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# „Big Data at Work: Age and Labor Productivity in the Service Sector"

AUTOREN: AXEL BÖRSCH-SUPAN, CHRISTIAN HUNKLER, MATTHIAS WEISS

# Big Data at Work: Age and Labor Productivity in the Service Sector

Axel Börsch-Supan, Christian Hunkler, Matthias Weiss

*Abstract*: Does productivity decline with age? Does population aging harm economic growth? We exploit process-generated data from a large and typical service-sector company. We find no decline in average productivity in the age range of 20-60. This result is precisely measured. Our innovative identification strategy corrects for sample selection, endogeneity of age composition and age-cohort confounding. Our big data are essential to extract the signal from the noise that has marred many previous studies. While average productivity stays flat, we find variation according to task complexity. Productivity increases with age in teams with more demanding tasks and decreases in routine tasks.

*JEL:* J24, J14, D24

*Keywords:* Age-productivity profiles, Service industry, Demographic change

*Axel Börsch-Supan, corresponding author,* is the director of the Munich Center for the Economics of Aging (MEA) at the Max Planck Institute for Social Law and Social Policy, and a professor of economics at Technical University of Munich, Germany, and research associate at the National Bureau of Economic Research (NBER), Cambridge, Mass.

*Christian Hunkler* is a senior researcher at Humboldt University Berlin, Germany, and fellow at the Munich Center for the Economics of Aging (MEA) at the Max Planck Institute for Social Law and Social Policy. Corresponding author: Christian.Hunkler@hu-berlin.de.

*Matthias Weiss* is a professor of economics at Ostbayerische Technische Hochschule (OTH) Regensburg, fellow at the Munich Center for the Economics of Aging (MEA) at the Max Planck Institute for Social Law and Social Policy, and fellow at the Research Centre for Education and the Labour Market (ROA), Maastricht University, Netherlands.

The data used in this article are proprietary data supplied by an insurance company that we cannot make readily available. The data used for this research were extracted by the company free of charge. We will make the data preparation and analysis code and programs available and can offer any researcher the possibility to visit us to analyze the data or to have us run their code on the data in a timely fashion.

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## I. Introduction

The development of productivity in an aging population is a key issue for the economics of aging. It stands in the middle of a yet unresolved controversy (e.g., Lee 2014; Lee and Mason 2010). On the pessimistic side, some see population aging as a major threat to economic growth and a reason for secular stagnation and the observed productivity slowdown (e.g., Gordon 2016; Summers 2013; Feyrer 2007). This pessimistic view is built on the notion that aging economies dispose of fewer human resources than young economies. Since population aging has so far resulted in an aging of the workforce but not in its shrinking, a necessary condition for the validity of this argument is that older workers were less productive than their younger peers. The belief that older workers are less productive is widespread and influences discussions about aging, employers' personnel decisions (e.g., Lahey 2008) and employees' retirement choices, especially in Europe.

Others, however, are more optimistic and argue that better education and other cohort effects (e.g., Kwon et al. 2010) and the emerging opportunities created by new technologies (e.g., robots or artificial intelligence) will dwarf demographic effects (e.g., Kluge et al. 2014; Mokyr 2014; Glaeser 2014). Moreover, Acemoglu and Restrepo (2017) studied the relation between conventional measures of aging and GDP per capita. They found no negative relation and argue that directed technical change has compensated for an aging workforce because demographic change has provided an incentive to invest more in automation.

The microeconometric evidence on age-productivity profiles is controversial as well and often inconclusive since important human resources of older individuals (e.g., experience and size and quality of network) are hard to measure as will be discussed below. In an earlier study published in this journal, we have argued that good management makes productivity essentially independent of age in taylorized standard manufacturing jobs (Börsch-Supan and Weiss 2016). However, this finding refers to only a small share of jobs in modern economies.

This paper complements Acemoglu and Restrepo's macroeconomic findings and our earlier research by providing microeconometric evidence from the service industry. Our main result is striking: We find that the age-productivity profile averaged over all tasks is flat and this can be estimated fairly precisely in spite of the heterogeneity of jobs in our sample. These results are based on an innovative identification strategy, which overcomes the methodological difficulties that have marred so many previous studies as will be discussed below. It purges the data from selectivity and other biases by only exploiting the variation in the assignment of workers to work teams while differences between workers and differences between teams are removed by fixed effects for individual-team pairs.

Our findings pertain to a wide range of tasks that are typical for the service industry. We find that the age-productivity profile differs considerably among different types of work tasks. It is flat for the large majority of tasks. However, the age-productivity profile increases in all age groups in the units with intellectually more demanding tasks, while we observe the opposite phenomenon for basic routine tasks. Hence, work content has a considerable influence on the relationship between age and productivity. This observation also suggests that experience offsets the physical and, presumably more relevant, cognitive decline well after the age of 60 in the more demanding tasks.

Labor economists have been interested in estimating age-productivity profiles for a long time (e.g., Mark 1957, or Kutscher and Walker 1960)[i]. Indeed, numerous empirical studies have been published on the subject. They face a host of methodological challenges which are summarized in Göbel and Zwick (2012) and Börsch-Supan and Weiss (2016). The largest challenge is selectivity. Less productive workers are likely to leave the company earlier; the remaining workers are then a positive selection. Another positive selection occurs when managers assign easier tasks to workers who become less productive. The same happens if workers self-select into easier jobs when they become less productive. If workers were to become less productive with age, these selectivity effects would upwardly bias the slope of the age-productivity profile, i.e., they would suggest a rising profile when it is flat or a flat one when it is negative.

Our contribution to this literature avoids these methodological shortcomings by employing an innovative identification strategy that exploits the day-to-day variation in team composition, while removing differences between workers and differences between teams by fixed effects for individual-team pairs. This eliminates the variation responsible for the various selectivity biases that have marred much of the previous estimates of the age-productivity relation. In order to detect the remaining small productivity signal, we use a very large panel data set of an internationally operating financial company with a wide range of tasks typical for the service industry.

We classify previous research into three types. The first type uses wage and salary data or manager evaluations as a measure of individual productivity (e.g., Kotlikoff and Gokhale 1992;

Laitner and Stolyarov 2005; McEvoy and Cascio 1989). Both measures reflect productivity to some extent but have major drawbacks: The widespread use of pay schemes, and especially seniority-based pay scales, means wages will often increase, and, more importantly, rarely fall, with increasing age regardless of the progression of productivity. Hence, the relationship between age and productivity may be positively biased. By contrast, subjective evaluations may be distorted in the opposite direction if a substantial share of manager evaluations is influenced by the aforementioned belief that older workers are less productive. Moreover, this individualistic approach neglects the fact that work is often organized in work teams or units. More experienced, and therefore often older, employees may devote some of their time to helping their younger colleagues, thereby increasing their peers' productivity at the cost of their own.

The second type of study relates plant-level productivity figures to the age structure of these plants (e.g., Hellerstein and Neumark 1995; Haltiwanger, Lane, and Spletzer 1999; Hellerstein, Neumark, and Troske 1999; Daveri and Maliranta 2007). Whereas both are relatively accurate and directly observable, for example, from balance sheets and personnel records, the first shortcoming of this approach is that the age structure of a plant might be endogenous because it is partly a function of the plant's productivity. More productive firms are usually more profitable and therefore often expand and increase their workforce. Because new hires are likely to be younger (Quimet and Zarutskie 2013), the workforce of more productive firms rejuvenates relative to the less productive firms. The second shortcoming is that plant-level figures aggregate over heterogeneous jobs and positions. For example, the productivity of production workers on the shop floor could peak, on average, earlier than that of managers who might still have ambitions for a top-level position. Hence, averaging over all possibly very different and non-linear age-productivity profiles within a plant is likely to create aggregation biases, especially considering that in plant-level analysis, individuals might have varying impacts on the overall output.

The third type of study is based on direct productivity measures, for example, the number of publications in academic research (Oster and Hamermesh 1998), Nobel Prizes (Jones 2010), the value of artists' paintings (Galenson and Weinberg 2001), performance in sports (Fair 1994), or the number and quality of completed court cases (Backes-Gellner, Schneider, and Veen 2011). Although these studies assess productivity quite accurately, they are limited in terms of the range of professions they can feasibly measure. Moreover, these studies typically focus on individual top performers who probably differ from the average worker and a normal work setting.

Börsch-Supan and Weiss (2016, "BSW") study age and productivity in a truck assembly plant to address these issues directly. The authors use a physical productivity measure that pertains to "normal" work, namely, not top performers but average workers in work settings found in many companies, and their unit of observation is work teams, that is, an aggregation level between the individual and an entire plant. BSW exploit the day-to-day variation of the team composition and adjust for team- and individual-level heterogeneity by team and individual fixed effects. They find no decline in productivity in the age range between 25 and 65 years for this specific blue-collar production work type. The limitation of their study, however, is its focus on a single plant in auto manufacturing with a relatively homogenous set of tasks.

This paper uses a similar methodology as BSW and applies it to a large set of tasks in the service industry. Although jobs in manufacturing may require more physical strength, dexterity, and agility, which tend to decline with age, the manufacturing sector has become less relevant, especially in countries with the most severe demographic aging. By contrast, the service-industry sector is expanding not only in economic importance and share of the labor force, but also in terms of the diversity of tasks performed by different teams (Uppenberg and Strauss 2010). This diversity of tasks performed is of importance because we can expect systematic differences in the age composition between different types of teams. Though the majority of jobs in this sector are not physically demanding, technological change and new or changing work tasks may pose related challenges to older employees, resulting in reduced productivity.

The sequel of the paper is structured as follows. Section II describes the work environment and the various tasks in a typical financial company. Section III discusses our data, and section IV discusses our productivity measure, whereas section V introduces our econometric identification strategy. Section VI presents our main results, and section VII presents analyses on employee fluctuation, retirement, and other censoring events. Section VIII concludes.

## II. Work Teams in the Financial Industry

We study the productivity of work teams in a large internationally operating Germany-based financial company which have tasks that are typical for the service industry. During a normal business day, some work teams in this company handle hundreds of short phone calls; others deal with many straightforward or a few complicated customer queries. Yet other teams enter new contracts into the company's computer system. Work is organized in small teams (on average about 10 employees, Table 3) dealing with very similar tasks, which allows more experienced workers to help their less experienced colleagues with difficult cases.

We use the company's reporting conventions to classify teams into four different types of tasks. In order of complexity, the first team type, referred to as "*advanced specialists,*" deals with the most complex tasks. They are, for instance, in charge of the business-to-business tasks and have access to contracts, a privilege that no other team type has. About seven percent of employees work in such teams. The second type, the "*non-routine professional*" teams, deal with standardized but still customized matters, for example, a claim for a car accident that involves ordering appraisals. Such tasks make up the majority of jobs; almost 59 percent of employees work in these teams. According to the narrative of the company representatives, the third type of team, the call-center-like "*customer service*" teams, is special in the sense that dealing with customers via phone requires a talent that cannot easily be acquired by training. This team type covers about 13 percent of employees. Finally, about 21 percent of employees work in "*routine basic*" teams that deal with typical routine tasks, for example, typing up a form or contract or evaluating a standard insurance claim. An example is the evaluation and processing of a bill for the repair of a damaged windshield. Overall, the advanced specialists and, to a lesser degree, also the non-routine-professional teams have more complex and difficult work tasks, whereas the routine-basic and the customer-service teams deal with rather basic tasks and requests.

Employees frequently leave their team and return to it after a few days. Employees have 30 days of vacation per year. Out of 250 working days, this is 12 percent. With an additional 6 percent sick leave, employees are about 18 percent of the time absent from their team. Hence, on an average day and for an average team with 12 members, at least two employees will be absent. This fluctuation is an important element of our identification strategy. In contrast, there is very little mobility of employees between work teams of different types of tasks (Section VII). If so, transitions from less demanding to more demanding tasks are more than four times more frequent than transfers from harder to easier tasks.

While this paper stresses the importance of measuring productivity at the team level and therefore deviates from an individualistic concept of productivity, we are aware of age-related and other complementarities within a team and will therefore account for them in our regression analyses.

## III. Data

The company provided us with data on all Germany-based non-management employee teams for the years 2010 through 2012. Parts of these nonreactive data are at the team level, and others are at the individual level.[ii] Teams comprise, on average, about 12 members, who work closely together; thus, daily output is measured at the team level. Examples are the number of claims processed, the number of phone inquiries dealt with, or the number of contracts of a specific degree of complexity that have been set up during the day. At the individual level, we acquired information on which employee was working in which team on which day, as well as basic demographic information drawn from personnel registers, especially the age of each individual employee.

The data are constructed from three main sources covering the years 2010 to 2012. The first source is an extract of the productivity monitoring system. It provides daily team-level output figures. The second data set is a daily extraction of the personnel time-recording system. This system stores information on all employees, including which team they were assigned to and their clock-in and clock-out times. Additionally, we merged the previous information with basic demographic information, for example, age, sex, education, and job tenure, drawn from the company's personnel registers. We also use an auxiliary data source that supplies information on the type of work task. The resulting data set is an unbalanced panel of 10,290 employees in 1,454 work teams that we observe on 908 days, representing 514,254 team days and 4,568,641 employee days.[iii]

Our data set is of high volume, high frequency (daily information on team performance), and high complexity (extracts from flat and relational databases supplied in various formats). On the one hand, such big data are necessary to identify the rather small and subtle age effects in productivity that are overlaid by many other and potentially much larger effects, such as education, personality traits, day-to-day variation in performance, and environmental influences. These data permit us to exploit only the variation within the same individual within the same work team over time, as we will explain in the following section. On the other hand, process-generated data may raise concerns about their quality (i.e., inconsistency across time), their veracity (i.e., whether to trust the data's accuracy), and their complexity (e.g., errors when linking multiple sources) (Japec et al. 2015, p. 842). Because the company uses the productivity and personnel data for several optimization and payment-related processes, for example, productivity monitoring and optimization, determination of premiums, and overtime compensation, we can trust the data and their consistency over time.

Table 1 shows the demographic composition of the employees in the financial company. Education is defined in years of primary and secondary schooling,[iv] because later education and training, that is, higher tertiary or dual vocational training, is only partially included in the personnel records available. Because we can only control for the mean level of schooling of the work teams and not for individual degrees in our fixed-effects analysis as explained in section V, we compute the mean years of schooling of all present team members for each day.[v]

**Table 1: Employee characteristics**

| | N employees | N observat. | Mean | S.D. | Min. | .25 | Quartiles Median | .75 | Max. |
|---|---|---|---|---|---|---|---|---|---|
| Age (in years) | 10,290 | 4,568,641 | 42.02 | 10.08 | 18.76 | 34.50 | 42.97 | 50.02 | 65.31 |
| Female | 10,285 | 4,563,117 | 0.61 | 0.49 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| Tenure (years) | 10,285 | 4,563,022 | 18.01 | 10.26 | 0.00 | 10.22 | 18.52 | 25.10 | 48.72 |
| Education (in years) | 8,641 | 3,848,682 | 11.39 | 1.49 | 8.00 | 10.00 | 12.00 | 13.00 | 13.00 |

*Notes:* The column "N employees" refers to the assignment at the median observation time point of each employee. All other statistics are based on the employee-day-level estimation sample (N=4,568,641).

Table 2 shows the employee-level demographic information broken down by team type. The advanced specialists, the team type with the most complex work tasks, and even more so, the customer-service employees, are, on average, considerably younger than the employees in the other team types (all $t > 107.4$, all $p < 0.001$, the difference between customer service and specialist is also significant, $t = 47.4$, $p < 0.001$). Because longer education, which could explain the age differentials, does not significantly vary across employee types, except for the routine-basic teams, which have considerably less secondary education, the younger average age in the advanced-specialists teams indicates steering by management, technology-driven placement, or self-selection of younger employees into more difficult work tasks. This pattern highlights the importance of separating the estimation of age-productivity profiles from potential cohort effects or selection bias without having to make assumptions on the kind of selection. Besides the differences in age, the considerably lower share of females in the professional teams and the lower tenure in the customer service teams stand out.

**Table 2: Employee characteristics by team type**

| Team type | N employees | Age (mean) | Female (share) | Education in years (mean) | Tenure in years (mean) |
|---|---|---|---|---|---|
| Specialist | 563 | 40.47 | 0.65 | 11.42 | 17.59 |
| Professional | 5,858 | 42.51 | 0.54 | 11.53 | 18.46 |
| Cust. Serv. | 1,470 | 39.35 | 0.71 | 11.26 | 14.61 |
| Routine | 2,326 | 42.73 | 0.71 | 11.07 | 18.97 |
| Not Assigned | 73 | 47.78 | 0.37 | 10.73 | 22.84 |
| Total | 10,290 | 42.02 | 0.61 | 11.39 | 18.01 |

*Notes:* The column "N employees" refers to the assignment at the median observation time point of each employee. All other statistics are based on the employee-day-level estimation sample (N=4,568,641).

## IV. Measuring Productivity

The starting point for measuring productivity is the physical output, that is, the number of transactions each team deals with per day. Depending on the respective team, the transactions can be inbound phone calls, forms, contracts, bills, or claims to be processed or entered into a database. Because each team is responsible for a specific product or specific type of service, counting the transactions within a team over time is a reasonably good measure of daily variation in a team's output. We divide the output by the hours put in by all employees working on the respective day for the team to have a comparable number of transactions.[vi] For example, if five employees put in eight hours each, that is, 40 hours, to complete a total of 160 phone inquiries, the number of transactions per person-hour is four.

Figure 1 shows the box-plot representation of the distribution of the number of transactions per person-hour, both overall and by the four team types. The advanced specialist teams make up 6.6 percent of the observed team days, the non-routine professionals teams account for 61.6

percent of the team day observations, 11.3 percent come from customer-service teams, and 20.6 percent come from routine-basic teams. The median number of tasks per person and hour in the non-routine-professional and advanced-specialist teams is 4.3 and 5.5, respectively. Routine-basic and the customer-service teams deal with more tasks per hour and person; the median number of transactions is 7.7 and 8.1, respectively. This difference corresponds to the assessment of the managers that the routine-basic and customer-service teams handle less complex and less difficult work tasks than the non-routine-professional and advanced-specialist teams. The overall distribution looks very similar to the distribution of the non-routine professionals, because they make up the majority of observed team days.

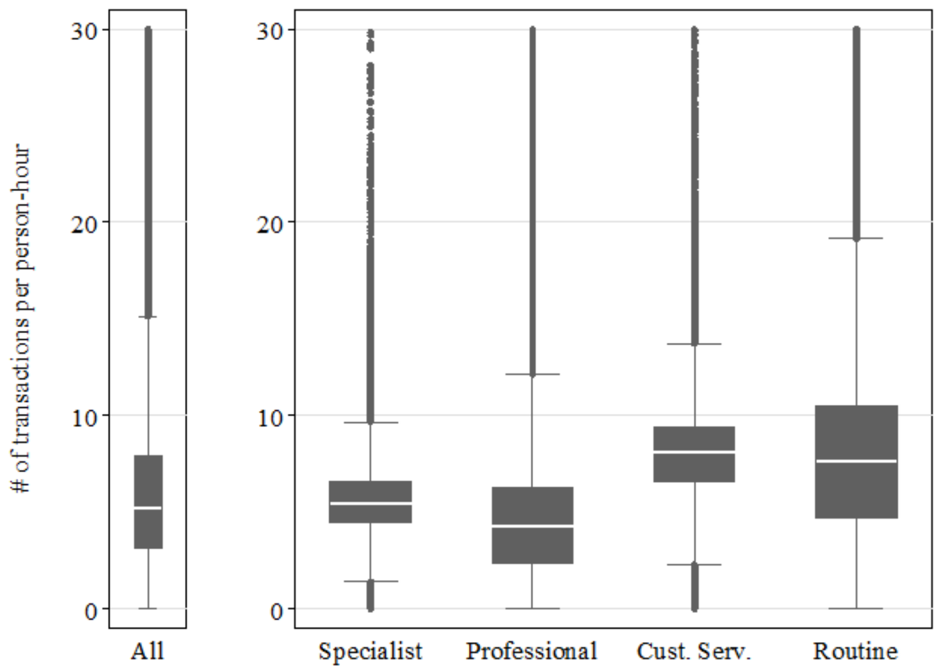


**Figure 1: Distribution of the number of transactions per person-hour by type of team**

*Notes*: The lower bound of the box in a box plot denotes the first quartile; the white middle line is the median; and the upper bound denotes the third quartile of the distribution of the respective variable. The difference between the upper and lower bound of the box defines the so-called interquartile range. The upper and lower fences mark 1.5 times the interquartile range below the first and above the third quartile, respectively (or the minimum/maximum of the distribution). The dots represent observations outside the fences. Based on N= 510,384 team days.

Figure 1 shows a remarkably large tail of the distribution. In all team types, the number of transactions recorded can reach very high numbers, such that many observations are outside the upper whiskers and even outside the figure's upper limit, which has been set at 30. In the less than 1 percent of cases not plotted, on several days, we observe very high numbers of transactions per person-hour of, for example, 2,025 or even 35,600 tasks. Such massive numbers arise if, for example, all customers of a popular product get an annual account report statement. Such a transaction constitutes several thousand tasks in the system, which, however, could have been accomplished with a mere mouse click by a single employee, regardless of his or her age. We drop these extreme outliers and define extreme outliers as observations where the number of transactions per person-hour is higher than two times the 95$^{th}$ percentile of the respective work team's distribution or lower than 0.5 of the 5$^{th}$ percentile. This procedure affects about 1 percent of all team days, almost evenly distributed across the four team types.[vii]

Because of the team-oriented nature of the work, the number of transactions per person-hour and thus productivity is measured at the team level. Within a team, the tasks are comparable. However, the complexity of the work task varies considerably, and therefore so does the average number of transactions across teams. For example, for one team, we count how many mailed-in contracts were entered into the computer system, a rather standardized routine task, whereas for another team, we count the number of calls dealt with, which can be a very demanding task for complex insurance products. We therefore need to standardize the number of transactions in order to arrive at a comparable productivity measure. We do so by dividing the number of transactions per person-hour by its team-specific mean.[viii] Let $y_{jt}$ denote the number of transactions per person-hour of team *j* on day *t*. Then standardized productivity $p_{jt}$ at the team level is defined as in Equation 1

(1) $$p_{jt} = \frac{y_{jt}}{\overline{y_j}}, with\ \overline{y_j} = \frac{1}{T_j} \cdot \sum_{t=1}^{T_j} y_{jt},$$

where $T_j$ is the number of days team *j* is observed.

This transformation achieves comparability of the productivity measure across different teams regarding the means as well as the deviations from the means. The mean of productivity across days is one in each team. Moreover, the daily deviations from the mean are now expressed as percentage deviations from the team means and are thus of a comparable range across different teams. As will become clear in the following section, the key to our identification strategy is the variation of $p_{jt}$ by whether a specific employee *i* participates in this team *j* on a given day *t*. Hence, the fluctuation into and out of the work team described in Section II identifies the contribution of an individual employee to the productivity of the entire team, which we denote by $\tilde{p}_{ijt}$. This individual contribution is not directly observable, because we measure productivity at the team level. However, we can calculate it by comparing team productivity at different dates, depending on whether individual *i* participates. Our focus is thus on employee-team pairs at a given date.

## V. Econometric Methodology

We want to estimate a regression equation relating individual employees' age to the productivity of their team, i.e., of the following type, where the unit of observation is an employee-team pair at a given day:

(2) $$\tilde{p}_{ijt} = \beta_1 \cdot \mathrm{age}_{it} + \beta_2 \cdot x_{jt} + \alpha_{ij} + \epsilon_{ijt},$$

where $\tilde{p}_{ijt}$ is the not directly observable contribution of individual employee *i* to the productivity of team *j* at day *t*. $age_{it}$ is the age of employee *i* at day *t*, and $x_{jt}$ are descriptors of the team-level variables, for example, size or female share of team *j* at day *t* and calendar effects at day *t*, for example, weekday or month dummies.[ix] We account for employee-team-pair-specific and time-constant unobserved heterogeneity by the term $\alpha_{ij}$ The standard remaining idiosyncratic error term at the employee-team-day level is denoted by $\epsilon_{ijt}$.

The estimation of such an age-productivity profile raises serious econometric challenges. Besides the various selectivity mechanisms that are likely to bias the measured slope of the age-productivity profile, a major challenge is to distinguish age effects from cohort and time effects. Distinguishing age effects from cohort effects is important since 30-year-olds differ from 60-year-olds not only in their age but also in the time period in which they grew up. This time period goes along with, for example, a difference in the average level of education or, maybe more important for our analysis, with differences in the curriculum. Although today's 30-year-old employees have had at least some basic IT lessons in secondary school, the current 60-year-old employees' curriculum, for example, in secondary school, did not include any IT-related content.[x] Because IT literacy is an important qualification in the workforce, this difference causes a challenge in correctly identifying a relation. Further examples for "cohort effects" that might blur the age-productivity relation are differences in nutrition and healthcare in childhood which in turn depend on the economic conditions in young age (Kwon et al. 2010). Our identification strategy must therefore be designed to avoid confusing cohort effects with the relation between age and productivity. We also have to rule out time effects, e.g., resulting from changes in technology or organization that could affect the productivity measure. Indeed, one reason to observe only a short period of three years was the adoption of new IT systems in several sites a year after our data stops. Over the time period we investigate, there is no trend in productivity (see Online Appendix 1).[xi]

The other group of challenges causes biases due to selectivity (e.g., Mark 1957). Older employees are underrepresented not only in the labor market in general, but also in the company under investigation. We can reasonably assume, as already pointed out, that people who remain in the workforce at older ages represent a positive selection because their less productive colleagues have already left the company. Moreover, managers may assign older employees to specific work fields due to (mis-)conceptions about age and productivity; for example, older workers may be systematically assigned to work teams with lower average output. Similar selectivity may occur within firms if older employees self-select into different work fields or teams within the firm. If older workers are systematically assigned or self-selected to easier tasks, the slope of the age-productivity profile will be upwardly biased. However, also the reverse bias may occur if workers with higher productivity are assigned or self-select into managerial positions at some point since our data do not include employees in management positions.

A fixed-effects estimator, which removes those differences between employees that are constant over time, helps to deal with two challenges: cohort effects and selectivity due to early exits from the company. If belonging to a certain cohort implies an advantage or disadvantage in productivity that is constant over age, this cohort effect is removed by the fixed-effects estimator so that the remaining variation of productivity over age can be attributed to age. Selection bias that results from less productive employees leaving the sample earlier than more productive employees can also be corrected by a fixed-effects estimator that removes interpersonal differences. The same holds for the opposite case of highly productive workers becoming managers. The identification of the fixed-effects estimator does not hinge on the comparison of older employees with younger employees. Instead, it relies only on the comparison of individuals with themselves over time so that the bias is avoided.

However, there may still be selection biases that result from systematic selection or assignment of employees into work teams. Comparing employees with themselves over time does not remove selectivity bias if the individuals are assigned to ever-less-productive work teams as they grow older. We therefore need to purge our productivity measure simultaneously from both individual- and team-specific effects. All differences between employee-team pairs are removed by pair-specific fixed effects.

The key step of our identification strategy is therefore to estimate the age-productivity relation only by comparing individuals with themselves over time *within* one work team. Our unit of observation is then an employee-team pair at a given day. We identify the evolution of an employee's productivity over time during an episode in which an employee works in a team with specific tasks. If this employee transfers to another work team, either by assignment or self-selection, our analysis treats this as a new episode with a separate fixed effect. Results of this "double-fixed-effects" estimation strategy as well as of the conventional worker fixed-effects strategy described above will be presented in Section VI.

The double-fixed-effects estimation strategy has the advantage of purging the variation in the data that might generate a large number of selectivity biases that have been ignored in previous research. However, this advantage has its price. First, since little variation is left, we need a very large data set exhibiting the necessary remaining variation. We have obtained such a data set. Second, while we capture all productivity changes within each employee-team episode, we would miss productivity changes between episodes, e.g., due a switch from a high-productivity to a low-productivity assignment.

More specifically: Whenever a worker switches work teams from date t to date t+1, we cannot quantify the productivity change that occurs between date t and date t+1, since the standardization of our productivity measure (equation 1) will reset the productivity *level* after each transfer. In that case we would identify the declining *slope* of the age-productivity profile only during each successive episode. This would be particularly harming if productivity were declining with age and employees would transfer into ever easier work teams until they finally leave the company.

The evidence presented in Section VII shows that this concern is minor. As mentioned in Section II, most fluctuation of employees into and out of work teams is within the same task type and due to vacation and sick leave. There is very little mobility of employees between work teams of different types of tasks. Among team changes, transitions from a less demanding to a more demanding task are more than four times as frequent as a transfer to easier tasks.[xii] Moreover, about 80 percent of employees remain in our sample for the entire duration of our study. We will analyze the about 20 percent of employees who leave the company before the end of our observation period separately in Section VII.

We spare the reader a formal presentation of the well-known conventional worker-fixed-effects estimator. The double-fixed-effects estimator is implemented by subtracting from all variables their employee-team-pair-specific mean over time resulting in Equation 3:

(3) $$\mathrm{p_{jt}} - \overline{\mathrm{p}_{ij}} = \beta_a \cdot \left(\mathrm{age_{it}} - \overline{\mathrm{age}_{ij}}\right) + \beta_x \cdot \left(\mathrm{x_{jt}} - \overline{\mathrm{x}_{ij}}\right) + \overbrace{\left(\alpha_{ij} - \overline{\alpha_{ij}}\right)}^{=0} + \epsilon_{ijt} - \overline{\epsilon_{ij}}.$$

The dependent variable is the difference between standardized productivity of team *j* at time *t*, denoted by $p_{jt}$ and defined by equation 1, and the standardized productivity of that team averaged over those days in which employee *i* worked in team *j*, denoted by $\overline{p_{ij}}$ and defined by Equation 4

(4) $$\overline{\mathrm{p}_{ij}} = \frac{1}{\mathrm{T_{ij}}} \cdot \sum_{t=1}^{\mathrm{T_{ij}}} \mathrm{p_{jt}}.$$

The age effect is identified by the difference between $age_{it}$ and $\overline{age_{ij}}$, which is the average age of employee *i* during his or her participation in team *j* as in Equation 5:

(5) $$\overline{\mathrm{age}_{ij}} = \frac{1}{\mathrm{T_{ij}}} \cdot \sum_{t=1}^{\mathrm{T_{ij}}} \mathrm{age_{ijt}}.$$

If employee *i* works in different teams *j*, $\overline{age_{ij}}$ will assume different values within *i* across *j*. Similarly, the work conditions of team *j* on day *t* are measured in relation to the mean of those conditions over the days on which employee *i* worked in this team as in Equation 6:

(6) $$\overline{\mathrm{x}_{ij}} = \frac{1}{\mathrm{T_{ij}}} \cdot \sum_{t=1}^{\mathrm{T_{ij}}} \mathrm{x_{jt}}.$$

Taking out all differences between employees and between work-team conditions leaves little variation in the productivity measure. The large number of team-employee pairs and the large number of days on which we observe these pairs, however, compensates for this dearth of variation.

Finally, $\alpha_{ij} = \bar{\alpha}_{ij}$ because the employee-team fixed effects are, by definition, independent of time such that the second-to-last term in equation 3 drops out.

We suggest a linear age effect in equations 2 and 3 only for expositional clarity. In our actual estimation equation, we allow for a non-linear and flexible relationship between age and productivity over the age range. We employ a piecewise linear specification with nine five-year linear splines where the first spline covers ages 18 to 25, the second 26 to 30, and so forth. Thus, we restrict the relationship between age and productivity to be linear only within the splines, but not across the entire age range. Although the volume of our data would permit shorter spline ranges for the majority of the age distribution, the specification turns out to be very robust with respect to the choice of age categories. For instance, using a piecewise linear specification with two-year linear splines basically results in the same patterns of effects as using five-year splines (Figures C1 and C2 in Online Appendix 3).

## VI. Results

Table 3 shows the statistics of the variables that enter the regressions broken down by team type, in addition to sex and education shown in Table 2. In the regressions, with the exception of age, of course, we enter the employees' characteristics as means or shares computed per team and day, because individual non-changing traits are part of the fixed effect so that their effects cannot be estimated. These means are computed ignoring the missing values on sex (very few) and the education variable to maximize the number of cases in the regression analyses.

**Table 3: Work-team-level variables**

| Team type | N teams | N observations | Productivity standardized (mean) | (S.D.) | Age coefficient of variation | Team size (mean) | # of days observed (mean) |
|---|---|---|---|---|---|---|---|
| Specialist | 106 | 310,745 | 0.99 | 0.26 | 0.24 | 10.31 | 316.92 |
| Professional | 846 | 2,673,752 | 0.98 | 0.40 | 0.20 | 9.82 | 372.88 |
| Cust. Serv. | 129 | 605,117 | 0.99 | 0.29 | 0.25 | 11.66 | 449.22 |
| Routine | 364 | 964,784 | 0.98 | 0.40 | 0.21 | 11.08 | 290.02 |
| Not assigned | 9 | 14,243 | 1.06 | 1.57 | 0.15 | 10.89 | 187.22 |
| Total | 1,454 | 4,568,641 | 0.99 | 0.39 | 0.21 | 10.37 | 353.68 |

*Notes:* "Team size" refers to employees observed working. The "# of days observed" was computed on the team level (N=1,454 teams). All other statistics are based on the employee-day-level estimation sample (N=4,568,641).

The dependent variable, the standardized productivity score, has a mean of about 1.0. The deviations are due to the standardization of the productivity measure on team-day level, whereas we tabulate employee-day level. The teams are observed for, on average, 354 days. Because we examine working days, that is, for the most part only Monday through Friday, this period corresponds to an average observation window of almost one and a half years.

We estimate the effect of age on productivity jointly for all observed employees and separately for the four team types. We always add a set of controls based on the team members who are present on the respective day. These controls are the share of female employees, the average education using the mean years of schooling, and the number of team members working.[xiii] Moreover, we control for seasonal effects using single month indicators and for weekday effects using another set of binary indicators.[xiv] We do not add an additional trend specification or a set of period controls to account for possible changes in productivity over time, because we find no indication of a productivity trend in the observation window (see Online Appendix 1).

We begin with the conventional fixed-effects estimator. Figure 2 displays the estimated age-productivity profile with its two-standard-deviation error bands and adds a histogram of the age distribution of the company in the background. The corresponding table of regression coefficients is relegated to Online Appendix 2. We find no indication of any significant decrease or increase in productivity over the whole age range. The profile is flat between age 20 until the age of 60, and very precisely estimated between age 30 and age 55. After age 60, the normal retirement age in this company, the confidence band becomes wide.

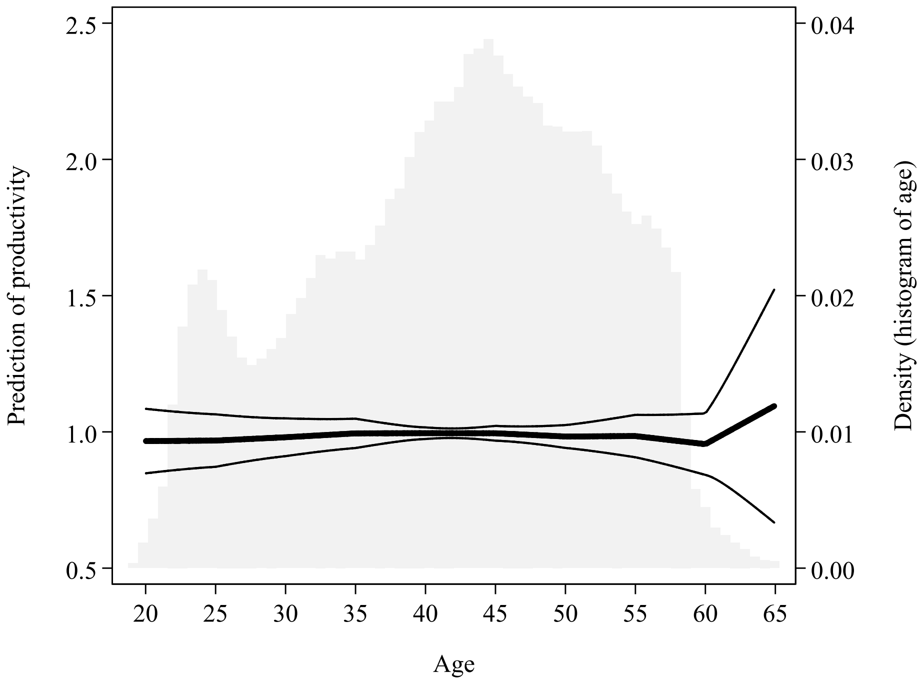


**Figure 2: Age-productivity profile and histogram of age distribution**

*Notes*: Prediction of dependent variable productivity and two-standard-deviation error bands, based on the conventional worker fixed-effects regression presented in Online Appendix 2. All control variables held at the estimation sample means. Background: histogram of age distribution.

However, as described in Section V, this finding may not be robust if older employees are systematically assigned to teams with easier tasks. We therefore employ the double-fixed-effects method in which the unit of observation is an employee-team pair at a given day. Figure 3 displays the resulting age-productivity profile based on the regression coefficients presented in Table 4. Using the double-fixed-effects estimation technique increases the standard errors as compared to Figure 2 because the average observation length of employee-team pairs is substantially shorter than the average observation length of employees. However, our main result remains: we find no indication of any significant decrease or increase in productivity over the whole age range. The profile is rather flat between age 20 until the age of 60. After the company's normal retirement age, no conclusions can be drawn. Hence, within the limits of statistical significance, we find no indication of a decline in productivity; rather, the overall age-productivity profile in this company is flat.

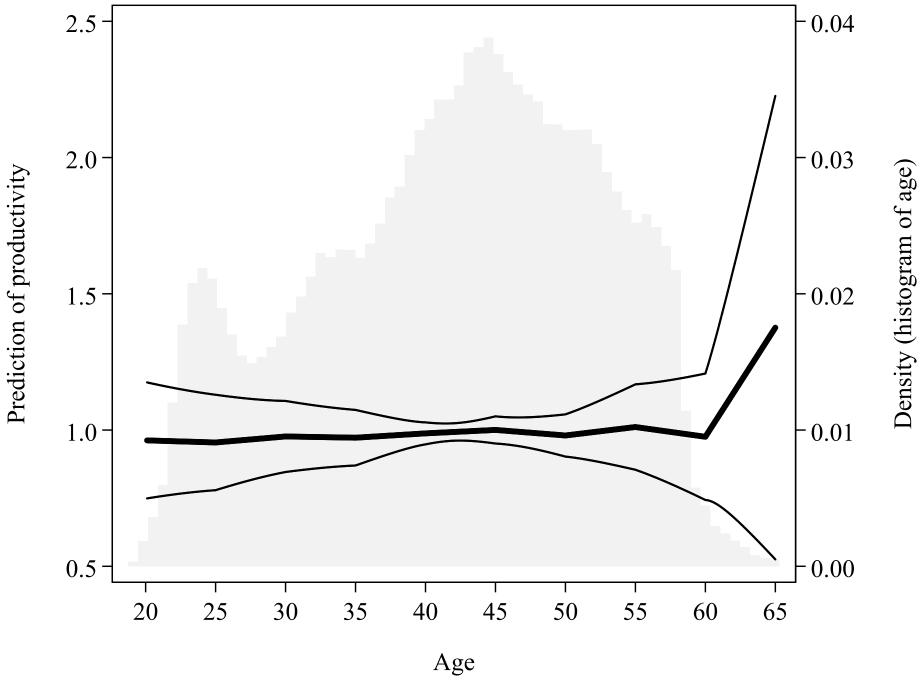


**Figure 3: Age-productivity profile and histogram of age distribution**

*Notes*: Prediction of dependent variable productivity and two-standard-deviation error bands, based on double-fixed-effects regression presented in Table 4. All control variables held at the estimation sample means. Background: histogram of age distribution.

Table 4 presents the coefficients of the age splines and the control variables. We find a strong weekday pattern. Compared to Mondays, the productivity decreases significantly toward the middle of the week, whereas on Fridays, the productivity is significantly higher than on every other regular workday. Otherwise, only the team size has a measurable impact. With more people present, the productivity by person-hour decreases. This effect might represent decreasing marginal productivity caused by either slack labor or increased coordination efforts by one or more team members, who then are less productive in terms of output recorded. We also included a measure of age diversity in order to detect possible complementarities between workers of different ages. We specified various measures (variance of age, degree of uniformity of the age distribution). In Table 4 we report results using the coefficient of variation (CV) of age within the respective team on the respective day. Its coefficient is small and insignificant. The other measures and specifications yielded similar results. We conclude that age diversity neither promotes nor harms productivity in this financial service company.

**Table 4: Regression of standardized productivity at team level (all task types)**

| | | |
|---|---|---|
| *Age splines* | | |
| 18-25 years | -0.0015 | (0.0080) |
| 25-30 years | 0.0044 | (0.0082) |
| 30-35 years | -0.0009 | (0.0059) |
| 35-40 years | 0.0032 | (0.0082) |
| 40-45 years | 0.0025 | (0.0064) |
| 45-50 years | -0.0041 | (0.0065) |
| 50-55 years | 0.0062 | (0.0100) |
| 55-60 years | -0.0071 | (0.0112) |
| 60-65 years | 0.0801 | (0.0705) |
| *Control variables* | | |
| Age coefficient of variation | -0.0131 | (0.0525) |
| Share females | -0.0067 | (0.0211) |
| Average education | -0.0029 | (0.0059) |
| Team size | -0.0201*** | (0.0015) |
| *Weekday (Ref.: Mon.)* | | |
| Tuesday | -0.0265*** | (0.0032) |
| Wednesday | -0.0312*** | (0.0032) |
| Thursday | -0.0235*** | (0.0031) |
| Friday | 0.0217** | (0.0073) |
| *Season (Ref.: Jan.)* | | |
| February | 0.0040 | (0.0040) |
| March | -0.0043 | (0.0072) |
| April | -0.0096 | (0.0058) |
| May | -0.0082 | (0.0058) |
| June | -0.0014 | (0.0064) |
| July | -0.0059 | (0.0060) |
| August | -0.0101 | (0.0066) |
| September | -0.0075 | (0.0089) |
| October | -0.0021 | (0.0064) |
| November | -0.0030 | (0.0058) |
| December | 0.0094 | (0.0053) |
| $R^2$ within | 0.017 | |
| $R^2$ between | 0.004 | |
| observations | 4,370,358 | |
| employees | 21,533 | |
| work teams | 1,410 | |

*Notes:* Clustered (work team) standard errors in parentheses. Double-fixed effects of employee-team pairs included. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5 shows the results of the regressions run for each of the four team types, and Figure 4 shows the corresponding age-productivity profiles. The results are striking. In routine-basic teams, which deal with the least demanding tasks, productivity declines over the whole age range. The decline is significant for employees in the 30-55 age group. For the largest group, the non-routine professionals, who deal with more complex tasks, we find again the flat profile that was visible already in the overall analysis above. Keeping in mind that all age coefficients are insignificant in this estimation, the fact that the confidence bands are tight is nonetheless noteworthy. By contrast, the advanced specialists show a steadily increasing profile over all age groups.

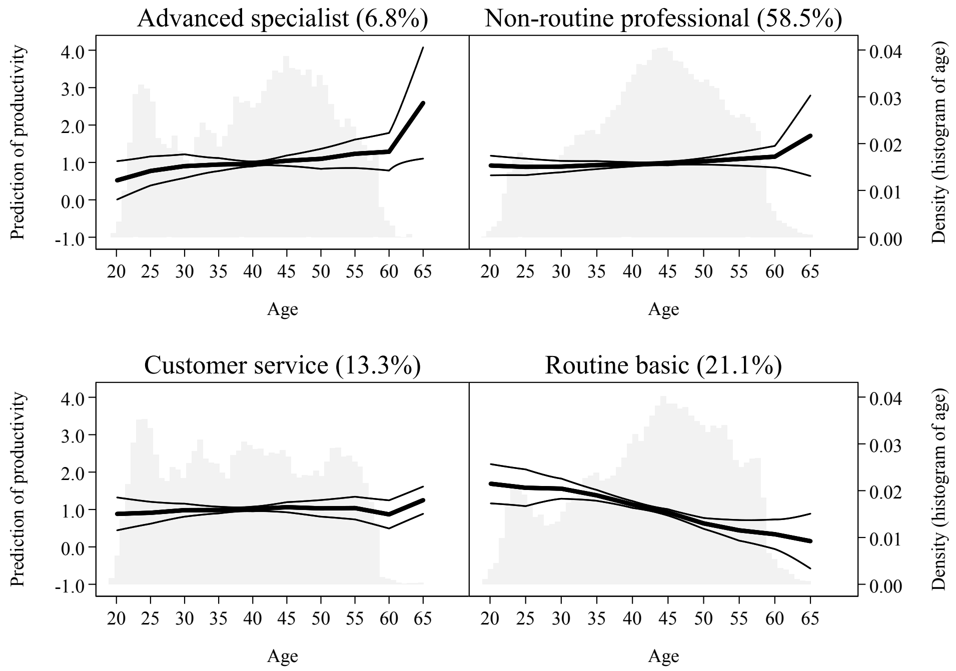


**Figure 4: Age-productivity profiles by team type**

*Notes*: Predictions of dependent-variable productivity and two-standard-deviation error bands by team type based on double-fixed-effects regressions presented in Table 5; percentage of employee-days in parentheses. All control variables held at the respective estimation sample means. Background: histograms of respective age distributions.

Our second main result is therefore that the work content strongly influences the age-productivity relation. When dealing with more demanding tasks, productivity increases with age, whereas we find a flat or even decreasing profile in those teams that deal with potentially boring routine work. This finding suggests experience is more important when dealing with more demanding work tasks to such a level that it can more than offset the physical and cognitive decline and other changes that accompany age.

The customer-service teams cannot easily be classified in terms of the task complexity involved; according to the company representatives, this job requires a certain talent. The profile estimated is rather flat with one significant decrease for the 55- to 60-year-olds and one increase in productivity for the over-60-year-old employees. Note the age distribution of the employees in these teams is remarkably different from the rest of the company. It is mostly flat and does not show the typical overrepresentation of young and middle-aged employees. Also, the "early retirement" typical underrepresentation of employees over 60 years old seems to start earlier and is more severe than in the rest of the company. This finding could be taken as an indication of strong selection into this type of work by employees who have a talent for it. Because this talent is apparently not age specific, it may be one of the reasons for the stable productivity profile observed across the whole age range.

Regarding the control variables, different team-type-specific seasonal-effect patterns emerge that canceled each other out in the overall analysis in Table 4 above. We again find the weekday pattern in most team types, though it is very weak for advanced specialists and not present in the customer-service teams. The team-size effect is present in all types of teams, which substantiates the interpretation of decreasing marginal productivity suggested above.

**Table 5: Regression of standardized productivity at team level by type of task**

| | Specialists | | Professional | | Cust. Serv. | | Routine | |
|---|---|---|---|---|---|---|---|---|
| *Age splines* | | | | | | | | |
| 18-25 years | 0.051* | (0.020) | -0.007 | (0.009) | 0.006 | (0.018) | -0.022 | (0.015) |
| 25-30 years | 0.026 | (0.014) | 0.002 | (0.011) | 0.014 | (0.017) | -0.005 | (0.033) |
| 30-35 years | 0.008 | (0.022) | 0.008 | (0.007) | 0.001 | (0.012) | -0.036* | (0.018) |
| 35-40 years | 0.003 | (0.016) | 0.004 | (0.006) | 0.006 | (0.010) | -0.049*** | (0.012) |
| 40-45 years | 0.017 | (0.016) | 0.005 | (0.007) | 0.009 | (0.012) | -0.042*** | (0.012) |
| 45-50 years | 0.010 | (0.017) | 0.011 | (0.009) | -0.006 | (0.011) | -0.059*** | (0.011) |
| 50-55 years | 0.027 | (0.019) | 0.013 | (0.012) | 0.002 | (0.011) | -0.037* | (0.017) |
| 55-60 years | 0.011 | (0.019) | 0.012 | (0.013) | -0.034** | (0.012) | -0.021 | (0.020) |
| 60-65 years | 0.261* | (0.127) | 0.112 | (0.087) | 0.076*** | (0.009) | -0.037 | (0.051) |
| *Control variables* | | | | | | | | |
| Age coefficient of variation | 0.045 | (0.116) | 0.040 | (0.072) | 0.126 | (0.131) | -0.041 | (0.088) |
| Share females | -0.048 | (0.042) | 0.013 | (0.026) | 0.120 | (0.064) | -0.055 | (0.039) |
| Average education | 0.012 | (0.011) | -0.006 | (0.006) | -0.023 | (0.015) | -0.001 | (0.012) |
| Team size | -0.017*** | (0.002) | -0.029*** | (0.002) | -0.009*** | (0.002) | -0.016*** | (0.002) |
| *Weekday (Ref.: Mon.)* | | | | | | | | |
| Tuesday | -0.018 | (0.010) | -0.030*** | (0.005) | -0.014** | (0.005) | -0.018** | (0.005) |
| Wednesday | -0.017 | (0.010) | -0.036*** | (0.005) | -0.048*** | (0.005) | -0.004 | (0.006) |
| Thursday | -0.020 | (0.010) | -0.030*** | (0.005) | -0.016** | (0.005) | -0.001 | (0.007) |
| Friday | 0.018 | (0.020) | 0.029* | (0.011) | -0.047*** | (0.008) | 0.047*** | (0.009) |
| *Season (Ref.: Jan.)* | | | | | | | | |
| February | -0.002 | (0.008) | 0.008 | (0.005) | -0.011 | (0.011) | 0.009 | (0.011) |
| March | -0.055*** | (0.013) | 0.008 | (0.011) | -0.021 | (0.014) | -0.014 | (0.013) |
| April | -0.094*** | (0.017) | -0.000 | (0.007) | -0.007 | (0.015) | -0.008 | (0.013) |
| May | -0.052*** | (0.015) | 0.006 | (0.008) | -0.016 | (0.013) | -0.022 | (0.012) |
| June | -0.019 | (0.021) | 0.009 | (0.008) | -0.010 | (0.014) | -0.018 | (0.013) |
| July | -0.002 | (0.020) | 0.005 | (0.008) | -0.012 | (0.016) | -0.037** | (0.013) |
| August | 0.006 | (0.019) | -0.009 | (0.008) | -0.032 | (0.019) | -0.027 | (0.014) |
| September | -0.012 | (0.018) | -0.001 | (0.008) | -0.046* | (0.020) | -0.034* | (0.014) |
| October | 0.000 | (0.018) | 0.006 | (0.008) | -0.024 | (0.013) | -0.027* | (0.012) |
| November | -0.020 | (0.018) | 0.016* | (0.008) | -0.023 | (0.013) | -0.039*** | (0.011) |
| December | -0.024 | (0.017) | 0.029*** | (0.007) | -0.034** | (0.012) | -0.011 | (0.012) |
| $R^2$ within | 0.041 | | 0.025 | | 0.012 | | 0.021 | |
| $R^2$ between | 0.0001 | | 0.0005 | | 0.001 | | 0.0001 | |
| observations | 309,212 | | 2,570,523 | | 574,559 | | 901,898 | |
| employees | 1,704 | | 11,677 | | 2,426 | | 5,633 | |
| work teams | 106 | | 817 | | 128 | | 350 | |

*Notes:* Clustered (work team) standard errors in parentheses. Double-fixed effects of employee-team pairs included. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We performed several robustness checks (Online Appendix 3). The presented results are not contingent on the definition of outliers. Re-estimating the 45 age coefficients from Tables 4 and 5 with the inclusion of outliers results in a change of significance or direction of effects in only four instances. These differences occur mostly for the age coefficients for the 18- to 25- and 30- to 35-year-old employees. The only exceptions are the estimates for the customer-service teams. If we include the observations defined as outliers here, the strong negative effect for 55- to 60-year-old employees disappears and the estimated significant increase in productivity for the over-60-year-olds gets considerably stronger.

## VII. Employee Fluctuation, Retirement and other Censoring Events

Employee fluctuation is the key element of our identification strategy. As described in Section II, most fluctuation is within teams due to vacation and sick leave. One may be concerned, however, about systematic biases created by other employee fluctuation, especially transfers to less demanding types of tasks, early retirement and removals from the company due to low productivity. This is addressed in this section.

There is very little mobility of employees between work teams of different types of tasks. Of the 4.5 million daily observations, only 1,861 observations start with the employee in a new team of a different task level. Among those, transitions from less demanding to more demanding tasks are more than four times as frequent as transfers from harder to easier tasks (Table D1 in Online Appendix 4). These transfers do not have a substantive age structure (Figure D1 in Online Appendix 4) except for a spike at very young ages (probably due to an initial misplacement by the managers) and a spike at ages 52 to 53 to a less demanding task that is affecting, however, only 16 out of 10,290 employees. We conclude that downgrading is not a major event in our data. Removal from the company due to low productivity is very hard since all employees of this company will have tenure after two years and cannot be fired due to the highly protective German labor laws.

Most of the employees are observed during the full observation window of 908 days (uncensored). Relatively few employees enter the company after the start of the observation window (left censored, Figure D2 in Online Appendix 4). Even fewer employees exit the company before the observation window ends (right censored, Figure D2 in Online Appendix 4).

Figure 5 depicts the age distribution of those employees who are right-censored, i.e., exit the company before the end of the observation window. The X-axis represents the observation window from day 1 to day 908, and the Y-axis the age at leaving the observation window. About 80 percent of employees are not right censored. Most censoring occurs at ages 56-59 which is the union-determined retirement window in this company.[xv] Most of the advanced specialists, however, leave the sample, if they do so, at earlier ages which suggests upgrading to a managerial position (Figure D3 in Online Appendix 4).

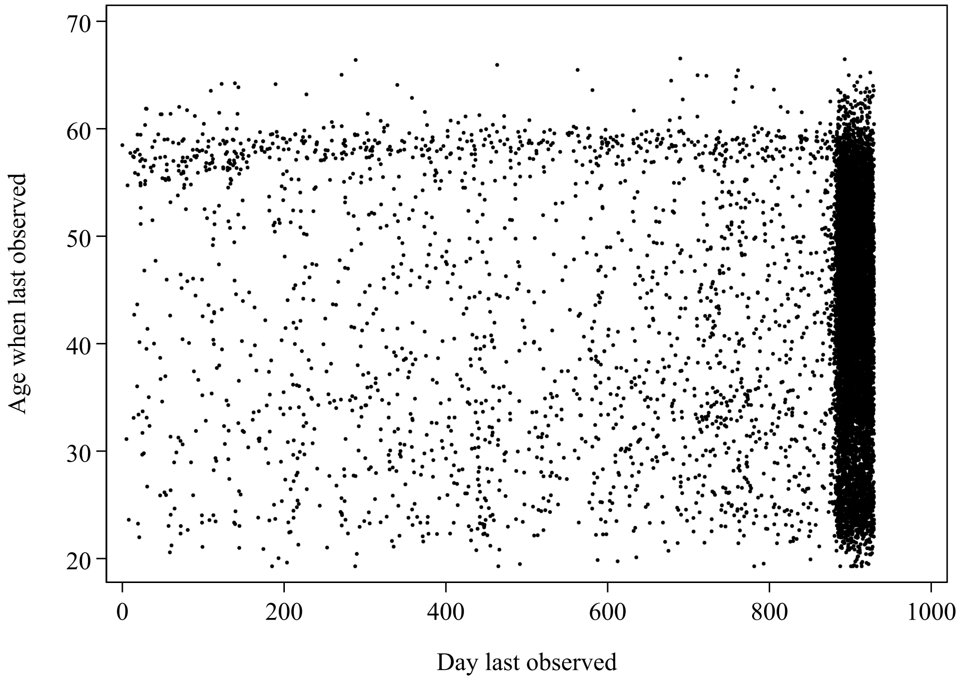


**Figure 5: Age at day when employee leaves the company**

*Notes*: We used jittering (5 percent) to reduce over plotting.

One may be concerned that the slope of the age-productivity profile among the right-censored employees is systematically different from those who remained in the company. We therefore apply the same double-fixed-effects estimation technique as in the previous section to the right-censored subsample only. Results by task type are shown in Figure 6. Regression results are reported in Tables D2 and D3 in Online Appendix 4. The lower right panel shows that the decline and imprecision of the age-productivity profile at older ages stems almost exclusively from the routine basic teams. The results for the other team types are essentially the same as in Figure 4 with upward flat sloping or flat age-productivity profiles. The stronger decline for the routine basic teams re-enforces our conclusion that these employees lack motivation especially when retirement is getting close and there is little incentive to make an effort.

In summary, we conclude that those employees who leave the company before our observation ends do not exhibit a different age-productivity profile than those who are not censored.

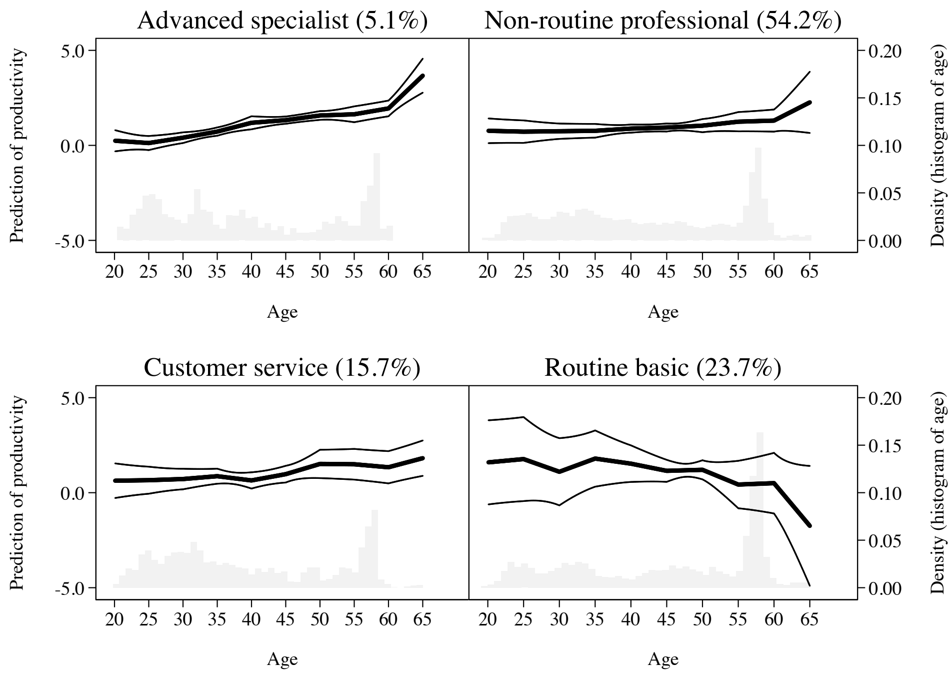


**Figure 6: Age-productivity profile and histogram of age distribution, right-censored employees by team type**

*Notes*: Predictions of dependent-variable productivity and two-standard-deviation error bands by team type based on models reported in Table D3 in Online Appendix 4; percentage of employee-days in parentheses. All control variables held at the respective estimation sample means. Background: histograms of respective age distributions.

## VIII. Conclusions and Discussion

We estimated conventional and double-fixed-effects regressions to study the relation between employees' age and their productivity in a large financial company. We used nonreactive and naturally occurring data, for example, in contrast to manager surveys on the productivity of different employees. We identified the age effects from the daily random presence of team members who differ in their age. This laboratory-like environment and the large number of daily observations in our big data set allow estimating pure age-productivity profiles without having to make strong assumptions on the processes that create selectivity biases. The profiles are very precise in the age range from 20 to 60 years. Even for the oldest observed group, the relatively few 60- to 65-year-old employees, who work beyond the typical retirement age in this company, we estimate an increasing productivity with age. However, these estimates lack precision due to the low number of employees in this age group.

Our results based on work-team-level productivity measures suggest that the age-productivity profile is flat for the majority of observations (72 percent) in this company. Moreover, the age-productivity profiles differ considerably between the types of work tasks. Whereas productivity increases in all age groups in the units with more demanding tasks (seven percent of observations), we observe the opposite phenomenon for routine basic tasks (21 percent of observations). This observation leads to the conclusion that work content has a considerable influence on the relationship between age and productivity, and suggests that experience offsets physical and cognitive decline in the more demanding tasks. A related effect is found by Backes-Gellner and Veen (2013) who show that the relation between productivity and age *diversity* depends on the type of task.

Population aging is often associated with negative effects, for example increasing dependency ratios with dramatic effects on the labor market that might result in a decline in productivity and in economic growth. Population aging may indeed cause secular stagnation of aggregate economic growth due to a shrinkage of the labor force and a shrinkage of aggregate demand. However, whether productivity and per capita growth will be negatively affected is less obvious and has been challenged recently. Kluge et al. (2014) discuss several potential advantages of the foreseeable demographic changes in Western societies. One argument is that, due to the ongoing educational expansion in aging populations, the share of the labor force with tertiary education will substantially increase and, depending on the scenarios simulated, may partially offset the drastic consequences of aging (see also Lee and Mason 2010). Acemoglu and Restrepo (2017) take this argument one step further and find in their cross-country analysis that population aging has been positively correlated with the investment in labor-saving automation which may have neutralized or even overcompensated any negative effects of aging.

Another core proposition in the arguments on the consequences of population aging is that older individuals are, on average, less productive or are unable to productively work after a specified age. This (often implicitly made) proposition is a forceful counterargument against extending the working life in proportion to longevity. Our contribution in this paper shows that this counterargument is invalid at least in the age range and the tasks for which we have obtained data. It is also important to realize that the age-productivity profile is different in a typical service-sector company with highly standardized tasks than for tasks of top performers in sports (Fair 1994) and science (Jones 2010).

Our results also carry important implications for individuals, companies, and policy makers. They suggest that older individuals can meaningfully contribute and, depending on the task, even excel their younger co-workers in the professional sphere. Our results also imply that the foreseeable aging of the workforce in most industrialized countries is not a threat to companies and entire economies, as long as companies allocate their older employees to teams or tasks in which their experience can offset the decline of physical and mental abilities. Arguably, the most important policy conclusion from this study is about the retirement age of public pension systems. Declining productivity, at least in highly standardized jobs and within the age range observed in this paper, is not an empirically valid counterargument against policy makers who intend to raise the effective retirement age in response to population aging. Our study overcomes several of the problems that limit the validity of previous research on the relation between workers' age and their productivity. However, the data analyzed and the statistical methods used are limited in a number of respects. As with any case study or "found" data, concerns with respect to the representative nature of the data are evident. However, since the company conducts a wide range of tasks typical for the service industry and operates internationally, we are confident that our results are representative for large-scale service providers and thus of general interest. While the large number of observations in the 20-60 age band provides sufficiently precise estimates for the flat age-productivity profile in this age range, the typical retirement age in this company precludes a precise measurement of the age-productivity profile for the arguably most interesting age group of 60- to 65-year-old employees. Our main conclusion is that our analyses clearly dispel the notion of a pronounced peak in productivity already at relatively young ages which has dominated the discussion about the effect of age on productivity.

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# Endnotes

[i] Mark (1957) analyze output figures of factory workers in 22 footwear and clothing establishments. Kutscher and Walker (1960) analyze office workers in 5 government agencies and 21 private companies. Both studies focus on workers with piece-rate pay schemes in jobs/establishments that counted the output. Both settings, factory and office work, experience little variation in average output per hour between age groups up to the age of 64, and the individual variation in performance within the age groups is always larger.

[ii] The data are nonreactive with respect to no researchers being present, who may have counted the output or clocked the minutes necessary to complete tasks. The workers are, however, aware in general that output is recorded automatically by the monitoring systems. This monitoring has been running for many years, however, and only the worker representatives were aware of the specific period for which the data were extracted for our research on the relation between age and productivity.

[iii] We dropped some outliers in the regressions reported below.

[iv] The years of schooling are coded based on the following degrees, with the square brackets denoting the assigned years: “no secondary degree" [8] 0.1 percent; “lower secondary degree" [9] 3.5 percent; “qualified lower secondary degree" [9.5] 4.0 percent; “medium secondary degree" [10] 40.0 percent; “advanced technical college entry qualification" [12] 11.7 percent; “higher education entrance qualification" [13] 40.5 percent. Employees with “Fachschulabschluss" were collapsed with those with advanced technical college-entry qualifications and assigned 12 years in the education variable.

[v] Team means can be included in the fixed-effects regression because they vary from day to day as the team composition changes. Individual education variables cannot be included, because they are constant within individuals.

[vi] An alternative to this is to use z-scores, i.e., computing for the period observed for each team the mean number of hourly transactions and the standard deviation and then subtracting the mean of each team's transactions from the daily observed transactions and dividing it by the standard deviation. This does not qualitatively change our results. The age-productivity profiles by team type are almost indistinguishable from those reported in Figure 4. Notable differences are that for specialists the age spline for the 60- to 65-year-olds is still positive but not significant on conventional levels. Moreover, in routine tasks some age splines become larger in size and are more often significant.

[vii] To check whether this truncation creates a selectivity bias, we replicated our analyses including these observations, but this approach did not yield substantially different results (see Online Appendix 3).

[viii] More precisely, we divide by the trimmed mean without outlying observations.

[ix] The data do not contain time-dependent employee characteristics.

[x] In addition to differences in formal education that could in principle be controlled for by adequate variables, younger generations have a considerably higher exposure to IT in everyday life, rendering them more at ease in the handling of computers.

[xi] Replicating our main results with additional day fixed effects yields a very similar pattern of age effects, suggesting that our results are not distorted by any relevant technological or organizational development.

[xii] From a theory point of view, team switches that generate large productivity declines are not optimal. A rational manager would leave workers in a team with harder tasks as long as their productivity has declined at least to the level of the new team with easier tasks.

[xiii] We tested different non-linear specifications of the team-size effect (square root, quadratic, cubic, and quartic). Adding one of the polynomial specifications improves the model fit in most of the regressions below. We show a parsimonious model with a simple linear effect. It represents the relationship sufficiently well, and the substantial results are robust to all specifications tested.

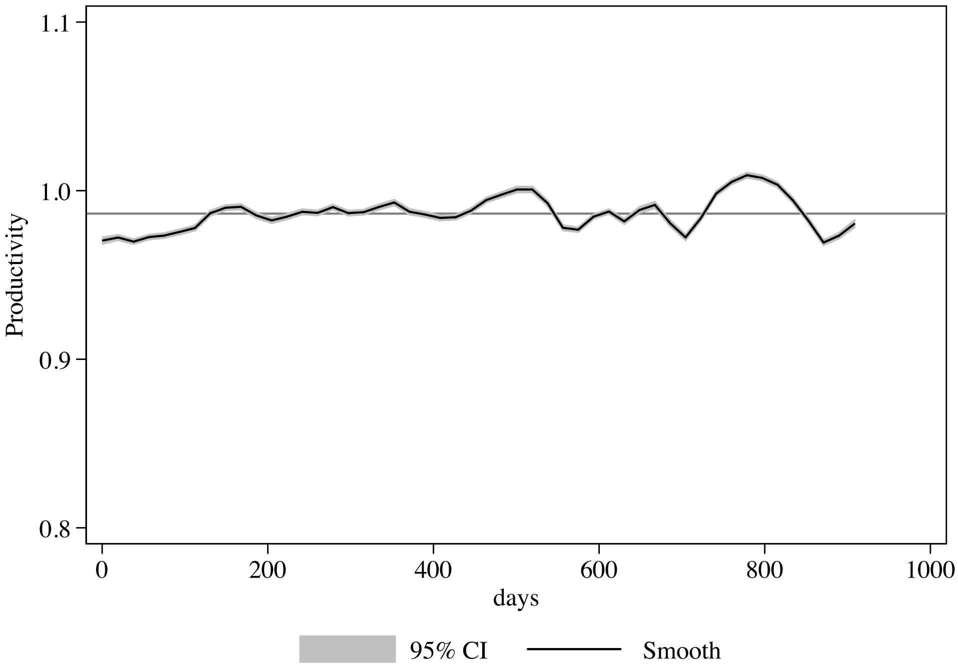
[xiv] The reference category for the day-of-the-week binary indicator set in all regressions shown below actually is Mondays, Saturdays, and Sundays. We have so few observations on Sundays (21 worker-days) and Saturdays (29,286 worker-days, which is 0.65 percent of all days) that we did not include additional indicators for them. A replication excluding the Saturday and Sunday observations revealed virtually the same results, also with respect to effect patterns of the weekday indicators.

[xv] Normal retirement age in Germany at the time of our data was 65, and early retirement with actuarial deductions started at age 63. Since these deductions were less than actuarially neutral, most employees retired at that age. In addition, the social partners in the service-sector introduced partial retirement that defined a window of several years in which workers could reduce their working hours. Since workers could choose a reduction of up to zero hours, partial retirement effectively allowed earlier retirement than 63 with deductions that were larger than actuarially neutral. About a quarter of the employees took this option.

# Online Appendix 1: No trends in productivity in the observation period

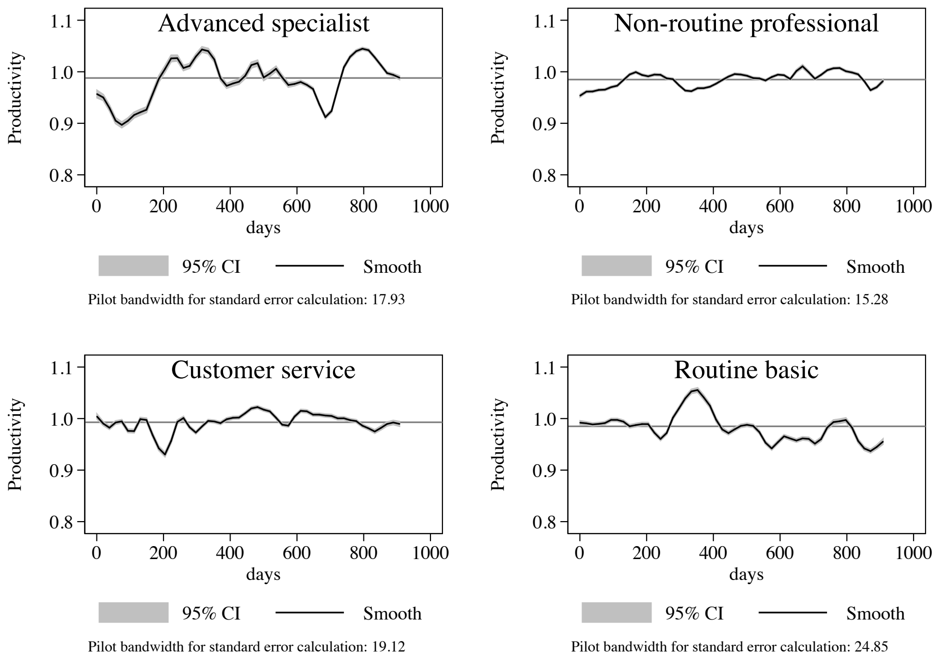
We use kernel-weighted local polynomial regressions of productivity on time (in days) to generate graphs of the smoothed values to see if trends in productivity are present in the observation period. The figures indicate productivity has been fluctuating by as much as 4 percent overall, with larger fluctuations in some of the job types, but we find no indication of an increasing or decreasing trend in productivity overall or in any of the job types in the period observed.

Figure A1: Local Polynomial Smooth of Productivity Overall




*Note:* Epanechnikov kernel function, degree of polynomial smooth: 0, kernel bandwidth: 15, pilot bandwidth for standard error calculation: 19.93.

Figure A2: Local Polynomial Smooth of Productivity by Team Type




*Note:* Epanechnikov kernel function, degree of polynomial smooth: 0, kernel bandwidth: 15.

# Online Appendix 2: Results for conventional fixed-effects regression

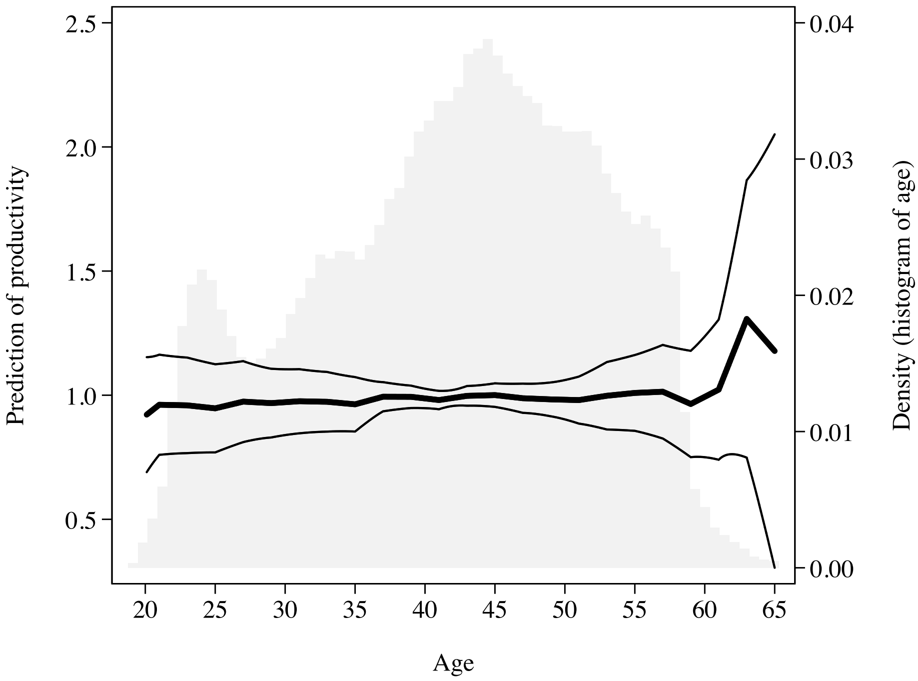
Table B1: Regression of standardized productivity at team level (all task types)

| | | |
|---|---|---|
| *Age splines* | | |
| 18-25 years | 0.0004 | (0.0047) |
| 25-30 years | 0.0024 | (0.0050) |
| 30-35 years | 0.0029 | (0.0035) |
| 35-40 years | 0.0001 | (0.0046) |
| 40-45 years | -0.0001 | (0.0034) |
| 45-50 years | -0.0024 | (0.0034) |
| 50-55 years | 0.0003 | (0.0047) |
| 55-60 years | -0.0059 | (0.0053) |
| 60-65 years | 0.0284 | (0.0367) |
| | | |
| *Control variables* | | |
| Age coefficient of variation | 0.0353 | (0.0409) |
| Share females | -0.0046 | (0.0167) |
| Average education | -0.0021 | (0.0045) |
| Team size | -0.0149*** | (0.0012) |
| *Weekday (Ref.: Mon.)* | | |
| Tuesday | -0.0299*** | (0.0032) |
| Wednesday | -0.0333*** | (0.0032) |
| Thursday | -0.0257*** | (0.0031) |
| Friday | 0.0254*** | (0.0073) |
| *Season (Ref.: Jan.)* | | |
| February | 0.0045 | (0.0039) |
| March | -0.0023 | (0.0070) |
| April | -0.0076 | (0.0056) |
| May | -0.0096 | (0.0058) |
| June | 0.0028 | (0.0062) |
| July | -0.0012 | (0.0059) |
| August | -0.0027 | (0.0064) |
| September | -0.0025 | (0.0088) |
| October | -0.0000 | (0.0062) |
| November | -0.0074 | (0.0057) |
| December | 0.0081 | (0.0053) |
| $R^2$ | 0.014 | |
| observations | 4,370,358 | |

*Note:* Clustered (work team) standard errors in parentheses. Conventional single-fixed effects (employee level) included. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

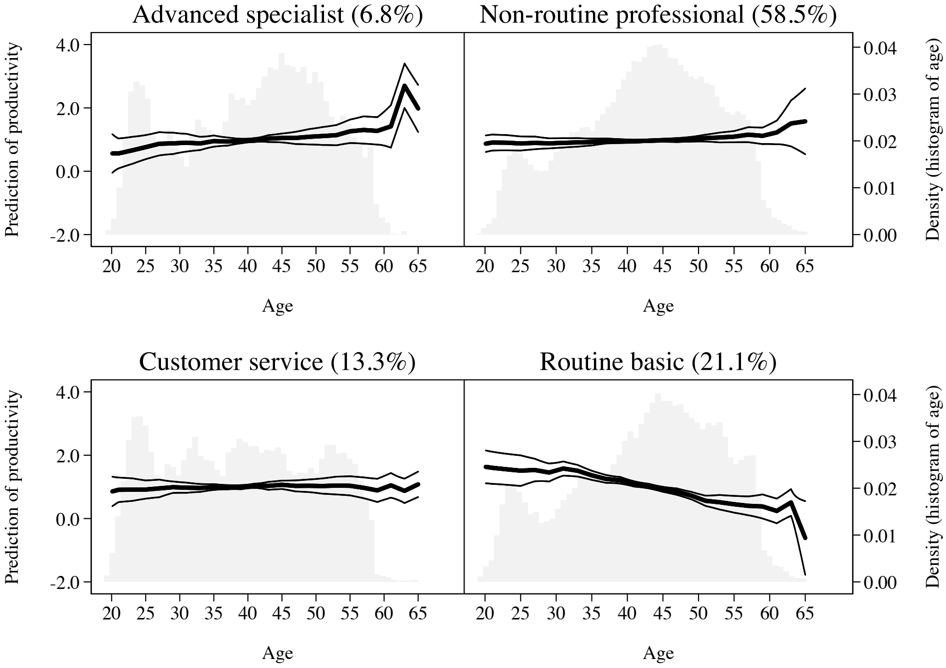
# Online Appendix 3: Robustness checks

Figure C1: Age-productivity profile using 2-year age splines overall




*Note:* Prediction of dependent-variable productivity and two-standard-deviation error bands, based on model with 2-year age splines. All control variables held at the estimation sample means. Background: histogram of age distribution.

Figure C2: Age-productivity profiles using 2-year age splines by team type




*Note:* Prediction of dependent-variable productivity and two-standard-deviation error bands, based on model with 2-year age splines. All control variables held at the estimation sample means. Background: histogram of age distribution.

Table C1: Comparison of regression results without versus including extreme outliers - overall

| | (1) Without extreme outliers | | (2) Including extreme outliers | |
|---|---|---|---|---|
| *Age splines* | | | | |
| 18-25 years | -0.002 | (0.008) | -0.009 | (0.010) |
| 25-30 years | 0.004 | (0.008) | 0.000 | (0.009) |
| 30-35 years | -0.001 | (0.006) | 0.001 | (0.010) |
| 35-40 years | 0.003 | (0.008) | 0.000 | (0.010) |
| 40-45 years | 0.003 | (0.006) | 0.001 | (0.007) |
| 45-50 years | -0.004 | (0.006) | -0.009 | (0.008) |
| 50-55 years | 0.006 | (0.010) | 0.007 | (0.010) |
| 55-60 years | -0.007 | (0.011) | -0.002 | (0.012) |
| 60-65 years | 0.080 | (0.071) | 0.082 | (0.073) |
| *Control variables* | | | | |
| Age coefficient of variation | 0.013 | (0.052) | -0.025 | (0.095) |
| Share females | -0.007 | (0.021) | -0.025 | (0.032) |
| Average education | -0.003 | (0.006) | -0.007 | (0.008) |
| Team size | -0.020*** | (0.001) | -0.022*** | (0.003) |
| *Weekday (Ref.: Mon.)* | | | | |
| Tuesday | -0.027*** | (0.003) | -0.031*** | (0.005) |
| Wednesday | -0.031*** | (0.003) | -0.037*** | (0.004) |
| Thursday | -0.023*** | (0.003) | -0.027*** | (0.005) |
| Friday | 0.022** | (0.007) | 0.097*** | (0.019) |
| *Season (Ref.: Jan.)* | | | | |
| February | 0.004 | (0.004) | 0.040 | (0.025) |
| March | -0.004 | (0.007) | -0.020 | (0.023) |
| April | -0.010 | (0.006) | -0.019 | (0.023) |
| May | -0.008 | (0.006) | -0.027 | (0.019) |
| June | -0.001 | (0.006) | -0.025 | (0.021) |
| July | -0.006 | (0.006) | 0.018 | (0.025) |
| August | -0.010 | (0.007) | -0.038 | (0.021) |
| September | -0.007 | (0.009) | -0.036 | (0.023) |
| October | -0.002 | (0.006) | -0.017 | (0.023) |
| November | -0.003 | (0.006) | -0.027 | (0.023) |
| December | 0.009 | (0.005) | -0.015 | (0.023) |
| $R^2$ within | 0.017 | | 0.002 | |
| observations | 4,370,358 | | 4,398,894 | |

*Note:* Clustered (work team) standard errors in parentheses. All specifications control for double-fixed effects. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C2: Comparison of regression results without versus including extreme outliers by team type

| | Advanced Specialist | | | | Non-routine professionals | | | |
|---|---|---|---|---|---|---|---|---|
| | w/o outliers | | w/ outliers | | w/o outliers | | w/ outliers | |
| *Age splines* | | | | | | | | |
| 18-25 years | 0.051* | (0.020) | 0.038 | (0.026) | -0.007 | (0.009) | -0.023* | (0.011) |
| 25-30 years | 0.026 | (0.014) | 0.051 | (0.029) | 0.002 | (0.011) | -0.006 | (0.013) |
| 30-35 years | 0.008 | (0.022) | 0.026 | (0.060) | 0.008 | (0.007) | -0.002 | (0.010) |
| 35-40 years | 0.003 | (0.016) | -0.002 | (0.019) | 0.004 | (0.006) | -0.003 | (0.009) |
| 40-45 years | 0.017 | (0.016) | 0.011 | (0.019) | 0.005 | (0.007) | 0.005 | (0.007) |
| 45-50 years | 0.010 | (0.017) | 0.040 | (0.038) | 0.011 | (0.009) | 0.004 | (0.012) |
| 50-55 years | 0.027 | (0.019) | 0.041 | (0.026) | 0.013 | (0.012) | 0.014 | (0.013) |
| 55-60 years | 0.011 | (0.019) | 0.016 | (0.035) | 0.012 | (0.013) | 0.018 | (0.015) |
| 60-65 years | 0.261* | (0.127) | 0.310* | (0.124) | 0.112 | (0.087) | 0.108 | (0.090) |
| *Control variables* | | | | | | | | |
| Age coefficient of variation | 0.045 | (0.116) | 0.273 | (0.301) | 0.040 | (0.072) | -0.099 | (0.136) |
| Share females | -0.048 | (0.042) | -0.071 | (0.085) | 0.013 | (0.026) | -0.018 | (0.041) |
| Average education | 0.012 | (0.011) | 0.074 | (0.047) | -0.006 | (0.006) | -0.018 | (0.011) |
| Team size | -0.017*** | (0.002) | -0.009 | (0.014) | -0.029*** | (0.002) | -0.031*** | (0.004) |
| *Weekday (Ref.: Mon.)* | | | | | | | | |
| Tuesday | -0.018 | (0.010) | -0.055* | (0.026) | -0.030*** | (0.005) | -0.039*** | (0.006) |
| Wednesday | -0.017 | (0.010) | -0.044 | (0.028) | -0.036*** | (0.005) | -0.045*** | (0.005) |
| Thursday | -0.020 | (0.010) | -0.058* | (0.025) | -0.030*** | (0.005) | -0.033*** | (0.007) |
| Friday | 0.018 | (0.020) | 0.099 | (0.102) | 0.029* | (0.011) | 0.093*** | (0.027) |
| *Season (Ref.: Jan.)* | | | | | | | | |
| February | -0.002 | (0.008) | 0.149 | (0.220) | 0.008 | (0.005) | 0.011 | (0.036) |
| March | -0.055*** | (0.013) | -0.146 | (0.084) | 0.008 | (0.011) | -0.024 | (0.036) |
| April | -0.094*** | (0.017) | -0.175* | (0.085) | -0.000 | (0.007) | -0.031 | (0.035) |
| May | -0.052*** | (0.015) | -0.139 | (0.084) | 0.006 | (0.008) | -0.022 | (0.030) |
| June | -0.019 | (0.021) | -0.070 | (0.088) | 0.009 | (0.008) | -0.030 | (0.034) |
| July | -0.002 | (0.020) | -0.074 | (0.088) | 0.005 | (0.008) | -0.002 | (0.034) |
| August | 0.006 | (0.019) | -0.081 | (0.087) | -0.009 | (0.008) | -0.052 | (0.033) |
| September | -0.012 | (0.018) | -0.104 | (0.085) | -0.001 | (0.008) | -0.040 | (0.035) |
| October | 0.000 | (0.018) | -0.082 | (0.086) | 0.006 | (0.008) | -0.029 | (0.036) |
| November | -0.020 | (0.018) | -0.107 | (0.085) | 0.016* | (0.008) | -0.021 | (0.038) |
| December | -0.024 | (0.017) | -0.117 | (0.085) | 0.029*** | (0.007) | -0.005 | (0.037) |
| $R^2$ within | 0.041 | | 0.002 | | 0.025 | | 0.003 | |
| observations | 309,212 | | 310,706 | | 2,570,523 | | 2,586,944 | |

*Note:* Clustered (work team) standard errors in parentheses. All specifications control for double-fixed effects. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C3: Comparison of regression results without versus including extreme outliers by team type (continued)

| | Customer Service | | | | Routine Basic | | | |
|---|---|---|---|---|---|---|---|---|
| | w/o outliers | | w/ outliers | | w/o outliers | | w/ outliers | |
| *Age splines* | | | | | | | | |
| 18-25 years | 0.006 | (0.018) | 0.016 | (0.021) | -0.022 | (0.015) | -0.029 | (0.016) |
| 25-30 years | 0.014 | (0.017) | 0.018 | (0.019) | -0.005 | (0.033) | -0.024 | (0.035) |
| 30-35 years | 0.001 | (0.012) | 0.008 | (0.018) | -0.036* | (0.018) | 0.012 | (0.054) |
| 35-40 years | 0.006 | (0.010) | 0.044 | (0.029) | -0.049*** | (0.012) | -0.070*** | (0.016) |
| 40-45 years | 0.009 | (0.012) | 0.021 | (0.016) | -0.042*** | (0.012) | -0.046*** | (0.012) |
| 45-50 years | -0.006 | (0.011) | -0.007 | (0.013) | -0.059*** | (0.011) | -0.069*** | (0.012) |
| 50-55 years | 0.002 | (0.011) | 0.014 | (0.016) | -0.037* | (0.017) | -0.042* | (0.019) |
| 55-60 years | -0.034** | (0.012) | -0.018 | (0.021) | -0.021 | (0.020) | -0.024 | (0.021) |
| 60-65 years | 0.076*** | (0.009) | 0.249*** | (0.030) | -0.037 | (0.051) | -0.046 | (0.057) |
| *Control variables* | | | | | | | | |
| Age coefficient of variation | 0.126 | (0.131) | 0.351 | (0.328) | -0.041 | (0.088) | -0.056 | (0.108) |
| Share females | 0.120 | (0.064) | 0.144 | (0.108) | -0.055 | (0.039) | -0.045 | (0.047) |
| Average education | -0.023 | (0.015) | -0.037 | (0.021) | -0.001 | (0.012) | 0.001 | (0.013) |
| Team size | -0.009*** | (0.002) | -0.011** | (0.004) | -0.016*** | (0.002) | -0.021*** | (0.003) |
| *Weekday (Ref.: Mon.)* | | | | | | | | |
| Tuesday | -0.014** | (0.005) | 0.011 | (0.017) | -0.018** | (0.005) | -0.016* | (0.006) |
| Wednesday | -0.048*** | (0.005) | -0.032** | (0.012) | -0.004 | (0.006) | -0.003 | (0.006) |
| Thursday | -0.016** | (0.005) | -0.006 | (0.011) | -0.001 | (0.007) | -0.002 | (0.007) |
| Friday | -0.047*** | (0.008) | 0.097 | (0.050) | 0.047*** | (0.009) | 0.111*** | (0.020) |
| *Season (Ref.: Jan.)* | | | | | | | | |
| February | -0.011 | (0.011) | 0.075** | (0.028) | 0.009 | (0.011) | 0.071*** | (0.020) |
| March | -0.021 | (0.014) | 0.025 | (0.037) | -0.014 | (0.013) | -0.005 | (0.014) |
| April | -0.007 | (0.015) | 0.028 | (0.021) | -0.008 | (0.013) | 0.034 | (0.043) |
| May | -0.016 | (0.013) | -0.006 | (0.014) | -0.022 | (0.012) | -0.016 | (0.014) |
| June | -0.010 | (0.014) | -0.005 | (0.015) | -0.018 | (0.013) | -0.015 | (0.014) |
| July | -0.012 | (0.016) | 0.158 | (0.102) | -0.037** | (0.013) | 0.008 | (0.019) |
| August | -0.032 | (0.019) | -0.001 | (0.031) | -0.027 | (0.014) | -0.033* | (0.016) |
| September | -0.046* | (0.020) | -0.049* | (0.024) | -0.034* | (0.014) | -0.034* | (0.017) |
| October | -0.024 | (0.013) | 0.048 | (0.045) | -0.027* | (0.012) | -0.025 | (0.015) |
| November | -0.023 | (0.013) | -0.023 | (0.015) | -0.039*** | (0.011) | -0.028* | (0.013) |
| December | -0.034** | (0.012) | -0.037* | (0.014) | -0.011 | (0.012) | -0.008 | (0.012) |
| R-$R^2$ within | 0.012 | | 0.001 | | 0.021 | | 0.003 | |
| observations | 574,559 | | 579,401 | | 901,898 | | 907,602 | |

*Note:* Clustered (work team) standard errors in parentheses. All specifications control for double-fixed effects. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

# Online Appendix 4: Employee fluctuation

Table D1: Transitions between different types of tasks

| | Frequency | Percent | Age (mean) |
|---|---|---|---|
| *No change in task level* | 4,566,732 | 99.9582 | 42.02 |
| *Lateral change in task level* | 35 | 0.0008 | 32.96 |
| Cust. Serv. to Routine | 17 | 0.0004 | 32.98 |
| Routine to Cust. Serv. | 18 | 0.0004 | 32.94 |
| *Change with one task level missing* | 13 | 0.0003 | 40.10 |
| *Change to less demanding task level* | 371 | 0.0081 | 38.49 |
| Professional to Cust. Serv. | 6 | 0.0001 | 34.29 |
| Professional to Routine | 244 | 0.0053 | 38.80 |
| Specialist to Cust. Serv. | 11 | 0.0002 | 43.63 |
| Specialist to Professional | 78 | 0.0017 | 38.51 |
| Specialist to Routine | 32 | 0.0007 | 35.06 |
| *Change to more demanding task level* | 1,490 | 0.0326 | 38.76 |
| Cust. Serv. to Professional | 44 | 0.0010 | 37.19 |
| Cust. Serv. to Specialist | 367 | 0.0080 | 39.56 |
| Professional to Specialist | 103 | 0.0023 | 38.86 |
| Routine to Professional | 493 | 0.0108 | 37.44 |
| Routine to Specialist | 483 | 0.0106 | 39.63 |
| *Total* | 4,568,641 | 100.0000 | 42.02 |

*Note:* The table shows all changes between different types of tasks on the employee-day-level, i.e., more than one change can have occurred to a single employee.

Figure D1: Age at change of task level

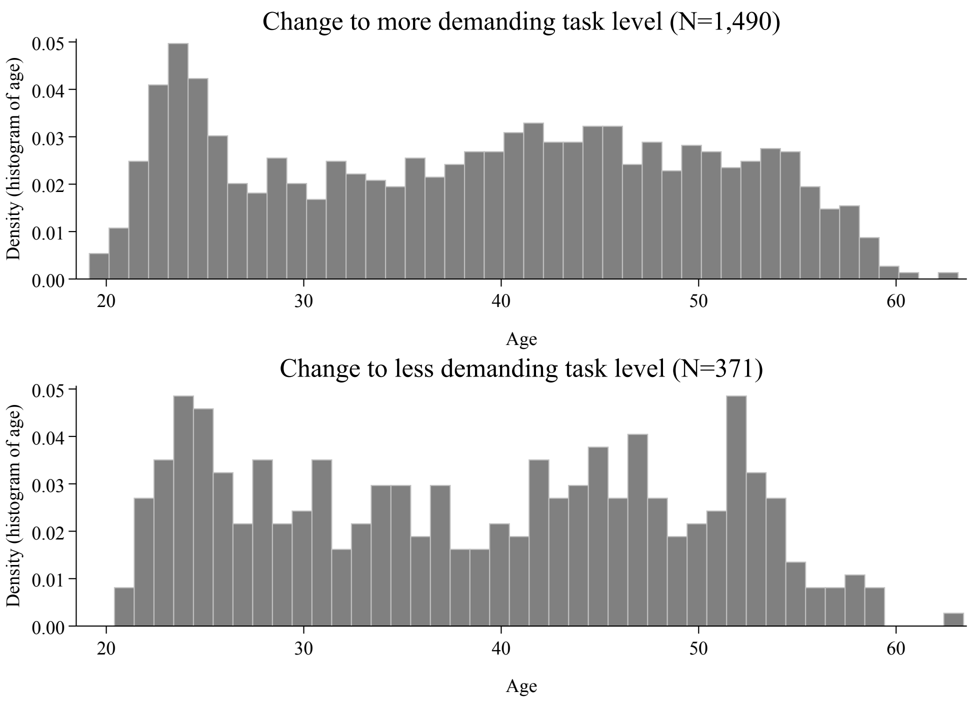


Figure D2: New hires and exits during the observation period

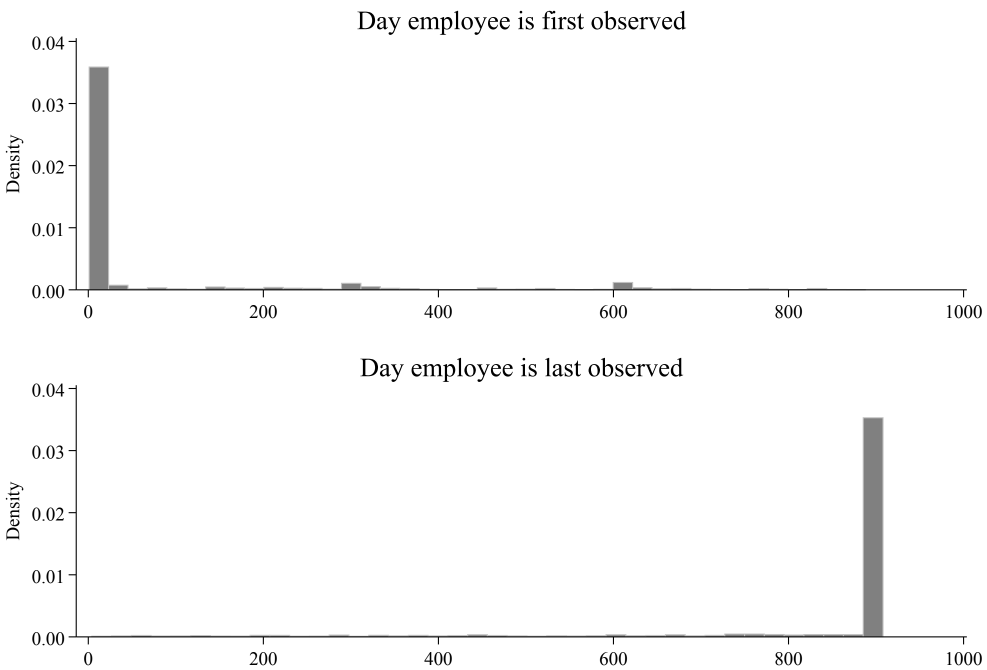
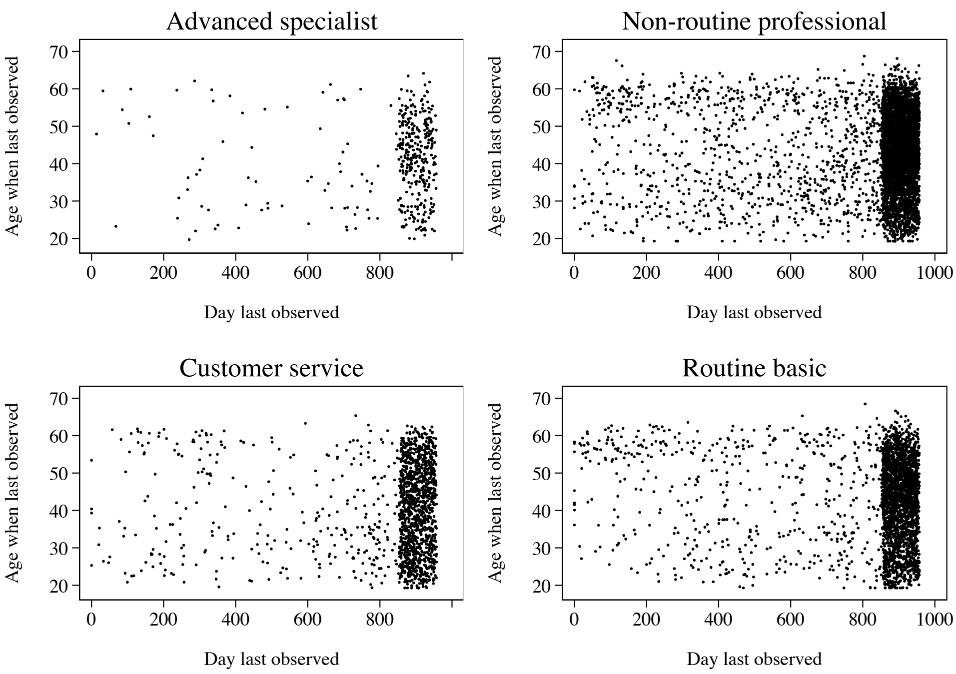


Figure D3: Age at day when employee leaves the company, by team type




*Note:* We used jittering (5 percent) to reduce over plotting.

Table D2: Regression of standardized productivity for right-censored observations (all task types)

| | | |
|---|---|---|
| *Age splines* | | |
| 18-25 years | -0.0046 | (0.0173) |
| 25-30 years | -0.0032 | (0.0240) |
| 30-35 years | 0.0179 | (0.0181) |
| 35-40 years | 0.0316 | (0.0399) |
| 40-45 years | -0.0273 | (0.0369) |
| 45-50 years | 0.0160 | (0.0359) |
| 50-55 years | -0.0644 | (0.0591) |
| 55-60 years | -0.0278 | (0.0363) |
| 60-65 years | 0.0328 | (0.1415) |
| *Control variables* | | |
| Age coefficient of variation | 0.1130 | (0.1032) |
| Share females | 0.0036 | (0.0455) |
| Average education | -0.0009 | (0.0179) |
| Team size | -0.0130* | (0.0059) |
| *Weekday (Ref.: Mon.)* | | |
| Tuesday | -0.0261*** | (0.0061) |
| Wednesday | -0.0270*** | (0.0065) |
| Thursday | -0.0206*** | (0.0059) |
| Friday | 0.0265* | (0.0123) |
| *Season (Ref.: Jan.)* | | |
| February | 0.0214 | (0.0124) |
| March | 0.0062 | (0.0160) |
| April | 0.0018 | (0.0154) |
| May | 0.0201 | (0.0199) |
| June | 0.0153 | (0.0193) |
| July | 0.0115 | (0.0155) |
| August | 0.0284 | (0.0194) |
| September | 0.0025 | (0.0195) |
| October | 0.0144 | (0.0171) |
| November | 0.0173 | (0.0143) |
| December | 0.0207 | (0.0111) |
| $R^2$ within | 0.008 | |
| $R^2$ between | 0.0005 | |
| observations | 450,200 | |

*Note:* Clustered (work team) standard errors in parentheses. Double-fixed effects of employee-team pairs included. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D3: Regression of standardized productivity for right-censored observations by type of task

| | Specialists | | Professional | | Cust. Serv. | | Routine | |
|---|---|---|---|---|---|---|---|---|
| *Age splines* | | | | | | | | |
| 18-25 years | -0.024 | (0.049) | -0.009 | (0.021) | 0.005 | (0.040) | 0.035 | (0.054) |
| 25-30 years | 0.056* | (0.025) | 0.005 | (0.030) | 0.012 | (0.040) | -0.134 | (0.147) |
| 30-35 years | 0.064* | (0.030) | 0.005 | (0.013) | 0.030 | (0.028) | 0.139 | (0.103) |
| 35-40 years | 0.093** | (0.034) | 0.023 | (0.034) | -0.045 | (0.056) | -0.054 | (0.074) |
| 40-45 years | 0.028 | (0.029) | 0.011 | (0.021) | 0.066 | (0.041) | -0.076 | (0.053) |
| 45-50 years | 0.049** | (0.015) | 0.020 | (0.040) | 0.108 | (0.073) | 0.011 | (0.085) |
| 50-55 years | 0.013 | (0.039) | 0.042 | (0.039) | -0.004 | (0.020) | -0.155 | (0.108) |
| 55-60 years | 0.062*** | (0.016) | 0.012 | (0.019) | -0.031 | (0.021) | 0.014 | (0.059) |
| 60-65 years | 0.345*** | (0.081) | 0.192 | (0.129) | 0.095** | (0.033) | -0.449 | (0.249) |
| *Control variables* | | | | | | | | |
| Age coefficient of variation | 0.356 | (0.245) | 0.130 | (0.106) | 0.087 | (0.166) | -0.025 | (0.259) |
| Share females | 0.095 | (0.137) | 0.021 | (0.032) | 0.136 | (0.082) | 0.043 | (0.098) |
| Average education | -0.004 | (0.021) | 0.002 | (0.010) | -0.029 | (0.026) | -0.033 | (0.032) |
| Team size | -0.015*** | (0.003) | -0.026*** | (0.002) | -0.012*** | (0.003) | -0.015*** | (0.003) |
| *Weekday (Ref.: Mon.)* | | | | | | | | |
| Tuesday | -0.029 | (0.018) | -0.033*** | (0.009) | -0.022** | (0.007) | -0.014 | (0.008) |
| Wednesday | -0.027 | (0.021) | -0.036*** | (0.009) | -0.047*** | (0.007) | 0.003 | (0.007) |
| Thursday | -0.023 | (0.019) | -0.031** | (0.009) | -0.014* | (0.006) | 0.009 | (0.009) |
| Friday | 0.008 | (0.028) | 0.018 | (0.017) | -0.027 | (0.014) | 0.067*** | (0.016) |
| *Season (Ref.: Jan.)* | | | | | | | | |
| February | 0.008 | (0.012) | 0.016 | (0.009) | -0.018 | (0.014) | 0.059 | (0.050) |
| March | -0.061*** | (0.017) | -0.002 | (0.017) | -0.019 | (0.020) | 0.034 | (0.048) |
| April | -0.087*** | (0.023) | -0.009 | (0.017) | -0.006 | (0.023) | 0.023 | (0.037) |
| May | -0.072** | (0.022) | 0.034 | (0.029) | -0.037* | (0.019) | 0.020 | (0.035) |
| June | -0.060* | (0.027) | 0.020 | (0.023) | -0.031 | (0.018) | 0.006 | (0.038) |
| July | -0.019 | (0.034) | 0.026 | (0.024) | -0.011 | (0.025) | -0.023 | (0.030) |
| August | 0.002 | (0.039) | 0.020 | (0.018) | -0.051 | (0.032) | 0.042 | (0.046) |
| September | -0.053 | (0.032) | -0.011 | (0.017) | -0.066 | (0.037) | 0.030 | (0.051) |
| October | -0.001 | (0.034) | 0.005 | (0.017) | -0.035 | (0.029) | 0.029 | (0.040) |
| November | -0.011 | (0.028) | 0.044* | (0.022) | -0.013 | (0.021) | -0.031 | (0.024) |
| December | -0.013 | (0.025) | 0.042** | (0.015) | -0.048* | (0.018) | 0.016 | (0.024) |
| $R^2$ within | 0.046 | | 0.017 | | 0.018 | | 0.023 | |
| $R^2$ between | 0.0096 | | 0.0013 | | 0.0135 | | 0.0005 | |
| observations | 24,554 | | 248,632 | | 71,672 | | 99,056 | |

*Note:* Clustered (work team) standard errors in parentheses. All specifications control for double-fixed effects of employee-team pairs. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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