The Impact of Automation on the Unemployed *

Maarten Goos   Emilie Rademakers   Anna Salomons   Bert Willekens †

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Abstract

This paper examines the distributional consequences of routine-task biased technological change across unemployed job seekers with different task competencies. Using representative data on unemployed job seekers and vacancies from an online job platform, we predict a job seeker's expected unemployment duration from the tightness (i.e. the ratio of vacancies over unemployed job seekers) in detailed jobs for which she fully or partially qualifies based on her task competencies. The first main contribution is to show that the labor market is, at least in part, organized along jobs and their task content, in that tightness in jobs for which an unemployed job seeker fully qualifies in terms of her task competencies is predictive of her unemployment duration. We also find that overlap across jobs in terms of task content matters – i.e. unemployed job seekers also compete for jobs for which they only partially qualify based on their task competencies. However, the importance of this task overlap is limited: unemployed job seekers can only compete in markets where they possess at least 80% of the required task competencies. This implies that adverse task-biased shocks are likely to have pronounced distributional consequences on unemployment durations of job seekers with different task competencies. The second main contribution of this paper therefore is to quantify the distributional impact on unemployed job seekers of ongoing routine-biased technological change. In particular, our results show that unemployment durations for job seekers with mainly routine-task competencies are four times longer compared to a single market scenario where unemployed job seekers can compete for jobs irrespective of their task competencies. This paper therefore reveals that ongoing technological progress imposes substantial labor adjustment costs that are highly unevenly distributed across unemployed job seekers with different task competencies.

Keywords: Jobs, task competencies, job search, unemployment duration, routine-biased technological change, distributional effects

JEL: J24, J62, J64, O33

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†Goos and Salomons: Utrecht University School of Economics, P.O. Box 80125, 3508 TC Utrecht, the Netherlands. Rademakers: University of Leuven, Department of Economics, Naamsestraat 69, 3000 Leuven, Belgium and PhD Fellow of Flemish Research Foundation. Willekens: University of Leuven, Department of Economics, Naamsestraat 69, 3000 Leuven, Belgium.

1 Introduction

A long and growing literature has shown that labor markets are undergoing structural change due to ongoing technological progress: as codifiable or “routine" tasks are automated by digital technologies, the demand for labor in jobs which intensively perform routine tasks is reduced relative to other tasks (see Acemoglu and Autor (2011) for an overview). Consequently, workers in routine-task intensive jobs will reallocate towards jobs that are less routine-task intensive, leading to structural change in the composition of jobs and their relative wages. For example, Goos et al. (2014) argue that ongoing technological progress is an important driver for economy-wide job polarization, i.e. the empirical phenomenon that employment in labor markets is polarizing into non-routine low-paid and high-paid jobs at the expense of routine, middling jobs.

In practice, this reallocation of workers towards new jobs can be costly for those workers if they cannot easily switch to other jobs for which they are less specialized in terms of their task competencies: In the scenario where markets for different jobs overlap in terms of task contents, the impact of an adverse routine-biased task shock would tend to diffuse, lessening its impact on any one group of workers. But if job markets are mostly insular, an adverse routine-biased task shock is mainly felt locally by workers with routine-task competencies, leading to those workers carrying most of the burden of adjustment costs due to ongoing technological progress.

However, relatively little empirical evidence exists about the distributional consequences of routine-biased technological change for labor market outcomes, including for the duration of unemployment spells for unemployed job seekers with different task competencies.[1] This paper therefore (i) examines whether the labor market is organized along jobs, defined as detailed occupation-experience cells and their corresponding tasks, and estimates the importance of overlap across jobs based on common task content; and (ii) uses these estimates to assess the distributional consequences of routine-biased technological change for unemployment durations across unemployed job seekers with different task competencies. Regarding (i), we find that the labor market is, at least in part, organized along jobs for which an unemployed job seeker fully qualifies in terms of her task competencies. We also find that there is overlap across jobs in terms of their task content – i.e. unemployed job seekers also compete for jobs for which they

[1] Unemployment spells are a particularly important margin to consider given their long-term scarring effects on the careers of workers as well as their adverse health consequences (Jacobson et al. 1993; Sullivan and von Wachter 2009; Davis and von Wachter 2011).

only partially qualify in terms of their task competencies. But the extent of this task overlap is quite limited: unemployed job seekers can only compete for jobs for which they have the large majority of all required task competencies. Regarding (ii), limited importance of task overlap across jobs implies that routine-biased technological progress can have pronounced distributional consequences for unemployment durations across unemployed job seekers with different task competencies. In particular, unemployed job seekers with mainly routine-task competencies will be disproportionately hurt by ongoing technological progress.

Our empirical approach is to estimate a well-established empirical model capturing job search externalities (see Petrongolo and Pissarides (2001) for an overview), making use of the positive relationship between the re-employment probability of an unemployed job seeker and her labor market tightness, defined as the number of vacancies divided by the number of unemployed job seekers across all relevant jobs. In particular, we relate a job seeker's expected unemployment duration to the average tightness she faces across jobs for which she fully or partially qualifies in terms of her task competencies. By including in the definition of an unemployed job seeker's relevant labor market also those jobs for which she only partially qualifies, we account for the importance of task overlap across jobs in labor markets.

To model this task overlap, we build on Manning and Petrongolo (2017) who estimate the extent of spatial overlap in job search. Their analysis defines markets as disaggregated geographical units but allows local labor markets to overlap, i.e. for tightness in geographically close-by markets to influence the re-employment probability of a job seeker in a given locality.[2] Their estimates show evidence of high costs of distance, but they also find that policies targeted at a specific local labor market have limited impact because important ripple effects diffuse their impacts through surrounding areas. Our analysis adapts their approach by defining distance as task dissimilarities between jobs.

A first main contribution of this paper is that it provides direct evidence in support of the idea that labor markets are, at least in part, organized along detailed jobs and their corresponding tasks. To show this, we use representative data on unemployed job seekers and vacancies from an online job search platform in Belgium. The data contains detailed information on unemployed job seekers' task competencies as well as vacancies' task requirements across jobs, where a job is defined as an occupation-experience cell taken from the highly disaggregate ROME-V3

[2]In particular, Manning and Petrongolo (2017) use unemployment and vacancy data on 8850 Census wards in England and Wales, and combine these with micro data on wages and the use of transport modes to model commuting costs as the distance between any two wards.

classification of jobs and their related task descriptions. We observe over 2,000 jobs and 3,000 tasks, with each job consisting of 7 tasks on average. For each of the 139,944 unemployed job seekers we observe on the online platform in 8 repeated cross-sections during 2013-2014, we merge individual-level administrative data from different sources on their employment histories between 2010-2015 and a number of person characteristics. Based on these data, the importance of jobs and their task content is shown by the predictive power of their tightness over re-employment probabilities of unemployed job seekers. Moreover, we show the existence of spillovers in search externalities between jobs that have more than 80% of their tasks in common. However, we also find substantial rigidities for unemployed job seekers to compete for jobs for which they do not have the large majority of required task competencies. These rigidities have important consequences for the distributional impacts of task-biased shocks.

Therefore, the second main contribution of this paper is to analyze the distributional effects of an adverse routine-biased task shock in labor demand on job seekers' unemployment durations. The assumed adverse routine-biased task shock is a reduction in the number of job vacancies that are routine-task intensive to capture ongoing technological change. The size of the shock corresponds to the actually observed decline of the routine employment share documented in Goos et al. (2014). In a benchmark scenario of a single labor market where task competencies don't matter and each unemployed job seeker can compete for each vacancy, expected unemployment duration would increase the same for all job seekers in response to the shock. We then compare this increase to the distribution of changes in unemployment durations under the actually estimated importance of task overlap across jobs, finding substantial differences between unemployed job seekers with different task competencies. Indeed, unemployed job seekers with non-routine task competencies are largely insulated from routine-biased technological change, whereas unemployed job seekers with mainly routine-task competencies experience a disproportionately large increase in their unemployment durations compared to the single labor market scenario. In sum, unemployed job seekers with routine-task competencies are disproportionately hurt by ongoing technological progress, suggesting that active labor market policies should be focused on directing those disadvantaged job seekers towards jobs with higher tightness.

2 Related literature

Closely related to our paper is Cortes et al. (2016) who examine worker flows due to ongoing technological progress or other shocks that could explain economy-wide job polarization. In particular, they study transition rates of US workers between routine jobs, non-routine jobs, and unemployment or labor force non-participation. In their analyses, two-thirds of the long-run decline in routine employment between 1976 and 2012 is explained by two changes. The first is a rise in the job-separation rate from routine jobs into non-participation, especially before 2007. The second is a decrease in job finding rates for the unemployed and non-participants into routine jobs, especially after 2007.[3] This recent fall in job finding rates for unemployed job seekers in routine jobs is consistent with our findings, although the set-up in our paper deviates in several important ways from Cortes et al. (2016)). Perhaps the most important differences are that we use an alternative empirical strategy that exploits the heterogeneity across unemployed job seekers in terms of their task competencies, and that we explicitly assume an adverse routine-biased task shock in vacancies to quantify the distributional consequences of ongoing technological progress across heterogeneous unemployed job seekers.

Also closely related to our paper is Autor and Dorn (2013) who use US Census data between 1950 and 2005 to assess the importance of routine-biased technological change on relative employment and wages across occupations within local labor markets, and on migration patterns by skill-type between local labor markets. Consistent with our results, they find that routine-biased technological change has reduced employment in routine-task intensive jobs, especially in local labor markets where the share of workers doing routine tasks was high initially. However, Autor and Dorn (2013) do not explicitly examine the impact of ongoing technological progress on the transition from unemployment into employment, as we do in this paper. Autor et al. (2013) use the same US local labor markets as their level of analyses to show direct evidence that international trade can increase unemployment locally. In particular, they find that local labor markets that are exposed to China's rising competitiveness in product markets experience an increase in unemployment.[4] This is evidence that free trade not only produces winners (e.g.

[3]Cortes et al. (2016) also examine for which demographic groups these transition rates from unemployment and non-participation into routine jobs have fallen the most. They find that lower propensities to transition into routine manual jobs are particularly acute for males, the young, and low levels of education. Moreover, the fall in the propensity to transition from unemployment into routine cognitive jobs is particularly strong for whites, females, the prime-aged, and those with higher levels of education. Related evidence is presented in Cortes et al. (2017).

[4]Comparing the impact of task-biased technological change and increased import competition from China on employment in local labor markets, Autor et al. (2015) conclude that rising Chinese imports results in signifi-

consumers who can buy some products for less money) but also some clear losers. These findings have sparked a lively debate about the distributional consequences of international trade for workers.[5] We add to this debate by quantifying the adjustment costs for those unemployed job seekers with task competencies adversely affected by ongoing technological progress.

None of the studies that were mentioned so far in this section explicitly consider the possibility that there is task overlap across jobs in labor markets. There is, however, a small but growing literature that explicitly addresses the importance of task overlap across jobs. Most recently, Cortes and Gallipoli (2017) use monthly data of US workers to estimate their costs of occupational switching, where the distance between any two occupations depends on their task overlap. Starting from a model of occupational choice, they derive an empirical expression that relates worker flows to the task distance between occupations as well as to occupation-specific entry costs that are independent of task overlap. Consistent with our findings, Cortes and Gallipoli (2017) find that task distance between occupations is important in explaining worker flows between occupations. However, our paper differs from theirs in that our study doesn't look at job-to-job mobility but at transitions of unemployed job seekers into employment. Moreover, as is common in this literature, Cortes and Gallipoli (2017) analyse fewer than 40 occupations and 15 tasks, whereas we use a much more finely grained job classification based on detailed occupation-experience cells and related task descriptions for each of these cells. This is important since broad occupational categories may be very heterogeneous in terms of the experience and tasks they require, and using a finely grained occupation-experience and task classification is needed to avoid mismeasurement.

Other studies on the costs of job switching have relied exclusively on wage data, particularly on the wage changes experienced by workers when transiting into employment in a new firm, occupation or industry. Using this empirical approach, Gathmann and Schonberg (2010) and Poletaev and Robinson (2008) also find evidence for the importance of task overlap across job markets and of task-specific human capital for wages. More recently, Robinson (2018) distinguishes between wage changes after voluntary and involuntary job switches. Even though the task distance may be equal for two sets of occupations, the implication for task specific human capital and therefore wage changes may be different depending on the type of switch. Robinson (2018) finds that task dissimilarity leads to negative wage effects only when the switch

cant falls in employment, whereas local labor markets specialized in routine-task intensive activities experience occupational polarization but not a net decline in employment.

[5] See, for example, `https://www.technologyreview.com/s/602101/the-trade-offs-of-free-trade/`.

was involuntary. Consistent with our findings, these results suggest that the mobility of workers after job displacement based on task competencies is limited.

Finally, our empirical approach is based on a search-and-matching framework by relating job seekers' unemployment durations to their labor market tightness, defined as the ratio of vacancies to unemployed job seekers in occupation-experience cells for which unemployed job seekers fully or partially qualify in terms of their task competencies. The market dimension for most applications of search-and-matching frameworks has been geographic units or sectors. For example, Manning and Petrongolo (2017) allow for spatial overlap in job search to conclude that there are high costs of geographical distance, but also that there are important ripple effects of local labor market policies through surrounding areas. These findings are corroborated in a recent study by Marinescu and Rathelot (2016) who find that workers dislike applying to geographically distant jobs, but that this distaste for distance is fairly inconsequential for aggregate unemployment because job seekers tend to be close enough to vacancies on average. Moreover, there is a small but growing literature that uses a search-and-matching framework to analyse markets for jobs that are not necessarily geographically close or in the same sector. For example, using German administrative data Fahr and Sunde (2004) show that there is substantial heterogeneity in the job creation process at the disaggregated occupational level. Dengler et al. (2016) use similar data to estimate an occupation-specific matching efficiency, finding substantial heterogeneity linked to different levels of standardization and variation in job requirements. Stops (2014) looks at correlations between occupational markets on the basis of training requirements in the German labor market to improve estimates of occupational matching elasticities. But none of these studies considers task overlap across jobs, as we do here.

The remainder of this paper is organized as follows. We first describe our data in section 3. Next we outline our empirical approach and unemployment duration model estimates in section 4. Section 5 considers what these estimates imply for the distributional consequences of a routine-biased task shock. Finally, section 6 concludes.

3 Data

Our main data are of job seekers and vacancies taken from the Flemish public employment service (VDAB) in 2013-2014: we refer to this as the VDAB sample.[6] Auxiliary data come from social security records containing the employment history between 2010-2015 and personal characteristics of each job seeker observed in the VDAB sample. Subsection 3.1 first describes the institutional setting, 3.2 describes the VDAB sample, and 3.3 then discusses our auxiliary data sources.

3.1 Institutional setting: VDAB's online job platform

Our main data are taken from VDAB's online job platform, called "Mijn Loopbaan" (which translates to "My Career"), introduced by VDAB in 2012 to help match job seekers to vacancies. For job seekers, the platform serves as a portal to various services provided by the public employment service, including the creation of a task-competency profile.

Any individual can register as a job seeker on VDAB's online job platform free of charge. For job seekers claiming unemployment benefits, registration is compulsory and use of the platform is part of mandatory meetings with caseworkers. When registering, each job seeker must create an application profile listing at least one occupation and her level of experience in that occupation.[7] Job seekers list their occupation-specific experiences by indicating at least one occupation-experience cell in ROME-V3.[8] ROME-V3 was originally designed by the French public employment service as an inventory of jobs, defined as detailed occupation-experience cells and their task content, that can be consulted by job seekers and employers for orientation, similarly to the US O*NET. This results in 676 occupations and 3 experience levels in each of these occupations (less than two years; between 2 and 5 years; and more than 5 years of experience), or a potential 2,028 (676 occupations $\times$ 3 experience levels) occupation-experience cells, which we call jobs. Related to these 2,028 jobs are 3,489 tasks, with each job containing 7 tasks on average. The task measures related to the occupation-specific experiences listed by job seekers allow us to construct job seekers' task-competency profiles.

[6] 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 some 11.3 million for the entire country.

[7] As part of the application profile, job seekers must also indicate whether they are looking for full-time or part-time employment or are open to both. This information will also be used in the analyses below.

[8] ROME-V3 stands for Répertoire Opérationnel des Métiers et des Emplois, 3rd version. ROME-V3 can be mapped into the more standard ISCO88 occupation classification. For more details about ISCO88, see `http://www.ilo.org/public/english/bureau/stat/isco/isco88/major.htm`.

Job vacancies come from two broad sources. Firstly, private and public employers can directly post vacancies on VDAB's online job platform free of charge. This channel accounts for around 55% of all vacancies. Employers that directly post a vacancy on the platform must register online and submit a form with details about location, occupation, and required experience based on ROME-V3. Secondly, VDAB exchanges vacancy information with several private and public labor market intermediaries (e.g. Randstad, Manpower, regional public employment services) making up for the remaining 45% of vacancies. Each of these exchanged vacancies is registered as requiring a certain occupation and experience level that is matched by VDAB to the ROME-V3 classification of jobs.

3.2 VDAB sample

Our VDAB sample is a sample of unemployed job seekers and vacancies taken from VDAB's online job platform at the end of the first month of every quarter of 2013 and 2014, resulting in 8 cross-sections.[9] To further organize the discussion of our VDAB sample, 3.2.1 and 3.2.2 discuss the data we collected from the online job platform about unemployed job seekers and job vacancies respectively. Next, 3.2.3 explains in more detail how information about tasks is organized in our data. Finally, 3.2.4 ends with a discussion of the representativeness of our VDAB sample.

3.2.1 Job seekers

Although any individual, either employed or unemployed, can register as a job seeker on VDAB's online job platform, we restrict our analyses to unemployed job seekers since our focus is on unemployment durations as the outcome variable. Columns (1) and (2) of Table 1 show shares of unemployed job seekers' listed occupation-experience cells to indicate their task competencies in ROME-V3, aggregated across 27 2-digit ISCO88 occupation groups and averaged across our 8 cross-sections. Given that unemployed job seekers can list more than one occupation-experience cell to state their task competencies, column (1) of Table 1 reports shares only using the first listed occupation-experience cell by each unemployed job seeker, whereas column (2) uses all listed occupation-experience cells.[10]

[9] See Appendix A for further details about the sampling procedure.

[10] To discount for the possibility that an unemployed job seeker can state multiple occupation-experience cells, column (2) weighs each occupation-experience cell by the inverse of the total number of occupation-experience cells listed by the same unemployed job seeker. Job seekers list 2.6 occupation-experience cells on average.

Column (1) shows that the fraction of jobs stated by unemployed job seekers is high for medium-skilled “other associate professionals” (2-digit ISCO88 code 34), performing a wide range of practical white-collar tasks; medium-skilled “office clerks” (41); various less-skilled personal services (51, 52 and 91); and less-skilled (often assisting) “laborers in mining, construction, manufacturing and transport” (93). Occupations for which unemployed job seekers have relatively few task competencies are in part more sector specific such as “armed forces” (01); medium-skilled “teaching associate professionals” (33), mainly providing education and care for children below primary school age; medium-skilled “precision, handicraft, printing and related trades workers” (73), making or repairing specific products such as musical instruments, jewellery, precious metalwork, ceramics, porcelain, or book-binding; or less-skilled “agriculture, fishery and related laborers” (92). Other jobs for which unemployed job seekers have relatively few task competencies require high skill levels, such as “legislators and senior officials” (11); "general managers" (13); “physical, mathematical and engineering science professionals” (21); or “life science and health professionals” (22). Finally, note that the shares in column (2) differ little from those in column (1).

The bottom three rows of Table 1 provide additional information about the size of the VDAB sample. The third last row of column (1) (labelled "N occupation-experience cells") reports that, in the average cross-section, unemployed job seekers indicate 1,158 different occupation-experience cells out of a potential 2,028 jobs in ROME-V3. The before-last row of column (1) (labelled "N sample") indicates that there are 17,493 unemployed job seekers in the average cross-section, resulting in a 139,944 (17,493 unemployed job seekers per cross-section $\times$ 8 cross-sections) unemployed job seekers and, hence, unemployment spells in our VDAB sample. The last row of Table 1 (labelled "N platform") aggregates the number of unemployed job seekers in our VDAB sample to all unemployed job seekers registered on VDAB’s online job platform in the average quarter during the period 2013-2014, equal to 229,535.[11]

3.2.2 Vacancies

Column (3) of Table 1 shows how vacancies are distributed across aggregate 2-digit ISCO88 occupation groups, with shares again averaged across the 8 cross-sections in our sample. The rank correlation coefficient between columns (1) and (3) is a high and statistically significant

[11] The total number of unemployed job seekers registered on VDAB’s online job platform is taken from `https://arvastat.vdab.be` and is the number of registered unemployed job seekers in any month averaged over the period 2013-2014.

0.77, mainly reflecting that some jobs are generally larger than others in the labor market. But there are also substantial differences between the shares reported in columns (1) and (3) for some occupation groups. For example, the share of vacancies posted for less-skilled laborers (ISCO88 93) is much lower than its share of unemployed job seekers for these occupations. On the other hand, the shares of vacancies for high-skilled corporate managers (ISCO88 12) and physical, mathematical and engineering (associate) professionals (ISCO88 21 and 31) are much higher than their shares for unemployed job seekers' task competencies. All in all, this suggests that there is substantial variation across jobs in their labor market tightness, defined as the number of vacancies over the number of unemployed job seekers for any given job.

The third row from the bottom in column (3) informs that, in the average cross-section in our sample, employers post vacancies in 877 different occupation-experience cells out of a potential 2,028 that are allowed by ROME-V3. The before-last row in column (3) gives the average number of vacancies in each cross-section in our sample, equal to 11,228, whereas the last row of column (3) uses sampling weights to estimate that the total number of vacancies posted on the job platform is 70,407. Comparing the last row in columns (1) and (3) suggests that there are on average 3 unemployed job seekers per vacancy at each point in time between 2013-2014. This is in line with other estimates for this period: 3.5 for the Netherlands (CBS Statline); 6.2 in Germany, 4.3 in Norway, 4 in Sweden, and 2.1 in the UK (OECD STATS); and 2.5 in the US (JOLTS and BLS).

3.2.3 Tasks in ROME-V3

ROME-V3 allows us to link the occupation-specific experiences listed by unemployed job seekers to a set of task competencies. The task classification in ROME-V3 is very detailed: there are 3,489 tasks linked to 2,028 occupation-experience cells. On average, an occupation-experience cell consists of 7 different tasks. Some of these tasks are specific to any one occupation-experience cell, but many are not. In particular, Figure 1 plots a histogram of the number of occupation-experience cells in which any one task appears in ROME-V3. This shows that the same task appears in 4 occupation-experience cells on average. The median is 2, and the first and third quartiles are 2 and 3 respectively. For ease of inspection, we censored the figure at any task occurring in 50 occupation-experience cells.[12] Examples of tasks that are most common across occupation-experience cells are stock taking; ordering of inputs with suppliers; accepting pay-

[12]Some tasks appear in up to 168 occupation-experience cells.

ments; or the coordination of teams.

Another way to summarize the task data in ROME-V3 is by defining task overlap across occupation-experience cells. As an example, column (1) of Table 2 shows the 8 tasks for the most frequent occupation-experience cell stated by unemployed job seekers in our VDAB sample: “production worker with less than two years of experience”. Defining task overlap for an occupation-experience cell as the % of tasks this cell has in common with another occupation-experience cell, Columns (2) and (3) illustrate task overlap for “production workers with less than two years of experience” with two other occupation-experience cells. The checkmarks show that “production workers with less than 2 years of experience" have 8 of the 11 tasks in common with “packers with more than 5 years experience”, giving an overlap of 8/11 or 73%. Similarly, “production workers with less than 2 years of experience" have half of the tasks in common with “finisher-repairers of textile goods with less than 2 years of experience", giving or an overlap of 1/2 or 50%.

To see more generally for which occupation-experience cells there is task overlap, Figure 2 plots a heat map illustrating the similarity of task bundles across occupation-experience cells in ROME-V3. For example, consider the point in the upper-left corner of Figure 2 for 2-digit ISCO88 groups 11 on the x-axis and 93 on the y-axis. For each occupation-experience cell in 11 we keep the maximum % task overlap it has with any occupation-experience cell in 93. We take the average of these maxima for every occupation-experience cell in 11 across all cells in 93. We then average this across all occupation-experience cells in 11, and plot this average in the upper-left corner of Figure 2. The diagonal line in Figure 2 highlights that occupation-experience cells that belong to the same 2-digit ISCO88 group are likely to have similar task bundles. However, the existence of off-diagonal hotspots also shows that there is substantial task overlap across 2-digit ISCO88 occupation groups. For example, task bundles are relatively similar between occupation groups 71 to 83. Tasks that are common across occupation groups 71 to 83 mainly involve basic maintenance and repair of machines or other equipment; the registration and dissemination of information related to production processes; and packaging and transportation of products. As will become clear below, the variation in task overlap between occupation-experience cells illustrated in Figure 2 is predictive of the probability for unemployed job seekers to find a job, i.e. labor markets overlap across jobs based on common task content.

3.2.4 Representativeness of the VDAB sample

For unemployed job seekers, VDAB's online job platform includes the entire population of unemployed job seekers that claim unemployment benefits, given that benefits can only be claimed conditional on registering on the platform. The VDAB further reports that for the period 2013-2014 these benefit claimants account for about 75% of all unemployed job seekers registered on the platform. This fraction is in line with economy-wide survey data taken from the European Union Labor Force Survey (EULFS): of all Flemish unemployed job seekers registered with VDAB in 2011-2015, 72% report receiving unemployment benefits. Moreover, of all Flemish unemployed job seekers in the EULFS, only 14% report not being registered with VDAB. What this suggests is that VDAB's online job platform captures 86% of the entire population of unemployed job seekers in Flanders.[13]

3.3 Auxiliary data for unemployed job seekers

Every unemployed job seeker in our VDAB sample is merged with two parts of their individual social security records. One source is used to construct (un)employment spells for the period 2010-2015. The other source contains person characteristics of each unemployed job seeker in our VDAB sample. We briefly discuss each of these two data sources in turn.

Firstly, for each unemployed job seeker in one of the 8 cross-sections in our VDAB sample, an (un)employment record is reconstructed from the Dimona database, which is the online application for firms to file employment records for tax purposes, for the period 2010-2015. Dimona contains the beginning and end of every contract that a job seeker agreed with any firm in half-month intervals. Consequently, for every unemployed job seeker in our VDAB sample we observe the start and end of every (un)employment spell between 2010-2015 on a bi-weekly basis. We observe a start as well as end date for 73% of all unemployment spells. Right censored unemployment spells for which a start but not an end date is observed account for the remaining 27%.[14]

Secondly, person characteristics of each unemployed job seeker in our VDAB sample are taken

[13] Appendix A further argues that also the vacancy data in our VDAB sample are representative of the labor market as a whole.

[14] We excluded from the VDAB sample those unemployed job seekers for whom we observe an end date but not a start date of unemployment, i.e. for whom the unemployment spell is left censored. Our Dimona data show that this is the case for only 7% of all unemployed job seekers. The reason for excluding unemployed job seekers with left-censored unemployment spells from the VDAB sample is that these unemployment spells would be discarded in the duration framework used in the empirical analyses below.

from the Datawarehouse Labor Market and Social Security, which collects individual records from different institutes within the social security system. Information about an unemployed job seeker's person characteristics is updated to the most recent year, based on when the unemployed job seeker was observed in our VDAB sample. Table 3 shows that 55% of unemployed job seekers are men and 66% have lifetime Belgian nationality. Around 15% of unemployed job seekers did not complete high school; 63% obtain a high school level diploma; and 23% attended some form of higher education. We also observe for each unemployed job seeker in the VDAB sample the region of residence at the NUTS3 level, resulting in 24 separate regions.[15]

4 Job search in labor markets with task overlap

This section relates an unemployed job seeker's probability of finding a job to the number of vacancies and other job seekers in her listed occupation-experience cell(s), for which she possesses all of the required task competencies, as well as in other occupation-experience cells, for which she only partially qualifies in terms of her task competencies because of task overlap. Such a relationship provides evidence in support of the idea that labor markets are, at least in part, organized along workers' task competencies. Subsection 4.1 outlines our empirical specification and identification, and 4.2 and 4.3 present our main estimates. Based on these estimates, section 5 then simulates the distributional consequences of an adverse routine task-biased shock in vacancies to capture the impact of ongoing technological progress on unemployment durations of job seekers with different task competencies.

4.1 Empirical specification

Define i as an unemployed job seeker observed in our VDAB sample after pooling our 8 cross-sections. Assume that i's probability of finding employment positively depends on tightness in her labor market, defined as the number of vacancies, $\tilde{V}_i$, divided by the number of unemployed job seekers, $\tilde{U}_i$, relevant to i in terms of her own task competencies. In particular, assume that the impact of (the log of) labor market tightness for unemployed job seeker i on her job finding probability is given by θ_i:

$$\theta_i = \alpha_1 \, ln(\tilde{V}_i) + \alpha_2 \, ln(\tilde{U}_i) \qquad (1)$$

[15]These regions are on average 615 square kilometres in size with 290 085 inhabitants on January 1, 2013. http://statbel.fgov.be/nl/statistieken

We expect that $\alpha_1 > 0$, capturing the positive externality from additional vacancies for which an unemployed job seeker (in part) qualifies in terms of her task competencies. We also expect that $\alpha_2 < 0$, capturing the negative externality from additional unemployed job seekers also (in part) qualifying for the task profile required in those vacancies.

In equation (1), i's relevant vacancies, $\tilde{V}_i$, is a weighted sum of vacancies for i's listed occupation-experience cells for which i has all of the required task competencies as well as occupation-experience cells for which i does not have all of the required task competencies but with which there is task overlap. Similarly, $\tilde{U}_i$ is the weighted sum of other unemployed job seekers that fully or partially qualify for i's relevant vacancies. In particular, we define $ln(\tilde{V}_i)$ and $ln(\tilde{U}_i)$ as:

$$\begin{aligned} ln(\tilde{V}_i) &\equiv ln(V_i^{all} + \sum_{j=1}^{4} \gamma_j V_{ij}^{some}) \\ ln(\tilde{U}_i) &\equiv ln(U_i^{all} + \sum_{j=1}^{4} \beta_j U_{ij}^{some}) \end{aligned} \tag{2}$$

where V_i^{all} is the number of vacancies and U_i^{all} the number of other unemployed job seekers in individual i's listed occupation-experience cell(s) for which i has all of the required task competencies, and V_{ij}^{some} and U_{ij}^{some} are the number of vacancies and other unemployed job seekers in occupation-experience cells for which i does not have all of required task competencies but with which there is some degree of task overlap. In particular, we distinguish four groups j: $j = 1$ counts all vacancies and other unemployed job seekers in cells for which i possesses at least 80% of the required set of task competencies; $j = 2$ in cells for which there is 60% to 79% task overlap; $j = 3$ in cells for which task overlap is between 30% and 59%; and $j = 4$ in cells for which i possesses more than 0% but less than 30% of the required task competencies. Note that this definition of task overlap is identical to the task overlap illustrated in Table 2, but aggregated across those occupation-experience cells for which i has a given fraction of the required task competencies. Also note that $\tilde{V}_i$ and $\tilde{U}_i$ are specific to each unemployed job seeker i. That is, labor markets and their tightness are individual specific in that they depend on an unemployed job seeker's listed occupation-experience cell(s) when registering on the platform and their task overlap with other occupation-experience cells according to ROME-V3.

Together with α_1 and α_2, parameters γ_j and β_j capture the importance for i's job finding probability of labor market tightness in cells that are not i's listed occupation-experience cells but for which i possesses at least some task competencies. For example, $\alpha_1 > 0$ and $\alpha_2 < 0$ but $\gamma_j = \beta_j = 0$ for $j = 1, ..., 4$ would imply that each occupation-experience cell is insular in the sense that job seekers who are not fully qualified based on their task profile cannot compete there. In this case, task overlap across occupational markets would be unimportant for job seekers' unemployment durations. But if subsets of tasks and their overlap across occupation-experience cells do matter, one would expect to find that $\gamma_j > 0$ and $\beta_j > 0$ for at least some for $j = 1, ..., 4$. Also note that $\gamma_j > 0$ and $\beta_j > 0$ have an intuitive interpretation. For example, $\gamma_1 = 0.33$ would imply that the increase in i's tightness from one additional vacancy for which i has all required task competencies is the same as the increase in i's tightness from three additional vacancies in occupation-experience cells for which i has at least 80% of the required task competencies. Similarly, $\beta_1 = 0.33$ would imply that one additional job seeker who is fully task-proficient in i's listed occupation-experience cells decreases i's tightness by the same amount as 3 additional job seekers who have between 80-99% of the required task competencies.

To consistently estimate the impact of an unemployed job seeker's labor market tightness on her probability of finding a job, we need to account for duration dependence in unemployment spells. To do this, we use the following proportional hazard model:

$$h(\tau_i) = k\tau_i^{k-1}\, exp[\theta_i + X_i^{'}\delta] = k\tau_i^{k-1}\, exp[\alpha_1\, ln(\tilde{V}_i) + \alpha_2\, ln(\tilde{U}_i) + X_i^{'}\delta] \tag{3}$$

where $h(\tau_i)$ is the hazard rate.[16] The hazard rate is the conditional probability that an unemployed job seeker i finds a job conditional on having been unemployed for τ periods. The term $k\tau_i^{k-1}$ with $k > 0$ is a Weibull specification of the baseline hazard that models the impact of unemployment duration on the hazard rate. If $0 < k < 1$, an increase in unemployment duration decreases the hazard rate and duration dependence is negative. If $k > 1$, an increase in unemployment duration increases the hazard rate and duration dependence is positive. An increase in labor market tightness θ_i is expected to shift the hazard function up: for any given unemployment duration τ_i, the probability that unemployed job seeker i finds a job is higher if her labor market tightness θ_i is higher. Similarly, lower labor market tightness θ_i is expected to shift the hazard function down.

The vector X_i contains a number of controls that could be important in job search, i.e. person characteristics other than an unemployed job seeker's labor market tightness that could

[16]Equation (3) will be estimated using a maximum likelihood specification that accounts for right-censored unemployment spells in our data. For an overview of duration modelling, see Van den Berg (2001).

also shift the hazard function up or down. Controls in X_i will include unemployed job seekers' preferences to work only full-time, only part-time, or be open to both, taken from the VDAB sample. X_i will also include gender, nationality, and educational attainment of unemployed job seekers, taken from Datawarehouse Labor Market and Social Security as discussed above. Finally, some of our estimates will include location (i.e. 3-digit NUTS region of residence of unemployed job seekers taken from Datawarehouse Labor Market and Social Security) and time fixed effects to control for endogenous shocks that are time and location specific.

For our analyses to be informative not only about job finding probabilities but also unemployment durations, the survival function corresponding to the estimated hazard function has to be specified. To see how this is done, consider a hazard and survival function that are both related to the same probability density function (dropping subscripts i for simplicity) $f(\tau)$: the probability of finding a job τ periods after becoming unemployed . The survival function then is the reverse cumulative distribution function of $f(\tau)$: $S(\tau) = 1 - F(\tau)$, with $F(\tau) = \int_0^t f(\tau)d\tau$. It measures the cumulative probability of staying unemployed for τ periods. The hazard rate is then defined as $h(\tau) = f(\tau)/S(\tau)$. It is the probability of finding a job after τ periods, conditional on not having found one earlier. Also note that, by definition, $f(\tau) = dF(\tau)/d\tau = d(1 - S(\tau))/d\tau = -dS(\tau)/d\tau$. This implies that $h(\tau) = f(\tau)/S(\tau) = (-dS(\tau)/d\tau)/S(\tau)$ or that $dlnS(\tau)/d\tau = -h(\tau)$. Integrating both sides over τ and taking the exponential then gives: $S(\tau) = exp[\int_0^\infty -h(\tau)d\tau]$.

Using the Weibull proportional hazard model from equation (3) above, the corresponding survival function can be written as:

$$S(\tau_i) = exp[-\tau_i^k exp[\theta_i + X_i^{'}\delta]] = exp[-\tau_i^k exp[\alpha_1\, ln(\tilde{V}_i) + \alpha_2\, ln(\tilde{U}_i) + X_i^{'}\delta]] \tag{4}$$

The survival function is decreasing in τ_i given that $k > 0$. An increase in labor market tightness θ_i shifts the survival function down, whereas a decrease in labor market tightness shifts it up. Finally note that unemployed job seeker i's expected unemployment duration is given by $E[S(\tau_i)] = \int_0^\infty S(\tau_i)d\tau_i$. Consequently, an increase in i's labor market tightness not only shifts the survival function down but also reduces i's expected unemployment duration. Similarly, a decrease in i's labor market tightness increases i's expected unemployment duration.

In sum, observing τ_i, $\tilde{V}_i$, $\tilde{U}_i$, and X_i for each unemployed job seeker i observed in one of the 8 cross-sections in our VDAB sample allows us to estimate parameters k, α_1, α_2, δ, and γ_j and

β_j for $j = 1, ..., 4$ using equation (3). In particular, estimates of γ_j and β_j for $j = 1, ..., 4$ are informative about the importance of task overlap across occupation-experience cells in predicting the probability of finding employment. This is what we will do in the remainder of this section. Moreover, based on estimates of equation (3), a job seeker's expected unemployment duration can be predicted using equation (4). For example, one can simulate the impact of a decrease in the number of routine-task intensive vacancies on expected unemployment durations of job seekers with different task competencies to assess the distributional consequences of ongoing technological progress on unemployment spells. That is what we will do in section 5.

4.2 Estimates without allowing for task overlap

Using our data discussed in section 3, this subsection first presents estimates of α_1 and α_2 assuming that $\gamma_j = \beta_j = 0$ for $j = 1, ..., 4$ in equations (2). Therefore, this subsection presents baseline estimates assuming that there is no task overlap across occupation-experience cells in unemployed job seekers' labor markets. Equation (1) then simplifies to the following expression:

$$\theta_i = \alpha_1 \, ln(V_i^{all}) + \alpha_2 \, ln(U_i^{all}) \tag{5}$$

Substituting the right-hand side of equation (5) into (3) and using τ_i, V_i^{all}, U_i^{all} and X_i from our data, parameters α_1, α_2, δ and k can be estimated. Table 4 reports estimates of α_1, α_2, and δ as odds ratios: that is, estimates $exp(\hat{\alpha_1})$, $exp(\hat{\alpha_2})$ and $exp(\hat{\delta})$ are shown, which should be interpreted relative to unity.[17]

The first and second rows of Table 4 report estimates of $exp(\hat{\alpha_1})$ and $exp(\hat{\alpha_2})$ respectively. Column (1) excludes X_i from the analysis, finding that $exp(\hat{\alpha_1}) = 1.126$. What this means is that a 1 log-point increase in the number of vacancies increases the hazard rate by 12.6%. Conversely, a 1 log-point increase in the number of other unemployed job seekers decreases the hazard rate by 7.5%, since $exp(\hat{\alpha_2}) = 0.925$. In sum, these estimates suggest that $\alpha_1 > 0$ and $\alpha_2 < 0$ and that labor markets are in part organized along bundles of tasks captured by our detailed classification of occupation-experience cells for which workers fully qualify in terms of their task competencies. As is well documented in literature (e.g. see van den Berg and van

[17] The number of observations reported at the bottom of Table 4 are somewhat lower than the number of possible unemployment spells in our VDAB sample, given by 139,944 (an average of 17,493 unemployed job seekers per cross section $\times$ 8 cross-sections). This is because the analyses necessarily exclude unemployed job seekers for whom there are no vacancies in their listed occupation-experience cells and for whom personal characteristics listed in Table 3 are missing.

Ours 1996 and Kroft et al. 2013), the estimate for k at the bottom of column (1) suggests that there is negative duration dependence.

Panels (a) of Figures 3 and 4 show what these estimates mean for standard deviation changes in log vacancies and log job seekers, which equal 1.6 and 1.7 log-points respectively. Corresponding with the estimated sign of α_1 and α_2, the hazard function shifts up proportionally with an increase in vacancies and down with an increase in job seekers. Subsection 4.1 explained how these estimates can be used to predict the impact of tightness on unemployment durations. To highlight this further, Panels (b) of Figures 3 and 4 show the shift in the survival function for the same standard deviation changes in log vacancies and job seekers. For example, our estimates predict that the expected unemployment duration decreases by 11 weeks from an average of 30 weeks when the number of vacancies in an occupation-experience cell increases by a standard deviation from the mean.

Column (2) of Table 4 adds some of the personal characteristics discussed in Table 3 as controls in X_i to the analysis. Estimates of α_1, α_2, and k are almost identical to those of column (1). Moreover, the coefficients for the controls themselves are as expected. Looking for part-time rather than full-time employment significantly shifts the hazard function down. Women have significantly lower hazard rates than men, which is in line with findings in Diamond and Sahin (2016) who look at long-run data for the US. Relative to unemployed job seekers who have lifetime Belgian nationality, those with acquired Belgian or foreign nationality have significantly lower hazard rates. The inclusion of location and time fixed-effects rules out that our point estimates are contaminated by common regional or time specific shocks – see Borowczyk-Martins et al. (2013) for further discussion of the importance of such shocks.

Finally, to ensure that our specification of jobs as detailed occupation-experience cells is not mainly capturing variation in unemployed job seekers' educational attainments, columns (3) and (4) repeat the analyses in columns (1) and (2) while adding education as a control. Estimates for α_1 and α_2 decrease somewhat, but remain statistically significant. The coefficients on the educational controls themselves show that, compared to job seekers with no high school qualifications, having a high school degree or having obtained tertiary education shifts the hazard function upwards. That is, all else equal, unemployed job seekers with higher educational attainments are expected to have shorter unemployment durations.

4.3 Estimates allowing for task overlap

The previous subsection showed the importance of labor market tightness in our detailed classification of occupation-experience cells for understanding unemployment durations. However, in setting $\gamma_j = \beta_j = 0$ for all $j = 1, ..., 4$, it assumed that these occupational markets are entirely insular, despite the significant degree of task overlap shown in Figures 1 and 2. Should markets overlap because of task similarities, then accounting for this overlap is important for understanding the impact on individual unemployment durations of shocks to task demand. In that case, one would expect to find that $\gamma_j > 0$ and $\beta_j > 0$ for at least some $j = 1, ..., 4$. Therefore, this subsection provides estimates of α_1, α_2, γ_j and β_j while not restricting the analysis to $\gamma_j = \beta_j = 0$ for all $j = 1, ..., 4$.

However, if γ_j and β_j are not all zero for $j = 1, ..., 4$, equation (1) is no longer linear in parameters α_1 and γ_j or in α_2 and β_j, such that their values can no longer be estimated using equation (3). To solve this problem, first define $V_i \equiv V_i^{all} + V_{i1}^{some}$ as the count of vacancies in individual i's listed occupation-experience cell(s) and other cells with which there is at least 80% task overlap. Similarly, define $U_i \equiv U_i^{all} + U_{i1}^{some}$ as a headcount of unemployed job seekers in individual i's target occupation-experience cells and other cells with at least 80% task overlap. Next approximate equation (1) by the following linearization:[18]

$$\begin{aligned} \theta_i \approx \alpha_1 ln(V_i) + \alpha_2 ln(U_i) + \alpha_1 \frac{1-\gamma_1}{\gamma_1} \frac{V_i^{all}}{V_i} + \alpha_2 \frac{1-\beta_1}{\beta_1} \frac{U_i^{all}}{U_i} + X_i^{'}\delta \\ + \alpha_1 \sum_{j=2}^{4} \frac{\gamma_j}{\gamma_1} \frac{V_{ij}^{some}}{V_i} + \alpha_2 \sum_{j=2}^{4} \frac{\beta_j}{\beta_1} \frac{U_{ij}^{some}}{U_i} \end{aligned} \tag{6}$$

Substituting the right hand side of equation (6) into (3), the estimated coefficients on $ln(V_i)$ and $ln(U_i)$ are point estimates of α_1 and α_2 respectively and, together with estimated coefficients on V_i^{all}/V_i and U_i^{all}/U_i, allow us to back out estimates for γ_1 and β_1. Given these point estimates for α_1 and γ_1, one can then compute a value for γ_j from the estimated coefficient on V_{ij}^{some}/V_i for $j = 2, 3, 4$. Similarly, having an estimate for α_2 and β_1 allows us to calculate a value for β_j from the estimated coefficient on U_{ij}^{some}/U_i for $j = 2, 3, 4$.

The first two rows of Table 5 report estimates $exp(\hat{\alpha_1})$ and $exp(\hat{\alpha_1})$, respectively. These estimates are qualitatively similar to those in Table 4. For example, column (4) shows that $exp(\hat{\alpha_1}) = 1.114$ and $exp(\hat{\alpha_2}) = 0.945$ in the model with a full set of controls. The point

[18]See Appendix B for details.

estimate on V_i^{all}/V_i is 1.251, larger than the estimate for $exp(\hat{\alpha_1})$, which implies $0 < \gamma_1 < 0.5$. Similarly, the estimated coefficient on U_i^{all}/U_i is 0.805, which is further below unity than the estimate for $exp(\hat{\alpha_2})$, meaning that $0 < \beta_1 < 0.5$. Estimated coefficients on V_{ij}^{some}/V_i and U_{ij}^{some}/U_i are unity, suggesting that $\gamma_j = \beta_j = 0$ for $j = 2, 3, 4$.

To summarize our findings, Table 6 reports imputed values for γ_j and β_j, where the column numbers correspond to the column numbers from Table 5. Table 6 shows that $\gamma_1 = 0.35$ and $\beta_1 = 0.29$, whereas $\gamma_j = \beta_j = 0$ for $j = 2, 3, 4$. The finding that γ_1 and β_1 are strictly positive implies that tightness in labor markets for which unemployed job seekers possess a substantial (at least 80%) subset of the required task competencies is predictive of finding a job. Given that an occupation-experience cell consists of 7 different tasks on average, this means that unemployed job seekers can fail to qualify for 1 or 2 of the required tasks and still be matched to those jobs. However, also note that the impact on job finding probabilities of tightness in those labor markets is only a third of what it is in occupation-experience cells for which unemployed job seekers fully qualify in terms of their task competencies. For example, the increase in an unemployed job seeker's hazard rate would be the same for one additional vacancy for which she has all required task competencies as for three additional vacancies in occupation-experience cells for which she has at least 80% of the required task competencies.

Table 6 also reports that, robustly across model specifications from Table 5, $\gamma_j = \beta_j = 0$ for $j = 2, 3, 4$. On the one hand, these estimates are intuitive as the importance of tightness in more distant task markets is expected to be lower. On the other hand, $\gamma_j = \beta_j = 0$ for $j = 2, 3, 4$ suggests that markets for which unemployed job seekers do not possess a substantial (less than 80% or fewer than 5 out of 7 tasks) subset of the required task competencies are unimportant. This lack of mobility for unemployed job seekers to take up jobs requiring tasks outside their competency profiles has important distributional consequences if the labor market is subject to task-biased shocks, as will be shown in section 5 below. The next subsection first reports a number of robustness checks.

4.4 Additional analyses

4.4.1 Excluding the effect of occupational careers

In ROME-V3, tasks for different experience levels are additively structured within an occupation: within the same occupation, the tasks required at higher experience levels are the sum of all tasks required at lower experience levels plus some extra tasks. For example, the cell "production worker with more than 5 years of experience" adds only a few tasks to "production worker with 2 to 5 years of experience", and having all competencies for the former mechanically creates a very high task overlap with the latter. More generally, the importance of task overlap with higher experience levels within the same occupation in part explains why there is a diagonal in Figure 2: one third of task overlap of at least 80% is due to overlap with higher experience levels within the same occupation.

On the one hand, task overlap with higher experience levels within the same occupation is intuitive because unemployed job seekers clearly possess some but not all of the task competencies to do these more experienced jobs. This is why task overlap with higher experience levels within the same occupation was included in our definition of task overlap in the analyses above. On the other hand, such task overlap with higher experience levels within the same occupation may simply reflect career mobility within the same occupation. It could be argued that this is in practice a single labor market, thereby inflating our estimates of the importance of task overlap for the probability of finding a job. Therefore, this section excludes task overlap with higher experience levels within the same occupation.[19]

Table 7 repeats the analyses in Table 5 while excluding task overlap with higher experience levels within occupations. Estimates of α_1 and α_2 in Table 7 are very similar to those of Table 5. If anything, coefficients on V_i^{all}/V_i are somewhat higher and on U_i^{all}/U_i somewhat lower than in Table 5. This suggests that the estimates for γ_1 and β_1 are still statistically significant but somewhat lower: this indicates that occupational careers are one reason, but not the only reason, why labor markets overlap across jobs because of common task contents.

4.4.2 Results without the linearization of job finding probabilities

The right-hand side of equation (6) is a linear approximation to an unemployed job seeker's job finding probability. To see whether this linearization is in part driving our results, this section provides an alternative approach to estimating the importance of task overlap for hazard rates.

[19]It is also questionable whether lower experience levels within the same occupation – with which there always is 100% task overlap by construction – should be considered as separate and more distant labor markets. Therefore, our definition of task overlap used in the analyses above excluded lower experience levels within an occupation for which an unemployed job seeker has the same percentage of task competencies. For example, the lower experience levels within an occupation listed by an unemployed job seeker when registering on the platform, for which she has all the required task competencies by construction, were excluded in the definition of task overlap in the analyses above.

Specifically, we estimate our model separately for $j = 1, ..., 4$:

$$h(\tau_i) = k\tau_i^{k-1}\, exp[\nu_{1j}\, ln(V_{ij}) + \nu_{2j}\, ln(U_{ij}) + X_i'\delta] \tag{7}$$

where X_i contains the same controls as in column (2) of Table 4.

Results are reported in Table 8: to save space, coefficients on controls are not reported as these all have the expected signs. For comparison, column (1) of Table 8 replicates the estimates of column (2) in Table 4 by setting $V_{ij} = V_i^{all}$ and $U_{ij} = U_i^{all}$ in equation (7). We expect ν_{1j} to capture $\alpha_1\gamma_j$ and ν_{j2} to capture $\alpha_2\beta_j$. If γ_j and β_j are strictly positive and decreasing in j, we would expect the same of ν_{1j} and ν_{2j}. Results shown in columns (2) to (6) for $j = 1, ..., 4$ show that this is indeed the case. Moreover, the substantial decrease between columns (1) and (2) suggests that γ_1 and β_1 are substantially below one, in line with our previous results. Estimates of ν_{1j} and ν_{2j} for $j = 2, 3, 4$ are close to unity, suggesting that γ_j and β_j for $j = 2, 3, 4$ are zero, again in line with our previous findings. In sum, Table 8 complements our main findings and supports that the evidence in Table 5 is not driven by the linear approximation in equation (6).

5 Distributional impact of ongoing technological progress on unemployed job seekers

The estimates in section 4 allow us to analyze the impact of ongoing technological progress on job finding probabilities and unemployment durations for unemployed job seekers with different task competencies. In particular, we will analyze an adverse shock in labor demand that is biased against routine-task intensive vacancies. We will show that such a routine-biased task shock leads to substantial heterogeneity in changes in hazard rates and unemployment durations across unemployed job seekers with different task competencies.

5.1 Routine tasks in ROME-V3

To simulate a routine-biased task shock in vacancies, we first need to define which tasks in ROME-V3 are routine. To do so, we define three groups of tasks as being routine. Firstly, tasks related to the logging of activity data and the sharing of information. Examples of such tasks are counting and registering the number of pieces produced; or collecting and disseminating information about irregularities in the production process. Secondly, tasks related to assembly line work are also labelled as routine. Examples are providing workstations with materials or checking the stock; clearing and cleaning the work area of materials; or monitoring the flow and progress of products on a production or transport line and, if necessary, unblock and remove elements. Thirdly, some administrative tasks are also classified as routine. Examples are registering and sorting of mail; coding and classifying and archiving of documents; searching, sending and managing of documents; checking the availability of products; or registering of orders. By and large, these tasks correspond to routine tasks used in the literature – see, for example, Goos et al. (2014).

Based on this classification, we calculate the share of routine tasks in every occupation-experience cell in ROME-V3. Figure 5 shows the average of this share across occupation-experience cells within each 2-digit ISCO88 occupation group. For example, the average fraction of tasks that are routine across occupation-experience cells in 2-digit ISCO88 occupation group 81 is about 20%. Figure 5 shows that routine task intensity is relatively high for "office clerks" (41); "stationary-plant and related operators" (81); "machine operators and assemblers" (82); "agriculture, fishery and related laborers"(92); "laborers in mining, construction, manufacturing and transport" (93); and "customer services clerks" (42). By and large, this variation corresponds to other occupational measures capturing routine task intensity, such as the Routine Task Index (RTI) reported in Table 1 of Goos et al. (2014).[20]

5.2 Winners and losers from ongoing technological progress

The variation in routine task intensity illustrated in Figure 5 implies that a decrease in routine-task intensive vacancies will affect some job seekers more than others. That is, a negative labor demand shock that is biased against routine tasks can have important distributional consequences for job seekers' hazard rates.

To predict the impact of a negative routine-biased task shock to vacancies on job seekers'

[20] One difference with Goos et al. (2014) is that routine intensity for occupation groups (73) and (74) is higher in their data than in ours. However, Table 1 shows that these occupation groups only contain 1.46% of unemployed job seekers in our VDAB sample.

hazard rates, we use equation (6) and parameter estimates shown in column (2) of Table 5:

$$\begin{aligned}\hat{\theta}_i \approx\ & 0.12ln(V_i) - 0.08ln(U_i) + 0.24\frac{V_i^{all}}{V_i} - 0.21\frac{U_i^{all}}{U_i} \\ & +0.01\frac{V_{i2}^{some}}{V_i} + 0.00\frac{V_{i3}^{some}}{V_i} - 0.00\frac{V_{i4}^{some}}{V_i} \\ & +0.02\frac{U_{i2}^{some}}{U_i} + 0.00\frac{U_{i3}^{some}}{U_i} - 0.00\frac{U_{i4}^{some}}{U_i}\end{aligned} \tag{8}$$

Substituting equation (8) into equation (3), we predict two hazard rates for each job seeker i. The first prediction uses i's actual relevant vacancies V_i, V_i^{all}, and V_{ij} for $j = 2, 3, 4$. The second prediction uses an alternative set of vacancies assuming a reduced demand for routine labor tasks to capture routine-task biased technological progress. In particular, we assume a 25% reduction of vacancies multiplied by the share of routine tasks in each occupation-experience cell. For example, if 50% of all tasks in an occupation-experience cell are routine, the number of vacancies in that cell is reduced by 12.5%. Assuming that all vacancies result in jobs, the overall size of this shock corresponds to a 1 percentage-point reduction in the share of routine jobs over the two-year period 2013-2014. This is in the same order of magnitude as the actual percentage-point change in routine employment shares found by Goos et al. (2014).[21] Finally, for each job seeker i we then calculate the percent difference between her hazard rates based on her actual and shocked set of relevant vacancies.

The black line in Figure 6 shows the cumulative distribution of percentage differences in hazard rates across all job seekers. It is clear from the figure that the hazard rate decreases on average, as would be expected from a negative shock to vacancies. However, it is also clear that the impact of the shock is distributed unequally across unemployed job seekers. In particular, Figure 5 showed that routine tasks are concentrated in 2-digit ISCO88 groups 41, 42, 81, 82, 92, and 93. Also, columns (1) and (2) of Table 1 showed that these 2-digit ISCO88 occupation groups capture over 30% of all task competencies of unemployed job seekers. That is, ongoing technological progress disproportionately reduces the job finding probabilities for a sizeable group of job seekers that are locked into unemployment by their routine-task competencies.

To further quantify the distributional consequences, we can compare the black line in Figure 6 with a counterfactual outcome of the same shock while assuming that there is a single market for all unemployed job seekers irrespective of their task competencies. Because unemployed job

[21] Goos et al. (2014) find that the change in the share of routine occupations over 1993 to 2010 is 6.84 percentage-points, or around 0.8 percentage-points for every two-year period.

seekers are assumed to be perfectly mobile across occupation-experience cells in this counterfactual scenario, tightness must be equal across all labor markets. As a result, the burden of any adverse shock in vacancies, even if it's task-biased, is shared equally across all unemployed job seekers. To construct this counterfactual outcome, first define the number of vacancies and other unemployed job seekers relevant to individual i as the sum of all vacancies and job seekers in the aggregate labor market: V and U. We can then use equation (5) and the parameter estimates in column (2) of Table 4 to predict:

$$\hat{\theta}_i = 0.13\, ln(V) - 0.08\, ln(U) \tag{9}$$

Substituting equation (9) into equation (3), we again predict two hazard rates: one using the actual number of total vacancies V, and one assuming a reduction in vacancies that is equal to the reduction in the total number of vacancies in Figure 6. In this single market scenario, the hazard rate decreases by -0.16% for each unemployed job seeker, given by the vertical red line in Figure 6. The increase in expected unemployment duration corresponding to this decrease in the hazard rate is 0.40%, or an increase by 0.06 weeks from 14 weeks on average.

Relative to this single market scenario, the black line in Figure 6 shows that 49% of unemployed job seekers win (i.e. are right of the red line) and 51% lose (i.e. are left of the red line), due to their differences in task competencies that protect winners from and expose losers to routine-task biased technological progress. Across the 51% losers, the hazard rate decreases by -0.63% on average. Compared to the single market outcome, this decrease is four times as large (-0.63% versus -0.16%). Also, the average increase in expected unemployment duration across the 51% losers is 1.55%, or an increase of 0.62 weeks from 35 weeks on average. Compared to the single market outcome, this increase is four times as large (1.55% versus 0.40%).

In sum, task-biased shocks in labor demand or supply can have important distributional consequences for unemployed job seekers that differ in their task competencies. For example, we showed that ongoing technological progress, captured by an adverse routine-task biased shock in vacancies, results in winners and losers across unemployed job seekers. The winners are specialized in non-routine task competencies, protecting them from an adverse routine-biased shock in vacancies. To the contrary, losers get locked into unemployment because of their routine-task competencies following technological progress. Relative to a labor market in which competencies don't matter, the average loser experiences fourfold decrease in her job finding probability and a equal increase in her expected unemployment duration. These are large effects stemming from the heterogeneity in task competencies across unemployment job seekers together with limited task overlap across jobs in labor markets.[22]

5.3 Why are job seekers with routine-task competencies locked in?

The losers from ongoing technological progress lose because their routine-task competencies expose them to an adverse routine-task biased shock in vacancies. There are two broad reasons for this exposure. Firstly, losers cannot effectively compete for jobs that are intensive in non-routine tasks because they possess at least one but not all of the required task competencies to do these jobs. That is, there is limited mobility for losers into jobs with which there is some degree of task overlap. This is captured by the estimates for γ_j, β_j being smaller than 1 for $j = 1$ and zero for $j = 2, 3, 4$ in the analyses above. Secondly, losers are exposed because they cannot compete for jobs for which they have none of the required task competencies: this is reflected in any remaining difference between the single market scenario and the predicted outcome when setting $\gamma_j = \beta_j = 1$, $\forall j = 1, ..., 4$.

To assess the importance of both factors, we perform the following exercise. Firstly, for unemployed job seekers with at least one routine-task competency we assume that $\gamma_j = \beta_j = 1$, $\forall j = 1, ..., 4$. This assumes that those unemployed job seekers match equally well across all jobs for which they have all or only some of the required task competencies. For those unemployed job seekers, we can then predict their labor market tightness using:

$$\hat{\theta}_i = 0.13\, ln(V_i^{all} + \sum_{j=1}^{4} V_{ij}^{some}) - 0.08\, ln(U_i^{all} + \sum_{j=1}^{4} U_{ij}^{some}) \tag{10}$$

Substituting equation (10) into equation (3), we again predict two hazard rates: one before and one after the routine-task biased shock. For all unemployed job seekers with only non-routine task competencies, we also predict two hazard rates using equation (8) just as before.[23]

The grey and red lines in Figure 7 are taken from Figure 6 and are referred to as our baseline predictions with the observed amount of mobility. The black line draws the predicted distribution

[22] Note that the estimated percentage decreases in hazard rates and increases in expected unemployment durations depend on the size of the assumed shock to vacancies. To the contrary, the estimated fourfold decrease in job finding probabilities and increase in expected unemployment duration for the 51% losers relative to their single labor market outcome is independent of the size of the assumed shock.

[23] Note that for unemployed job seekers with only non-routine task competencies, their relevant number of vacancies in equation (8) still changes after a routine-task biased shock because some of the vacancies with which there is task overlap will still contain routine tasks.

of percentage changes in hazard rates from the same shock when unemployed job seekers with at least one routine-task competency can equally compete for all jobs with which there is some degree of task overlap, using equation (10). In this scenario, 49% of unemployed job seekers see their hazard rate decrease relative to their single market outcome. Among those losers, the average decrease in hazard rates is somewhat smaller compared to the baseline estimate: -0.52% (instead of -0.63% for the baseline predictions). Relative to the single market scenario which predicts a decrease of -0.16%, this decrease is three times as large. The average increase in unemployment duration across the 49% losers is 1.27%, or an increase of 0.37 weeks from 27 weeks on average (instead of 1.55% and 0.62 weeks from 35 weeks for the baseline predictions). Relative to the single market scenario which predicts an increase of 0.40% or 0.06 weeks, this is a threefold increase in the expected unemployment duration across losers.

What these numbers suggest is that there is only limited scope for policies directing unemployed job seekers with routine-task competencies to less routine-task intensive vacancies for which they also in part qualify. Instead, policies should direct affected unemployed job seekers to jobs in which there is high labor market tightness. Recent work by O'Connel et al. (2017) shows that when employer input on skill demand is taken into account in designing training programs, trainees' employment and earnings increase. A more general informational policy to direct workers to markets where tightness is higher could be a better option, although substantial retraining efforts may be required for job seekers to qualify for these jobs. Belot et al. (2016) provide experimental evidence in support of the importance of information as a barrier to occupational mobility: redirecting individuals towards tight labor markets increases their chance of getting a job interview. Such algorithmic recommendations are low cost and could be widely implemented on public and private job platforms.

6 Conclusions

Using data from an online job platform, we find that tightness in jobs for which an unemployed job seeker fully qualifies in terms of her task competencies is predictive of her unemployment duration, suggesting that the labor market is in part organized along detailed jobs and their task content. We also find that overlap across jobs in terms of task content matters – i.e. there is mobility of unemployed job seekers into jobs for which they only partially qualify based on their task competencies. However, this mobility is limited because our estimates show that unemployed job seekers cannot successfully compete for jobs for which they do not have the large majority of required task competencies.

This implies that some unemployed job seeker cannot easily shield themselves from task-biased shocks: if such shocks decrease tightness in jobs the unemployed worker has task competencies for, they cannot easily move into other, less exposed, jobs instead. Indeed, we find that a negative shock to vacancies intense in routine tasks has very uneven distributional impacts on unemployment durations across unemployed job seekers with different task competencies. Interesting extensions of this work would therefore be to evaluate the impact of randomized controlled trials aimed at decreasing specific barriers between jobs, such as (re)training programs and informational campaigns aimed at directing unemployed job seekers to jobs with a higher ratio of vacancies to job seekers.

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Table 1: Shares of Unemployed Job Seekers and Vacancies Across Occupation Groups

	% listed occupations, first (1)	% listed occupations, all (2)	% vacancies (3)
01: armed forces	0.03	0.03	0.04
11: legislators and senior officials	0.18	0.22	0.43
12: corporate managers	5.56	5.55	18.97
13: general managers	0.08	0.10	0.11
21: physical, mathematical and engineering science professionals	0.83	0.82	3.38
22: life science and health professionals	0.18	0.17	0.49
23: teaching professionals	2.96	3.11	2.13
24: other professionals	4.95	4.54	5.05
31: physical and engineering science associate professionals	2.17	2.13	7.69
32: life science and health associate professionals	1.68	1.56	1.67
33: teaching associate professionals	0.00	0.01	0.01
34: other associate professionals	8.91	8.54	15.46
41: office clerks	9.43	9.28	5.92
42: customer services clerks	2.93	3.31	1.88
51: personal and protective services workers	7.82	7.94	3.69
52: models, salespersons and demonstrators	8.14	8.24	5.30
61: market-oriented skilled agricultural and fishery workers	1.35	1.41	0.35
71: extraction and building trades workers	5.21	5.26	5.08
72: metal, machinery and related trades workers	3.26	3.07	6.16
73: precision, handicraft, printing and related trades workers	0.59	0.52	0.19
74: other craft and related trades workers	0.86	0.87	1.11
81: stationary-plant and related operators	0.29	0.31	0.32
82: machine operators and assemblers	3.18	3.37	2.99
83: drivers and mobile-plant operators	5.53	5.94	3.55
91: sales and services elementary occupations	7.56	8.81	6.40
92: agricultural, fishery and related labourers	0.64	0.70	0.10
93: labourers in mining, construction, manufacturing and transport	15.69	14.21	1.52
N occupation-experience cells	1158	1460	877
N sample	17 493	17 493	11 228
N platform	229 535	229 535	70 407

Source: VDAB: Mijn Loopbaan; VDAB Arvastat

Notes: Job seekers and vacancies are pooled across occupation cells to 2-digit ISCO groups, after applying samping weights. Shares are averaged across time observations.

Table 2: Examples of Occupation-Experience Cells and Their Task Contents in ROME-V3

(1) **Occupation-experience cell** Production worker, < 2 years (total n. of tasks=8) ISCO88=93	(2) **task overlap = 8/ 11** Packer, >5 years ISCO88=93	(3) **task overlap = 1/2** Finisher-repairer of textile goods, < 2years ISCO88=82
Logging activity data (number of pieces,...)	✓	✓
Transporting the products or waste to the storage, shipping or recycling zone	✓	
Providing the workstation with materials and products or checking the stock	✓	
Clearing and cleaning the work area (materials, fittings,...)	✓	
Packaging products according to characteristics, orders and mode of transport	✓	
Fitting, assembling and attachment of pieces. Check that the assembly has been correct (use, view)	✓	
Monitoring the flow and progress of products on a production or transport line. If necessary, unblock and remove elements	✓	
Detect and locate visible defect and sort them accordingly (surface, color,...)	✓	
Missing tasks		
	Check the products upon receipt, when completing the order or upon shipment	
	Labelling the product, branding and checking the information (expiration date,...)	
	Preventive or corrective basic maintenance of machines or equipment	
		Place design and presentation materials in the article (cardboard, ...) Packaging the articles

Source: ROME-V3

Table 3: Characteristics of Unemployed Job Seekers

	%
Sex	
Male	55.72
Female	44.28
.	0.00
Current nationality	
Belgian nationality: lifetime	65.95
Belgian nationality: acquired	17.78
Foreign, EU Nationality	7.38
Foreign, other nationality	8.62
.	0.27
1digit ISCED level	
0-2: no diploma	17.44
3-4: high school level diploma	61.83
5-6: higher education	19.07
.	1.66
Total	100.00
N	139,944

Source: Datawarehouse Labor Market and Social Security

Table 4: Explaining Job Finding Probabilities Without Task Overlap Across Jobs

VARIABLES	(1) odds ratio	(2) odds ratio	(3) odds ratio	(4) odds ratio
$\ln V_i^{all}$	1.126***	1.134***	1.112***	1.122***
	(0.004)	(0.004)	(0.004)	(0.004)
$\ln U_i^{all}$	0.925***	0.925***	0.943***	0.940***
	(0.003)	(0.003)	(0.004)	(0.004)
Female		0.971***		0.962***
		(0.009)		(0.009)
Belgian nationality: acquired		0.888***		0.906***
		(0.010)		(0.011)
Foreign, EU nationality		0.822***		0.845***
		(0.014)		(0.015)
Foreign, other nationality		0.915***		0.960***
		(0.014)		(0.015)
Part-time		0.757***		0.768***
		(0.012)		(0.013)
Part-time or full-time		0.915***		0.912***
		(0.009)		(0.009)
High School			1.253***	1.218***
			(0.016)	(0.016)
College			1.335***	1.297***
			(0.020)	(0.020)
Constant	0.433***	0.398***	0.334***	0.412***
	(0.007)	(0.011)	(0.001)	(0.010)
Observations	133,440	130,928	129,193	126,766
Location FE	NO	YES	NO	YES
Time FE	NO	YES	NO	YES
Weibull k	0.403	0.412	0.403	0.412

Source: VDAB: Mijn Loopbaan; Dimona; Datawarehouse Labor Market and Social Security
Notes: Standard errors in parentheses. Omitted categories for nationality, working regime preferences and education are lifetime Belgian national, full-time work and less than high-school qualification respectively.

Table 5: Explaining Job Finding Probabilities With Task Overlap Across Jobs

VARIABLES	(1) odds ratio	(2) odds ratio	(3) odds ratio	(4) odds ratio
$\ln V_i$	1.120***	1.128***	1.103***	1.114***
	(0.005)	(0.005)	(0.005)	(0.005)
$\ln U_i$	0.927***	0.927***	0.948***	0.945***
	(0.004)	(0.004)	(0.004)	(0.004)
V_i^{all}/V_i	1.235***	1.266***	1.218***	1.251***
	(0.031)	(0.032)	(0.031)	(0.033)
U_i^{all}/U_i	0.830***	0.814***	0.817***	0.805***
	(0.020)	(0.020)	(0.020)	(0.020)
V_{i2}^{some}/V_i	1.007	1.006	1.002	1.003
	(0.005)	(0.006)	(0.005)	(0.006)
V_{i3}^{some}/V_i	1.000	1.001	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
V_{i4}^{some}/V_i	1.000**	1.000*	1.000**	1.000*
	(0.000)	(0.000)	(0.000)	(0.000)
U_{i2}^{some}/U_i	1.014	1.015	1.041*	1.036
	(0.022)	(0.022)	(0.023)	(0.023)
U_{i3}^{some}/U_i	1.002	1.002	1.004	1.004
	(0.003)	(0.003)	(0.003)	(0.003)
U_{i4}^{some}/U_i	1.000	0.999*	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
Female		0.971***		0.962***
		(0.009)		(0.009)
Belgian nationality: acquired		0.886***		0.903***
		(0.010)		(0.011)
Foreign, EU nationality		0.821***		0.843***
		(0.014)		(0.015)
Foreign, other nationality		0.911***		0.955***
		(0.014)		(0.015)
Part-time		0.759***		0.770***
		(0.012)		(0.013)
Part-time or full-time		0.917***		0.913***
		(0.009)		(0.009)
High School			1.255***	1.219***
			(0.016)	(0.016)
College			1.349***	1.309***
			(0.021)	(0.021)
Constant	0.420***	0.385***	0.324***	0.411***
	(0.001)	(0.014)	(0.001)	(0.012)
Observations	134,793	132,257	130,428	127,979
Location FE	NO	YES	NO	YES
Time FE	NO	YES	NO	YES
Weibull k	0.403	0.411	0.403	0.411

Source: VDAB: Mijn Loopbaan; Dimona; Datawarehouse Labor Market and Social Security
Notes: Standard errors in parentheses. Omitted categories for nationality, working regime preferences and education are lifetime Belgian national, full-time work and less than high-school qualification respectively.

Table 6: The Importance of Task Overlap in the Probability of Finding a Job

	γ				β			
specification:	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
j :								
1	0.3501***	0.3388***	0.3318***	0.3253***	0.2907***	0.2695***	0.2088***	0.2078***
	(0.0284)	(0.0255)	(0.0304)	(0.0270)	(0.0281)	(0.0248)	(0.0235)	(0.0221)
2	0.0217	0.0177	0.0072	0.0082	-0.0540	-0.0525	-0.1562*	-0.1293
	(0.0163)	(0.0156)	(0.0185)	(0.0170)	(0.0815)	(0.0782)	(0.0866)	(0.0822)
3	0.0013	0.0015	0.0014	0.0014	-0.0082	-0.0085	-0.0156	-0.0149
	(0.0013)	(0.0012)	(0.0014)	(0.0013)	(0.0102)	(0.0095)	(0.0105)	(0.0098)
4	-0.0006**	-0.0005*	-0.0008**	-0.0005*	0.0017	0.0020*	0.0011	0.0016
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0011)	(0.0011)	(0.0011)	(0.0011)

Source: VDAB: Mijn Loopbaan; Dimona; Datawarehouse Labor Market and Social Security

Notes: Standard errors in parentheses. The imputed coefficients γ and β are calculated as a non-linear combination of estimated coefficients by means of the delta method.

Table 7: Explaining Job Finding Probabilities With Task Overlap Excluding Occupational Careers

VARIABLES	(1) odds ratio	(2) odds ratio	(3) odds ratio	(4) odds ratio
$\ln V_i$	1.122***	1.131***	1.106***	1.118***
	(0.004)	(0.005)	(0.005)	(0.005)
$\ln U_i$	0.928***	0.929***	0.950***	0.947***
	(0.004)	(0.004)	(0.004)	(0.004)
V_i^{all}/V_i	1.282***	1.312***	1.296***	1.320***
	(0.037)	(0.038)	(0.038)	(0.039)
U_i^{all}/U_i	0.793***	0.771***	0.746***	0.736***
	(0.026)	(0.025)	(0.025)	(0.025)
V_{i2}^{some}/V_i	1.006	1.005	1.001	1.002
	(0.005)	(0.006)	(0.006)	(0.006)
V_{i3}^{some}/V_i	1.001	1.001	1.001	1.001
	(0.000)	(0.000)	(0.000)	(0.000)
V_{i4}^{some}/V_i	1.000**	1.000**	1.000**	1.000**
	(0.000)	(0.000)	(0.000)	(0.000)
U_{i2}^{some}/U_i	1.002	1.009	1.023	1.025
	(0.023)	(0.023)	(0.020)	(0.020)
U_{i3}^{some}/U_i	1.001	1.002	1.003	1.003
	(0.002)	(0.002)	(0.002)	(0.002)
U_{i4}^{some}/U_i	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
Female		0.971***		0.962***
		(0.009)		(0.009)
Part-time		0.759***		0.770***
		(0.012)		(0.013)
Part-time or full-time		0.916***		0.913***
		(0.009)		(0.009)
Belgian nationality: acquired		0.886***		0.904***
		(0.010)		(0.011)
Foreign, EU nationality		0.821***		0.843***
		(0.014)		(0.015)
Foreign, other nationality		0.909***		0.952***
		(0.014)		(0.015)
High School			1.259***	1.222***
			(0.016)	(0.016)
College			1.356***	1.316***
			(0.021)	(0.021)
Constant	0.403***	0.390***	0.403***	0.317***
	(0.001)	(0.015)	(0.011)	(0.013)
Observations	134,722	132,187	130,361	127,913
Location FE	NO	YES	NO	YES
Time FE	NO	YES	NO	YES
Weibull k	0.403	0.411	0.403	0.411

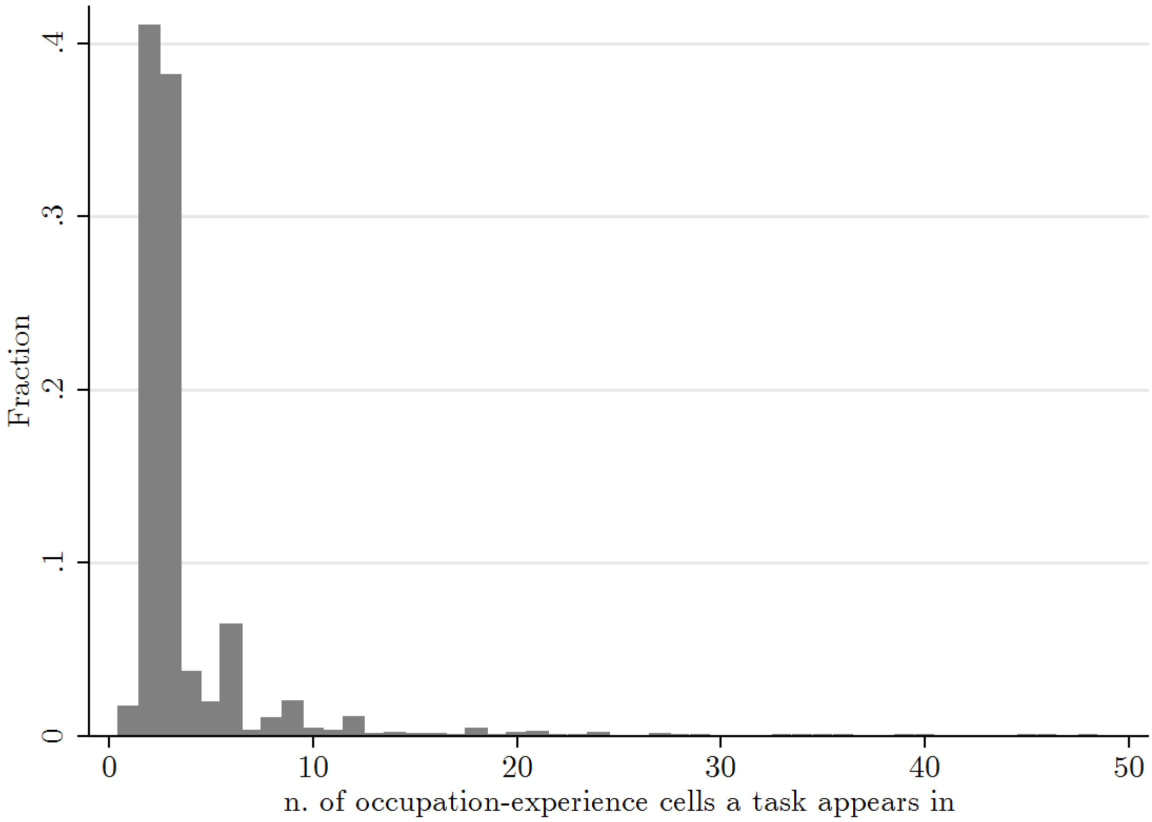
Source: VDAB: Mijn Loopbaan; Dimona; Datawarehouse Labor Market and Social Security
Notes: Standard errors in parentheses.

Table 8: Explaining Job Finding Probabilities By Degree of Task Overlap

VARIABLES	(1) odds ratio	(2) odds ratio	(3) odds ratio	(4) odds ratio	(5) odds ratio
lnV_i^{all}	1.134***				
	(0.004)				
lnU_i^{all}	0.925***				
	(0.003)				
lnV_{i1}^{some}		1.025***			
		(0.003)			
lnU_{i1}^{some}		1.016***			
		(0.004)			
lnV_{i2}^{some}			1.020***		
			(0.005)		
lnU_{i2}^{some}			0.972***		
			(0.005)		
lnV_{i3}^{some}				0.994	
				(0.004)	
lnU_{i3}^{some}				1.002	
				(0.004)	
lnV_{i4}^{some}					0.990**
					(0.005)
lnU_{i4}^{some}					1.002
					(0.006)
Constant	0.398***	0.416***	0.424***	0.387***	0.404***
	(0.011)	(0.011)	(0.021)	(0.012)	(0.014)
Observations	130,928	96,623	35,223	107,231	122,294
Controls	YES	YES	YES	YES	YES
Weibull k	0.412	0.416	0.424	0.404	0.402

Source: VDAB: Mijn Loopbaan; Dimona; DatawarehouseLabor Market and Social Security
Notes: Standard errors in parentheses.

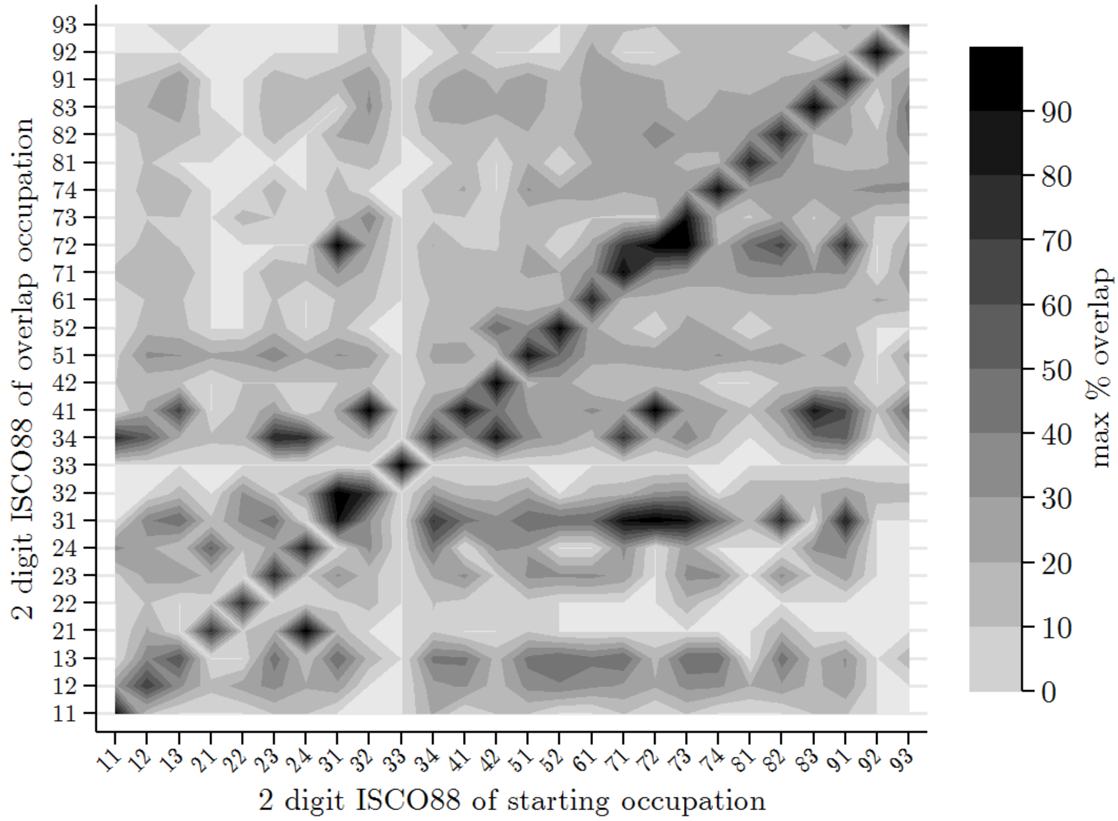
Figure 1: Density of the Number of Occupation-Experience Cells in which the Same Task Occurs



Source: ROME-V3

Notes: This histogram is right-censored for clarity. This discards 0.2% of the original distribution.

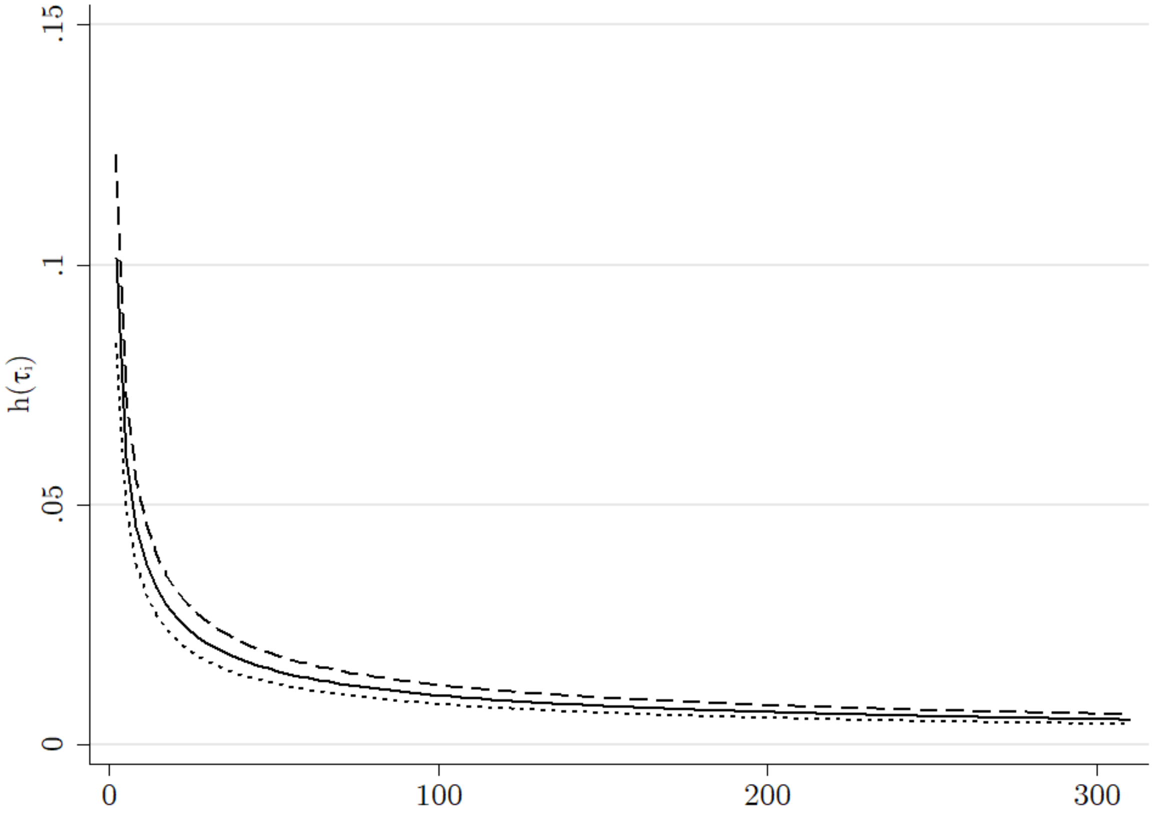
Figure 2: Task Overlap Across Occupation-Experience Cells



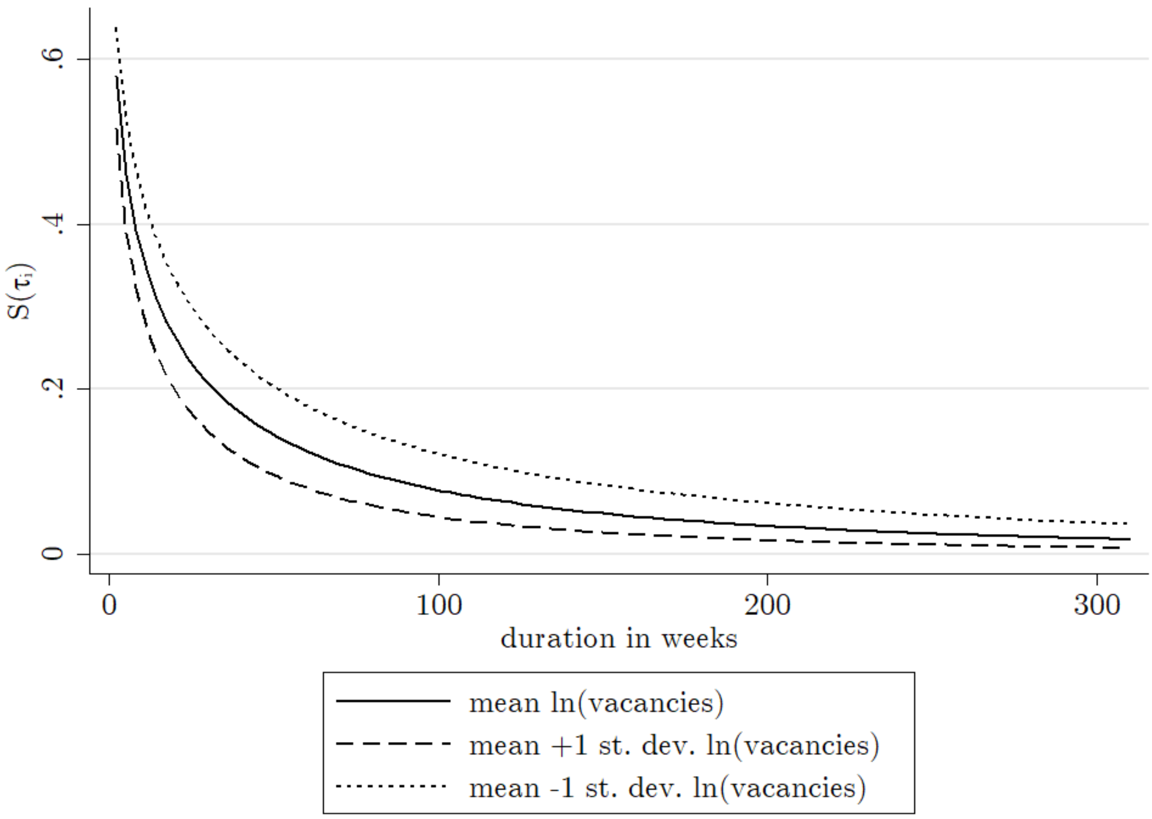
Source: ROME-V3

Figure 3: Hazard and Survival Functions for Different Levels of Vacancies

(a) Hazard Function



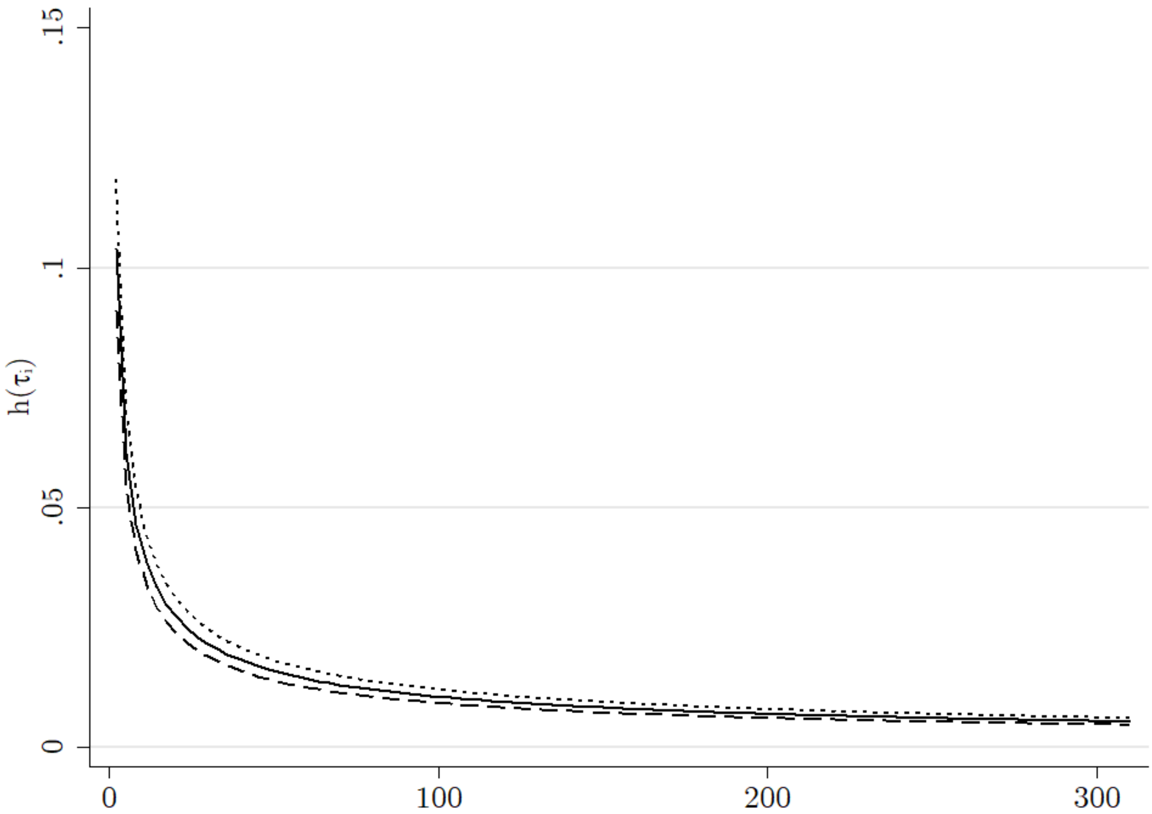
(b) Survival Function



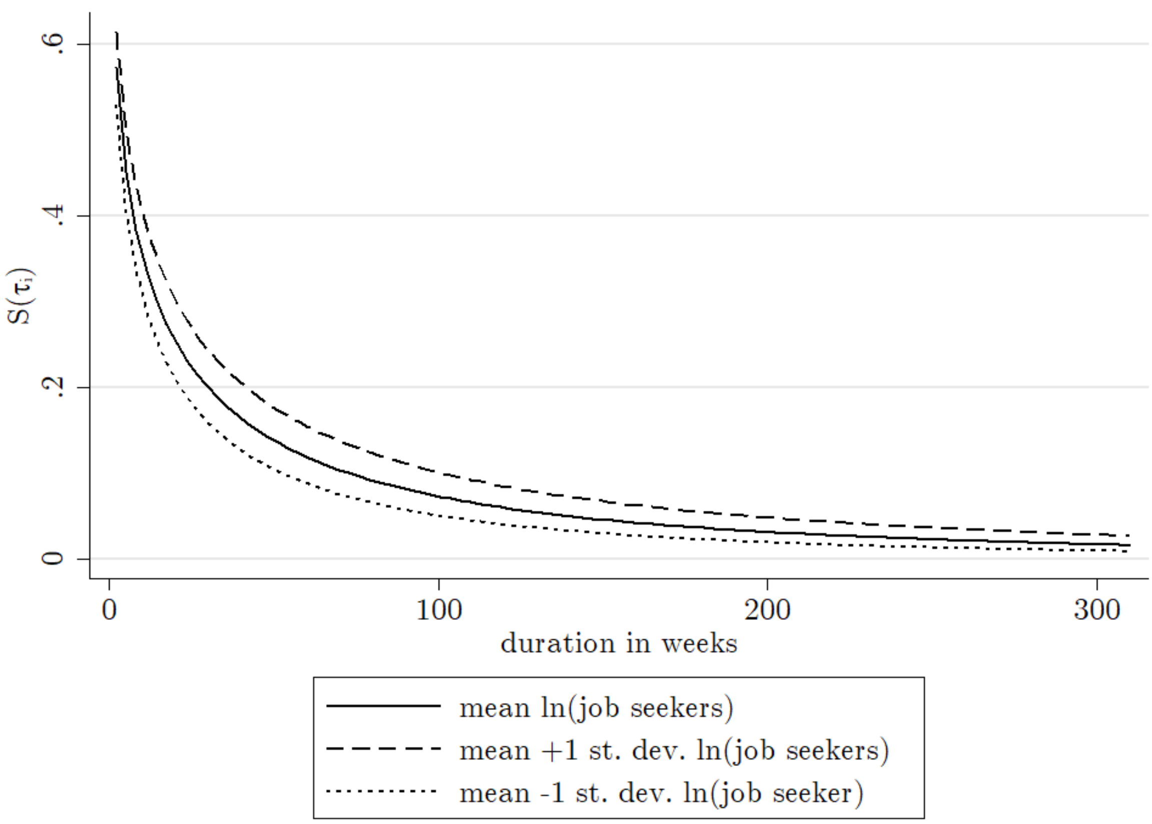
Source: VDAB: Mijn Loopbaan; Dimona; Datawarehouse Labor Market and Social Security
Notes: The level of job seekers is kept constant at the mean.

Figure 4: Hazard and Survival Functions for Different Levels of Unemployed Job Seekers

(a) Hazard Function

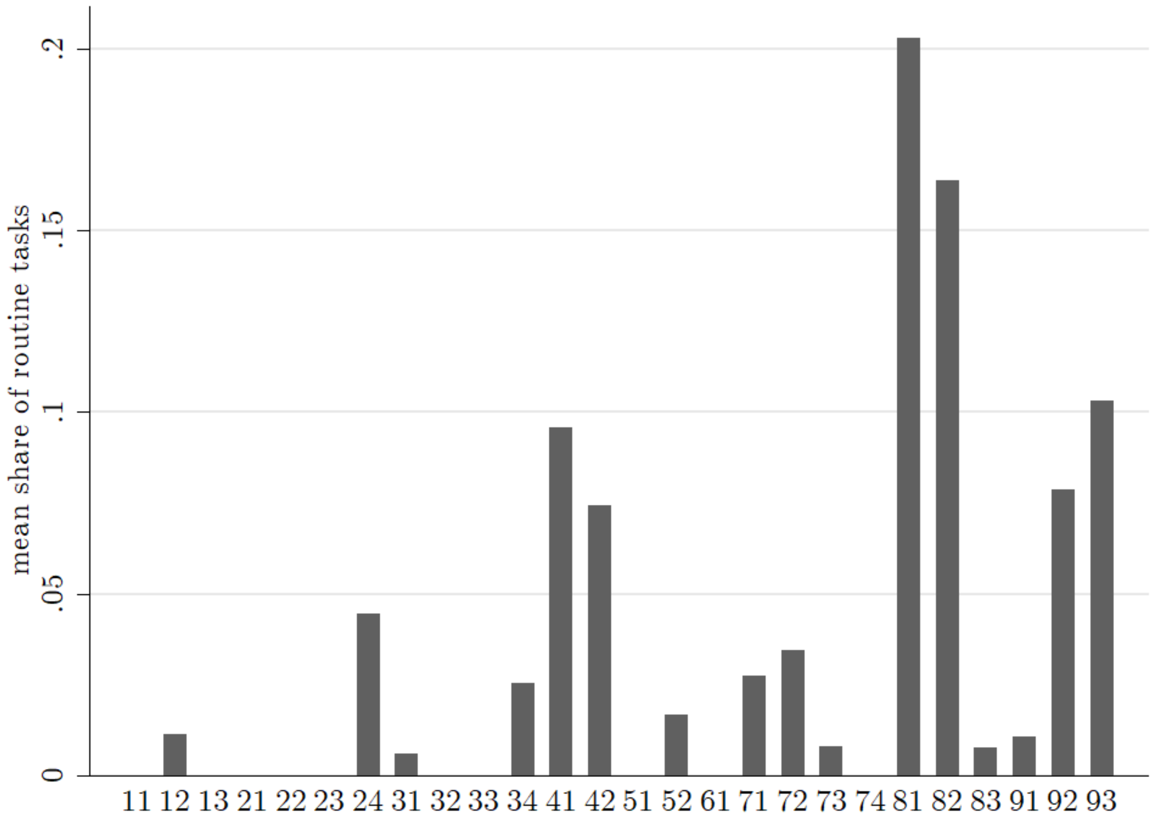


(b) Survival Function



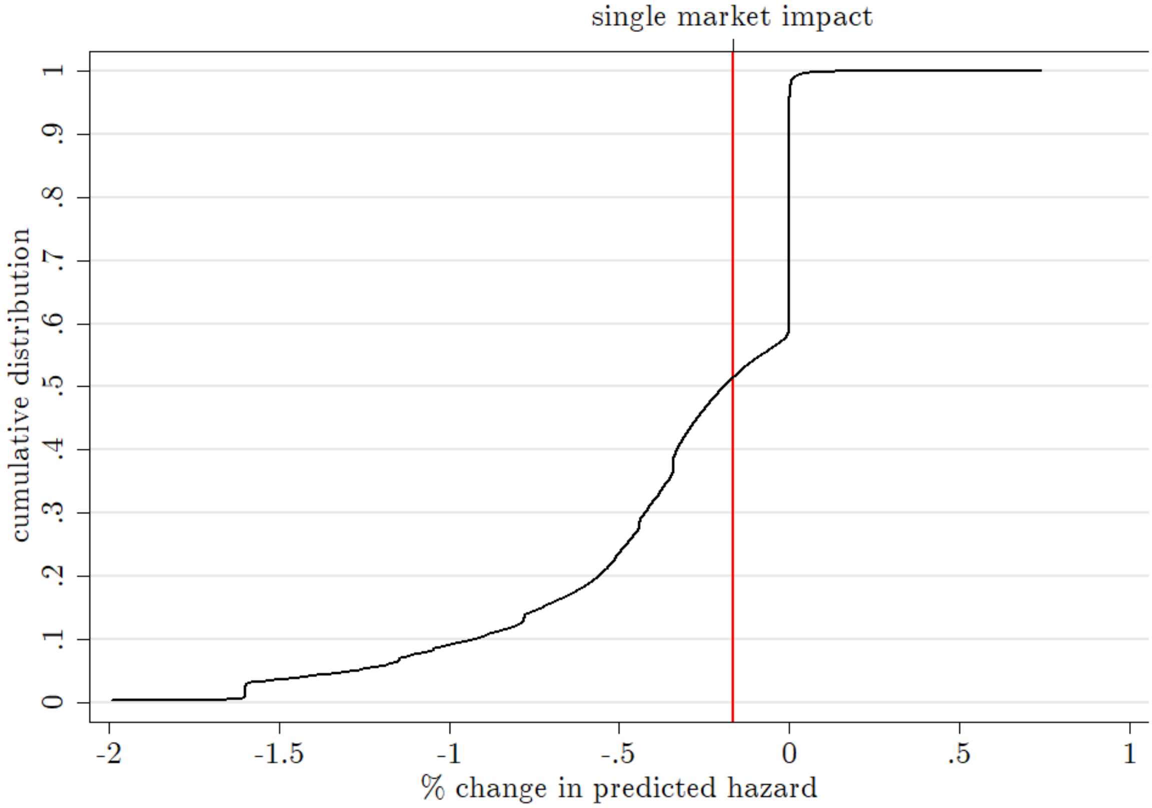
Source: VDAB: Mijn Loopbaan; Dimona; Datawarehouse Labor Market and Social Security
Notes: The level of vacancies is kept constant at the mean.

Figure 5: Mean Share of Routine Tasks in Occupation Experience Cells by ISCO88 2-digit groups



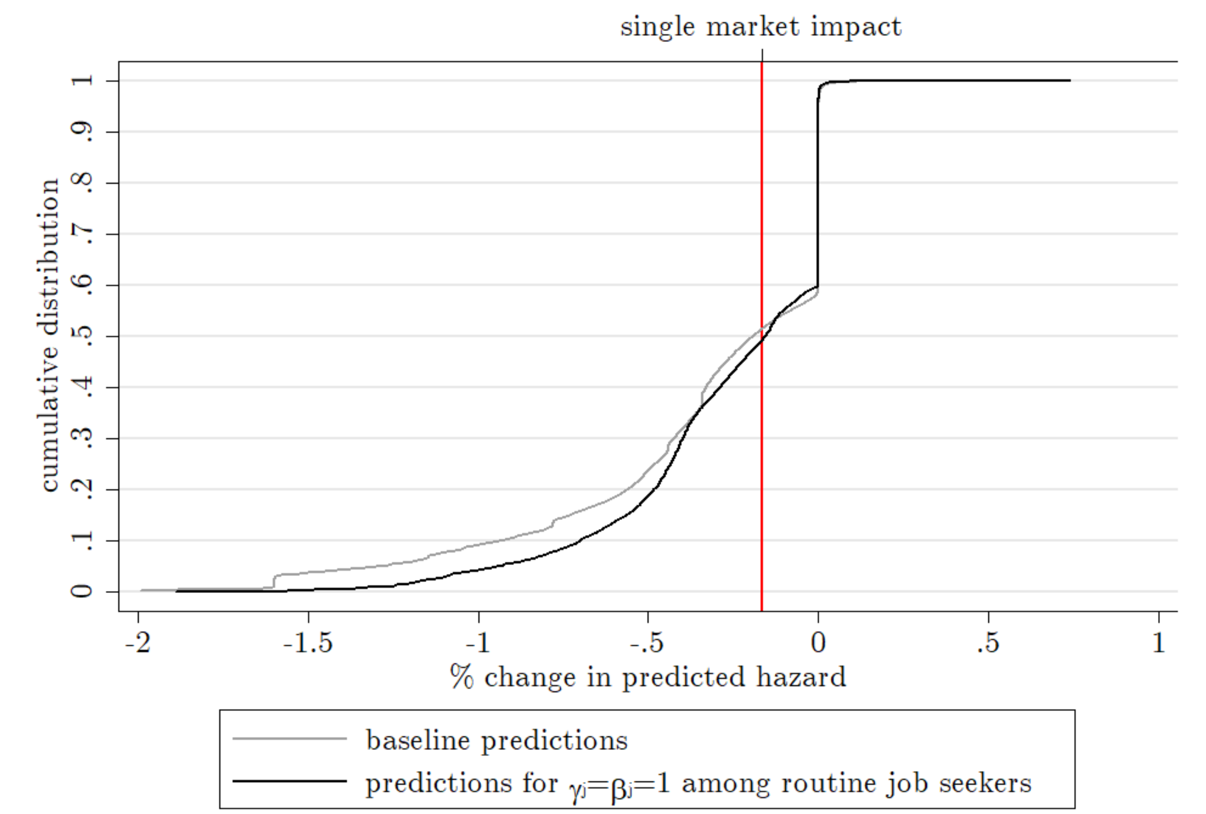
Source: ROME-V3

Figure 6: Distribution of Changes in Hazard Rates after negative shock



Source: VDAB: Mijn Loopbaan; Dimona; Datawarehouse Labor Market and Social Security
Notes: The figure is left censored at -2 for clarity. This discards 0.3% of observations.

Figure 7: Distribution of Changes in Hazard Rates after negative shock when the mobility of job seekers increases for routine job seekers and for all workers



Source: VDAB: Mijn Loopbaan; Dimona; Datawarehouse Labor Market and Social Security
Notes: The figure is left censored at -2 for clarity. This discards 0.3% of observations.

Appendix

A The VDAB sample

A.1 Sampling weights

Unemployed job seekers are sampled from the platform at the end of the first month of every quarter in 2013-2014, resulting in 8 cross-sections of unemployed job seekers with bi-weekly information about their (un)employment spells between 2010-2015. Because random sampling in these cross-sections would result in an over-representation of the long termed unemployed, leading to sample selection biases in our estimates. Therefore, each cross-section over-samples unemployed job seekers with shorter durations, using the percentages listed in Table A.1 of all unemployed job seekers registered on the platform. Moreover, each observation is weighted by the inverse of the total number of occupation-experience cells listed by an unemployed job seeker when registering on the platform.

Table A.2 shows how vacancies are sampled from the platform at the end of the first months of every quarter in 2013-2014. To make sure the sampling procedure represents the high turnover rate in vacancies, our sample contains 50% of all vacancies that closed in the month before sampling and 5% of all vacancies registered on the platform in the month before sampling. Because some vacancies are sampled twice in this stratification, we use the unique combination of all vacancies sampled, dropping any duplicates, to calculate the stock of vacancies. Again, we apply the inverse of the sampling probabilities to ensure representativeness throughout our duration analyses.

Table A.1: Sampling of Unemployed Job Seekers

Strata	Sampling Percentage of Total Population
Newly registered in last month	20%
1-2 months unemployed	20%
2-3 months unemployed	20%
3-6 months unemployed	10%
6-12 months unemployed	10%
More than 12 months unemployed	5%

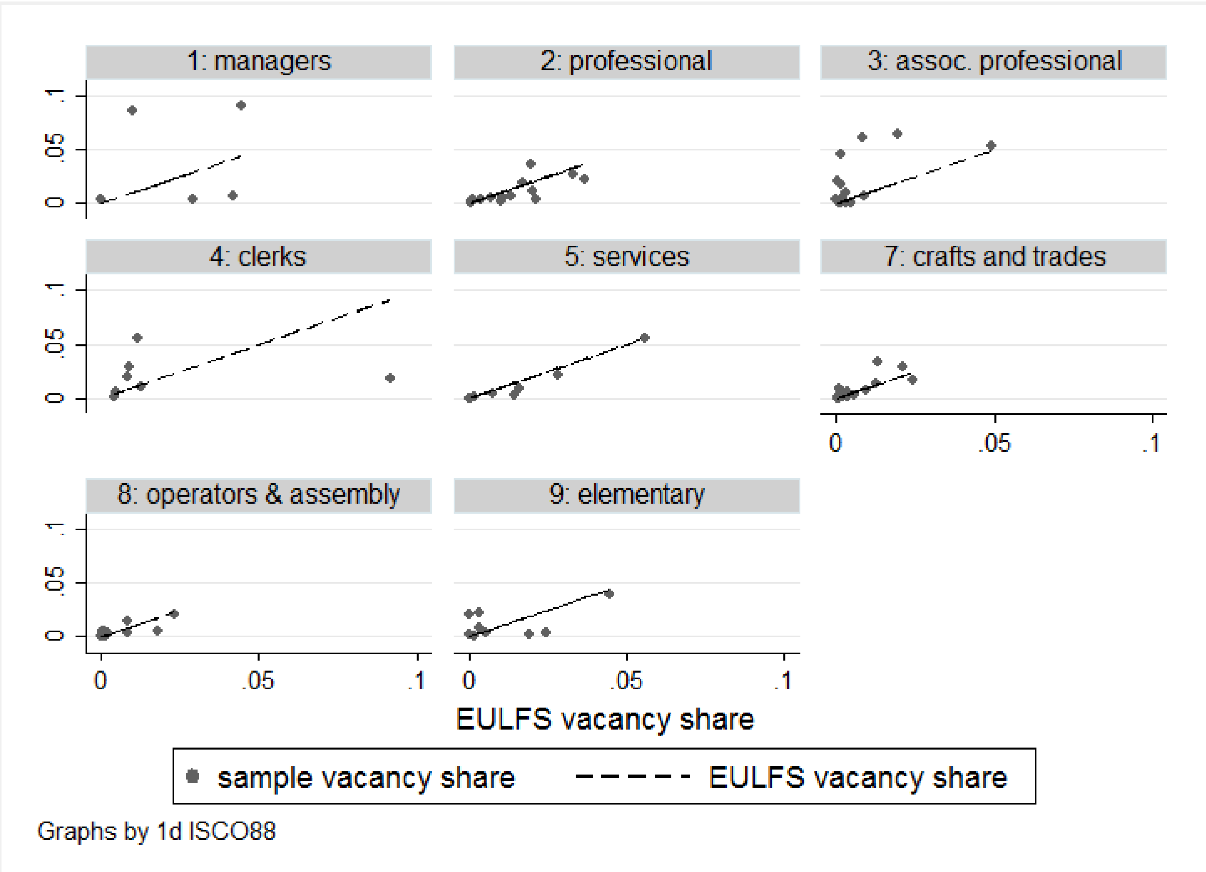
Table A.2: Sampling of Vacancies

Strata	Sampling Percentage of Total Population
Vacancies that closed in the past month	50%
All outstanding in the past month	5%

A.2 Representativeness of vacancies in the VDAB sample

To assess the representativeness of our vacancy data, we compare the share of vacancies across 3-digit ISCO88 occupation groups in our VDAB sample to vacancy information from a representative survey of Flemish firms provided by Belgium's office of national statistics. Figure A.1 plots the VDAB sample share (on the vertical axis) against the representative survey share (on the horizontal axis) by 1-digit ISCO88 occupation group and adding a 45-degree line to each panel. In general, shares are relatively close to the 45-degree line, suggesting that the composition of vacancies across occupations in our VDAB sample is representative of the labor market as a whole.

Figure A.1: Vacancy Shares at the 3-digit ISCO88 level by 1-digit group



Source: VDAB: Mijn Loopbaan; BELSTAT; EULFS

B Linearization of Tightness With Task Overlap Across Jobs

Following Manning and Petrongolo (2017), we apply a linear approximation to estimate γ_j and β_j. Substituting equation (2) into (1) results in:

$$\theta_i = \alpha_1\, ln(V_i^{all} + \sum_{j=1}^{4} \gamma_j V_{ij}^{some}) + \alpha_2\, ln(U_i^{all} + \sum_{j=1}^{4} \beta_j U_{ij}^{some}) \tag{11}$$

Because this equation is not linear in its parameters γ_j and β_j we use a Taylor approximation. First, define $V_i = V_i^{all} + V_{i1}^{some}$ and $U_i = U_i^{all} + U_{i1}^{some}$. Next, rearrange the components inside the log sum accordingly:

$$\begin{aligned}\theta_i = \alpha_1\, ln &\left(\gamma_1(V_i^{all} + V_{i1}^{some}) + (1-\gamma_1)V_i^{all} + \sum_{j=2}^{4} \gamma_j V_{ij}^{some}\right)\\ + \alpha_2\, ln &\left(\beta_1(U_i^{all} + U_{i1}^{some}) + (1-\beta_1)U_i^{all} + \sum_{j=2}^{4} \beta_j U_{ij}^{some}\right)\end{aligned} \tag{12}$$

and divide by our reference point multiplied by γ_1 and β_1 respectively:

$$\begin{aligned}\theta_i &= \alpha_1\, ln(V_i) + \alpha_2\, ln(U_i)\\ &+ \alpha_1\, ln\left(1 + \frac{(1-\gamma_1)}{\gamma_1}\frac{V_i^{all}}{V_i} + \sum_{j=2}^{4} \frac{\gamma_j}{\gamma_1}\frac{V_{ij}^{some}}{V_i}\right)\\ &+ \alpha_2\, ln\left(1 + \frac{(1-\beta_1)}{\beta_1}\frac{U_i^{all}}{U_i} + \sum_{j=2}^{4} \frac{\beta_j}{\beta_1}\frac{U_{ij}^{some}}{U_i}\right)\end{aligned} \tag{13}$$

Now this can be approximated according to a first-order Taylor expansion. While the choice of reference point is arbitrary, it should be chosen such that the shares are not too large.

$$\begin{aligned}\theta_i \approx \alpha_1 ln(V_i) + \alpha_2 ln(U_i) + \alpha_1 \frac{1-\gamma_1}{\gamma_1}\frac{V_i^{all}}{V_i} + \alpha_2 \frac{1-\beta_1}{\beta_1}\frac{U_i^{all}}{U_i}\\ + \alpha_1 \sum_{j=2}^{4} \frac{\gamma_j}{\gamma_1}\frac{V_{ij}^{some}}{V_i} + \alpha_2 \sum_{j=2}^{4} \frac{\beta_j}{\beta_1}\frac{U_{ij}^{some}}{U_i}\end{aligned} \tag{14}$$