupations, *Industrial Relations: A Journal of Economy and Society*, 56 (3), pp. 393-410. https://doi.org/10.1111/irel.12179.

Castellano, K., S. Rabe-Hesketh and A. Skrondal (2014), Composition, Context, and Endogeneity in School and Teacher Comparisons, *Journal of Educational and Behavioral Statistics* , 39 (5), pp. 333-367.

Cavaglia, C. and B. Etheridge (2020), Job polarization and the declining quality of knowledge workers: Evidence from the UK and Germany, *Labour Economics*, 66. https://doi.org/10.1016/j.labeco.2020.101884.

Consoli, D., F. Vona and F. Rentocchini (2016), That was then, this is now: skills and routinization in the 2000s, *Industrial and Corporate Change*, 25 (5), pp. 847–866, doi: 10.1093/icc/dtw030.

Cortes, G.M. (2016), Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data, *Journal of Labor Economics*, 34 (1), pp. 63-105.

Dauth, W., S. Findeisen, J. Suedekum and N. Woessner (2021), The Adjustment of Labor Markets to Robots, *Journal of the European Economic Association*, 00(0), pp. 1–50. DOI: 10.1093/jeea/jvab012. Accessed on 15 July 2021.

De La Rica, S., L. Gortazar and P. Lewandowski (2020), Job Tasks and Wages in Developed Countries: Evidence from PIAAC, *Labour Economics*, 65, https://doi.org/10.1016/j.labeco.2020.101845.

Deming, D. (2017), The Growing Importance of Social Skills in the Labor Market, *Quarterly Journal of Economics*, 132(4), pp. 1593–1640. DOI:10.1093/qje/qjx022.

De Vries, G., E. Gentile, S. Miroudot and K. Wacker (2020), The rise of robots and the fall of routine jobs, *Labour Economics*, 66. https://doi.org/10.1016/j.labeco.2020.101885.

Ehrl, P. and L. Monasterio (2021), Spatial skill concentration agglomeration economies, *Journal of Regional Science*, 61(1), pp. 140–161. DOI: 10.1111/jors.12505.

Falck, O., A. Heimisch-Roecker and S. Wiederhold (forthcoming), Returns to ICT skills, *Research Policy*, Accessed 8 April 2021, Available from: https://doi.org/10.1016/j.respol.2020.104064.

Fletcher, J. and B. Wolfe (2016), The importance of family income in the formation and evolution of non-cognitive skills in childhood, *Economics of Education Review*, 54, pp. 143–154.

Gathmann, C. and U. Schönberg (2010), How General Is Human Capital? A Task-Based Approach, *Journal of Labor Economics*, 28 (1), pp. 1-49.

Gottschalk, P., D. Green and B. Sand (2015), Taking Selection to Task: Bounds on Trends in Occupational Task Prices for the U.S., 1984-2013, mimeo.

Hall, Anja (2009), Die BIBB/BAuA-Erwerbstätigenbefragung 2006. Methodik und Frageprogramm im Vergleich zur BIBB/IAB-Erhebung 1998, Wissenschaftliche Diskussionspapiere No. 107, Bundesinstitut für Berufsbildung (BIBB), Bonn.

Hall, A., A. Siefer and M. Tiemann (2015), BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2012. suf_4.0; Research Data Center at BIBB (ed.); GESIS Cologne (data access); Bonn: Federal Institute for Vocational Education and Training. doi:10.7803/501.12.1.1.40.

Hanushek, E., G. Schwerdt, S. Wiederhold and L. Woessmann (2015), Returns to skills around the world: Evidence from PIAAC, *European Economic Review*, 73, pp. 103–130.

ILO (2012), International Standard Classification of Occupations ISCO-08, Volume 1 – Structure, Group Definitions and Correspondence Tables, International Labour Office (ILO), Geneva. URL: https://www.ilo.org/public/english/bureau/stat/isco/isco08/, last accessed on April 15, 2019.

ILO (2012b), International Standard Classification of Occupations 2008, Part III - Definitions of Major Groups, Sub-Major Groups, Minor Groups and Unit Groups, International Labour Office (ILO), Geneva. URL: https://www.ilo.org/public/english/bureau/stat/isco/isco08/, last accessed on April 15, 2019.

Lindquist, M., J. Sol and M. Van Praag (2015), Why Do Entrepreneurial Parents Have Entrepreneurial Children?, *Journal of Labor Economics*, 33(2), pp. 269-296.

Maurin, E. (2002), The impact of parental income on early schooling transitions: A re-examination using data over three generations, *Journal of Public Economics*, 85(3), pp. 301–332.

Mihaylov, E. and K. G. Tijdens (2019), Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations, Tinbergen Institute Discussion Paper 2019-035/V.

Murray, M. (2006), Avoiding Invalid Instruments and Coping with Weak Instruments, *Journal of Economic Perspectives*, 20 (4), pp. 111–132.

OECD (2010), PISA 2009 Results: Learning to Learn – Student Engagement, Strategies and Practices (Volume III), http://dx.doi.org/10.1787/9789264083943-en.

Rohrbach-Schmidt, D. and A. Hall (2013), BIBB/BAuA Employment Survey 2012, BIBB-FDZ Data and Methodological Reports Nr. 1/2013, Version 4.0, Bonn: BIBB.

Rohrbach-Schmidt, D. and M. Tiemann (2013), Changes in workplace tasks in Germany—evaluating skill and task measures, *J Labour Market Res.*, 46, pp. 215–237, DOI 10.1007/s12651-013-0140-3.

Rohrbach-Schmidt, D. (2019), Putting Tasks to the Test: The Case of Germany, *Social Inclusion*, 7 (3), pp. 122–135.

Rohrbach-Schmidt, D. (2009), The BIBB/IAB- and BIBB/BAuA-Surveys of the Working Population on Qualification and Working Conditions in Germany, BIBB-FDZ Data and Methodological Manual Nr. 1/ 2009, Bonn: BIBB.

Roodman, D. (2009), How to do xtabond2: An introduction to difference and system GMM in Stata, *The Stata Journal*, 9 (1), pp. 86–136.

Ross, M. (2015), Skill Biased Technical Change: Panel Evidence of Task Orientation and Wage Effects, Department of Economics, University of Connecticut.

Ross, M. (2017), Routine-biased technical change: Panel evidence of task orientation and wage effects, *Labour Economics*, 48, pp. 198–214.

Saltiel, F. (2019), Comparative Evidence on the Returns of Tasks in Developing Countries, Duke University, December 2019, mimeo.

Scoppa, V. (2009), Intergenerational transfers of public sector jobs: a shred of evidence on nepotism, *Public Choice*, 141(1-2), pp. 167-188.

Spitz-Oener, A. (2006), Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure, *Journal of Labor Economics* 24(2), pp. 235–270.

Staiger, D. and J. H. Stock (1997), Instrumental variables regression with weak instruments, *Econometrica* 65(3), pp. 557–586.

Stinebrickner, R., T. Stinebrickner and P. Sullivan (2019), Job Tasks, Time Allocation, and Wages, *Journal of Labor Economics*, 37 (2), pp. 399-433. https://doi.org/10.1086/700186.

Storm, E. (2020), On the Measurement of Tasks: Conceptual Benefits of Using Survey over Expert-based Data, Carleton College, October 2020.

Wooldridge, J. (2002), *Econometric Analysis of Cross Section and Panel Data*, MIT Press Cambridge, Massachusetts.

A Appendix

A.1 Figures and tables

Figure A1 depicts the mean routine task-intensity for nine major occupation groups. As the graph shows, the RTI is highest for the group of Elementary Occupations and Plant and Machine Operators and Assemblers, while it is lowest for the group of Professionals and Managers.

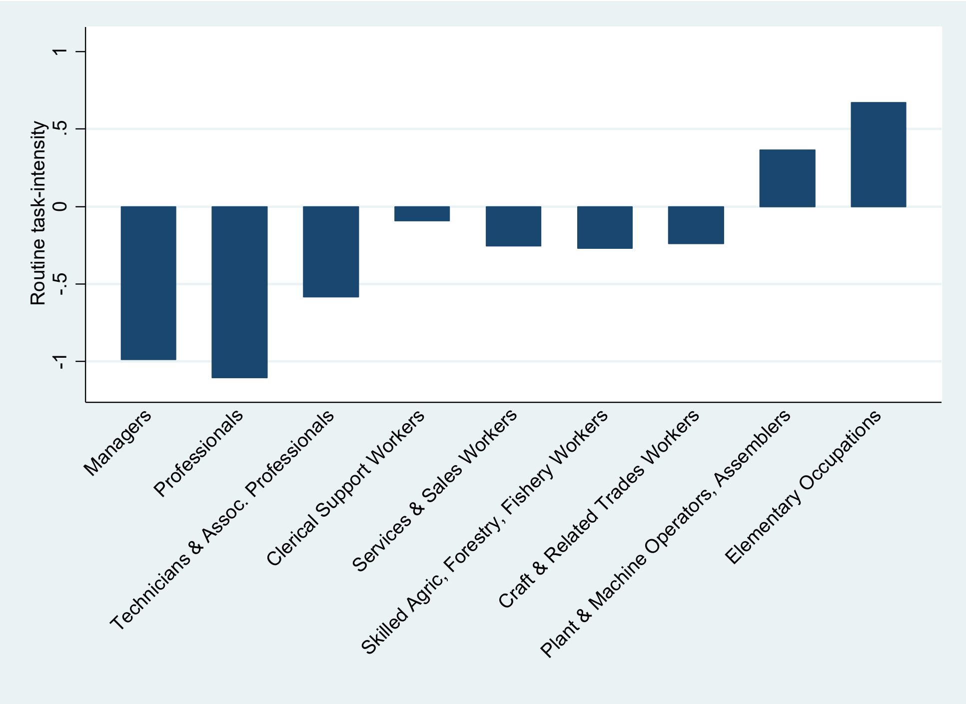

Figure A1. Routine task-intensity by major occupation groups (weighted, 4,255 observations)

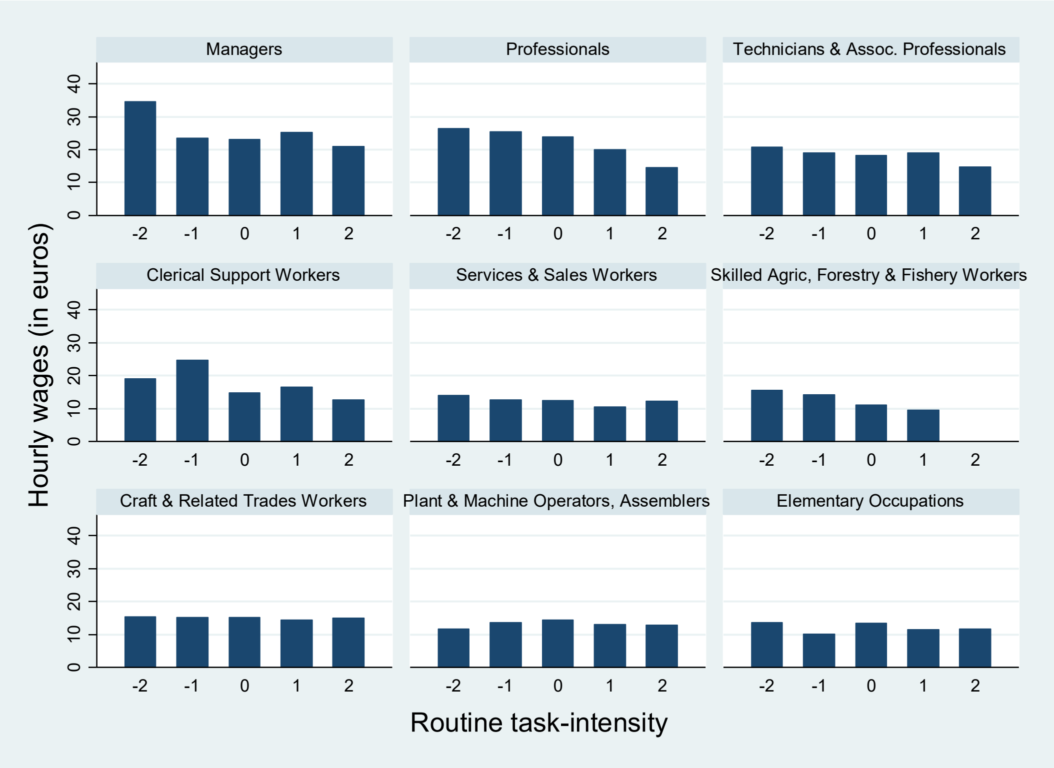

Figure A2. RTI and hourly wages per occupation group (weighted, 4,255 observations)

Table A1. Instrumental variables estimation results log(hourly wages)

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI					
RTI father's occupation 1979	.324***	.138***	.107**	.108**	.130***
	(8.71)	(3.97)	(3.22)	(3.24)	(3.80)
F-test excluded instruments	75.92	15.79	10.38	10.50	14.45
Hausman endogeneity [p]	[0.0001]	[0.0012]	[0.0045]	[0.0046]	[0.0019]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.351***	-.359**	-.359*	-.357*	-.357**
	(-6.03)	(-2.93)	(-2.34)	(-2.35)	(-2.75)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	3,981	3,981	3,981	3,981	3,981

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.
[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure,

number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

Table A2. Instrumental variables estimation results log(hourly wages)

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI					
RTI own occupation 1979	.722***	.459***	.226***	.223***	.410***
	(20.94)	(10.82)	(3.58)	(3.51)	(8.84)
F-test excluded instruments	438.55	117.04	12.80	12.35	78.06
Hausman endogeneity [p]	[0.0000]	[0.0000]	[0.0098]	[0.0096]	[0.0000]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.400***	-.293***	-.283*	-.288*	-.271***
	(-14.84)	(-7.15)	(-2.42)	(-2.41)	(-5.46)
RTI father's occupation 1979	.0148	-.0116	-.00893	-.00831	-.0135
	(0.69)	(-0.70)	(-0.47)	(-0.43)	(-0.83)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	4,255	4,255	4,255	4,255	4,255

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

A.2 Alternative definition routine task-intensity measure – RTI2

To construct the RTI2 measure, we utilize information provided by survey respondents on the frequency of performing sixteen work activities. The sixteen activities cover a wide range of tasks, such as manufacturing and producing of goods, teaching and training, cleaning and recycling, etcetera (see Table A3). The survey respondents are asked to indicate how often each of these activities occur in their work – often, sometimes or never.

Table A3. Work activities in the 2012 BIBB/BAuA survey

Work activity	Classification
Manufacturing, producing goods and commodities	RM
Measuring, testing, quality control	RC
Monitoring, control of machines, plants, technical processes	RM
Repairing, refurbishing	NRM
Purchasing, procuring, selling	NRI
Transporting, storing, shipping	NRM
Advertising, marketing, public relations	NRI
Organising, planning and preparing work processes	NRI
Developing, researching, constructing	NRA
Training, instructing, teaching, educating	NRI
Gathering information, investigating, documenting	NRA
Providing advice and information	NRI
Entertaining, accommodating, preparing food	NRM
Nursing, caring, healing	NRM
Protecting, guarding, patrolling, directing traffic	NRM
Cleaning, removing waste, recycling	NRM

Note: Classification is based on Spitz-Oener (2006) and Antonczyk, Fitzenberger and Leuschner (2009). NRA, NRI, RC, RM and NRM denote non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks, respectively.

The calculation of RTI2 involves few steps. First, following Spitz-Oener (2006), the sixteen work activities are assigned into one of the five task categories – non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual. Second, the task answers are re-coded to take on values 0 (never) and 1 (often, sometimes) and are then used to calculate the share of tasks each worker performs in the five task categories:

(8) TI_{ij} = (Number of activities in category j performed by i) / (Total number of activities in category j)

where *i* stands for a survey respondent, *j* indicates the five task categories and TI denotes the five task indices non-routine analytic (NRA), non-routine interactive (NRI), routine cognitive (RC), routine manual (RM) and non-routine manual (NRM). To reduce dimensionality, we combine the five indices into a single composite measure of routine task-intensity (RTI2):

(9) $RTI2_i = RC_i + RM_i - NRA_i - NRI_i - NRM_i$

The RTI2 measure is positively related to routine cognitive and manual tasks, and negatively related to non-routine analytic, interactive and manual tasks. Figure A3 depicts RTI2 for nine major occupational groups. As the graph shows, routine task-intensity is highest for the groups of Plant and Machine Operators and Assemblers and Elementary Occupations, and it is lowest for the groups of Managers and Professionals.

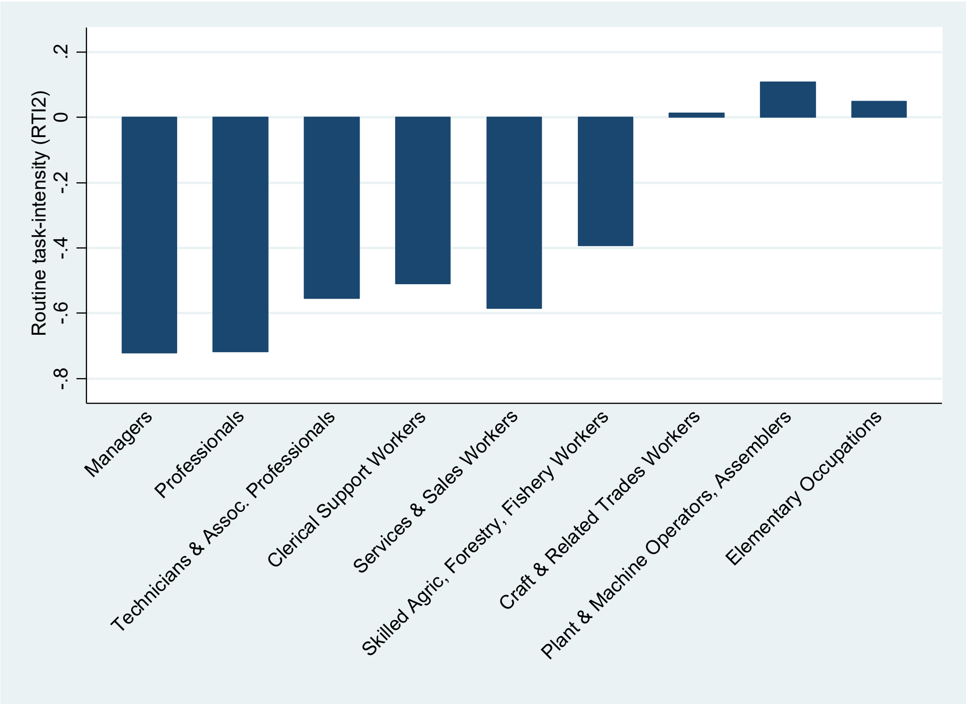

Figure A3. RTI2 by major occupation groups (weighted, 4,236 observations)

Figure A4 shows the relationship between RTI2 and log hourly wages. The downward slope of the fitted line indicates the existence of a negative relationship between both variables – the correlation coefficient between both is -.14.

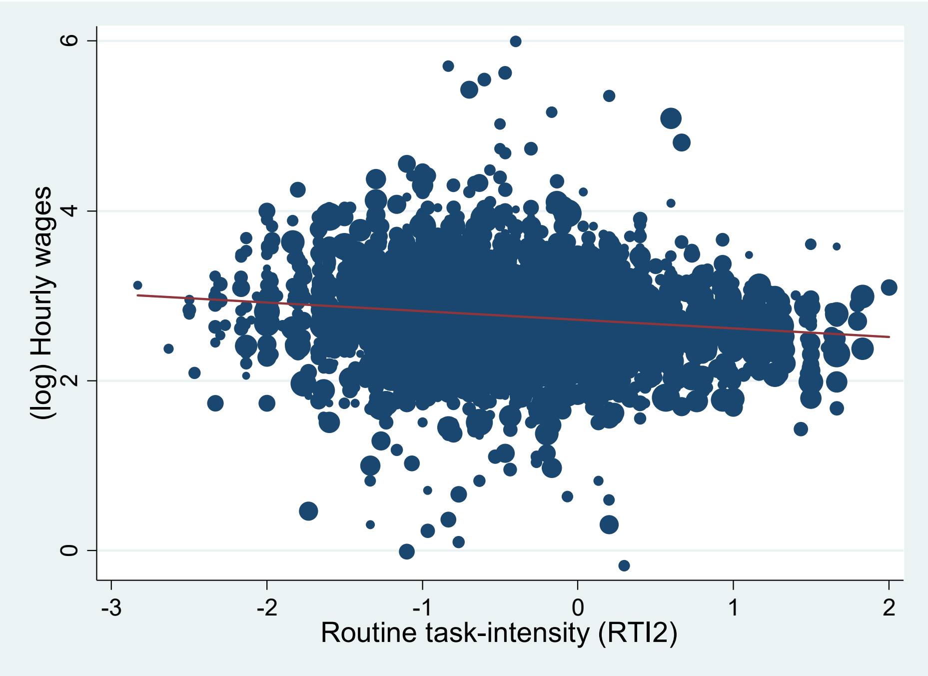

Figure A4. Correlation RTI2 and hourly wages (weighted, 4,236 observations)

B Appendix

B.1 Definition of variables

Log hourly income – the gross hourly income is calculated by dividing the gross monthly income from occupational activity by (the actual working hours worked last week * 4.4).

Years of schooling – the educational level of respondents is coded according to ISCED-97. We convert the ISCED-97 levels of education into years of schooling using the conversion table in OECD (2010, Table A1.1, p.109). For example, for Germany the ISCED Level 1 (primary education) corresponds to 4 years of schooling, ISCED Level 2 (lower secondary education) corresponds to 10 years of education, etcetera.

Marital status (married) – a dummy variable that takes the value 1 for married or cohabiting persons, and 0 otherwise.

Children (yes/no) – a dummy variable that takes the value 1 for individuals who have children.

Migration background – a dummy variable that takes the value 1 for people with migration background and foreigners.

Health condition – a dummy variable that takes the value 1 for people with excellent, very good and good health, and 0 for people with not so good and bad health.

Age – age of respondents.

Experience – potential experience is calculated as a difference between the year of the survey (2012) and the year of first occupational activity (other than apprenticeship training, summer jobs or internships).

Tenure – tenure is calculated as a difference between the year of the survey (2012) and the year when respondent started working for current employer/operating the firm/working as an independent contractor.

 # employers since first job – number of employers since first occupational activity, including current occupational activity and periods of self-employment and employment by a temporary work agency.

Ever been unemployed (yes/no) – a dummy variable that takes the value 1 if the respondent has ever been unemployed in the course of her/his working life.

Duration unemployment (years) – measures the total duration of unemployment, given in approximate full years (unemployment durations of less than a half year count as 0.5 years).

Supervisory position (yes/no) – a dummy variable that takes the value 1 for respondents who have colleagues to whom they are the immediate supervisor.

Share of time working on a computer (%) – percentage of working hours respondent spends working on a computer.

Working hours per week – actual working hours worked last week.

Regular working hours, 7 am – 7 pm (yes/no) – a dummy variable that takes the value 1 if working hours are typically between 7 a.m. and 7 p.m.

Working on weekends (yes/no) – a dummy variable that takes the value 1 if respondent works, even if only occasionally, on Saturdays, Sundays or both weekend days.

On stand-by duty (yes/no) – a dummy variable that takes the value 1 if respondent is on standby or on-call duty.

Longer working-in period required to perform activity (yes/no) – a dummy variable that takes the value 0 if a quick briefing at the workplace is sufficient to perform occupational activity, and 1 if a longer working-in period in the firm if required.

Firm size – contains six dummy variables for firm size (1-9 persons, 10-49 persons, 50-99 persons, 100-249 persons, 250-499 persons, 500 or more persons).

Firm location (17 dummies) – contains 17 dummy variables for the location of the firm (one dummy for each of the 16 German Federal states and one for abroad).

Firm sector (21 dummies) – contains 21 binary variables for sector of economic activity, defined according to WZ2003.

Current occupation (38 dummies) – contains 38 dummy variables for current occupation of survey respondents. The 38 dummies correspond to two-digit ISCO-2008 occupation groups.

Individual routine task-intensity (RTI_i) – measures the individual routine task-intensity of survey respondents. This variable is described in detail in Section 4.2.

Occupational routine task-intensity (RTI_{occ}) – measures the average routine task-intensity of the current occupation of survey respondents. This variable is constructed from external data (O*NET) and appended to the three-digit ISCO-2008 occupation code of survey respondents. It is calculated as follows: $RTI_{occ} = RC_{occ} + RM_{occ} – NRA_{occ} – NRI_{occ} – NRM_{occ}$. Whereas RC_{occ}, RM_{occ}, NRA_{occ}, NRI_{occ} and NRM_{occ} stand for the average routine cognitive, routine manual, non-routine cognitive analytical, non-routine cognitive interpersonal and non-routine manual physical task content of occupations, respectively. The five components of RTI_{occ} are downloaded from Acemoglu and Autor (2011) and converted to three-digit ISCO-2008 occupation groups[61].

In Section 8.1, we will present an alternative occupational RTI variable that is calculated on the basis of the survey data.

[61] The five task measures are downloaded from the personal website of David Autor (https://economics.mit.edu/faculty/dautor/data/acemoglu), accessed on February 11, 2019. See Mihaylov and Tijdens (2019, Chapter 7) for further details on the conversion of the measures to three-digit ISCO-2008 occupation groups.

B.2 Occupational classification systems in the 1979 and 2012 German Employment Surveys

Occupations are the key element for linking the 1979 and 2012 waves of the survey. However, as Table B2 shows, the occupational titles of workers are coded to different classification schemes in both survey years. In the 2012 survey, the current occupation of the worker and the occupation of the father are coded according to the International Standard Classification of Occupations (ISCO, versions 2008 and 1988) and the German Classification of Occupations (KldB, versions 2010 and 1992), while in the 1979 survey an earlier version of the German Classification of Occupations is used (KldB, version 1970)[62]. In order to link occupations in 2012 to their counterparts in 1979, we used the KldB-1988 classification scheme[63] and linked occupations at the three-digit level of aggregation, resulting in 335 unique occupation codes.

Table B2. Occupational classification systems in the German Employment Surveys

	1979 survey	2012 survey
Current occupation respondents	KldB-1970	ISCO-2008
		ISCO-1988
		KldB-2010
		KldB-1992
Occupation father	-	ISCO-2008
		ISCO-1988
		KldB-2010
		KldB-1992

Source: Adapted from Rohrbach-Schmidt and Hall (2013, p.8) and Hall (2009, Table 6, p.34).

[62] The 1970 version of the German KldB classification system is nearly identical with the 1988 version (see Hall, 2009, footnote 17).

[63] The KldB-1988 occupation codes are not included in the 1979 and 2012 surveys. We are very grateful to Dr. Daniela Rohrbach-Schmidt from the Federal Institute for Vocational Education and Training (BIBB) for making the KldB-1988 codes available for the occupations in the 2012 survey, and for providing a crosswalk between KldB-1970 and KldB-1988 for the 1979 wave of the survey.

C Heterogenous Effects of RTI on Wages

C.1 Heterogenous Effects of RTI on Wages – OLS results

Tables C1-C9 present OLS regression results for nine major ISCO-2008 occupation groups – Managers, Professionals, Technicians and Associate Professionals, Clerical Support Workers, Services and Sales Workers, Skilled Agricultural, Forestry and Fishery Workers, Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, and Elementary Occupations. The results in Tables C1-C9 are based on the same model specifications as in Table 4.

Table C1. Managers

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.164***	-.164***	-.142***	-.140***	-.157***
	(-4.66)	(-5.16)	(-4.32)	(-4.31)	(-5.12)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.07	0.51	0.53	0.55	0.54
N	306	306	306	306	306

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

Table C2. Professionals

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.0800**	-.0592**	-.0657***	-.0651***	-.0562**
	(-3.28)	(-3.08)	(-3.54)	(-3.49)	(-2.91)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.01	0.38	0.41	0.41	0.39
N	972	972	972	972	972

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

Table C3. Technicians and Associate Professionals

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.0506***	-.0192	-.0178	-.0178	-.0192
	(-3.50)	(-1.54)	(-1.45)	(-1.45)	(-1.54)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.01	0.41	0.42	0.42	0.41
N	1,054	1,054	1,054	1,054	1,054

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

Table C4. Clerical Support Workers

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.0832*	-.00122	-.0166	-.0142	.00170
	(-2.40)	(-0.04)	(-0.54)	(-0.47)	(0.05)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.03	0.48	0.52	0.54	0.49
N	332	332	332	332	332

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

Table C5. Services and Sales Workers

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.0511*	-.0324	-.0307	-.0322	-.0334
	(-1.97)	(-1.31)	(-1.23)	(-1.27)	(-1.33)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.01	0.56	0.56	0.56	0.56

N	310	310	310	310	310

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

Table C6. Skilled Agricultural, Forestry and Fishery Workers

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.181**	-.125	-.132	-.176*	-.158*
	(-3.19)	(-1.69)	(-1.68)	(-2.11)	(-2.08)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.13	0.78	0.78	0.80	0.80
N	70	70	70	70	70

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

Table C7. Craft and Related Trades Workers

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.0321*	-.0134	-.0143	-.0143	-.0136
	(-2.04)	(-0.94)	(-1.00)	(-1.00)	(-0.95)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.006	0.35	0.36	0.36	0.35
N	745	745	745	745	745

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

Table C8. Plant and Machine Operators and Assemblers

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.0319	-.0419*	-.0427*	-.0459*	-.0462*
	(-1.33)	(-2.16)	(-2.20)	(-2.36)	(-2.38)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.005	0.61	0.61	0.61	0.61
N	331	331	331	331	331

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

Table C9. Elementary Occupations

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
RTI	-.0183	.0576	.0474	.0472	.0574
	(-0.34)	(1.44)	(1.31)	(1.30)	(1.42)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
R-squared	0.001	0.73	0.76	0.76	0.73
N	135	135	135	135	135

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses. The control variables are the same as in Table 4. Dependent variable is log hourly wages.

C.2 Heterogenous effects of RTI on wages – 2SLS results

Tables C10-C13 present the 2SLS regressions results for different groups of occupations. The results in Table C10 and C11 are based on the first instrument (i.e., RTI of the father's occupation in 1979), while those in Table C12 and C13 are based on the second instrument (i.e., RTI of the worker's own occupation in 1979). In order to save space, we report only results from two model specifications - the least extensive and the most extensive model specification.

Table C10. Instrumental variables estimation results log(hourly wages)

	Managers, Professionals, Technicians & Associate Professionals		Services & Sales Workers, Skilled Agricultural, Forestry & Fishery Workers, Craft & Related Trades Workers		Clerical Support Workers, Plant & Machine Operators & Assemblers, Elementary Occupations	
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI						
RTI father's occupation 1979	.205***	.086*	.106	.065	.280***	.142
	(5.00)	(2.18)	(1.51)	(1.00)	(3.53)	(1.91)
F-test excluded instruments	25.03	4.77	2.27	1.00	12.44	3.63
Hausman endogeneity [p]	[0.0039]	[0.0030]	[0.3649]	[0.7702]	[0.5410]	[0.2907]
B. Second-stage results: dependent variable is log hourly wages						
RTI	-.406**	-.657	.211	-.118	-.157	-.218
	(-3.25)	(-1.87)	(0.64)	(-0.36)	(-1.10)	(-1.05)
Control variables[1]	-	yes	-	yes	-	yes
38 occupation dummies	-	yes	-	yes	-	yes
RTI occupation (mean value)	-	yes	-	yes	-	yes
N	2,332	2,332	1,125	1,125	798	798

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

Table C11. Instrumental variables estimation results log(hourly wages)

	Managers, Professionals, Technicians & Associate Professionals, Clerical Support Workers, Skilled Agricultural, Forestry & Fishery Workers		Services & Sales Workers, Craft & Related Trades Workers, Plant & Machine Operators & Assemblers, Elementary Occupations	
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI				
RTI father's occupation 1979	.265***	.109**	.164**	.086
	(6.55)	(2.91)	(2.74)	(1.55)
F-test excluded instruments	42.96	8.49	7.51	2.40
Hausman endogeneity [p]	[0.0016]	[0.0018]	[0.5398]	[0.5861]
B. Second-stage results: dependent variable is log hourly wages				
RTI	-.368***	-.515*	.0561	-.128
	(-4.29)	(-2.33)	(0.34)	(-0.60)
Control variables[1]	-	yes	-	yes
38 occupation dummies	-	yes	-	yes
RTI occupation (mean values)	-	yes	-	yes
N	2,734	2,734	1,521	1,521

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

Table C12. Instrumental variables estimation results log(hourly wages)

	Managers, Professionals, Technicians & Associate Professionals		Services & Sales Workers, Skilled Agricultural, Forestry & Fishery Workers, Craft & Related Trades Workers		Clerical Support Workers, Plant & Machine Operators & Assemblers, Elementary Occupations	
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI						
RTI own occupation in 1979	.583***	.166	.245*	.161	.490***	.268*
	(8.51)	(1.73)	(2.42)	(1.45)	(5.47)	(1.97)
F-test excluded instruments	72.49	3.01	5.84	2.10	29.95	3.90
Hausman endogeneity [p]	[0.0000]	[0.0264]	[0.5203]	[0.2058]	[0.4655]	[0.4793]
B. Second-stage results: dependent variable is log hourly wages						
RTI	-.387***	-.524	.0655	-.333	-.0130	.0809
	(-5.84)	(-1.56)	(0.37)	(-1.05)	(-0.15)	(0.50)
Control variables[1]	-	yes	-	yes	-	yes
38 occupation dummies	-	yes	-	yes	-	yes
RTI occupation (mean value)	-	yes	-	yes	-	yes
N	2,332	2,332	1,125	1,125	798	798

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

Table C13. Instrumental variables estimation results log(hourly wages)

	Managers, Professionals, Technicians & Associate Professionals, Clerical Support Workers, Skilled Agricultural, Forestry & Fishery Workers		Services & Sales Workers, Craft & Related Trades Workers, Plant & Machine Operators & Assemblers, Elementary Occupations	
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
A. First-stage results: dependent variable is RTI				
RTI own occupation in 1979	.711***	.187*	.558***	.179
	(12.58)	(2.19)	(7.76)	(1.89)
F-test excluded instruments	158.22	4.78	60.26	3.56
Hausman endogeneity [p]	[0.0000]	[0.0687]	[0.4982]	[0.0322]
B. Second-stage results: dependent variable is log hourly wages				
RTI	-.366***	-.359	-.00864	-.396
	(-9.06)	(-1.68)	(-0.16)	(-1.53)
Control variables[1]	-	yes	-	yes
38 occupation dummies	-	yes	-	yes
RTI occupation (mean values)	-	yes	-	yes
N	2,734	2,734	1,521	1,521

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

D Additional Firm-Specific Control Variables

In Table D1 and D2, we test the sensitivity of the results to the inclusion of four additional firm-specific control variables in the model – these include one dummy variable measuring the economic situation of the firm (the dummy takes the value of 1 if the economic situation is very good or good, and 0 if the situation is not so good or bad), and three dummy variables indicating whether the firm has relocated or outsourced firm units, merged with another firm, or strongly expanded in the past two years, respectively (the three dummies take the value of 1 if the answer is yes, and 0 if it is no). The additional variables are a valid skip for some workers, and therefore the sample size in Table D1 and D2 is much smaller. However, as both tables show, the estimated effect of routine tasks on wages is very robust to the inclusion of these additional firm-specific variables in the model. The results in Table D1 and D2 are based on the first and second instrument, respectively.

Table D1. Instrumental variables estimation results log(hourly wages)

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
A. First-stage results: dependent variable is RTI					
RTI father's occupation 1979	.335***	.133**	.086*	.087*	.122**
	(7.89)	(3.36)	(2.23)	(2.25)	(3.12)
F-test excluded instruments	62.22	11.28	4.98	5.04	9.71
Hausman endogeneity [p]	[0.0001]	[0.0051]	[0.0430]	[0.0430]	[0.0089]
B. Second-stage results: dependent variable is log hourly wages					
RTI	-.386***	-.367*	-.362	-.360	-.367*
	(-5.62)	(-2.45)	(-1.60)	(-1.61)	(-2.23)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	3,069	3,069	3,069	3,069	3,069

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size, 1 dummy for economic situation of the firm, 1 dummy for relocation of firm units, 1 dummy for merger with another firm, 1 dummy for expansion of the firm. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.

Table D2. Instrumental variables estimation results log(hourly wages)

	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
C. First-stage results: dependent variable is RTI					
RTI own occupation 1979	.738***	.450***	.177*	.168*	.403***
	(18.95)	(9.25)	(2.33)	(2.21)	(7.47)
F-test excluded instruments	359.05	85.59	5.43	4.88	55.84
Hausman endogeneity [p]	[0.0000]	[0.0000]	[0.0565]	[0.0569]	[0.0000]
D. Second-stage results: dependent variable is log hourly wages					
RTI	-.428***	-.310***	-.304	-.319	-.288***
	(-13.70)	(-6.21)	(-1.64)	(-1.60)	(-4.74)
Control variables[1]	-	yes	yes	yes	yes
38 occupation dummies	-	-	yes	yes	-
RTI occupation (mean value)	-	-	-	yes	yes
N	3,069	3,069	3,069	3,069	3,069

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *t*-statistics in parentheses.

[1] Control variables include: demographic characteristics (marital status, children, health condition, immigration background), education (years of schooling), employment history (experience, experience squared, tenure, number of employers since first job, previous unemployment, duration of unemployment), job characteristics (job complexity, supervisory position, irregular working hours, working on weekends, stand-up duty, share of worktime working on computers, number of working hours), 17 dummies for firm location, 21 dummies for firm sector and 6 dummies for firm size, 1 dummy for economic situation of the firm, 1 dummy for relocation of firm units, 1 dummy for merger with another firm, 1 dummy for expansion of the firm. Regressions are weighted by the population weights provided in the data. Hausman test tests the null hypothesis that the endogenous regressor can be treated as exogenous.