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Routine-Biased technical change: Individual-Level evidence from a plant closure☆

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ABSTRACT

Routine-biased technical change (RBTC) argues that digitisation decreases job opportunities for workers with routine task competencies, but increases job opportunities for workers with nonroutine task competencies. While there is considerable evidence for RBTC at the aggregate level, its effects on individual workers are yet to be fully understood. Therefore, this paper uses unique survey data of workers at a large car plant who became unemployed when the plant closed. In line with the RBTC hypothesis, we find that re-employment probabilities 1,5 years after the plant's closure are substantially higher for workers with nonroutine task competencies and with digital skills. Moreover, for the subset of individuals who were re-employed 1,5 years after the plant's closure, we find that the nonroutine content of job tasks is higher, wages are lower, and contracts are less permanent. Finally, our paper shows that a crude age-based early retirement policy that was negotiated as part of the plant's closure and that ignores workers' skills, results in significant foregone employment of older workers with nonroutine task competencies.

1. Introduction

An extensive literature has documented that digital technologies favour skilled workers. Katz and Murphy (1992) were among the first to present evidence that technological progress increases the demand for skilled relative to unskilled workers, a result that became known as Skill-Biased Technological Change (SBTC). Together with fluctuations in relative skill supplies, SBTC successfully accounts for some of the key patterns in the evolution of wage inequality from the 1970s to the late 1990s in many advanced economies. Due its theoretical parsimony and its empirical success, this simple demand-supply framework is also referred to as 'the canonical model'. (Goldin and Katz, 2008).

Recently, Autor et al. (2003), Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018) introduced a more nuanced view of the impact of digital technologies on labour demand. Their view is that digital technologies can perform routine tasks, where routine tasks are defined as predictable and repetitive such that they can be codified in software. Consequently, digitisation increases the routine task intensity with which goods and services are produced, leading to routine-biased technical change (RBTC). For workers, RBTC implies that those doing routine tasks will be displaced from their jobs because their tasks will be automated by digital technologies. However, the jobs of workers doing nonroutine tasks cannot be automated and some could even be complementary to digital technologies. In sum, digitisation increases the demand for nonroutine relative to routine task competencies of workers. An important difference with SBTC is that workers' task competencies are not monotonically related to their skill levels (Atalay et al., 2018; Autor, 2015; Autor and Dorn, 2013; Nedelkoska and Quintini, 2018).[1]

So far, studies examining RBTC have largely focussed on aggregate outcomes such as the aggregate skill premium or economy-wide changes in occupational employment. Yet, it is important to also examine the impact of digitisation on individual workers and firms (Consoli et al.,

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[1] For example, previous studies suggest that workers with middling levels of skill are most likely to do routine tasks. Consequently, digitisation leads to a decrease in the relative demand for middling jobs, resulting in an economy-wide phenomenon known as job polarization (Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2014; Spitz-Oener, 2006).

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2016; Vona and Consoli, 2015). Consider, for example, the economy-wide decrease in employment shares for routine occupations that has been extensively documented in the literature. At a more disaggregate level, this decrease could work through various channels. One channel could be through job-to-job switches of workers from routine to nonroutine jobs. An alternative channel could be that automation displaces older workers from routine jobs without leaving them the chance of finding new jobs, while younger workers enter the labour market mainly in nonroutine jobs (Cortes et al., forthcoming). Depending on which of these two channels is more important, the optimal policy response to digitisation will differ. For example, if only job-to-job switches from routine to nonroutine jobs are important, policies should facilitate these transitions for workers. However, if automation displaces older workers with displaced older workers not being able to find new jobs, an early retirement policy would be preferred from a welfare point of view.

To shed some light on the issue of what the impact of digitisation is on individual workers and adequate policy responses, this paper presents quantitative evidence from the recent shut-down of 'Ford Genk', a large car factory of the Ford Motor Company and its local suppliers in Genk (Belgium). The motivation for analysing this shut-down is twofold.

First, it allows us to test for RBTC by examining re-employment probabilities for individuals who were employed at the plant and its local suppliers before the plant's closure. In particular, RBTC would predict that individuals with more routine task competencies or less digital skills are less likely to find new jobs. The reason for this is that it is difficult for those workers to find new jobs in labour markets where employers increasingly value nonroutine task competencies and digital skills due to RBTC. Second, the shut-down is a mass-layoff of all workers at Ford Genk and its local suppliers that we can use for identification because the observed sample of individuals suffers less from sample selection bias. For example, if we would use job-to-job moves instead, the analyses would be complicated if workers decide to move between jobs based on some unobserved characteristic other than task competencies or digital skills.

We collaborated with several outplacement agencies to collect a rich set of individual-level data through interviews with displaced workers at different points in time. Our sample mainly consists of individuals with at most a high school diploma and at least 16 years of experience at Ford Genk, blue-collar work, men, and native Dutch speakers. We also collected individual-level data on workers' routine and nonroutine task competencies, which is important for examining the individual-level impacts of digitalisation across this group of displaced workers. Using these data, we find that job finding rates are lower for displaced workers that were specialised in doing routine tasks at Ford Genk: for an individual with one standard deviation higher routine task competencies compared to the average individual in our sample, the probability of having found a new job 1,5 years after the plant's closure is 49% compared to our sample's overall average of 61%. For the subset of individuals who were in new jobs 1,5 years after displacement, we also find a decline in their routine task content. We show that our results continue to hold when controlling for worker characteristics, such as educational attainment, age, gender, native language, or self-reported search motivation. We also show that our results are robust when we replace our measure of a worker's nonroutine task competency with a self-reported measure of digital skills. The latter result is consistent with research showing high returns to ICT skills in OECD countries (Falck et al., 2020).

Given that job finding rates differ for displaced workers with different routine and nonroutine task competencies, there could be substantial foregone employment from policies that ignore job seekers' task competencies. To document this, we quantify the employment losses from an early retirement scheme that resulted from negotiations between the Ford Motor Company, unions and the government after the announcement to shut down Ford Genk. This early retirement scheme gave all displaced workers that were 52 years or older on the day of the plant's closure the option to early retire, which most of them did. However, we show that a substantial number of these early retirees would have been employed if not given the option to early retire, because they possessed the required nonroutine task competencies to start new jobs.

One problem in quantifying the employment losses of a purely age-based early retirement policy that ignores job seekers' task competencies is that a worker's age also affects her job finding rate. If, for example, it is more difficult for older workers to find new jobs, it would be wrong to assume that the counterfactual job finding rate of a 58 year old early retiree would be the actual job finding rate of a 45 year old individual with otherwise similar characteristics. The true job finding rate for the 58 year old early retiree would be lower than that of the 45 year old, such that the lost employment from the early retirement scheme would be overestimated.

To address this issue, we use a Regression Discontinuity Design (RDD) that exploits the sharp age-based cut-off in eligibility for early retirement (52 years old on the day of the plant's closure) that allows us to identify the intent-to-treat effect of the early retirement policy. Our RDD estimates suggest that the counterfactual re-employment probability for early retirees relatively close to this cut-off would have been 48 percentage points higher on average in the absence of the early retirement policy. Importantly, our estimates also suggest that for an early retiree with one standard deviation higher nonroutine task competencies, the counterfactual re-employment probability would be even 11 percentage points higher. In sum, these estimates suggest that a crude age-based early retirement policy for displaced workers does not exploit the re-employability of older workers with nonroutine task competencies that would still be productive in the digital economy.

Our work is closest to a recent analysis of German displaced workers by Blien et al. (2018) who use a timing-of-events framework on occurrences of mass lay-offs in Germany between 1980 and 2010. Because the authors do not directly measure the task competencies of their displaced workers, they merge out-of-sample information about the task content of 2-digit occupations with occupational information in their data. In line with our results, they find a significantly slower recovery for displaced workers previously employed in routine task intensive jobs, both in terms of employment and earnings. However, there are also notable complementarities between their study and ours. First, we directly measure the task competencies of displaced workers by asking them about the tasks they performed at Ford Genk before it shut down. Second, we based our survey on the very rich questionnaire constructed as part of Princeton's Data Improvement Initiative by Autor and Handel (2013) such that our task measures are comparable to those commonly used in the literature. Third, our case study also allows us to evaluate the lost employment from an early retirement policy that ignores the economic value of early retirees' nonroutine task competencies.[2]

Also related to our work is Cortes et al., forthcoming, who track individuals over time in the US to estimate individual-level adjustments from digitalisation. The authors quantify the importance of different labour market transitions and worker flows for the economy-wide decline in routine employment. Complementary to the findings from our case-study, the authors report that an increased propensity of non-employment for individuals with routine task competencies is an important contributing factor. This finding is corroborated by Fossen and Sorgner (2020) on the basis of individual-level panel analysis in the

[2] Similarly, Kauhanen and Riukula (2019) measure the heterogeneity in employment and earnings losses from mass lay-off's that occurred in Finland between 2001 and 2016. They find that workers that were initially employed in jobs with high routine task content experienced larger declines in employment and wages. Conversely, workers previously employed in jobs with high social interaction experience the smallest losses. The limitations and complementarity of this study using Finnish linked employer-employee data are similar to the study by Blien et al. (2018).

US. They find that individuals employed in occupations at risk of digitization face a higher probability of entering non-employment. Bessen et al. (2019) present novel evidence from automation events at firms and following affected workers over time. They find that automation at a firm increases the probability of workers separating from their employers and decreases days worked. They also find that these effects are disproportionately borne by older workers and workers with longer firm tenure. However, they have no information about different transitions for workers with different task competencies, as we have in our paper.[3]

This paper also relates to the influential literature on the significant and persistent effects of job displacement, sparked by the seminal work of Jacobson et al. (1993). There are numerous other papers that use administrative as well as survey data to measure both labour market (Davis and Von Wachter, 2011; Farber, 2017; Foote et al., 2019) and health outcomes (Sullivan and von Wachter, 2009) from job displacement. We contribute to this line of research by documenting significant heterogeneity in displacement effects due to workers' routine and nonroutine task competencies and how this interacts with age-based welfare eligibility.

The remainder of this paper is structured as follows. Section 2 provides information on the institutional environment in which the shutdown of Ford Genk and its suppliers took place. The data collection is presented in Section 3 along with descriptive statistics and a discussion of sample selection and attrition. Section 4 analyses the re-employment probabilities for displaced workers, conducts robustness tests and investigates changes in job attributes between the job at Ford Genk and a new found job 1,5 years after the closure. Next, Section 5 presents evidence on the relationship between ongoing digitalisation and worker skills and task competencies in our case study. In Section 6 quantifies the costs in terms of foregone employment from a crude age-based early retirement policy that effectively fully depreciated the economic value of nonroutine task competencies of older workers. Finally, Section 7 concludes.

2. Institutional environment

2.1. Closure of ford genk

"Genk Body & Assembly" was a Ford Motor Company automobile factory in Genk, Belgium, just over an hour to the west of the company's European head office in Cologne. The plant opened in the early1960′s. The first mainstream car built there was Ford's first front wheel drive volume model, the Ford Taunus P4. Later on the plant focused on producing mid-sized family cars including the company's Sierra, Mondeo, S-MAX and Galaxy models.

On 24 October 2012 Ford announced that it would be closing its Genk plant on 31 December 2014 in response to over-capacity problems in Europe. This announcement was unexpected for Ford Genk's employees as two months earlier, in August 2012, Ford publicly confirmed its promise to maintain employment levels until 2020. At the time, around 4300 workers were employed directly by Ford Genk and approximately the same amount of workers were employed by Ford's suppliers. Therefore, the closure of Ford's Genk plant caused a mass layoff of workers in the Genk area (European Commission, 2015).

The closure of Ford Genk presents a distinct case study of a mass layoff in the car manufacturing industry subject to local labour market conditions. At the time of closure, Ford Genk was one of the main employers in the area. Moreover, the unemployment rate in the region of Limburg was around a high 8% in December 2014, similar to the average of Flanders, but declining.[4] Overall, the results of this study should be interpreted in the setting of a recovering labour market.

In Belgium, mass lay-offs due to plant closures are governed by specific regulations. These include that Ford Motor Company had to provide job search assistance to displaced workers through an outplacement programme. Therefore, Ford Motor Company contracted outplacement agencies during the first half of 2015 to help displaced workers make a swift transition to a new job. The top row of Fig. 1 summarizes the timing of events regarding the plant's closure.

2.2. Outplacement, training and early retirement

Between the announcement in October 2012 and the plant's closure at the end of 2014, some workers left Ford Genk. For those workers who did not, it was compulsory to enter the outplacement programme in the beginning of 2015 if they wanted to claim unemployment benefits (Rijksdienst voor Arbeidsvoorziening, 2019). For displaced workers who were younger than 44 years old on 31 December 2014, the outplacement programme lasted for a maximum of 3 months. For workers older than 44 years, outplacement took place over the course of a maximum of 6 months. At the end of the outplacement period, workers could find a new job, remain unemployed or become inactive.

Outplacement contains a variety of services, and is based on the needs of job seekers. Displaced workers were able to receive help with CV-checking and job interviews, as well as labour market orientation and information on re-training options. Outplacement services were not targeted towards displaced workers with particular backgrounds, although there is likely to be need-based variation correlated to worker characteristics. Around a quarter of job seekers reported to have undertaken additional training, during or after outplacement. This is higher among white-collar workers (46%) than among blue-collar workers (22%). Examples are training in basic computer skills, but also specialized technical training, such as technical drawing and forklift driving.

A special arrangement applied to workers who were at least 52 years old on 31 December 2014. From 1 January 2015, these workers could enter "early retirement". Technically, workers who opted for this early retirement scheme receive unemployment benefits (without having to search actively for jobs) and a supplementary income from the Ford Motor Company until the legal retirement age of 65 is reached.[5] The unemployment benefit component is a constant 60% of the last earned gross wage, independent of the worker's household situation (Rijksdienst voor Arbeidsvoorziening, 2018a). The supplement paid by the Ford Motor Company amounts to half of the difference between the last earned gross wage and the unemployment benefit (Rijksdienst voor

[3] In addition to focussing on transitions for individual workers, there are several recent studies examining the impact of the digital transformation on regions and occupations (Acemoglu and Restrepo, 2017; Ciarli et al., 2018; Lee and Clarke, 2017), firm-level employment (Domini et al., 2020; Harrigan et al., 2020) or industries (Autor and Salomons, 2018).

[4] Flanders, the Flemish Region of Belgium, is the Dutch-speaking area in the country's north, and one of 3 Belgian regions. It has a population of about 6.5 million, out of approximately 11.3 million for the entire country. The data on unemployment rates can be retrieved from https://arvastat.vdab.be/arvastat_basisstatistieken_werkloosheid.html.

[5] Next to the age-eligibility threshold of 52 years, workers who entered early retirement also had to have at least 10 years of work experience in the same sector within the last 15 years of employment or 20 years of work experience independent of the sector (Federale Overheidsdienst Werkgelegenheid, 2019; Rijksdienst voor Arbeidsvoorziening, 2019). In addition, workers had to be eligible for unemployment benefits. This means that they had to have worked for at least 624 days within 3 years before displacement (Rijksdienst voor Arbeidsvoorziening, 2019). These additional restrictions are met by all workers who are at least 52 years old at the time of displacement in our sample below. Therefore, we only use the age of 52 or older at the time of displacement as a sharp criteria for possibly entering early retirement.

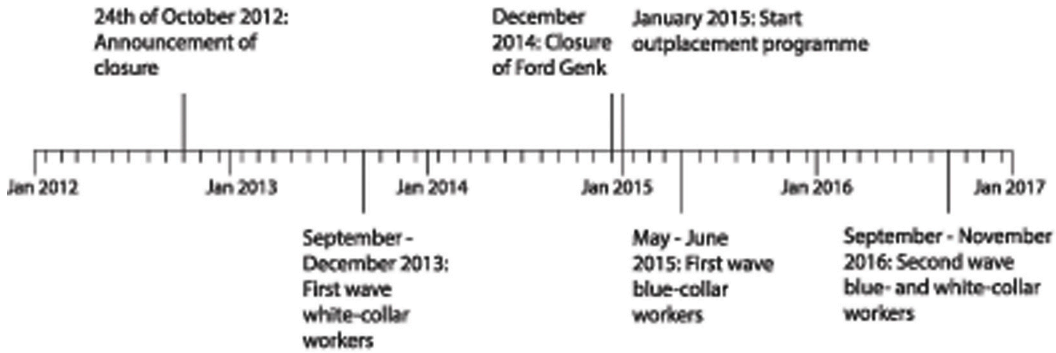

Fig. 1. Timeline of data collection and plant closure at Ford Genk.

Arbeidsvoorziening, 2018a).[6]

3. Data description

We collected unique survey data, consisting of two waves of workers who got displaced either directly by Ford Genk or by one of its local suppliers. For ease, we commonly refer to both types of workers being displaced by 'Ford Genk'.

3.1. Data collection and summary statistics

The first wave of data was collected in collaboration with two outplacement agencies, one assisting white-collar workers and another assisting blue-collar workers.[7] We asked placement officers at an outplacement agency for white-collar workers to survey those workers at the end of 2013, one year after the announcement of the plant closure and one year before the closure actually took place. We asked placement officers at another outplacement agency for blue-collar workers to survey those workers during the outplacement programme in 2015, just after the plant closure. In total, 1123 displaced workers participated in our survey. Of those, 143 where white-collar workers and 980 were blue-collar workers.

The second wave was a follow-up survey of 30 minutes in-home interviews of white-collar and blue-collar workers in mid 2016, 1,5 years after the plant closure.[8] Of the 1123 participants in the first wave, 548 also participated in the second wave. There are several reasons why we could no longer survey the 575 workers that we observe in the first but not the second wave. The main reasons are missing contact details and individuals not wanting to participate in the follow-up survey. Out of the 1123 initial participants, 995 individuals shared their contact details for follow-up. Of the 995 contacted, 548 (55%) decided to participate in the follow-up survey. The bottom row of Fig. 1 summarizes the timing of our data collection. The sample used in the empirical analyses below is the panel of 548 displaced workers observed in both survey waves.

Collecting survey data for this study provides advantages and disadvantages. On the one hand, conducting a survey comes with potential sample selection and limited number of observations. We return to these concerns in subsection 3.3 below, after the introduction of our baseline variables. On the other hand, collecting data using a survey enabled us to gather a large variety of unique and individual level data.

Table 1 shows the density of various worker characteristics for two age groups: those younger than 52 years and at least 52 years old. Of the 548 individuals, 351 were at least 52 years old on 31 December 2014. The table further shows that of those younger than 52 years, 59% had found a new job and 36% was still unemployed 1,5 years after displacement. Of those at least 52 years old, 86% entered early

Table 1
Worker characteristics for workers observed in both survey waves.

	Age<52 Col %	Age>=52 Col %	Total Col %	N
Employment status 1,5 years after displacement				
Employed	58.9	4.0	23.7	130
Unemployed	36.0	5.4	16.4	90
Inactive	3.6	4.3	4.0	22
Early retirement	1.5	86.3	55.8	306
Total	100.0	100.0	100.0	548
Education				
No diploma	13.9	24.6	20.8	109
High school diploma	71.1	68.9	69.7	366
College degree	15.0	6.5	9.5	50
Total	100.0	100.0	100.0	525
Work experience at Ford Genk				
1 to 15 years	7.7	10.1	9.2	50
16 to 30 years	89.8	29.6	51.3	279
31 to 44 years	2.6	60.3	39.5	215
Total	100.0	100.0	100.0	544
Female workers				
Men	85.5	89.1	87.8	475
Women	14.5	10.9	12.2	66
Total	100.0	100.0	100.0	541
Native language: Dutch				
No	7.3	6.7	6.9	37
Yes	92.7	93.3	93.1	498
Total	100.0	100.0	100.0	535
Worker statute				
White-collar worker	11.7	3.4	6.4	35
Blue-collar worker	88.3	96.6	93.6	513
Total	100.0	100.0	100.0	548
Search motivation				
Low search motivation	2.2	51.4	34.1	175
Moderate search motivation	69.4	43.8	52.8	271
High search motivation	28.3	4.8	13.1	67
Total	100.0	100.0	100.0	513

[6] This supplement is paid until the legal retirement age of 65 is reached, even if the worker would become re-employed and loose her unemployment benefit (Federale Overheidsdienst Werkgelegenheid, 2019; Rijksdienst voor Arbeidsvoorziening, 2018b)

[7] Belgium is one of the last European countries where a distinction is made in a worker's statute between blue-collar and white-collar workers. Blue-collar workers are generally considered employees who provide manual labour, whereas white-collar workers are generally considered employees who provide intellectual labour. This distinction is evident in the working conditions, the method of payment of salary, notice periods (which are much shorter for blue- than white-collar workers) and the benefits provided to blue- and white-collar workers.

[8] The timing of follow-up was the result of the trade-off between capturing as much re-employment variation as possible, and maximizing the response rate by maintaining the momentum and interest among displaced workers following the first data collection. Statistics from the Flemish public employment service report that among unemployed job seekers in the region, 57% is unemployed for less than a year, and another 18% is unemployed between 1 and 2 years. See https://arvastat.vdab.be/arvastat_detailtabellen_werkloosheid.html This motivated our choice to survey displaced workers 1,5 years after the plant closure.

retirement immediately after displacement. Our sample mainly consists of individuals with at most a high school diploma and at least 16 years of experience at Ford Genk, blue-collar work, men, and native Dutch speakers. Those younger than 52 years are moderately to highly motivated to search for a new job, whereas search motivation is lower among those who are at least 52 years old.[9]

3.2. Routine task intensity (RTI) of jobs at ford genk

We also collected information about the tasks workers performed in their jobs at Ford Genk. In particular, we follow Autor and Handel (2013) to construct three task dimensions used extensively in the literature to examine the impact of ongoing digitalisation on relative labour demand. These three dimensions are Abstract, Routine and Manual tasks performed in a job.

Abstract tasks are measured by (1) the extent of mathematics used in the job; (2) the length and difficulty of documents to read; (3) the extent of dealing with unforeseen situations; and (4) the extent of supervising, managing and delegating tasks to other employees. Routine tasks performed are measured by (5) the extent of performing short, manual or repetitive tasks; (6) the extent of working with high precision with machines or equipment; (7) the extent of strictly following a tempo set by machinery or equipment; and (8) the degree of lacking social interaction with people other than colleagues, e.g. customers or students. Manual tasks are measured by (9) the extent of operating machinery, e.g. a truck or drill; (10) the importance of hand-eye coordination and dexterity; and (11) the extent of physical tasks in the previous job including standing for a long time or lifting heavy objects. Each of these 11 task measures are scored on a scale from 1 to 5 by survey participants.

For each individual, we calculate the average score across these task measures within the same task dimension. For example, for each individual we calculate an Abstract measure by taking her average score on task measures (1) to (4) above. This way, for each individual i we obtain an Abstract task measure, T_i^A, a Routine task measure, T_i^R, and a Manual task measure, T_i^M. In line with Goos et al. (2014) simple averages are calculated. Alternatively, Autor and Handel (2013) use the first score from a principal component analysis (PCA). In subsection 4.3, we show that the results using PCA are very similar.

To measure the routine intensity of tasks performed, we make use of the Routine Task Intensity (*RTI*) index developed by Autor and Dorn (2013). Specifically, we construct:

$$RTI_i = ln\left(T_i^R\right) - ln\left(T_i^M\right) - ln\left(T_i^A\right) \tag{1}$$

where T_i^A, T_i^R and T_i^M are the Abstract, Routine and Manual task measures for individual i's job at Ford Genk before displacement. Finally, the RTI index is normalized to have mean 0 and standard deviation of 1.

Table 2 shows the average of the RTI index across employment status 1,5 years after the plant closure, highest diploma obtained, experience at Ford Genk, gender, native language, worker statute and search motivation. The RTI index is relatively high for those still unemployed 1,5 years after displacement, workers with no diploma and low work experience at Ford Genk, women, non-Dutch native speakers, and workers with high search motivation at the time of displacement.

Finally, we zoom in on the worker statute of being a blue-collar or white-collar worker, which is a distinction that is specific to Belgian labour law. Fig. 2 plots the kernel density of RTI separately for these two groups. The RTI of blue-collar workers is centred around zero given that they represent the majority of our sample. The RTI of white-collar workers is on average lower and less dispersed. However, we also find that the RTI of both groups heavily overlap. To give a few examples, the most common occupation among blue-collar workers is machine operator. This is associated with an average RTI of 0.536. However, blue-collar workers were also engaged as technicians and team supervisors. These occupations had a mean RTI of -0.634 and -0.788 respectively. This is similar to white-collar workers engaged in management.[10] Further examples can be found in Appendix Table A.1.

Table 2
Mean and standard deviation of the RTI index, by worker characteristics.

	N	Mean	Sd
Employment status 1,5 years after displacement			
Employed	130	-0.183	0.959
Unemployed	90	0.352	0.928
Inactive	22	-0.272	0.824
Early retirement	306	0.001	1.026
Total	548	0.000	1.000
Education			
No diploma	109	0.359	1.055
High school diploma	366	-0.056	0.959
College degree	50	-0.518	0.800
Total	525	-0.023	0.989
Work experience at Ford Genk			
1 to 15 years	50	0.401	1.031
16 to 30 years	279	0.066	0.991
31 to 44 years	215	-0.171	0.977
Total	544	0.003	1.001
Age			
Age<52	197	0.013	0.970
Age>=52	351	-0.008	1.018
Total	548	0.000	1.000
Female workers			
Men	475	-0.042	0.985
Women	66	0.397	1.086
Total	541	0.005	1.004
Native language: Dutch			
No	37	0.355	0.783
Yes	498	-0.039	1.012
Total	535	-0.010	1.002
Worker statute			
White-collar worker	35	-0.579	0.746
Blue-collar worker	513	0.044	1.004
Total	548	0.000	1.000
Search motivation			
Low search motivation	175	0.030	1.055
Moderate search motivation	271	0.012	0.987
High search motivation	67	0.117	0.949
Total	513	0.032	1.002

Notes: The RTI index is created using composite measures of abstract, routine and manual tasks. Each of these composite task measures are simple averages across the separate task variables. The RTI index is normalized to have mean 0 and standard deviation 1.

3.3. Sample selection and attrition

Both waves of survey data collection may be affected by selection. First, our first wave of data collection took place after the announcement of the plant closure (for white-collar workers) or even after the plant closure (for blue-collar workers). This means that workers may have left in anticipation of the closure and before the first survey was conducted. Therefore, our results should be interpreted as the re-employment probabilities for workers who remained at Ford Genk until its closure. The consequences of this for a possible sample selection bias are difficult

[9] Search motivation is measured in the first survey wave, thus at the time of displacement and consists of three categories: low, moderate and high search motivation.

[10] Note from Fig. 1 that the timing of the first wave is also different for blue-collar and white-collar workers: white-collar workers report their task content while still being employed at Ford Genk, whereas blue-collar workers provide this information retrospectively. This may have resulted in different RTI indices for blue-collar and white collar workers. However, these examples show that this is unlikely to be important.

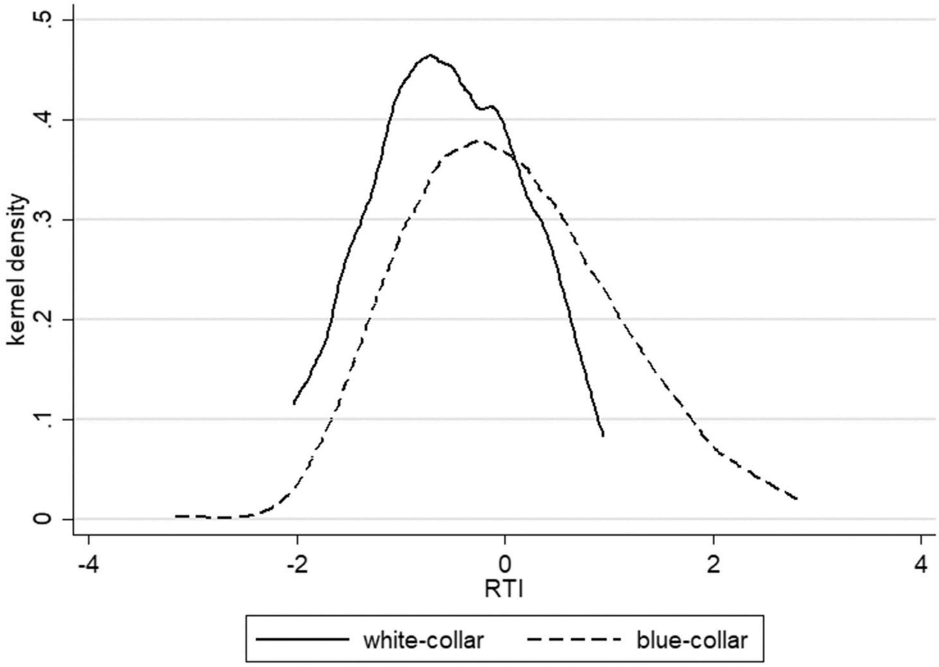

Fig. 2. Density of RTI index for blue- and white-collar workers Note: The sample includes all workers who participated in both survey waves, i.e. all workers included in the panel sample. The RTI index is created using composite measures of abstract, routine and manual tasks performed in the job at Ford Genk. The RTI index is normalized to have mean 0 and standard deviation 1 within the panel sample. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Worker characteristics and attrition between wave 1 and wave 2.

	(1)		(2)		(3)
	full wave 1		panel		diff
	mean	sd	mean	sd	b
Education	2.02	0.60	1.89	0.54	-0.13***
Years of experience with last employer	27.07	8.73	28.98	8.03	1.91***
Age	0.49	0.50	0.64	0.48	0.15***
Female workers	0.15	0.36	0.12	0.33	-0.03
Native language: Dutch	0.96	0.21	0.93	0.25	-0.02*
Search motivation	1.89	0.64	1.79	0.65	-0.10**
RTI index	-0.04	1.03	0.04	0.97	0.09
Observations	573		548		1121

Notes: *, ** and *** stand for 10, 5 and 1% statistical significance respectively. Education is a categorical variable, where the first category describes 'No diploma', the second category describes 'High school diploma' and the third category describes a 'College degree'. The RTI index is created using composite measures of abstract, routine and manual tasks. Each of these composite task measures are simple averages across the separate task variables. The RTI index is normalized to have mean 0 and standard deviation 1 in the full sample of workers.

to measure given the absence of worker data before our survey started. If those who left Ford Genk before the start of our survey had re-employment rates higher than the ones observed in our sample, it is possible that we underestimate the re-employment probability among all displaced workers. Alternatively, severance pay may have provided an incentive to stay at the plant until its closure, even for workers with higher re-employment prospects.

Second, attrition between the first and second survey wave may have been non-random. Table 3 compares the full sample of the first data collection with our panel sample on a number of important characteristics. The *t*-test comparison reveals that some negative selection took place between waves. On average, our panel sample is slightly lower educated, had 2 years of experience more at Ford Genk and was 0.15 years older. The respondents in the second wave were also somewhat less motivated to search for a new job. To account for potential attrition bias in our estimates, we also estimate a sample selection model below.

4. Routine task competencies and job finding probabilities

If changes in labour demand are biased against routine task competencies due to digitalisation, we would expect job seekers with a higher RTI index to have a lower re-employment probability. We would also expect that individuals who are employed again 1,5 years after displacement have moved into jobs that are less routine intensive on average. This section examines these two hypotheses.

Because workers who were older than 52 years at the time of displacement had the additional option of taking up early retirement, they are excluded from the estimation sample in this section. Hence, this section only considers individuals younger than 52 years of age observed in both the first and second wave of our data. In Section 6, we will include workers who are at least 52 years old again in our analyses.

4.1. RTI And job finding probabilities

This subsection 4.1 regresses an individual's re-employment status 1,5 years after displacement onto her RTI index and other individual characteristics. That is, we estimate the following linear probability model:[11]

[11] Our results are unaffected when using a probit estimator instead. In addition, we used exact re-employment dates to have duration of unemployment as an outcome. We estimated the equivalent of equation (2) using a Cox proportional hazard model. We find qualitatively identical results of the negative relationship between the RTI index and re-employment probabilities. However, given the stronger functional form assumptions of duration analysis and our limited sample size, we prefer the linear probability model for our main analysis.

$$P(Employed_i) = \beta_0 + \beta_1 RTI_i + \beta_2 Educ_i + \beta_3 Age_i + \beta_4 Age_i^2 + \beta_5 Female_i + \beta_6 Dutch_i + \beta_7 BlueCollar_i + \epsilon_i \quad (2)$$

where $P(Employed_i)$ is a dummy for whether individual i is employed 1,5 years after displacement and RTI_i captures the routine task intensity of i's job at Ford Genk. We expect β_1 to be negative due to routine-biased technical change (RBTC). Additional control variables are worker characteristics commonly used in the literature: $Educ_i$ is a vector of dummies for i's highest obtained education level (no diploma, high school diploma, or a college degree), Age_i is i's age at the time of displacement, $Female_i$ is a dummy equal to 1 if i is a woman, and $Dutch_i$ is a dummy equal to 1 if i's native language is Dutch.[12] In a separate specification, we also include the dummy $BlueCollar_i$, which equals one if individual i is a blue-collar worker.[13]

Column (1) of Table 4 shows that, consistent with the hypothesis of routine-biased technical change, workers with routine task competencies are less likely to be employed 1,5 years after displacement: a one standard deviation increase in the RTI index decreases the average re-employment probability by 13 percentage points, from 61% to 48%.

Column (2) adds worker characteristics that are commonly used in the literature. Taking point estimates at face value, having a college degree increases an individual's re-employment probability by 23 percentage points, all else equal. Women have higher re-employment probabilities than men in our sample. This is in line with the aggregate finding that especially women move from routine task intensive jobs to jobs with mainly abstract tasks (Acemoglu and Autor, 2011). Finally, native Dutch speakers have better re-employment prospects. Importantly, although significance of the coefficient on RTI_i falls to 10% when controlling for these worker characteristics, it remains negative and comparable in size with an 8 percentage point lower probability of re-employment associated with a one standard deviation increase in the RTI index. What this suggests is that even within narrowly defined demographic groups, workers with more routine task competencies are less likely to find work.

Column (3) of Table 4 adds a dummy for blue-collar workers. As illustrated by Fig. 2, this will likely absorb some of the variation in the RTI index. Nevertheless, we find that the coefficient on RTI_i decreases very little. A standard deviation in the RTI index among blue-collar workers, for example those engaged as a technician or supervisor in comparison to machine operators, still predicts a 7.7 percentage points higher probability to find a job, even after controlling for education, age, gender and native language.

Columns (4), (5) and (6) of Table 4 decompose the RTI index into its three task dimensions: Abstract, Routine and Manual tasks. The three task dimensions are highly correlated and the sample size is limited, which makes it difficult to precisely estimate the impact of each measure separately. For example, a person who performs a lot of abstract tasks on the job is likely to perform less routine tasks and vice versa. This multicollinearity increases the standard errors, partially explaining the loss of statistical significance.[14] Nevertheless, the sign and magnitude of our estimates suggest that having Routine task competencies lowers job finding rates compared to having Abstract and Manual task competencies. This implies that the negative coefficients on RTI_i in columns (1), (2) and (3) are not exclusively driven by just one but by all three task dimensions. This is further evidence in support of the routine-biased technical change hypothesis. Column (6) of Table 4 again includes a dummy variable for blue-collar workers. This decreases the significance of the coefficients on Abstract, Routine and Manual tasks further, however, it does not affect our main conclusion.[15]

In sum, the heterogeneity in worker competencies matters in explaining observed differences in re-employment probabilities 1,5 years after displacement: Workers who were performing routine tasks before displacement are less likely to be re-employed 1,5 years later. This evidence supports the routine-biased technical change hypothesis, arguing that ongoing digitalisation is lowering the demand for workers with routine task competencies relative to workers with nonroutine task competencies. These findings are robust to including other worker characteristics commonly used in the literature (i.e. education, age, gender and native language) as well as blue-collar or white-collar status.

4.2. The importance of search motivation

There could be other variables omitted from equation (2) that are both correlated to workers' task competencies as well as directly correlated to re-employment probabilities. For example, Table 2 suggests that, if anything, workers with routine task competencies put more effort into searching for a new job. If so, the estimated adverse impact of RTI_i on $P(Employed_i)$ in Table 4 is too small (in absolute value) such that we underestimated the impact of ongoing digitalisation on the probability to find a new job.

Therefore, Table 5 includes dummies for low and high search motivation as explanatory variables, with moderate search motivation being the excluded category. For ease of comparison, columns (1) to (3) of Table 5 are the columns (1) to (3) of Table 4. Columns (4), (5) and (6) include search motivation as a control in the regression equations. As expected, workers who are highly motivated to search for a new job have higher re-employment probabilities compared to moderately

[12] We include Age_i as well as Age_i^2 as is usually done in a Mincer specification to capture the relationship between a worker's human capital and her productivity on the job. Using years of work experience at Ford Genk instead of age does not qualitatively change our results.

[13] The blue-collar worker dummy is defined as all workers under a blue-collar statute who received assistance from the blue-collar outplacement agency.

[14] When we compute the Variance Inflation Factor (VIF) for specifications in Columns (4), (5) and (6), we find mean factors of 1.69, 2.04 and 2.12 respectively. However, there is no absolute reference of interpretation for these inflation factors. Rather, researchers have relied on rules of thumb, see Chatterjee and Hadi (2015). In general, these rules suggest that there is evidence of multicollinearity if there is a variable with a VIF larger than 10 (or more conservatively, 30) and if the mean VIF is considerable larger than 1. Although neither of our three separate task measures has a VIF larger than 10, we do find consistent mean VIF's larger than 1.

[15] The importance of Ford Genk as a regional employer implies that a sizeable share of jobs in the area disappeared without a simultaneous increase in alternative job offers, in particular for blue-collar workers. However, note that our estimated coefficients for the RTI index in columns (3) and (6) of Table 4 control for worker characteristics, including blue-collar status. Therefore, our results are not mainly driven by a negative local labour demand shock following a mass lay-off, mainly of blue-collar workers.

Table 4
The probability of finding a job and workers' task competencies.

	(1)	(2)	(3)	(4)	(5)	(6)
RTI index	-0.126***	-0.081*	-0.077*			
	(0.036)	(0.041)	(0.042)			
Abstract tasks (average)				0.096**	0.062	0.059
				(0.042)	(0.048)	(0.050)
Routine tasks (average)				-0.092**	-0.079	-0.077
				(0.046)	(0.049)	(0.050)
Manual tasks (average)				0.031	0.030	0.034
				(0.043)	(0.047)	(0.049)
Blue-collar workers			-0.123			-0.052
			(0.112)			(0.127)
High school diploma		0.015	0.014		0.026	0.026
		(0.112)	(0.113)		(0.114)	(0.114)
College degree		0.232*	0.172		0.137	0.123
		(0.130)	(0.137)		(0.147)	(0.146)
Age at displacement		-0.115	-0.095		-0.091	-0.086
		(0.181)	(0.183)		(0.182)	(0.183)
Age at displacement^2		0.001	0.001		0.001	0.001
		(0.002)	(0.002)		(0.002)	(0.002)
Female workers		0.241**	0.244**		0.256***	0.257***
		(0.095)	(0.095)		(0.094)	(0.094)
Native language: Dutch		0.217	0.216		0.204	0.204
		(0.136)	(0.137)		(0.137)	(0.138)
Constant	0.612***	2.981	2.498	0.578***	2.416	2.275
	(0.035)	(3.841)	(3.902)	(0.199)	(3.880)	(3.901)
Observations	182	170	170	182	170	170

Notes: Robust standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. The sample is restricted to the workers who are younger than 52 years of age at the time of displacement. The RTI index is created using composite measures of abstract, routine and manual tasks. Each of these composite task measures are simple averages across the separate task variables measured on a scale from 1 to 5. The RTI index is normalized to have mean 0 and standard deviation 1.

Table 5
The probability of finding a job, workers' task competencies and search motivation.

	(1)	(2)	(3)	(4)	(5)	(6)
RTI index	-0.126***	-0.081*	-0.077*	-0.124***	-0.087**	-0.084**
	(0.036)	(0.041)	(0.042)	(0.039)	(0.043)	(0.043)
Low search motivation				-0.233	-0.355	-0.293
				(0.369)	(0.317)	(0.297)
High search motivation				0.189**	0.201**	0.225***
				(0.077)	(0.082)	(0.085)
Blue-collar workers			-0.123			-0.272**
			(0.112)			(0.130)
High school diploma		0.015	0.014		0.054	0.051
		(0.112)	(0.113)		(0.118)	(0.119)
College degree		0.232*	0.172		0.287**	0.196
		(0.130)	(0.137)		(0.140)	(0.142)
Age at displacement		-0.115	-0.095		-0.147	-0.069
		(0.181)	(0.183)		(0.189)	(0.192)
Age at displacement^2		0.001	0.001		0.002	0.001
		(0.002)	(0.002)		(0.002)	(0.002)
Female workers		0.241**	0.244**		0.255**	0.260**
		(0.095)	(0.095)		(0.112)	(0.112)
Native language: Dutch		0.217	0.216		0.207	0.202
		(0.136)	(0.137)		(0.132)	(0.135)
Constant	0.612***	2.981	2.498	0.545***	3.595	1.738
	(0.035)	(3.841)	(3.902)	(0.045)	(4.029)	(4.139)
Observations	182	170	170	166	155	155

Notes: Robust standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. The sample is restricted to the workers who are younger than 52 years of age at the time of displacement. The RTI index is created using composite measures of abstract, routine and manual tasks. Each of these composite task measures are simple averages across the separate task variables measured on a scale from 1 to 5. The RTI index is normalized to have mean 0 and standard deviation 1. Search motivation is measured in the first survey wave, thus at the time of displacement and consists of three categories: low, moderate and high search motivation. Moderate search motivation is the reference category.

motivated workers. Our estimates also suggest that the impact of being highly motivated is sizeable and comparable to having a college degree, being a women or a native Dutch speaker. Column (6) shows that this also holds when including a blue-collar dummy.

Importantly, Table 5 shows that the estimated coefficients for our task-competency measure are not qualitatively affected by including search motivation as an explanatory variable. This shows that the negative impact of having routine task competencies on the probability of finding a new job is not driven by lower search effort of workers with routine task competencies. Instead, our results suggests that lower re-employment probabilities for workers with routine task competencies are better explained by fewer job opportunities for these workers, as is consistent with the hypothesis of routine-biased technical change.

Table 6
Robustness analysis for job finding probabilities, workers' task competencies and worker characteristics.

	(1)	(2)	(3)	(4)	(5)
RTI index	-0.081*	-0.077	-0.077*	-0.076*	
	(0.041)	(0.047)	(0.041)	(0.041)	
RTI index (pca)					-0.093**
					(0.042)
Gross hourly wage		0.010			
		(0.012)			
Labour market experience			-0.002		
			(0.015)		
Additional training				0.062	
				(0.072)	
High school diploma	0.015	0.025	0.031	0.011	0.010
	(0.112)	(0.124)	(0.118)	(0.113)	(0.111)
College degree	0.232*	0.181	0.244*	0.234*	0.174
	(0.130)	(0.181)	(0.147)	(0.130)	(0.137)
Age at displacement	-0.115	0.952	-0.114	-0.117	-0.098
	(0.181)	(0.931)	(0.182)	(0.179)	(0.179)
Age at displacement^2	0.001	-0.010	0.001	0.001	0.001
	(0.002)	(0.010)	(0.002)	(0.002)	(0.002)
Female workers	0.241**	0.387***	0.241**	0.233**	0.250***
	(0.095)	(0.112)	(0.094)	(0.094)	(0.094)
Native language: Dutch	0.217	0.182	0.217	0.209	0.203
	(0.136)	(0.139)	(0.142)	(0.138)	(0.136)
Constant	2.981	-23.210	2.949	3.034	2.606
	(3.841)	(22.412)	(3.859)	(3.792)	(3.799)
Observations	170	137	169	170	170

Notes: Robust standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. The sample is restricted to the workers who are younger than 52 years of age at the time of displacement. The RTI index is created using composite measures of abstract, routine and manual tasks. Each of these composite task measures are simple averages across the separate task variables. The RTI index is normalized to have mean 0 and standard deviation 1. Gross hourly wages are the wages in the previous job and are only available for blue-collar workers, explaining the drop in observations and potentially the loss of statistical power. Labour market experience is total years of labour market experience. Training is a measure of whether an individual followed additional training since the job loss. The RTI index (pca) is a composite measure of task measures created using the first components of a principal component analysis.

4.3. Robustness analyses

Subsections 4.1 and 4.2 included several worker characteristics as controls. Nevertheless, there could be other unobserved heterogeneity among workers correlated with routine task competencies that is driving re-employment probabilities. This would lead to biased estimates of the effect of RTI_i. Therefore, we repeat our main analysis from Table 4 and include additional variables. Across these different specifications, we find that our main effect on RTI_i is robust.

The first column of Table 6 shows the estimates from Column (2) of Table 4 for comparison. Column (2) includes gross wages from the job at Ford Genk as a proxy for productivity at the previous job. This column only includes blue-collar workers due to a lack of data for white-collar workers. The coefficient on RTI_i in Column (2) is very comparable to Column (1), however statistically insignificant. Alternatively, Column (3) includes the total years of labour market experience for the sample of blue- and white-collar workers. The coefficient on RTI_i is once again significant and comparable to previous estimates. Taken together, these estimations support the importance of routine task intensity for job finding probabilities.

Because outplacement also offered guidance for further (re-)training of job seekers, it could be the case that our estimates are in part picking up the tendency of some workers to invest more in their skills and possibly, to put more effort into their job search. Therefore, in Column (4) of Table 6 we introduce an indicator for whether workers followed additional training. This measure captures additional skill accumulation

Table 7
Heckman selection: Job finding probabilities, workers' task competencies and worker characteristics.

	(1)	(2)
RTI index	-0.081*	-0.089**
	(0.041)	(0.042)
High school diploma	0.015	0.010
	(0.112)	(0.111)
College degree	0.232*	0.204
	(0.130)	(0.126)
Age at displacement	-0.115	-0.090
	(0.181)	(0.178)
Age at displacement^2	0.001	0.001
	(0.002)	(0.002)
Female workers	0.241**	0.243***
	(0.095)	(0.094)
Native language: Dutch	0.217	0.194
	(0.136)	(0.140)
Constant	2.981	2.286
	(3.841)	(3.785)
Observations	170	417

Notes: Robust standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. Please note that the first column shows results for the sample of workers who are younger than 52 years of age at the time of displacement and who appear in both survey waves. The Heckman model is estimated using maximum likelihood. It is estimated using all individuals observed in the first wave of the survey who are younger than 52 years at the time of displacement.

of workers directly but may also indirectly capture differences in motivation of workers to re-enter the labour market. The coefficient on training is positive, although insignificant. Similar to the results in Columns (2) and (3), the estimate on RTI_i only mildly decreased.

In column (5), an alternative measure of the RTI index is used. The RTI index is computed using Abstract, Routine and Manual tasks that are estimated using the first component of a principal component analysis. This approach to creating the task measures implies a change in the underlying weights on Abstract, Routine and Manual. Therefore, it is difficult to compare the magnitude of the coefficient. Nevertheless, the sign and also size of the coefficient are very similar to the coefficient on RTI_i in Column (1).

As already document in the subsection 3.3, our sample was significantly reduced by attrition between the first and second wave of data collection. A comparison of our main explanatory variables in Table 3 showed that there is some evidence of non-random selection into the second wave follow-up. If workers with particularly bad job finding probabilities were more likely to enter our follow-up study, we are likely to underestimate the re-employment prospects of displaced of workers, which in turn could bias our results. We attempt to alleviate this attrition bias by estimating a Heckman selection model. Table 7 shows the estimates from our linear probability model for our preferred set of controls in Column (1). After accounting for attrition in Column (2), we find that the coefficient on RTI_i is qualitatively identical. However, the identifying assumptions for estimation are stringent, and therefore interpretation requires some caution. With these reservations in mind, these results imply that, if anything, sample attrition caused us to somewhat underestimate the effect of RTI_i on the probability to find new work.[16]

4.4. Changes in task content

If changes in labour demand are biased against routine task

[16] Another concern related to sample selection is that the first data collection for blue-collar workers occurred later than for white-collar workers, such that some white-collar workers may have found jobs in the meantime. Therefore, we drop the white-collar workers who found a job before the data collection of blue-collar workers. This does not affect our main estimate on RTI_i.

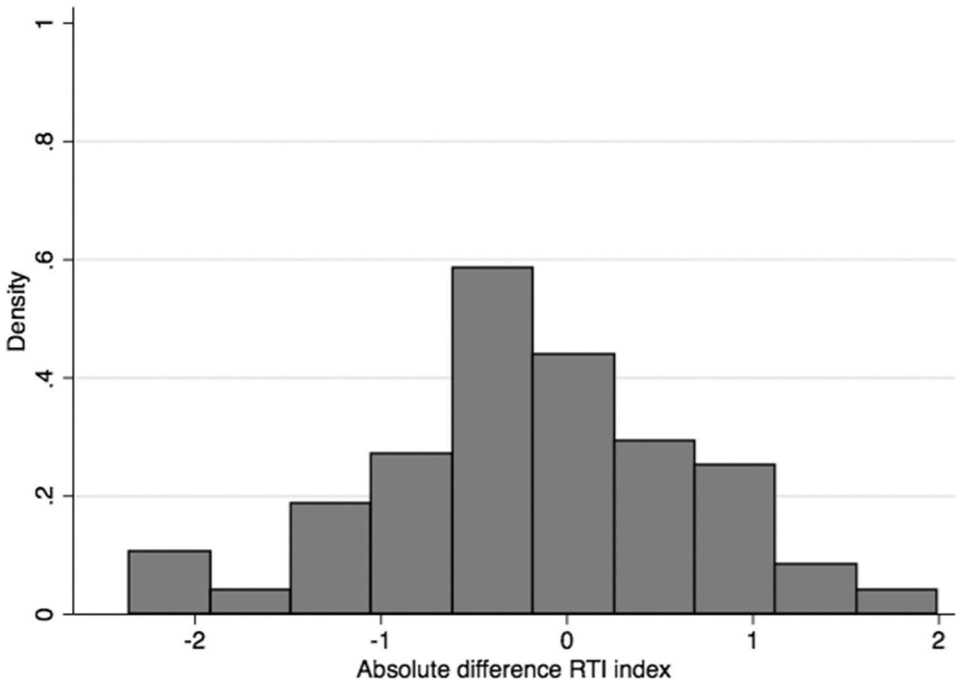

Fig. 3. Absolute difference in RTI index between the new job and the job at Ford Genk Note:The absolute difference of the RTI index is calculated using two RTI indices. One RTI index shows the RTI in the new job of workers and the other shows the RTI in the job at Ford Genk. Each of the RTI indices is created using composite measures of abstract, routine and manual tasks performed in the new job or in the job at Ford Genk. Subsequently, the difference between the RTI of the new job and the RTI of the job at Ford Genk is computed using the absolute values of the RTI indices. This figure uses the subsample of re-employed workers who are younger than 52 years. In total, there are 110 re-employed workers who are younger than 52 years and who have observations for both RTI indices.

Table 8
Transition of task content for re-employed workers, row %.

	Abstract	Routine	Manual	Total
Abstract	82	4	14	100
Routine	49	23	26	100
Manual	28	23	46	100
RTI>median	57	22	19	100

Notes: The sample is restricted to the workers who are younger than 52 years of age at the time of displacement and who are re-employed 1,5 years after the plant closure. Each of the composite task measures, abstract, routine and manual are simple averages across the separate task variables. The RTI index is normalized to have mean 0 and standard deviation 1. The rows capture the task a worker performed most in the previous job at Ford Genk (wave 1) and the columns capture what task a worker performed most in the new job (wave 2).

competencies due to digitalisation, we would also expect that individuals who are employed again 1,5 years after displacement have moved into jobs that are less routine on average. To examine this question, this subsection restricts the estimation sample to the 130 displaced workers below age 52 who are re-employed 1,5 years after the plant closure. For this subset of displaced workers, the follow-up survey asked to score the same 11 task measures as described in subsection 3.2 again in relation to their new job.

Fig. 3 shows the absolute difference in the RTI index between these workers' new jobs and their previous jobs at Ford Genk.[17] The figure shows that the average worker performs fewer routine tasks in her new job compared to her job at Ford Genk. The average change in routine task intensity in Fig. 3 is -.20 and is statistically significant at the 1% level. Although the decrease in routine task content is significant, it is also relatively small. This is in line with recent findings in Goos et al. (2019) showing that it is difficult for unemployed individuals with mainly routine task competencies to find new jobs that are less routine intensive but for which they partially qualify in terms of their nonroutine task competencies.

To understand whether this partial shift away from routine task content is driven by more abstract or manual content, Table 8 computes the transition shares based on each task measure separately. Each row represents the most important task performed during the job at Ford Genk, whereas each column represents the most important task done in the new job. Row percentages show the transition rates for each separate group. In line with the small net changes in Fig. 3, many individuals continue to perform the same type of task in their new job as they did in their old job. However, we also see that more workers have abstract tasks in their new job. This is particularly the case for workers who were initially performing mainly routine tasks.

To show the pervasiveness of this shift away from routine tasks, we regress the within-person, absolute change in RTI on various worker characteristics.[18] We find that the change in RTI differences are more positive for college degree holders, and more negative for female workers. There are no significant differences between blue- and white collar workers. Although the smaller decline in routine task content for college workers is somewhat counter-intuitive, this could be driven by the correlation between having a college degree and abstract task competencies. As our transition matrix in Table 8 showed, larger shifts were found for individuals who were previously most invested in routine task competencies.

These results suggests that new jobs often improved in terms nonroutine task content. To give further insight into the quality of new jobs found, Table 9 provides descriptive statistics on additional job attributes. 75% of re-employed workers state that they earn less in their

[17] This is the difference in the RTI index that is not standardized. We estimate the absolute difference in the RTI index because the average RTI is likely to differ between waves. Standardizing by wave would absorb this relevant variation.

[18] Results can be found in Table A.2.

Table 9
Changes in job characteristics for re-employed workers between the new and old job.

	Col %	N
Earnings relative to previous job		
Same	14.8	16
More	10.2	11
Less	75.0	81
Did worker move?		
No	95.6	108
Yes	4.4	5
Commuting		
No commuting old job and no commuting new job	13.4	11
No commuting old job but commuting new job	12.2	10
Commuting old job but no commuting new job	11.0	9
Commuting old job and commuting new job	63.4	52
Work in urban area		
Continued working in urban area	55.7	44
Stopped working in urban area	44.3	35
Change from full-time to part-time job?		
remain part-time	1.8	2
remain full-time	81.7	89
moved from full- to part-time	16.5	18
Contract type, % workers		
Temporary	51.8	57
Permanent	48.2	53
Total	100.0	116

Notes: The table shows the characteristics of new jobs found, also in comparison to the previous job. For this reason, the sample of re-employed workers who are below 52 years of age at the time of the displacement are considered. Moving is defined as a difference in the postal code of the residence of a worker between the first and second wave of the survey. Commuting is defined as a worker not living and working in the same postal code. This holds for the old and the new job. Postal codes of employers were used to determine whether workers worked in urban areas. Urban is defined as a postal code describing a city with at least 40 000 inhabitants. The information on the number of inhabitants of cities and the corresponding postal codes were retrieved from https://www.vlaanderen.be/gemeenten-en-provincies/provincie-limburg.

new job compared to the previous job at Ford Genk.[19] In terms of mobility, 4% of re-employed workers moved residence.[20] After comparing postal codes of residence and work location, we also find that commuting did not substantially increase: 63% of workers commuted for their previous job at Ford Genk and are commuting also for their new job.[21] Ford Genk was located in an urban environment. However, 44% of new found jobs are not in an urban area.[22] 98% of the re-employed workers were working full-time at Ford Genk, and the majority remains full-time employed in their new jobs. However, less than half of all new jobs have permanent, open-ended contracts. Both part-time work and short-term contracts could have contributed to the reported earnings losses. These changes in job attributes between the old and the new job are in line with research that has found large negative effects from job displacement for earnings and employment prospects of workers (Davis and Von Wachter, 2011; Farber, 2017; Foote et al., 2019; Jacobson et al., 1993).

To summarize our findings from Section 4, we have investigated how task competencies affect re-employment probabilities among workers who are younger than 52 years at the time of displacement. Our findings are in line with the routine-biased technical change (RBTC) hypothesis, as workers with more routine task competencies experience lower re-employment probabilities. We show that this result is robust to controlling for several worker characteristics. Finally, we provided further evidence in support of routine-biased technical change by showing that displaced workers who found a new job within 1,5 years after displacement moved into less routine task intensive jobs. However, are results also suggest that these new jobs are characterized by lower earnings and a higher share of temporary contracts.

5. The importance of digital skills

As proposed in the framework of Autor et al. (2003), our analysis builds on the idea that digital technologies are most able to substitute for workers in performing routine tasks. To further strengthen this link, we provide additional evidence on the importance of worker skills directly related to digital technologies and the increased investment in digital technologies by firms. Moreover, we show that digital skills are positively associated with more nonroutine task competencies.

We define digital skills as a composite measure calculated as the simple average of computer skills for blue-collar workers, including working with Microsoft Office and surfing the internet on a scale from 1 (not good at) to 3 (very good at). For white-collar workers, the measure is calculated as the average of computer and programming skills on a

Table 10
Job finding probabilities, digital skills and tasks .

	(1)	(2)	(3)	(4)
	Re-empl.	Re-empl.	RTI index	RTI index
Digital skills	0.090**	0.094**	-0.289***	-0.211***
	(0.036)	(0.038)	(0.067)	(0.071)
Blue-collar workers	-0.372***	-0.203*	0.869***	0.490*
	(0.078)	(0.121)	(0.198)	(0.284)
High school diploma		0.031		-0.467**
		(0.110)		(0.200)
College degree		0.178		-0.768**
		(0.139)		(0.298)
Age at displacement		-0.193		0.068
		(0.182)		(0.444)
Age at displacement^2		0.002		-0.001
		(0.002)		(0.005)
Female workers		0.260***		0.385*
		(0.089)		(0.206)
Native language: Dutch		0.269**		-0.462*
		(0.127)		(0.261)
Constant	0.901***	4.661	-0.693***	-1.324
	(0.067)	(3.879)	(0.185)	(10.008)
Observations	191	177	178	166

Notes: (Robust) standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance, respectively. The sample is restricted to the workers who are younger than 52 years of age at the time of displacement. Column 1 and 2 use the re-employment indicator as dependent variable. Column 3 and 4 use the standardized RTI index as dependent variable in order to show the relationship between the digital skills measure and our task-competency measure. Digital skills is a composite measure calculated as the simple average of computer skills (working with Microsoft Office, surfing the internet) on a scale from 1 (not good at) to 3 (very good at) for blue-collar workers. For white-collar workers, the digital skills measure is calculated as a simple average of computer and programming skills on a scale from 1 (not good at or less than average) to 3 (better than average or good at). This includes working with Windows or Office, computer programming and automation technology, e.g. PLC, veldbus, HMI. This simple average is standardized to have mean zero and standard deviation one among blue- and white-collar workers separately.

[19] This is based on a question that asked whether the respondent earned more or less, all monetary benefits considered. The lack of wage data for white-collar workers does not allow us to quantify this further.

[20] Of displaced workers under age 52 who did not find employment, a similar share of 6% moved residence.

[21] Commuting is defined as: A worker commutes to work whenever the worker does not live and work in the same place, i.e. the postal code of the worker's residence does not match the postal code of the worker's employer. This definition does not take into account whether the distance between the worker's residence and employer changes. Thus, it could be that the intensity of commuting has changed.

[22] Postal codes of employers were used to determine whether individuals worked in urban areas (in their previous and new job). Urban is defined as a postal code describing a city with at least 40 000 inhabitants. The information on the number of inhabitants of cities and the corresponding postal codes were retrieved from https://www.vlaanderen.be/gemeenten-en-provincies/provincie-limburg.

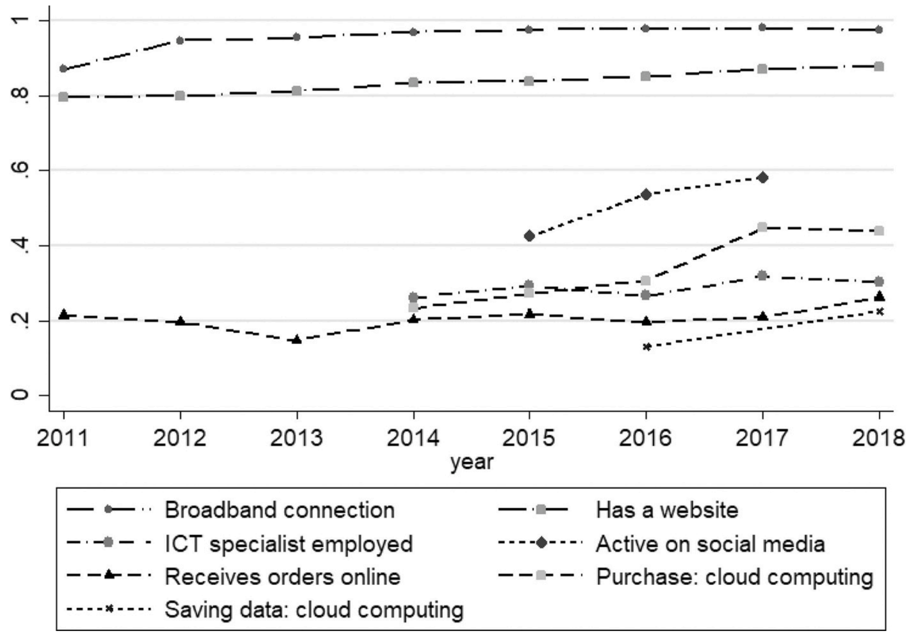

Fig. 4. Computer equipment of firms with more than 10 employees in Flanders, 2011–2018 Source: Statbel, Belgian statistical office.https://bestat.statbel.fgov.be/bestat/crosstable.xhtml?view=2bd302a0-aa37-4c26-afda-1a88f3387d1e. Notes: Annual data on firms' computer equipment collected by the Belgian statistical office.

scale from 1 to 3. This includes working with Windows or Office, computer programming and automation technology. To make coefficients comparable to our RTI index, we standardize this simple average. The difference between blue- and white-collar workers in the digital skills measure is accounted for by standardizing within each group separately.

We investigate the relationship between the skills necessary for working with digital technologies and job finding probabilities, as well as their relationship to task competencies in Table 10. Column (1) and (2) show the impact of digital skills on the re-employment probability of displaced workers. The main finding is that workers with more digital skills have higher re-employment probabilities. This positive correlation is statistically significant at the 5% significance level, also when controlling for additional worker characteristics. Note that due to the separate standardization, the dummy for blue-collar worker will now also absorb mean differences in digital skills along with any other residual variation between these two groups. Different to our specification in Table 4, Table 10 shows that blue-collar workers continue to have significantly lower re-employment probabilities compared to white-collar workers. This is likely to be driven in part by the higher complexity of skills measured for white-collar workers. Nevertheless, also blue-collar workers have higher job finding probabilities when they have more digital skills.

Because digital skills allow workers to do certain nonroutine tasks, we expect workers with more digital skills to have more nonroutine task competencies. Therefore, column (3) and (4) of Table 10 show the relationship between the measures for digital skills and routine task competencies. The results show that workers with more digital skills score lower on the RTI index. A one standard deviation increase in the level of digital skills is related to a 0.29 standard deviation decrease in the RTI index, ceteris paribus. Our estimate is statistically significant at the 1% significance level and is robust to controlling for other worker characteristics. This negative association is supportive of the complementarity between nonroutine competencies and interaction with digital technologies.

Finally, ongoing digitalisation should also be visible through the investments made by local firms in the area. Therefore, we provide circumstantial evidence of the increased usage of digital technologies for Flanders, Belgium, around the time of the closure. Fig. 4 shows the amount of firms with various computer equipment in Flanders between 2011 and 2018. Almost 100% of firms use computers, have access to the internet via a broadband connection and more than 80% of firms have a website. Between 2011 and 2018, we can see an increasing trend in the amount of firms making use of various computer technologies, e.g. having a website, purchasing and using cloud computing services or being active on social media.[23] From 2014 to 2018, there was a small increase in the amount of firms hiring ICT specialists from 25% to about 30%. In contrast, e-commerce of firms as measured by receiving orders online, remained relatively stable over the time period. Nevertheless, this suggests that there are increasingly more firms that make use of various digital technologies in Flanders, Belgium. Accordingly, these firms are likely to increase their relative demand for workers with nonroutine task competencies as they start applying more digital technologies.

In sum, this section argues that ongoing digitalisation has taken place in the context of our case study. We measure this by showing the importance of digital skills. In line with the RBTC hypothesis, we argue that this has been the underlying force that drives relative demand towards nonroutine task competencies.

6. The welfare cost of skill-blind policies

The previous sections showed that, due to digitalisation, job finding probabilities differ for displaced workers with different task competencies. This evidence also suggests that there could be substantial employment losses from policies that ignore job seekers' task competencies. In particular, this section quantifies the lost employment from an early retirement scheme that resulted from negotiations between the Ford Motor Company, unions and the government after the announcement to shut down Ford Genk.

This early retirement scheme gave all displaced workers that were 52 years or older on the day of the plant's closure the option to early retire, which most of them did. In this section, we quantify how many of these

[23] Being active on social media is measured by having a user profile, account or license on social media.

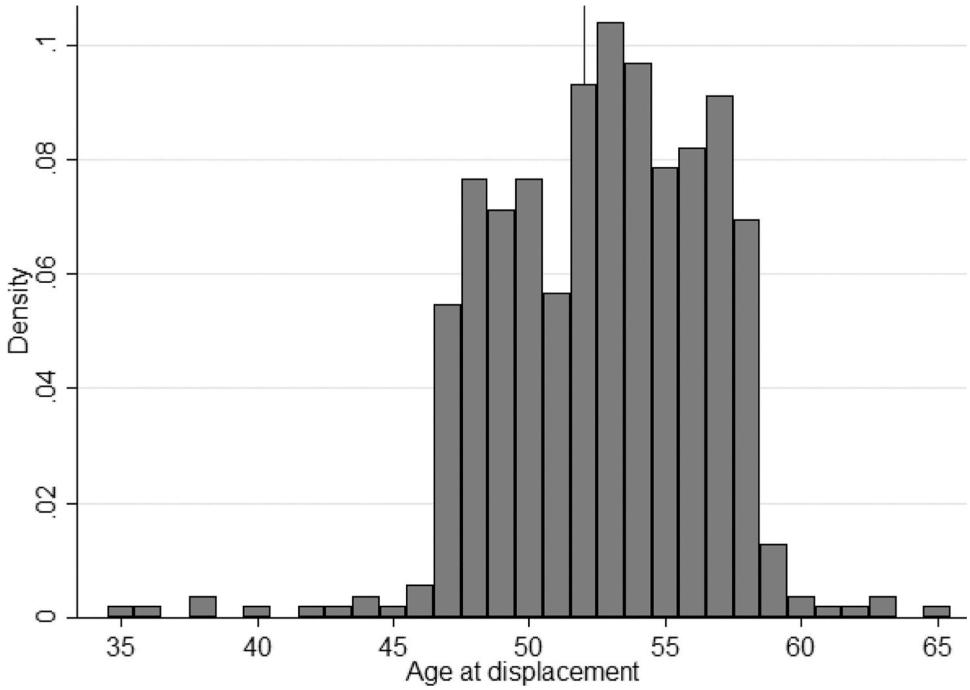

Fig. 5. Histogram of age at displacement.

early retirees would have been employed if not given the option to early retire. Importantly, we show that lost employment is particularly high for early retirees with nonroutine task competencies.

6.1. An early retirement policy as a regression discontinuity

Estimating the impact of early retirement on re-employment probabilities by means of OLS is likely confounded by the direct negative impact of age on re-employment that we illustrated in the previous section. Therefore, simply comparing job finding rates of older individuals that are eligible for early retirement to those of younger workers that are not, would overstate the impact of the early retirement policy on re-employment probabilities. Consequently, also the lost employment from the early retirement policy would be overestimated.

To address this issue, we use a Regression Discontinuity Design (RDD) that exploits the sharp age-based cut-off in eligibility for early retirement (52 years old on the day of the plant's closure) and that allows us to identify the intent-to-treat effect of the early retirement policy on job finding rates. The benefit of using an RDD is that it controls for the overall relationship between age and re-employment: The RDD estimator uses random variation created by the policy's ad hoc age-52 threshold by comparing younger and older individuals that are relatively close to this threshold. Note that, therefore, the RDD estimator identifies a Local Average Treatment Effect ('LATE'): It identifies the average impact of eligibility on job finding rates only around the age-52 threshold, such that our results cannot easily be extrapolated to other early retirement policies choosing different parameters such as a different age threshold.

The key identifying assumption for the RDD to be valid is that individuals cannot manipulate eligibility for early retirement. In particular, it requires that displaced workers (or government officials) cannot manipulate officially known ages. One way to test this assumption is to plot the density of age on the day of the plant's closure across all displaced workers (i.e. both younger as well as older than 52 years) in our sample. If there is bunching at age 52 or above, this could suggest that the officially known age of some displaced workers was wrongfully increased to 52 or above to make them eligible for early retirement.

Although it seems highly unlikely that manipulation could have happened in practice, Fig. 5 shows that there is some bunching at age 52 and above. A likely reason for this is the selection of displaced workers into our sample: displaced workers eligible for early retirement had a stronger incentive to remain at the plant until its closure. Importantly, this does not invalidate our RDD design. If anything, displaced workers younger than 52 years who stayed at Ford Genk until the time of our survey are likely to have relatively lower job finding rates compared to workers that left before our survey took place. If so, this would imply that our RDD estimates of lost employment due to a purely age-based early retirement policy are too low.

Although eligibility for early retirement is only an intention-to-treat effect, Fig. 6 shows that almost everyone eligible chose the option to early retire: 80% of workers aged 52 enters early retirement. This increases to more than 90% for workers aged 53 to 57. The fraction declines for workers older than 57, but the 95% confidence interval widens because of fewer observations.[24]

Fig. 7 shows the mean re-employment probability per one-year age bin of displaced workers 1,5 years after the plant closure and a 95% confidence interval. We can see a significant drop in the average re-employment probability from just below 60 percent for displaced workers who are 51 years old to less than 20 percent for displaced workers who are 52 years old at the time of displacement. For workers older than 53 the re-employment rate is very close to zero.

The regression equivalent of Fig. 7 makes use of the following RDD specification:

[24] Somewhat counter-intuitively, workers aged 58 and older are less likely to enter early retirement. In fact, some workers above 57 years of age report to be unemployed or inactive. Given the generous early retirement scheme, this seems unlikely, and may represent mismeasurement. Either way, this does not affect our regression discontinuity estimates because the local estimator mostly depends on the behaviour of individual observations close to the age-52 threshold. When excluding workers who are older than 57 years, the point estimates do not change qualitatively. Below age 52, there are 3 individuals who state to be in early retirement explaining the non-zero fraction in the figure at age 50 and 51. Given the clear policy rules against this, we consider this to be measurement error. The results do not qualitatively change when excluding these 3 observations from the estimation.

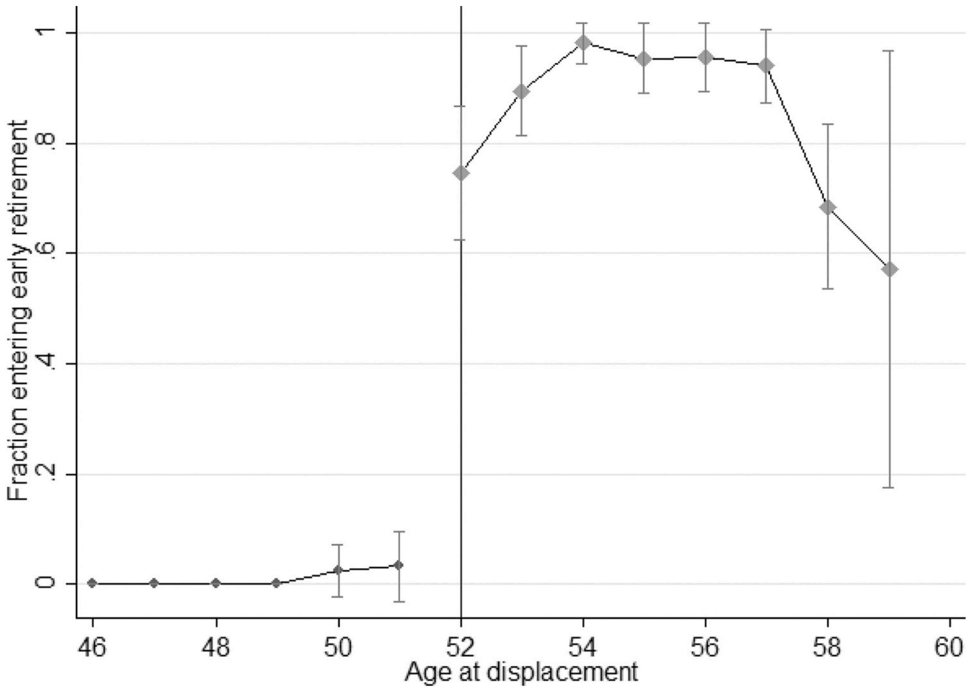

Fig. 6. Fraction of early retirement take-up by year of age Notes: The fraction of workers who took up early retirement is calculated using an early retirement dummy variable. This variable equals 1 whenever somebody takes up early retirement and 0 otherwise. The fraction of workers who take-up early retirement is calculated as the average of the early retirement dummy per year of age. There are two outliers at age 50 and age 51. These are two workers who worked at Ford Genk and who reported to be in early retirement. Below age 47 and above age 58, there are very few observations.

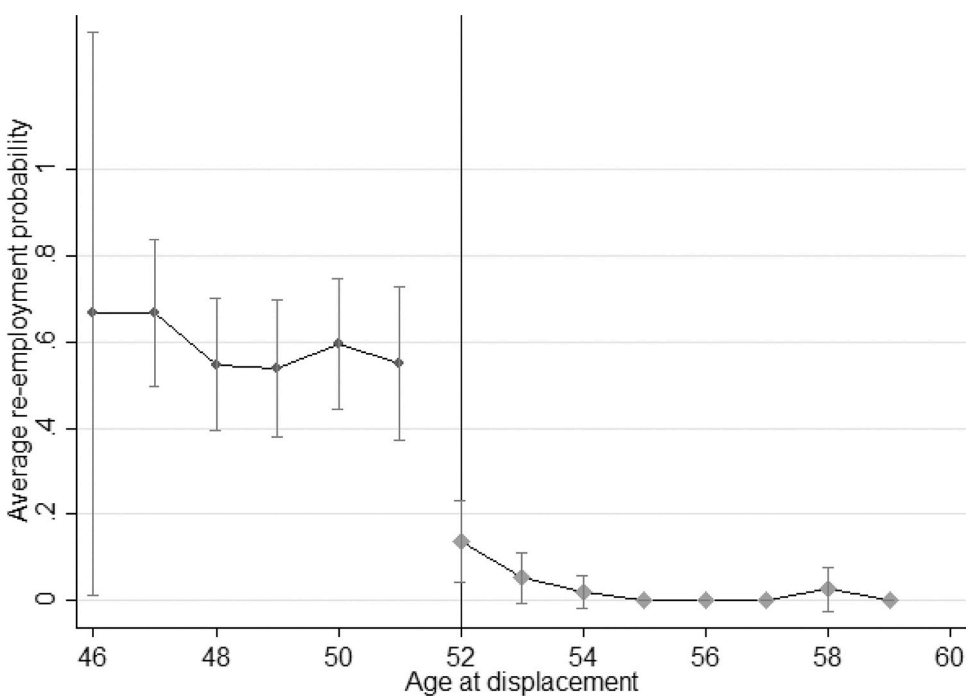

Fig. 7. Mean re-employment probabilitiy by year of age Notes: The mean re-employment probability is calculated by taking the average of the re-employment dummy variable per year of age. The re-employment dummy is a variable that equals 1 whenever somebody is re-employed 1,5 years after displacement and 0 otherwise. 95% confidence intervals are estimated for the re-employment averages per year of age and are shown as the vertical bars per re-employment average. Below age 47 and above age 58, there are very few observations.

$$P(Employed_i) = \beta_0 + \beta_1 Age52_i + \beta_2 Age_i + \beta_3 Age52_i \times Age_i + \epsilon_i \quad (3)$$

where $Age52_i$ is a dummy that is 1 if a worker is at least 52 years old on the day of the plant's closure, Age_i is a workers' age, and $Age52_i \times Age_i$ is the interaction of both variables. This interaction term controls for breaks at age 52 in an otherwise smooth linear relationship between age and re-employment. Our coefficient of interest is β_1, capturing the discontinuous effect at age 52 also illustrated in Fig. 7. Note that including other control variables is not necessary given that they do not correlate with the age threshold for eligibility after conditioning on age.

Column (1) of Table 11 presents the RDD estimates of coefficients in equation (3). At the discontinuity, workers who are 52 years old have a 44 percentage points lower re-employment probability than workers who are younger. Said differently, the counterfactual re-employment probability of the average 52-year old early retiree would have been 44 percentage points higher if the option to early retire would not exist. Or, almost half of the youngest early retirees would have been employed 1,5 years after the plant's closure in the absence of the early retirement

Table 11
The probability of finding a job and the option to enter early retirement at age 52 as a regression discontinuity design.

	(1)	(2)	(3)
Age52	-0.441***	-0.485***	-0.493***
	(0.0605)	(0.0599)	(0.107)
Age	-0.0259**	-0.0179*	-0.00992
	(0.0101)	(0.00979)	(0.0103)
Age52 x Age	0.0200	0.0115	0.00329
	(0.0129)	(0.0130)	(0.0131)
RTI index		-0.121***	-0.0777*
		(0.0362)	(0.0407)
Age52 x RTI index		0.111***	0.0729*
		(0.0377)	(0.0422)
High school diploma			0.0283
			(0.111)
College degree			0.280**
			(0.126)
Age52 x High school diploma			0.0182
			(0.112)
Age52 x College degree			-0.131
			(0.150)
Constant	0.499***	0.548***	0.516***
	(0.0536)	(0.0520)	(0.104)
Observations	548	498	477

Notes: Robust standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. Age52 is a dummy variable that equals 1 whenever a worker is at least 52 years old. The age variable is centered around the age cutoff, age 52. The RTI index is created using composite measures of abstract, routine and manual tasks. Each of these composite task measures are simple averages across the separate task variables measured on a scale from 1 to 5. The RTI index is normalized to have mean 0 and standard deviation 1.

Table A.1
Occupational groups of jobs at Ford Genk, panel sample.

occupation group	Blue-collar workers			N
	White-collar worker Mean RTI std	Blue-collar worker Mean RTI std	Total Mean RTI std	
manager	-0.485		-0.485	7
engineer	-0.972		-0.972	4
technician	-0.698	-0.634	-0.645	89
administrator	-0.077	-0.536	-0.261	10
forklift driver/ logistic		-0.093	-0.093	36
floor supervisor		-0.788	-0.788	23
quality control		-0.279	-0.279	38
machine operator		0.536	0.536	251
other	-1.212	-0.288	-0.311	89
Total	-0.607	0.044	-0.001	547
N	34	513	547	

Notes: The RTI index is created using composite measures of abstract, routine and manual tasks performed in the job at Ford Genk. Each of these composite task measures are simple averages across the separate task variables. The RTI index is normalized to have mean 0 and standard deviation 1.

programme.[25]

6.2. Lost employment from an early retirement policy

To further assess the cost in terms of foregone employment of the early retirement policy because it did not account for heterogeneity in individuals' task competencies, we augment our empirical specification as follows:

Table A.2
Absolute difference in RTI index between old and new job and worker characteristics.

	(1)
Blue-collar workers	-0.232
	(0.284)
High school diploma	0.203
	(0.257)
College degree	0.648*
	(0.328)
Age at displacement	0.392
	(0.471)
Age at displacement^2	-0.005
	(0.005)
Female workers	-0.583***
	(0.215)
Native language: Dutch	0.418
	(0.349)
Constant	-8.613
	(10.500)
Observations	113

Notes: Standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. The sample is restricted to the workers who are younger than 52 years of age at the time of displacement and who are re-employed 1,5 years after the plant closure. The dependent variable is the absolute difference between the RTI index created for all workers who participated in both survey waves and the RTI index created for the subsample of re-employed workers. The RTI index is created using composite measures of abstract, routine and manual tasks.

$$\begin{aligned} P(Employed_i) &= \beta_0 + \beta_1 Age52_i + \beta_2 Age_i + \beta_3 Age52_i \times Age_i \\ &+ \beta_4 RTI_i + \beta_5 Age52_i \times RTI_i \\ &+ \beta_6 Educ_i + \beta_7 Age52_i \times Educ_i + \epsilon_i \end{aligned} \tag{4}$$

where $Age52_i$, Age_i, and $Age52_i \times Age_i$ are defined as before, RTI_i is the routine task intensity index, and $Age52_i \times RTI_i$ captures the interaction between the treatment dummy and the routine task intensity index. $Educ_i$ is again a vector of dummies for i's highest obtained education level, also interacted with the $Age52_i$ treatment dummy. The coefficient of interest is β_5, which allows for the size of discontinuity documented in Fig. 7 to vary by the RTI index.

Column (2) of Table 11 shows that early retirees with one standard deviation higher nonroutine task competencies have counterfactual re-employment probabilities that are an additional 11 percentage points higher than the average increase of 48.5 percentage points if 52-year-olds would no longer be eligible for early retirement. What this shows is that a crude age-based early retirement policy that ignores workers' task competencies results in significant foregone employment of older workers with nonroutine task competencies that could still be productive in the digital economy.

As a robustness check, Column (3) of Table 11 further includes $Educ_i$ as well as its interaction with the treatment dummy $Age52_i \times Educ_i$. Consistent with results in Table 4, higher educational attainment increases a workers' job finding rate. Moreover, the counterfactual re-employment probability of a 52-year old early retiree with a college degree is an additional 13 percentage points higher than the average increase for all 52-year-olds if they would no longer be eligible for early retirement. Importantly, the coefficient on the interaction term $Age52_i \times RTI_i$ remains a positive 8 percentage points: The employment costs of ignoring valuable nonroutine task competencies among early retirees would only be partially mediated by accounting for differences in their levels of schooling.

Crude age-based early retirement policies successfully protect older job seekers with routine task competencies and low job finding rates. However, they also discourage older job seekers with nonroutine task

[25] Including a 2nd or 3rd order polynomial of age does change our results, see Table A.3 in the Appendix. Similarly, our results are unaffected by increasing the bandwidth of the RDD estimator to 3, 4, 5, 6 or 7 years. These results can be found in Tables A.4 and A.5 in the Appendix.

Table A.3
The probability of finding a job and the option to enter early retirement at age 52 as a regression discontinuity design, including polynomials of age.

	(1)	(2)	(3)	(4)	(5)
	empl	empl	empl	empl	empl
Age52	-0.460***	-0.441***	-0.427***	-0.449***	-0.408*
	(0.0596)	(0.0605)	(0.102)	(0.139)	(0.217)
Age	-0.0137**	-0.0259**	-0.00219	0.0144	-0.00584
	(0.00671)	(0.0101)	(0.0360)	(0.0791)	(0.189)
Age52 x Age		0.0200	-0.0609	-0.0747	-0.129
		(0.0129)	(0.0400)	(0.0863)	(0.196)
Age^2			0.00175	0.00498	-0.000985
			(0.00201)	(0.0131)	(0.0494)
Age52 x Age^2			0.00583*	0.00184	0.0451
			(0.00310)	(0.0155)	(0.0533)
Age^3				0.000146	-0.000454
				(0.000559)	(0.00440)
Age52 x Age^3				-0.0000975	-0.00538
				(0.000784)	(0.00533)
Age^4					-0.0000189
					(0.000125)
Age52 x Age^4					0.000292
					(0.000186)
Constant	0.541***	0.499***	0.550***	0.570***	0.552***
	(0.0435)	(0.0536)	(0.0962)	(0.133)	(0.212)
AIC	354.31	353.76	345.99	349.90	351.69
Observations	548	548	548	548	548

Notes: Robust standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. Age52 is a dummy variable that equals 1 whenever a worker is at least 52 years old. Age is the age at displacement, and Age^2, Age^3 and Age^4 represent the second, third and fourth order polynomial in age.

Table A.4
The probability of finding a job and the option to enter early retirement at age 52 as a regression discontinuity design, with different bandwidths.

	(1)	(2)	(3)	(4)	(5)	(6)
		BW: 3 years	BW: 4 years	BW: 5 years	BW: 6 years	BW: 7 years
Age52	-0.441***	-0.449***	-0.459***	-0.423***	-0.431***	-0.432***
	(0.0605)	(0.140)	(0.110)	(0.0949)	(0.0919)	(0.0898)
Age	-0.0259**	0.00720	0.00752	-0.0157	-0.0168	-0.0206
	(0.0101)	(0.0603)	(0.0370)	(0.0271)	(0.0260)	(0.0252)
Age52 x Age	0.0200	-0.0662	-0.0527	-0.0172	-0.00764	0.00323
	(0.0129)	(0.0656)	(0.0401)	(0.0290)	(0.0270)	(0.0260)
Constant	0.499***	0.577***	0.578***	0.529***	0.527***	0.517***
	(0.0536)	(0.133)	(0.104)	(0.0895)	(0.0876)	(0.0859)
Observations	548	273	358	433	486	525

Notes: Robust standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. Column 1 shows the original regression output, while columns 2 to 6 show the regression results using different bandwidths. These bandwidths range from 3 to 7 years on each side of the age threshold, age 52.

Table A.5
The probability of finding a job and the option to enter early retirement at age 52 as a regression discontinuity design, with different bandwidths and the RTI index.

	(1)	(2)	(3)	(4)	(5)	(6)
		BW: 3 years	BW: 4 years	BW: 5 years	BW: 6 years	BW: 7 years
Age52	-0.485***	-0.527***	-0.518***	-0.454***	-0.467***	-0.469***
	(0.0599)	(0.132)	(0.108)	(0.0934)	(0.0892)	(0.0869)
Age	-0.0179*	0.0343	0.0248	-0.0115	-0.0109	-0.0146
	(0.00979)	(0.0573)	(0.0374)	(0.0269)	(0.0252)	(0.0243)
Age52 x Age	0.0115	-0.0975	-0.0737*	-0.0241	-0.0157	-0.00424
	(0.0130)	(0.0637)	(0.0410)	(0.0291)	(0.0264)	(0.0252)
RTI index	-0.121***	-0.163***	-0.123***	-0.112***	-0.119***	-0.120***
	(0.0362)	(0.0475)	(0.0415)	(0.0381)	(0.0369)	(0.0368)
Age52 x RTI index	0.111***	0.152***	0.115**	0.106***	0.116***	0.114***
	(0.0377)	(0.0532)	(0.0448)	(0.0406)	(0.0386)	(0.0382)
Constant	0.548***	0.665***	0.646***	0.569***	0.571***	0.561***
	(0.0520)	(0.125)	(0.101)	(0.0870)	(0.0839)	(0.0823)
Observations	498	252	327	397	443	477

*Notes:*Robust standard errors in parentheses. *, ** and *** stand for 10, 5 and 1% statistical significance respectively. Column 1 shows the original regression output, while columns 2 to 6 show the regression results using different bandwidths. These bandwidths range from 3 to 7 years on each side of the age threshold, age 52. The RTI index is created using composite measures of abstract, routine and manual tasks. Each of these composite task measures are simple averages across the separate task variables measured on a scale from 1 to 5. The RTI index is normalized to have mean 0 and standard deviation 1.

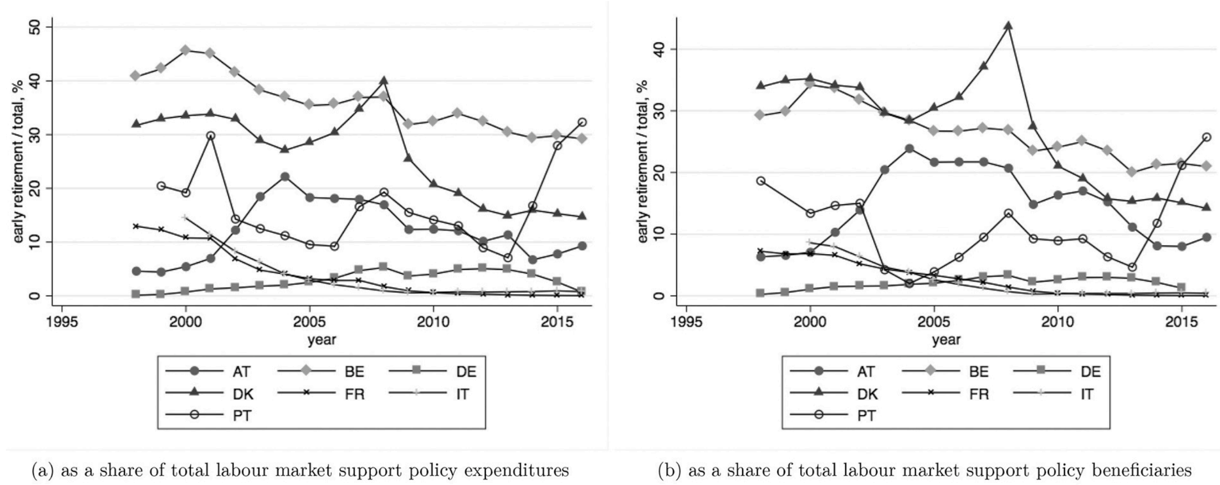

Fig. 8. Expenditures and beneficieries of early retirement policies, by country and year. (a)as a share of total labour market support policy expenditures (b)as a share of total labour market support policy beneficiaries *Source:* European Commission Employment, Social Affairs & Inclusion. https://webgate.ec.europa.eu/empl/redisstat/databrowser *Notes:* Total out-of-work income support is the combination of (i) early retirement and (ii) out-of-work income maintenance and support (mostly unemployment benefits). Public expenditures are measured on an annual basis. Beneficiaries of LMP supports are presented here as annual average stock, i.e. the data refer to the average number of persons benefiting from the LMP supports at any point during the year.

competencies and higher job finding rates to participate in the labour market, leading to foregone employment. Notwithstanding, age, as an objective eligibility threshold, may be considered the most fair criterion to determine early retirement eligibility. Fig. 8 illustrates the prevalence of early retirement policies in several EU countries, suggesting that the lost employment from such policies could be substantial for the economy as a whole. The figure shows shares of national expenditures, panel (a), and number of beneficiaries, panel (b), for early retirement schemes relative to all out-of-work welfare policies in a number of European countries. While Belgium is one of the most avid users of early retirement policies, Austria, Denmark and Portugal also spend a significant share: between 10 and 30% of their out-of-work welfare budget was spent on early retirement schemes in 2016. This budget is spent on 10 to 20% of all out-of-work welfare beneficiaries. Our findings highlight the lost employment due to an age-based early retirement policy.

7. Conclusions

On 24 October 2012 Ford announced that it would be closing its Genk plant on 31 December 2014. Consequently, around 4300 workers employed directly by Ford Genk and about the same amount of workers employed by Ford's local suppliers lost their jobs. For this paper, we collected unique survey data of these displaced workers before and 1,5 year after the plant's closure. This plant closure serves as an exogenous displacement shock for workers, which we use to investigate the adjustment process for individual workers with different task competencies. In addition, we measure a large variety of unique worker-level data, including individual-level task competencies. Based on these data, we made two contributions.

First, we find that re-employment probabilities 1,5 years after a mass lay-off differ considerably depending on displaced workers' task competencies: We find that individuals who were performing more routine tasks before displacement had a lower probability of finding a new job after displacement. These micro-effects are in line with the well-known hypothesis of routine-biased technical change (RBTC), arguing that digitalisation is increasing the relative demand for nonroutine labour task at the expense of routine-task labour tasks in the aggregate economy. We also showed that digital skills are particularly valuable to find new work. Further micro-level evidence in support of the RBTC hypothesis showed that re-employed workers moved into new jobs that are more nonroutine task intensive, are mostly full-time, pay lower wages and are less permanent.

Second, we used a Regression Discontinuity Design (RDD) that exploits the eligibility of displaced workers for an age-based early retirement scheme that was negotiated as part of the plant's closure. Our RDD estimates suggest that a crude age-based early retirement policy that ignores workers' task competencies results in significant foregone employment of older workers with nonroutine task competencies that could still be productive in the digital economy. Although it may also be difficult to target labour market policies to specific groups of workers, especially given fairness considerations, the employment costs of one dimensional policies such as early retirement schemes should be taken into account when making this trade-off.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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