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Pension Reform Effects in Times of Technological Change and Shifting Task Composition

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Abstract: We study heterogeneity in the effects of a pension reform in Germany: the introduction of the old-age pension for the very long-term insured, which lowered the threshold for full pension receipt from age 65 to 63. Using a regression discontinuity design (RDD) and rich administrative pension data, we estimate the effects of the reform on eligible workers who differ in a number of occupational characteristics. Transitions into the new early retirement scheme occurred more frequently from jobs involving mainly manual and routine tasks, which contributed to the changing composition of tasks in the workforce. While the introduction of new technologies, materials and machines in an industry was associated with more workers claiming early retirement, workers affected by frequent PC use and new PC programmes were less likely to use the early retirement scheme.

Keywords: effect heterogeneity; German public pension system; occupational tasks

JEL Classification: J18; J22; J26

1 Introduction

In many industrial countries, the employment rate of older workers has increased substantially over the last two decades. In Germany, for instance, employment

All authors contributed equally to this work.

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among individuals aged 60 to 64 increased by nearly 42 percentage points between 2000 and 2020 (OECD 2021, 177). In addition, working hours have increased among older workers, while unemployment rates have declined. These changes are often attributed to a paradigm shift in public pension policy. Over the last 30 years, various legislative acts have raised the regular retirement age and abolished early retirement schemes. However, fierce opposition to these reforms led several countries to reopen early retirement pathways, at least for certain groups. In Germany, the reform of the old-age pension for very long-term insured persons in 2014 was an example of the latter.

Numerous recent studies analyse the causal effects of pension reforms (see, for example, Dolls and Krolage 2023, Geyer and Welteke 2021, Riphahn and Schrader 2023 or Lalive, Staubli, and Magesan 2023). With the exception of Dolls and Krolage (2023), most of these studies examine the effects of tightening pension reforms. These studies show that pension reforms had a strong impact on individuals' choices, but in varying directions: while there was a substantial increase in the share of employed workers, there was also a rise in unemployment and some indication of an increase in transitions into retirement schemes such as disability pensions. By contrast, Dolls and Krolage (2023) analyse the effects of the reform of the old-age pension for the very long-term insured persons in Germany and find a substantial decrease in the average pension age as a result of the reform.

In this paper, we extend the recent literature on the effects of pension reforms. Taking the old-age pension for very long-term insured individuals as an example, our focus goes beyond average effects to examine heterogeneous reactions to the reform in light of changing occupational tasks, requirements, and technological advancements. Over the past 60 years, occupational tasks have undergone significant changes. Autor, Levy, and Murnane (2003) and Autor and Price (2013) show that, in the U.S., labour input for both routine manual and cognitive tasks declined between 1960 and 2009. However, the decline in non-routine manual tasks slowed after 1990 and then slightly reversed. In contrast, the input of analytical and interpersonal tasks grew steeply from 1970 to 2000, experienced a modest decline between 2000 and 2006, and then slightly increased thereafter. Overall, cognitive and interactive tasks were dominant in the early 2010s. In her study on Western Germany, Spitz-Oener (2006) identifies a similar trend for the years 1979–1999, which can be shown to persist at least until 2018.[1] Observed changes in task composition are closely linked to the adoption of new technologies, a relationship conceptualized in the task-polarisation literature. This literature acknowledges that technological progress can replace labour – though not all types to the same extent – while complementing

1 Table A1 in Appendix confirms this continuity using the same data employed by Spitz-Oener (2006), but for later years and with slightly modified task domain definitions as proposed by Alda (2013).

some tasks and substituting others (Autor 2022). Routine manual, cognitive, and service tasks are more likely to be replaced by new technologies, whereas non-routine manual, cognitive, and interpersonal activities are more likely to be enhanced (Acemoglu and Autor 2011, Autor and Dorn 2013, Goos, Manning, and Salomons 2014). Autor, Levy, and Murnane (2003) demonstrates that computerization substitutes routine tasks while complementing non-routine, complex tasks. Similarly, Spitz-Oener (2006) shows a connection between technological change (specifically, computer use) and shifts in task composition towards analytical and interactive tasks in Germany.[2] This relationship is particularly relevant for occupations heavily reliant on routine-manual tasks, as Acemoglu and Restrepo (2019) illustrates in the context of robot adoption. However, it is plausible that this phenomenon extends to other technologies and task domains, provided that these technologies substitute the respective tasks. In their model, Acemoglu and Autor (2011) demonstrate how task-replacing technological change *squeezes out* workers performing these tasks, leading to an excess labour supply and downward wage pressure. On the one hand, the pension reform under study may have provided an opportunity for employees affected by such changes to exit the labour market entirely.[3] On the other hand, the reform may have prompted employers to adjust to changing technological and task requirements by reshaping the workforce composition. If heterogeneities in the effects of the pension reform align with developments in task composition and technological progress, this would suggest that the new pension access option was used as a means of adapting to evolving task requirements.

To examine the role of occupational characteristics, we assess whether an occupation involves a high share of manual, routine, cognitive, or interactive tasks, as well as the extent to which a job is exposed to computerisation and technological change, considering these factors as influences and moderators of the impact of pension reforms on the retirement transitions of older workers. We analyse the heterogeneous effects within a regression discontinuity design (RDD) framework, employing subgroup analyses alongside a relatively recent technique – the sorted effects method – to capture the full range of effects. Additionally, we conduct a classification analysis (Chernozhukov, Fernández-Val, and Luo 2018). To that end, we use data from the German pension insurance, covering the entire population of 2.4 million insured individuals from birth cohorts around the onset of the reform. The data includes detailed monthly employment status information for individuals aged

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2 Recent developments in artificial intelligence, which may enable the substitution of non-routine tasks, as discussed in Autor (2022), have not been relevant for the birth cohorts studied here.

3 Leaving the workforce through a favourable retirement option might be particularly attractive for older employees with a high share of routine tasks, as they tend to transition into lower-skill jobs when their skills become outdated (Autor and Dorn 2009).

56 to 66. Additionally, it provides qualification details and a detailed occupational classification, which we use to merge occupational characteristics.

We find substantial heterogeneity in the reform effects on pension take-up. What is more, we find that differences in occupational tasks and technological change are linked to this effect heterogeneity. The effect of the reform on retirement is larger for individuals working in occupations with a large share of manual and routine tasks, meaning that individuals in occupations that are characterised by a large share of such tasks were more likely to enter retirement. For analytical and interactive tasks, the picture is reversed. This fits the findings described by Autor and Price (2013) for the US, i.e. that non-routine analytical and interpersonal task inputs have been increasing while other inputs have been decreasing. This result is complemented by our findings with regard to PC usage and technological change. We find that the effects of the reform are smaller where technologies are in use or have been introduced, which rather complement analytical or interactive tasks, such as PCs, new PC programmes, and new services. The introduction of new technologies, machines, and products or materials, all rather associated with routine manual task performance,[4] was related to larger reform effects. Once we interact tasks and technology indicators, our results show that indicators associated with computer use attenuate the reform effects, while those associated with frequent use of new technologies, machines, and new products or materials increase them. Using classification analysis, we examine whether these characteristics also differentiate observations at the extremes of the effect distribution. In line with what we find in the subgroup analysis, occupational tasks and technological change indicators significantly differ between most and least responsive individuals. Overall, we take this as an indicator that differences in the reform effects are linked to occupational change and different results of technological change throughout different occupational domains. An explanation may lie in the employers' wish to adapt the composition of the workforce to changing task requirements or the employees' wishes to leave a rapidly changing work environment; the pension reform may have offered employers and employees a way to do just this. The differences in tasks and technological progress may be associated with other differences, which can be relevant for the take-up of the new retirement possibilities, such as the physical demand of specific occupations.[5] We are

4 Figure A1 in Appendix shows the correlations between the task domains and technological change indicators at individual level in a heatplot.

5 In Boockmann, Herdegen, and Kroczek (2024) we show that effects of the reform considered here are also heterogeneous with regard to differences in several demand indicators. In the present paper, we focus on the role of tasks and technologies. The data we use for our analysis does not contain any observations for employees with a high share of analytical or interactive tasks who are at the same time heavily exposed to overall job demand. In the following, we will thus not further differentiate our results along the line of job demand. However, the respective results are available upon request.

therefore cautious in the interpretation of our results. The associations between increasingly important task domains, technological changes, and the decision to retire early using a new retirement scheme become clear, however.

Our study builds on and extends different strands of literature. Several studies analyse the relationship between occupational tasks and retirement. Blekesaune and Solem (2005) and Robroek et al. (2013) identify low job control as a risk factor for early retirement. Velde (2022) compares results for Germany and the UK, finding that workers in routine jobs have a significantly higher probability of early retirement in Germany but not in the UK. Radl (2013) examines data from 11 Western European countries and finds that workers who retire the latest are concentrated at both the upper and lower ends of the occupational ladder. He attributes late retirement among routine workers to low pension entitlements and limited access to occupational pension plans.

Friedberg (2003) uses the US Health and Retirement Study from 1992 until 1996 and shows that workers who use computers exit the labour market later than those who do not. Biagi, Cavapozzi, and Miniaci (2013) use Italian survey data from 2000 until 2004 and find that computer use on the job, combined with computer literacy, significantly reduces the probability of retirement. However, they do not find significant effects for computer literacy or computer use on the job in isolation. Hudomiet and Willis (2022) find that older workers unfamiliar with computers were significantly more likely to leave the labour force when their jobs became computerised. Technical change at the industry level can have varying effects on early retirement. Bartel and Sicherman (1993) and Burlon and Vilalta-Bufí (2016), for example, find that in industries with high technical change, the probability of later retirement is higher than in industries with low technical change. Ahituv and Zeira (2011) show in a general equilibrium model that aggregate technical change encourages individuals to work longer, whereas sector-specific technical change has the opposite effect. However, it should be noted that technological change can also be an endogenous response to autonomous shifts in skill supply (Acemoglu and Autor 2011).

Only a small number of studies have linked the effects of pension reforms to heterogeneity in retirement behaviour based on job characteristics. Among them, Giesecke (2018) and Ardito (2021) find that responses to pension reforms vary by occupational tasks. In contrast, Geyer et al. (2022) do not find differences in reactions to pension reforms due to variations in occupational demands. Similarly, Carrino, Glaser, and Avendano (2020) do not find differing employment effects of a pension reform across routine, intermediate, and managerial workers. Boockmann, Herdegen, and Kroczek (2023), however, identify heterogeneous responses to pension reforms concerning occupational demands, tasks, and individuals' exposure to technological change. However, all these studies focus on tightening pension reforms, such as increases in the full retirement age or reductions in pension benefits. By contrast, the reform we examine reintroduced the possibility of early retirement without deductions.

The remainder of the paper is organised as follows. Section 2 provides details on the reform under consideration. Section 3 outlines our identification strategy and describes the data. Section 4 presents the results for the full sample as well as for subgroups. Finally, Section 5 summarises our conclusions and highlights directions for future research.

2 The Old-Age Pension for the Very Long-Term Insured

The German public pension insurance is constructed as a pay-as-you-go system for dependent employees[6] with contributions paid by both individuals and their employers.[7] Benefits are roughly proportional to average lifetime labour market income and their amount is determined via a points system. In each year of contribution, insured earnings are divided by average national earnings of that year, resulting in one point if personal earnings equal the national average and more (less) points if personal earnings are higher (lower). A maximum of two points can be acquired per contribution year. To derive pension benefits, the sum of all points from insured earnings and from specific credited non-contributory periods is multiplied by the current pension value, an annually adjusted amount of money.

The regular old-age pension cannot be claimed early.[8] However, there are specific old-age pension types, e. g. for long-term insured persons, which allow for early retirement conditionally on having fulfilled specific eligibility criteria. Generally, for every month an individual retires before the regular retirement age, deductions of 0.3 % are due.

In 2007, the regular retirement age was legislated to increase from 65 to 67 years. This increase will take place stepwise between 2012 and 2031 and affects cohorts born in 1947 and thereafter.The old-age pension for the very long-term insured was also introduced in 2007 to shield individuals who had contributed to the public pension system for at least 45 years from the rising regular retirement age. For these

6 Civil servants are insured in a different and entirely separate system and the majority of self-employed have to save for retirement privately.

7 A detailed description of the German public pension system can be found in Börsch-Supan, Rausch, and Goll (2020).

8 In addition to old age pensions, the public pension insurance also grants disability pensions and surviving dependants' pensions. In the following, we will solely concentrate on old-age pensions.

individuals, retirement without any deductions remained possible from the former full retirement age of 65 years. In 2014, a reform came into place which lowered this threshold even further: Cohorts born before 1953 were now able to claim full pensions from the age of 63 (which led to the old-age pension for the very long-term insured commonly known as “pension at 63”). This threshold was however increased to age 65 for subsequent cohorts: It was set at age 63 and 2 months for the cohort born in 1963, at age 63 and 4 months for the cohort born in 1954 and so on. For the cohort born in 1964, decrement-free retirement age will be back at age 65 (where it was before the 2014 reform). Besides lowering the threshold for decrement-free benefit claiming, the 2014 reform loosened the eligibility criteria for this pension type so that more individuals were able to fulfil them.

Before 2014, individuals eligible to the old-age pension for the very long-term insured could claim full pension benefits from age 65 on. In case they wanted to retire earlier (which would have been possible only via another old-age pension type), they would have had to accept decrements of 3.6 % per year of early claiming. Once the reform was in effect in July 2014, decrement-free retirement age fell by two years to age 63 for eligible individuals.

3 Methods and Data

3.1 Identification and Estimation

3.1.1 Basic Approach

Our approach to identify and estimate the average effects of the lowered age for full benefit claiming builds on a regression discontinuity design (RDD) which has often been applied for analyses similar to ours (see Geyer and Welteke 2021 or Lalive, Staubli, and Magesan 2023). We expect a discontinuity around the onset of the reform in July 2014 and thus compare labour market status (employment, unemployment, retirement) of eligible individuals before and after this date. We focus our analysis on the cohorts born in 1951 and 1952 – i. e. those who turned 63 around the reform date or shortly afterwards. Our dataset contains all individuals of the respective cohorts who have ever been insured in the German pension system. We first estimate the effect for all eligible individuals and then differentiate it by tasks and local labour market characteristics.

As main outcome variable, we consider retirement as it captures whether affected individuals continued in employment despite the new possibility for full benefit claiming or whether they make use of it and retire. The effect on retirement thus shows the degree of compliance with the pension reform, i.e. the share of individuals directly affected.

Since the outcomes may vary with birth cohort, age, or time, we account for these (note that there is a linear dependence of the three, so we need to account only for two of them). In the basic regression without further differentiations, we estimate a linear model of the form

$$y_{it} = \alpha + \beta D_i + \gamma_0 (1 - D_i) f(z_i - c) + \gamma_1 D_i f(z_i - c) + \mathbf{X}_{it}' \boldsymbol{\delta} + \varepsilon_{it}, \tag{1}$$

where y_{it} is a (binary) outcome variable, D_i is a binary treatment indicator, which equals 1 if the labour market status in period t lies before or after the cut-off date, and $\gamma_0(1 - D_i)f(z_i - c)$ and $\gamma_1 D_i f(z_i - c)$ capture possibly different time trends around the reform cut-off c, where z_i indicates the month of birth of individual i and $f()$ represents a – in the main specification linear – function. The matrix $\mathbf{X}_{it}$ contains individual characteristics as controls. The main parameter of interest is β, which measures the effect of the pension reform on outcome y_{it}.

The RDD approach hinges on the assumption that we correctly capture trends in the outcome variable before and after the reform cut-off. If the respective trends are non-linear, the linear model in equation (1) is miss-specified and a non-linear trend may falsely be interpreted as discontinuity. In order to check for such miss-specification, we analyse pre- and post-reform trends graphically by depicting local linear regression estimations of the pre- and post-reform time trends. As pre- and post-treatment trends are reasonably linear and the discontinuities at the cut-off are apparent, we are confident that our RDD approach is valid.

3.1.2 Sorted Effects Method

Our objective is to analyse whether the pension reform affected different subgroups of the population heterogeneously. In essence, β measures the average treatment effect and we are interested in how it differs along individual-level characteristics W_i, i.e. we want to estimate treatment effects conditional on given characteristics,

$$\beta(w) = \mathbb{E}[Y(D = 1) - Y(D = 0) | W_i = w]. \tag{2}$$

To assess the overall heterogeneity in $\beta(w)$, we use the sorted effects method of Chernozhukov, Fernández-Val, and Luo (2018). The main idea is to estimate the entire set of partial effects sorted in increasing order and to rank them according to effect size, rather than to present one measure for the effect of interest, e. g. the average effect. To that end, we estimate an interactive linear model with an additive error term

$$Y_{ij} = g(Z_{ij}) + u_{ij}, \tag{3}$$

where $g(Z_{ij}) = Z'_{ij}\tau$, with $Z_{ij} = (D_{ij}, Q_{ij})$, where Q contains interactions between D and W to capture the treatment effect heterogeneity with respect to occupation and individual characteristics. The predictive effect (PE) is then given by

$$\beta(q) = (1, q)'\tau - (0, q)'\tau, \tag{4}$$

with q containing specific values of Q. Other than in the case of the standard interactive linear model, effect heterogeneity is now accounted for with respect to a number of different occupation characteristics in the same model. If μ is the distribution of W in the population, aggregation of the PEs over μ yields the average treatment effect. However, Chernozhukov, Fernández-Val, and Luo (2018) propose to report the entire set of PEs sorted in increasing order and indexed by ranking $u \in [0, 1]$. The u-th quantile of $\beta(Q)$ is the uth-sorted partial effect (u-SPE). Displaying the SPEs at different (increasing) values of u, i. e. at different quantiles of the estimated effect, yields a one-dimensional representation of the heterogeneity in the PEs.

Empirically, sample analogues of β and μ are employed to obtain estimators of the SPEs. In case of the interactive linear model with additive error, the PE estimator $\widehat{\beta(q)}$ is obtained by replacing τ in equation (4) with its ordinary least squares estimator $\hat{\tau}$.[9]

3.1.3 Subgroup Analysis

To assess specific factors that give rise to treatment effect heterogeneity, we interact the binary treatment indicator D_i with indicators for the subgroups as well as continuous measures of individual-level characteristics. Based on hypotheses from the literature, our focus is on effect differences between, first, individuals performing different types of tasks in their jobs; and second, individuals who differ in the extent to which their job is exposed to technological change. The respective indicators can be measured either continuously or discretely. We build discrete indicators from the underlying continuous information. This simplifies the interpretation of the results and allows us to analyse all differences with a similar approach. We estimate interaction effects and report point estimates for $\beta(w)$ performing tests for equality in the different subgroups.

3.1.4 Classification Analysis

To analyse associations between individual-level characteristics and effect heterogeneity, Chernozhukov, Fernández-Val, and Luo (2018) suggest undertaking a classification analysis (CA). Unlike subgroup analysis, CA focuses on the extremes of the

9 For an extensive description see Chernozhukov, Fernández-Val, and Luo (2018).

effect distribution, examining the factors that distinguish them. While subgroup analysis compares effect differences between two groups defined by a single variable, CA investigates how observations at the extremes of the effect distribution, e. g. in the upper and lower u percent of the effect distribution, differ in observable characteristics. In identifying the extremes of the effect distribution, CA builds on SPE, incorporating all characteristics used in the SPE estimation simultaneously to determine the u percent quantiles of the effect distribution, $\beta^*(u)$. The CA for the u-least and u-most affected subpopulation (u-CA) then comprises two steps:

1. Assign all observations with $\beta(Q) < \beta^*(u)$ to the *u-least affected* subpopulation, and all observations with $\beta(Q) > \beta^*(1-u)$ to the *u-most affected* subpopulation.
2. Obtain the moments and distribution of the characteristics of observations in the least and most affected subpopulation.

To obtain the empirical u-CA, $\beta(Q)$ and $\beta^*(u)$ are replaced by their sample analogues $\widehat{\beta(Q)}$ and $\widehat{\beta^*(u)}$. Then the moments and distribution of the characteristics of observations in the least and most affected sub-populations are estimated by their empirical analogues in the least and most affected subsamples.

Following Chernozhukov, Fernández-Val, and Luo (2018), we analyse differences between the upper and lower 10 % quantile of the effect distribution. As a central part of their paper, the authors further provide consistent estimators of measures of variation (standard errors and confidence bands) for both the SPE and the CA based on bootstrap procedures. Employing those, we can test whether differences between the groups are statistically significant accounting for multiple testing.

3.2 Data and Construction of the Sample

3.2.1 Administrative Pension Data

To examine whether and to which extent eligible individuals reacted to the reform, we use administrative data of the Rehabilitation Statistics Database (RSDLV, Reha Statistik Datenbasis Verlaufserhebung)[10] provided by the German Pension Insurance (Deutsche Rentenversicherung). Our dataset contains information on all insured individuals born in the years 1951 and 1952. Thus, the number of observations is quite large with more than 1.2 million individuals in every cohort. Due to computational capacity constraints, we drew a 10 % sample for our analyses. The data contains

10 The official title of the dataset is RSD insurance history survey 2017 and 2018, control group of the 66 year olds, header data, data on pensions and contributions, source: FDZ-RV, abbreviated: SPF. RSDV.2017-2018.1412-KO_RT_BY.

information on socio-economic variables such as gender, month and year of birth, place of residence (at the state level). Very importantly, the dataset also includes detailed information on the employment status on a monthly basis for the age span between 56 and 66. The different states contain regular employment, marginal employment, unemployment and part-time work in old-age. Furthermore, the dataset indicates whether an individual receives a pension, the type of pension, as well as month and year of retirement if applicable. Thus, the exact age at retirement can be inferred as well as whether an individual retired before or after the enactment of the reform.

As the previous section shows, the combined effects on employment and unemployment are the mirror image of those on retirement. Therefore, in this and the following sections, we focus exclusively on retirement. In addition, annual information on the so-called task code (Tätigkeitsschlüssel), a combined measure of occupational classification (according to the occupational classification of the German Statistical Office, KldB) and qualification, is contained in the data. For various reasons, the task code is sometimes missing in the data. To impute missing values of the task code, we replaced missing information with the task code of contiguous periods if available. After the imputation, 11.5 % of the individuals had no valid information for the task code over the whole observation period. We ran a series of linear probability models to analyse potential mechanisms of selectivity due to missing task codes. All in all, the principal reasons for missing task codes seem to be captured by observed covariates such as nationality or employment state duration, so that sample selection based on unobservables should not be a major issue.[11]

In addition to the Rehabilitation Statistics Database, we also use information from the data on pension entries for the years 2011 until 2021.[12] We use this data to determine whether individuals are eligible to claim an old-age pension for the very long-term insured.

3.2.2 Survey Data on Occupation Characteristics

Our main focus is on heterogeneity in the effect of pension reforms with respect to occupational tasks and the exposition to technological development. We use a measure of task intensities on occupational level based on the work of Spitz-Oener (2006) and Antonczyk, Fitzenberger, and Leuschner (2009). Like Spitz-Oener (2006) and Antonczyk, Fitzenberger, and Leuschner (2009) we employ data from a representative survey conducted by the German Federal Institute for Vocational Education and Training and the German Federal Institute for Occupational Safety and

11 The regression results are available upon request.

12 Precisely, this is the raw data of all pension entries 2011–2021, which is not publicly available.

Health (BIBB/BAuA Employment Survey) to calculate task intensities in five task categories: routine manual, non-routine manual, analytic, interactive and cognitive. Following Alda (2013), we adjust the calculation to account for different numbers of potentially executed tasks in each category and over time. We employ the waves 2006, 2012 and 2018 of the BIBB/BAuA Employment Survey to calculate the task sets of the occupations. We differentiate the occupations according to whether tasks from a domain are reported *often* or *rarely*. A task domain is defined to occur often if the task share is above the 7th decile of the distribution and rarely otherwise.

To measure exposure to technological development, we use two sets of indicators: one based on the use of computers at work and the other on the recent introduction of new technologies in the workplace. These indicators are generated in a manner analogous to the task indicators. Employing BIBB/BAuA Employment Survey data for the years 2006 and 2012, we calculate the share of individuals reporting to use a computer at work and the share reporting to frequently use a computer at work, by occupation. In order to calculate indicators for technological development, we rely on questions in the BIBB/BAuA Employment Survey data, in which individuals were asked to indicate whether certain changes in their work occurred in the two years previous to the survey. The questions concern the introduction of new technologies or new machines, the use of new products or materials, the provision of new services, or the employment of new computer programmes. As we focus on changes and developments arising previous to the enactment of the reforms, we employ the respective averages over the waves 2006 and 2012 of the BIBB/BAuA Employment Survey. To separate the occupations according to how strongly they are affected by technological change, we again use the 7th decile of the corresponding distribution.

We merge these indicators of task occurrence and technological change with the administrative pension data at the occupation level and conduct subgroup and SPE analyses to distinguish our estimates based on these indicators.

3.2.3 The Analysis Data Set

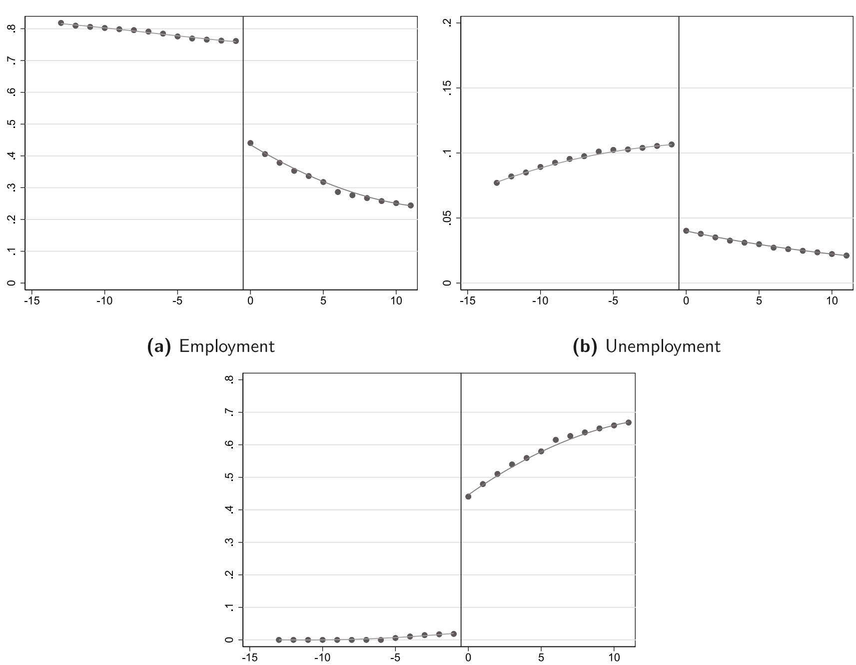
In our analysis, we focus exclusively on individuals who are eligible for the pension for very long-term insured. We first of all exclude individuals who are insured under the pension scheme for miners, as for them more favourable early retirement rules apply. We also exclude individuals receiving an old-age pension for disabled, as eligibility to this pension type includes suffering from severe health issues, which impedes comparability to other individuals. Furthermore, we exclude individuals who retired before the age of 63, who receive a disability pension, who have spent part of their employment career abroad and who will not be able to fulfil the eligibility criteria for the old-age pension for the very long-term insured until age 65.

Finally, we exclude all individuals who do not claim any pension by the age of 66. Table A2 in Appendix shows the composition of the analysis sample.

4 Results

4.1 Average Reform Effects

The panels of Figure 1 display mean values of the outcome variables employment, unemployment and retirement for individuals eligible for the old-age pension for the very long-term insured in monthly bins, respectively. The *x*-axis captures a time span of 12 months before to 12 months after the cut-off (i. e. the onset of the reform in July 2014). All outcome variables exhibit a clear discontinuity at the cut-off. To provide



(a) Employment (b) Unemployment

(c) Retirement

Figure 1: Local linear regression plots of reform of old-age pension for the very long-term insured relative to cut-off. Notes: Scatter plots display mean outcome values using monthly bins. Local linear regression plots are based on triangular kernel functions with a bandwidth of 12 months.

Table 1: Main reform effects – RDD results.

	Old-age pension for very long-term insured[a]		
	Employment	**Unemployment**	**Pension**
Overall	−0.316***[b]	−0.066***	0.424***
N			1,099,954
Male	−0.323***	−0.072***	0.434***
N			643,595
Female	−0.305***	−0.058***	0.409***
N			456,359

[a]Standard errors are clustered by individuals. [b]***, **, *: Asterisks indicate significance of coefficients at the conventional significance levels 1 %, 5 %, 10 %, respectively.

further evidence for the discontinuity at the cut-off, the panels of Figure 1 additionally display local linear regression plots with bandwidths of 12 months on both sides of the cut-off. If a non-linear relationship between the running variable and a dependent variable had been mistaken for the discontinuity, the non-parametric local linear regression would have provided evidence of such a relationship. However, the local linear regression plots also exhibit clear discontinuities at the cut-off, reinforcing our findings. Moreover, they provide additional evidence for a roughly linear trend in the dependent variables around the cut-off point. Taken together, we conclude that we can estimate the causal effect of the pension reforms on the displayed outcomes by employing a sharp RDD approach via estimation of a linear model of the form displayed in equation (1).

Table 1 presents the estimated effects of the retirement reform on individual employment, unemployment, and pension receipt for the entire eligible population. Overall, the results align with the descriptive evidence shown in Figure 1.

The reform had significant effects on the proportion of individuals in employment, in unemployment, and receiving pension payments. The increase in the share of individuals receiving a pension of more than 40 percentage points is accompanied by a decline in employment of about 32 percentage points and in unemployment of about 7 percentage points.[13] As shown in the table, women's responses to the pension reform were largely similar to those of men.

Taken together, the reform seems to have had a large impact on the labour market status of affected individuals, which will be investigated in more detail in the following.

13 These effects are similar to those found by Dolls and Krolage (2023).

4.2 Overall Heterogeneity in the Reform Effects

Next, we analyse how the reactions differ among affected individuals. To summarise the heterogeneity in the treatment effects, we plot sorted partial effects (SPE) following Chernozhukov, Fernández-Val, and Luo (2018). We employ measures for differences in occupational demands, occupational tasks, technological change (all measured at the occupation level), differences in local labour markets (measured at the level of labour market regions) and differences in employees' characteristics (share of older employees and share of employees with vocational education, measured at the level of occupations and federal states) to capture overall effect heterogeneity.

Our focus is on heterogeneous effects on retirement behaviour. At first sight, the reform might have offered an irresistibly attractive opportunity to retire early, so that everyone eligible made use of it. Against this background, heterogeneity in pension take-up is especially interesting. Figure 2 shows the sorted partial effects of the reform. In estimating the SPE, we do not separately account for heterogeneity with respect to every single characteristic, but incorporate all of them simultaneously. The plot shows considerable heterogeneity in the treatment effects. The

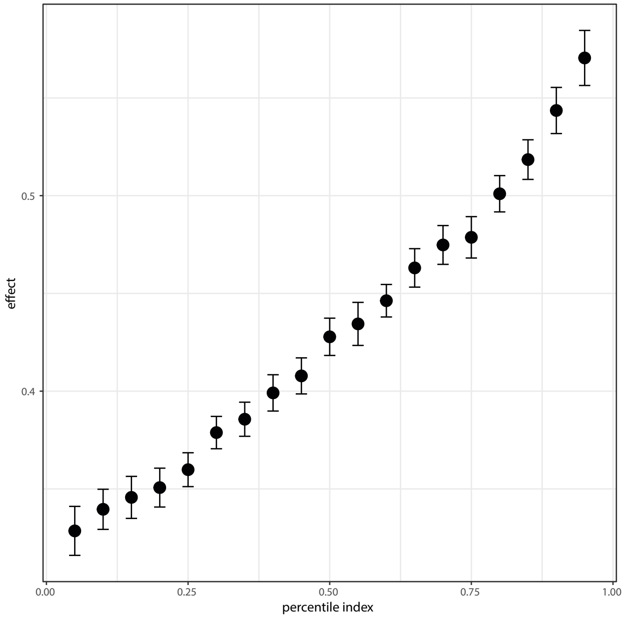


Figure 2: Sorted partial effects on retirement.

estimated SPE on retirement range from 0.33 to 0.57, accounting for heterogeneity with respect to individual, labour market, and occupational characteristics. Thus, even for those least affected by the reform, the reaction in pension take-up is considerable. Additionally, those affected the most show reactions almost twice as large as those affected the least. This shows that the assumption that the reform provided an equally attractive early retirement option for everybody does not hold. Some altered their retirement behaviour in reaction to the reform much more than others.

4.3 Heterogeneity with Respect to Occupational Tasks

To study how the effects of the reform on retirement differ with respect to differences in occupational tasks, we analyse and compare the effects in the subgroups defined by differing task compositions. We study each task separately. It is important to note that the differences in the treatment effects across subgroups are not interpreted causally.

Table 2 presents the reform effects differentiated along the occurrence of occupational tasks. We classify tasks as being performed often if their share of all tasks performed is above the 7th decile of the distribution and rarely otherwise. The table shows statistically significant differences in effect sizes with respect to all tasks considered.

The largest differences can be found for analytic and for routine manual tasks. In occupations in which analytic tasks are more important, we find a smaller increase

Table 2: Reform effects differentiated by occupational tasks.

	Old-age pension for very long-term insured[a]	
	Retirement	
Occurrence	**Rarely**	**Often**
Routine manual	**0.387*****[b]	**0.482*****
Non-routine manual	**0.403*****	**0.429*****
Analytic	**0.449*****	**0.346*****
Interactive	**0.429*****	**0.354*****
Routine cognitive	**0.404*****	**0.422*****
		N **= 875,286**

[a]Standard errors are clustered by individuals. [b]***, **, *: Asterisks indicate significance of coefficients at the conventional significance levels 1 %, 5 %, 10 % respectively. Bold coefficients indicate statistically significant difference between effects at rare and often occurrence of a respective task.

in retirement than in occupations in which these tasks only occur rarely. The difference amounts to more than 10 percentage points. We also find a difference amounting to almost 10 percentage points for routine manual tasks. Retirement increases by 48 percentage points in occupations in which routine manual tasks occur often and by 39 percentage points in occupations in which these tasks occur rarely.

We find smaller but still significant differences for the other task domains. For non-routine manual and routine cognitive tasks, the effect goes in the same direction as for routine manual tasks: a more frequent occurrence is associated with a larger increase in retirement. For interactive tasks, we see the same pattern as for analytic tasks: a more frequent occurrence is associated with a smaller increase in retirement.

Our results thus show that individuals largely performing tasks with declining importance over the past five decades (Autor, Levy, and Murnane 2003; Autor and Price 2013), i. e. routine cognitive and both routine and non-routine manual tasks, reacted much more strongly to the pension reform than individuals largely performing tasks with increasing importance, i. e. analytic and interactive tasks. In a next step, we want to find out whether we can also find heterogeneity in pension reform effects regarding the extent to which individuals are exposed to technological change.

4.4 Heterogeneity with Respect to Computer Use and Technological Change

We now analyse differences with respect to computer use and technological change in an individual's occupation. The upper part of Table 3 reports the reform effects differentiated along the occurrence of computer use in an occupation – either at all or frequently. The effects of the reform of the old-age pension for the very long-term insured differ substantially along the occurrence of PC use in the occupations. In occupations in which individuals are more likely to report using a PC at all, the effect on retirement is 8 percentage points lower. In occupations in which individuals state more often to frequently use PCs, the increase in retirement is almost 10 percentage points lower.

The lower part of Table 3 differentiates along the occurrence of new technologies, machines, products and materials, services, and PC programmes. We interpret these as measures of technological change. The largest differences can be found for the use of new machines, products or materials: In occupations in which the introduction of those is reported more often, the effect on retirement is 8–9 percentage points higher. For occupations in which the introduction of new technologies is reported more frequently, the effect on retirement is almost 6 percentage points

Table 3: Reform effects differentiated by indicators for technological change.

	Old-age pension for very long-term insured[a]	
	Retirement	
Occurrence	**Rarely**	**Often**
PC use at all	**0.430***[b]**	**0.347*** **
PC use frequently	**0.449*** **	**0.350*** **
	***N* = 875,286**	
New technologies	**0.400*** **	**0.457*** **
New machines	**0.391*** **	**0.471*** **
New products or materials	**0.390*** **	**0.479*** **
New services	**0.419*** **	**0.379*** **
New PC-programmes	**0.428*** **	**0.376*** **
	***N* = 873,889**	

[a]Standard errors are clustered by individuals. [b]***, **, *: Asterisks indicate significance of coefficients at the conventional significance levels 1 %, 5 %, 10 % respectively. Bold coefficients indicate statistically significant difference between effects at rare and often occurrence of an indicator for technological change.

higher than for occupations in which this is not the case. Regarding the use of new services and new PC-programmes, the relationship goes in the other direction: these are associated with a four to five percentage points smaller increase in retirement compared to occupations where such changes are only reported seldom.

Taken together, the direction of the relationship between pension reforms and technological change depends on the specific indicator. New technologies, machines, products or materials are associated with a larger increase in retirement. Possibly, these technological changes replace labour and thus induce individuals to retire. Also, as can be seen from Figure A1 in Appendix, occupations employing new technologies, machines, products or materials are to a large extent those in which the share of routine manual tasks is high. For new services and PC-programmes a frequent use is associated with a smaller increase in retirement. This finding corresponds to the results for PC use: No matter whether PC use at all or frequent PC use is considered, the increase in retirement is smaller the more common the use is in an occupation. Thus, technological changes connected with the use of computers rather seem to enhance labour than to replace it, thus leading to smaller reactions to early retirement opportunities. Again, occupations for which the use of computers and the introduction of new PC-programmes or services is reported more often are most likely those with a high share of analytical and interactive tasks. Thus, the heterogeneity in reactions to the pension reform with respect to indicators for technological change seem to both confirm our previous results for task domains and to fit the results for the changing task composition by Autor, Levy, and Murnane (2003) and Autor and Price (2013). In the next step, we take into account both tasks and technologies at the same time.

4.5 Heterogeneity with Respect to Tasks and Technologies Interacted

So far, our results show that different occupational tasks and different measures of technological change are associated with differences in the reaction to early retirement incentives. Now we depict how effects differ when we separate them along tasks and technologies simultaneously. We thus want to find out whether the use of technologies can for example attenuate the otherwise high retirement rates in certain occupations.

Table 4 indeed shows these attenuating effects, however their degree varies for the different tasks. In occupations with a high share of routine manual tasks, only frequent use of computers, new services and new PC-programmes is associated with significantly lower retirement rates. In a similar way, frequent PC use is accompanied by lower retirement rates in occupations with a high share of non-routine manual tasks. In contrast, the introduction of new technologies, machines and especially products or materials is associated with higher retirement rates. We find the same pattern for occupations with a high intensity of routine cognitive tasks: Indicators for technological change associated with computers show significantly lower retirement rates. This also holds for the introduction of new services. In contrast, the introduction of new machines and new products or materials is associated with a significant increase in retirement rates.

For occupations with a high share of analytic tasks, we find that PC use and new PC programmes are accompanied by lower retirement rates, whereas new machines are associated with increased rates. In occupations characterized by a high intensity of interactive tasks, only frequent computer use is associated with differences in the reform effect. Furthermore, we only find increased retirement rates where new technologies or new services have been introduced. For occupations with a high intensity in routine tasks (both manual and cognitive), the introduction of new services is associated with lower retirement rates.

Overall, our results show that PC use (both at all and frequent) and frequent use of new PC-programmes are associated with reduced retirement rates relatively homogeneously, whereas the introduction of new technologies, machines and new products or materials goes along with increases in retirement rates relatively

Table 4: Reform effects differentiated by tasks and technologies interacted.

		Task composition[a]									
		Routine manual		**Non-routine manual**		**Analytic**		**Interactive**		**Routine cognitive**	
		Rarely	**Often**	**Rarely**	**Often**	**Rarely**	**Often**	**Rarely**	**Often**	**Rarely**	**Often**
PC use at all	Rarely	**0.408**[b]	0.480	**0.429**	0.432	**0.450**	**0.364**	**0.437**	0.360	**0.430**	**0.431**
	Often	**0.341**	0.408	**0.337**	0.411	**0.380**	**0.336**	**0.349**	0.340	**0.343**	**0.325**
PC use frequently	Rarely	**0.425**	**0.480**	**0.459**	**0.434**	**0.449**	0.330	**0.452**	**0.372**	**0.435**	**0.462**
	Often	**0.352**	**0.384**	**0.350**	**0.396**	**0.384**	0.350	**0.366**	**0.340**	**0.346**	**0.364**
New technologies	Rarely	**0.390**	0.489	**0.387**	**0.429**	**0.440**	0.348	**0.427**	**0.344**	**0.374**	0.429
	Often	**0.364**	0.472	**0.443**	**0.497**	**0.465**	0.361	**0.447**	**0.464**	**0.449**	0.407
New machines	Rarely	**0.382**	0.469	**0.382**	**0.417**	**0.431**	**0.347**	**0.415**	0.345	**0.369**	**0.420**
	Often	**0.432**	0.484	**0.465**	**0.467**	**0.474**	**0.385**	**0.466**	0.431	**0.465**	**0.467**
New products or materials	Rarely	**0.386**	0.469	**0.378**	**0.418**	**0.428**	0.348	**0.414**	0.344	**0.364**	**0.420**
	Often	**0.425**	0.482	**0.458**	**0.558**	**0.486**	0.367	**0.472**	.	**0.461**	**0.533**
New services	Rarely	**0.392**	**0.483**	**0.411**	0.434	**0.451**	0.346	**0.436**	**0.332**	**0.404**	**0.431**
	Often	**0.378**	**0.435**	**0.369**	0.422	**0.420**	0.356	**0.408**	**0.363**	**0.388**	**0.317**
New PC-programmes	Rarely	**0.408**	**0.487**	**0.430**	0.431	0.448	**0.362**	**0.436**	0.362	**0.423**	**0.436**
	Often	**0.354**	**0.450**	**0.362**	0.435	0.437	**0.342**	**0.411**	0.341	**0.373**	**0.334**

[a]Standard errors are clustered by individuals. All coefficients are significant at the 1 % level. [b]Bold coefficients indicate statistically significant difference between effects at rare and often occurrence of the respective technology indicator considered.

homogeneously. The picture is more mixed for the introduction of new services: in occupations with large shares of routine tasks (both manual and cognitive) it is associated with a smaller effect on retirement rates, in occupations with a high share of interactive tasks the effect is (significantly) higher where the introduction of new services is reported more frequently.

We take these results as a hint that technology indicators associated with computer use are labour enhancing and thus make early retirement less attractive while technology indicators associated with developments in production (technologies, machines, products and materials) might be labour replacing and thus make early retirement a very attractive option in the face of high risks of unemployment or decreasing wages. Developments connected with services seem to have both a potential to enhance labour (for occupations with high shares of routine manual or routine cognitive tasks) or to replace it (for high shares of interactive tasks).

Overall, our results support the findings of the task polarisation literature: where task-complementing technologies are more likely to be used, we see a weaker response to the reduced full retirement age; where technologies are more likely to replace tasks, we see a stronger response. The differences in the effects with regard to the emergence of new technologies at task level largely underline this. Even taking these differences into account, however, it should be noted that the use of the new pension access option – i.e. the effect size – was very high across all groups of eligibles considered. Even in the groups which showed the smallest reaction, the take-up was very high.

4.6 Results of the Classification Analysis

Up to this point, we have analysed differences in effect sizes associated with variations in job tasks and technological change indicators, examining their magnitude and significance within respective subgroups. With CA, we take a different approach by investigating whether job characteristics differ between individuals with very high and very low response levels (10th and 90th percentiles), identifying the factors that distinguish extreme effect sizes. Table 5 shows the results. As for the role of task domains, our previous results are confirmed: Individuals who reacted most strongly to the reform perform routine manual, non-routine manual and routine cognitive tasks significantly more often than individuals who are in the lowest 10 % of the effect distribution. It is the other way round with analytic and interactive tasks: Individuals in the highest 10 % of the effect distribution conduct them significantly less often than individuals in the lowest 10 % of the effect distribution.

Table 5: Classification analysis – results.

	Retirement
Tasks	
Routine manual	0.645***[a]
Non-routine manual	0.278***
Analytic	−0.897***
Interactive	−0.780***
Routine cognitive	0.493***
PC use	
At all	−0.834***
Frequently	−0.887***
Use of new	
Technologies	0.313***
Machines	0.636***
Products or materials	0.674***
Services	−0.315**
PC-programmes	−0.617***

[a]***, **, *: Asterisks indicate significance of the differences between least an most affected individuals adjusted for multiplicity to account for joint testing of zero differences between all the variables in the table at conventional significance levels 1 %, 5 %, 10 %, respectively.

Regarding computer use at work, the results of the classification analysis are also entirely in line with the previous results: For both indicators the analysis shows that individuals who react most strongly to the reform report significantly less often to use a computer at work or to frequently use a computer at work.

The results for the indicators for the introduction of new technologies also confirm the findings shown above: While the frequent use of new technologies, machines and products or materials goes along with a stronger reaction to the reform, a frequent use of new services and PC-programmes is associated with a smaller reaction to the reform.

Taken together, our findings show that the indicators driving effect heterogeneity in the subgroup analysis also play a significant role at the extremes of the effect distribution.

5 Conclusions

We have studied the treatment effects of lowering the threshold for full pension receipt on employment, unemployment and retirement. In line with previous evidence (Dolls and Krolage 2023), we find large and significant effects on these outcomes. Our main contribution, however, is the analysis of the heterogeneity of estimated treatment effects with respect to occupational task domains and indicators for technological change. To this end, we analyse whether individuals were differently affected by the pension reform depending on tasks performed at work and the extent to which they were exposed to technological change. Using an SPE analysis, we account for these and other differences and find a wide range of treatment effect magnitudes.

Looking at occupational characteristics and indicators for technological change individually, we also find significant differences in treatment effects. The effect of the reform on retirement is higher for individuals performing more routine or non-routine manual tasks or routine cognitive tasks, whereas individuals performing more interactive or analytical tasks show a smaller increase in retirement. Indicators for technological change show a similar picture: while the frequent use of new technologies, machines, products or materials in the occupation is associated with a larger pension take-up, individuals in occupations where the use of new services or PC programmes is more wide-spread show a smaller reaction to the pension reform. Focussing on computer use, individuals who more often report to use a computer at work (both at all and frequently) make less use of the new option for early retirement. Once we interact tasks and technology indicators, our results show that indicators associated with computer use reduce retirement rates, while those associated with frequent use of new technologies, machines and new products or materials increase retirements rates. In contrast, frequent use of new services attenuates the reform effect only for occupations with a high intensity in routine and non-routine manual tasks as well as in routine cognitive tasks. However, for occupations with a high share of analytic and interactive tasks, retirement rates are significantly higher when new services are used frequently. As a final step, we perform a classification analysis, as suggested by Chernozhukov, Fernández-Val, and Luo (2018), to analyse whether these characteristics also differentiate observations at the extremes of the effect distribution. We find a similar pattern of differences in occupational tasks and indicators of technological change between the most and least responsive individuals as in the other parts of our analysis.

In particular, large reform effects are obtained for those tasks which decline in importance according to the findings of Autor, Levy, and Murnane (2003) and Spitz-Oener (2006). Additionally, we find that reform effects differ with regard to whether a technology used frequently can be seen as labour enhancing or labour replacing. Thus, we extend the important findings regarding the effects of occupational and technological change on labour markets of Acemoglu and Autor (2011), Autor and Dorn (2013) or Goos, Manning, and Salomons (2014) and others to the topic of reactions in labour supply due to pension reforms, which has – to be best of our knowledge – not been analysed before.

Our results highlight the interaction between labour market characteristics in general and pension reforms. Due to ongoing population ageing and increasingly severe impacts of technological change on skills and the entire labour market, this field provides many valuable implications for future research. Based on a proper identification strategy, estimating differentiated treatment effects along labour market and occupational characteristics helps to better understand to which extent pension reforms affect labour markets and vice versa. Although the results of subgroup analyses cannot be interpreted causally, they uncover areas where further analysis of causal mechanisms would be valuable.

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Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix

See Tables A1 and A2, Figure A1.

Table A1: Average share of tasks by domain.[a]

Year	*N*	Routine manual	Non-routine manual	Analytic	Interactive	Routine cognitive
2006	19,594.2	0.236	0.169	0.230	0.235	0.130
2012	19,421.9	0.235	0.162	0.243	0.235	0.124
2018	19,522.4	0.224	0.160	0.264	0.233	0.120

[a]Source: Own calculations based on BIBB/BAuA Employment Survey waves 2006, 2012 and 2018.

Table A2: Summary statistics.

	Cohort 1951						Cohort 1952					
	Age 62.5		Age 63		Age 63.5		Age 62.5		Age 63		Age 63.5	
	Mean	SD[a]	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Employed	0.80	[0.40]	0.78	[0.41]	0.41	[0.49]	0.79	[0.41]	0.79	[0.41]	0.27	[0.44]
Unemployed	0.09	[0.29]	0.11	[0.31]	0.04	[0.20]	0.10	[0.30]	0.11	[0.31]	0.02	[0.15]
Retired	0.00	[–]	0.00	[0.01]	0.47	[0.50]	0.00	[–]	0.00	[–]	0.64	[0.48]
Ret. Age (months)[b]	768.43	[11.41]	768.43	[11.41]	768.44	[11.41]	765.08	[11.57]	765.08	[11.58]	765.08	[11.58]
Earnings points	46.11	[14.60]	46.11	[14.61]	46.10	[14.61]	42.01	[15.71]	42.01	[15.72]	42.01	[15.72]
Non German	0.02	[0.14]	0.02	[0.14]	0.02	[0.14]	0.02	[0.14]	0.02	[0.14]	0.02	[0.14]
East German	0.28	[0.45]	0.28	[0.45]	0.28	[0.45]	0.28	[0.45]	0.28	[0.45]	0.28	[0.45]

[a]SD: Standard deviation.
[b]Average retirement age in months: 756 months equal to 63 years.

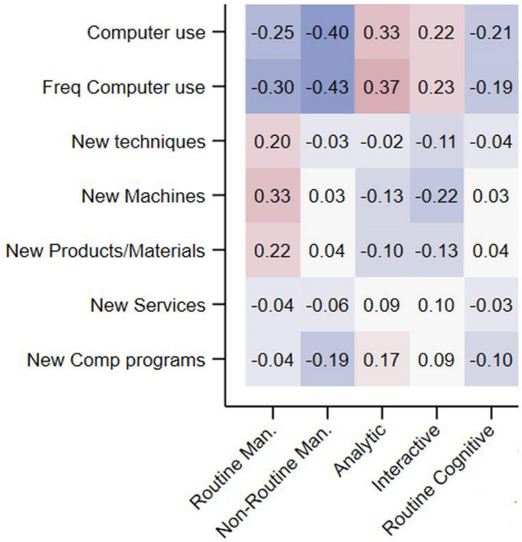

Figure A1: Heatplot showing correlations between task domains and technological change indicator on individual level. Source: Own calculations based on BIBB/BAuA employment survey waves 2006, 2012 and 2018.

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