

DISCUSSION PAPER SERIES

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Antoine Bertheau

Norwegian School of Economics and IZA

Birthe Larsen

Copenhagen Business School

Zeyu Zhao

University of Copenhagen

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ABSTRACT

What Makes Hiring Difficult? Evidence from Linked Survey-Administrative Data*

We designed an innovative survey of firms and linked it to Danish administrative data to yield new insights about the factors that can influence firms' hiring decisions. Several important findings stand out: (1) search and training frictions and economic uncertainty are as important as labor costs in hiring decisions; (2) search and training frictions are more likely to affect younger and smaller firms; (3) uncertainty is more likely to affect hiring decisions in low-productivity firms; (4) thirty percent of firms prefer to hire already employed persons over the unemployed, because they believe that unemployed workers have lower abilities due to negative selection or skill depreciation during unemployment; and (5) these firms are more likely to report that labor market frictions and labor costs considerations discourage them from hiring.

JEL Classification: J23, M12

Keywords: labor demand, hiring behavior, linked survey-administrative

data, employer perceptions

Corresponding author:

Antoine Bertheau Norwegian School of Economics Helleveien 30 5045 Bergen Norway

E-mail: antoine.bertheau@nhh.no

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1. Introduction

While hiring plays a crucial role in determining the level of employment and production, there is little evidence of how firms make their hiring decisions. Presumably, the decision to post a vacancy can be influenced by several factors, such as labor costs, uncertainty, or different forms of labor market friction. What are the factors that actually matter? Do they vary across firms? Answers to these questions can provide evidence that can be used by both policymakers and in search theories of the labor market.

Despite the high stakes of these questions, how employers search and make their hiring decisions is far less understood than the determinants of worker job search.¹ Recent literature has made progress in terms of understanding some aspects of hiring behaviors using vacancy data. For instance, it is well-documented that the job-filling rate for vacant positions varies with firm growth rate (Davis, Faberman, and Haltiwanger 2013).² However, such data are less suited to providing insights into how firms make hiring decisions.

This paper helps to fill this void by surveying Danish firms and linking responses to rich administrative data. Our survey collects responses from over 2,000 firms, which are a representative sample of the population of firms. We ask firms about the relevance of several hiring factors that can discourage them from hiring despite potential needs. We distinguish between skill shortages, labor costs, search time, training time, and economic uncertainty. We then associate the different reasons with firm characteristics (e.g., firm size, age, productivity) and the labor market they operate (e.g., tightness).

Besides firm and labor market characteristics, hiring decisions can be determined by firms' subjective beliefs. Our survey elicits firms' beliefs and sheds new light on how firms make hiring decisions. We first elicit beliefs about hiring job seekers with different statuses: those already employed and those who are unemployed. We ask whether they prefer to hire employed workers because they perceive the unemployed as having lower abilities, due to either negative selection or skill deterioration during the unemployment spell. We also investigate whether firms' labor cost concerns are

 $^{^1}$ Recent empirical studies on job search use novel survey or job search websites (e.g.,Fluchtmann, Glenny, Harmon, and Maibom (2022); Faberman, Mueller, Sahin, and Topa (2022)).

²See, e.g., Bagger, Fontaine, Galenianos, and Trapeznikova (2022), Carrillo-Tudela, Gartner, and Kaas (2022), Mueller, Osterwalder, Zweimüller, and Kettemann (2023), Lochner, Merkl, Stüber, and Gürtzgen (2021), Carrillo-Tudela, Kaas, and Lochner (2022), and Bagger and Galenianos (2022). Mercan and Schoefer (2020) and Elsby, Gottfries, Michaels, and Ratner (2023) are theoretical framework.

³Employers must report their perceptions using a 5-point Likert scale: strongly disagree, disagree, neutral, agree, or strongly agree. Our survey includes open-ended text answers to allow employers to express their opinions on other reasons.

related to firms' misperception of their own wage level. We measure misperception by comparing the firm's actual position in the wage distribution from administrative data to their beliefs. Overall, this paper is the first comprehensive study of the determinants of hiring decisions.

Our findings can be summarized as follows. First, we show that search and training frictions and economic uncertainty are as important as labor costs in hiring decisions. We find that around 70% of the firms agree that the lack of qualified workers discourages them from hiring despite their potential needs (labeled "skill shortage"). Around 40% agree that job seekers ask for a higher wage than the firm can offer (labeled "labor costs"). More than a third agree that search and matching frictions matter, and a similar percentage of respondents report that training new hires in firm-specific skills discourages them from hiring (labeled "search time" and "training time"). The uncertainty of economic activity is also a concern for more than a third of the respondents. We develop a DMP-style search and matching model and show that this model predicts these concerns.

Second, we associate factors that influence hiring decisions with firm characteristics. High-wage firms are less likely to consider labor costs a hiring obstacle. However, these firms are as likely to report skill shortages being a hiring obstacle as lower wage firms. This suggests that there are labor market frictions that cannot be resolved by only increasing wages. Wages do not affect search or training frictions either. On the other hand, smaller and younger firms are more likely to be affected by search and matching frictions. However, they are not more likely to experience difficulties due to skill shortages or labor costs than larger or older firms. Our evidence suggests that hiring frictions for younger firms can lead to the misallocation of labor resources. The uncertainty of economic activity is less likely to alter hiring decisions for high-productivity firms (as predicted in a search and matching model with uncertainty, e.g., Den Haan, Freund, and Rendahl (2021)). Our data on the full population of workers and firms enable us to provide novel evidence of the role of monopsony power in hiring decisions. We document that an increase in a firm's employment share in its local labor market is associated with lower search friction (as predicted in Manning (2021)).

Third, we show that subjective beliefs partly explain firms' hiring decisions. We start by documenting wide variation in the preferences for hiring employed workers over the unemployed. Around a quarter of employers prefer to hire employed workers, believing that skills deteriorate during unemployment. A similar share of firms indicate the same

⁴Our estimates control for detailed characteristics of the market, the firm, and the respondent.

preference because they believe that the unemployed have lower abilities on average. Our estimates reveal that the preference for hiring the employed over the unemployed increases the probability of agreeing that multiple factors discourage them from hiring by 10 percentage points. This effect is large compared to firm characteristics such as wage premiums. There may be concern that differences in abilities between employed and unemployed workers drive the correlation. To limit this concern, we estimate an AKM model and compare worker fixed effects (i.e., skills and other factors that are rewarded equally across firms) across workers with different employment statuses. We find that the unemployed do indeed have lower abilities on average, which is consistent with previous findings (e.g., Gregory, Menzio, and Wiczer (2022); Darougheh (2023)). Interestingly, including the difference between the abilities of the employed and the unemployed in our regressions does not have a strong quantitative impact on our estimates of preferring hiring employed workers on firms' hiring difficulties.

Moreover, we show that firms' misperception of their wages affects hiring decisions. When firms believe that they offer lower wages than their peers, while the administrative data show the opposite, they are more likely to agree that labor costs discourage them from hiring. This effect is also important in magnitude, as underestimating its wages increases the probability of reporting labor costs as an obstacle by 6 percentage points. Our results suggest that the stigma of the unemployed and firms' misperceptions of their wages could substantially influence firms' hiring decisions.

We conduct several tests to validate our survey and strengthen the credibility of our results. First, we show that survey responses regarding firm size and change in revenue are consistent with the same measures from the administrative data. Second, our estimates are robust when we change our baseline specification. Our estimates control for labor market conditions that could make hiring more or less difficult across firms, as well as the extent of job amenities that firms offer.

The institutional setting of the labor market, the economic context, and the representativeness of our survey limit the concern that our results are specific to Denmark. Danish firms are not subject to stringent hiring and firing regulations, and wages are typically set at the firm level. When we conducted our survey in the summer of 2021, the labor market was tight, but not historically tight, as it was in 2022. Hence, the empirical case of Denmark provides access to unique data without limiting external validity.

⁵For the unemployed, the worker effect is estimated before the last unemployment spell. This procedure limits the concern that previous unemployment spells bias worker effects.

⁶We measure the difference in the employed and the unemployed at the occupation level and construct a firm-level measure of the difference using the occupational composition of firms.

Contribution. The core contribution of this paper is a comprehensive descriptive analysis of the factors that influence firms' hiring decisions, how they vary with firm characteristics, and how they vary with firms' subjective beliefs. We do so by collecting novel data on firms' hiring decisions linked with detailed register data. The main difference between this paper and most of the literature is that we do not use vacancy data to study hiring behavior. Using vacancy data, recent literature has made important progress in terms of understanding some aspects of hiring behaviors, starting with seminal work by Davis, Faberman, and Haltiwanger (2013). However, factors influencing decisions to open a vacancy cannot be easily captured by data focusing on firms that post a vacancy. These factors are likely to matter, since the majority of firms report that they have hiring difficulties in the US and Europe (see Figure A.1). For this reason, we believe that this paper complements the literature in important ways.

First, to our knowledge, we are the first to compare the role of labor costs and matching frictions as factors affecting firms' hiring decisions. A closely related work is Bergeaud, Cette, and Stary (2022). They show that French manufacturing firms believe that labor shortage is a more prominent obstacle than labor costs. However, existing studies do not document the extent of search and matching frictions as we do. One key takeaway from this paper is that ex-ante and ex-post matching frictions (i.e., search and training times) are relevant factors in hiring decisions. This result is consistent with novel evidence that we provide of the expected time it takes for a new employee to be as productive as an average employee in a similar position. A quarter of firms believe it will take at least one year, which is consistent with evidence suggesting a slow productivity growth among new hires (Caplin, Lee, Leth-Petersen, Sæverud, and Shapiro 2022; Bertheau, Cahuc, Jäger, and Vejlin 2022). These results support labor market models (e.g., Faccini and Yashiv (2022)) that show how predictions differ when hiring costs include both vacancy posting and training costs.

Second, this paper is the first to link hiring obstacles to firms' financial situations, workforce characteristics, and labor market conditions. This unique linking of survey and administrative data yields several results. Two key findings stand out.

A more generous wage policy is associated with fewer hiring difficulties due to labor costs. However, our data show that paying higher wages is not associated with firms being less discouraged by skill shortages. Neither are these firms less likely to be concerned about ex-ante and ex-post matching frictions. This result suggests that labor market frictions cannot be completely resolved by only offering higher wages. These results complement Mueller, Osterwalder, Zweimüller, and Kettemann (2023).

They show that wage premiums can only account for a small fraction of the variation in vacancy-filling rates across establishments.

Search and training frictions are more likely to alter hiring decisions for younger firms. Heterogeneity on the age margin is important given the role young firms play in employment growth (Sterk, Sedláček, and Pugsley 2021; Sedláček and Sterk 2017). There are several explanations for this. Younger firms have a smaller network and are less capable of using referrals as hiring channels. Job seekers might also be reluctant to apply to younger firms because of low visibility and imperfect information about the quality of these firms. Future research could disentangle these channels.

Third, this paper is the first to associate hiring decisions with firms' subjective beliefs. After controlling for differences in workers' abilities between employed and unemployed, we find that firms' preference for hiring employed workers affects their hiring decisions. This finding complements Faberman et al. (2022), who show that the job search of the employed is more effective than that of the unemployed, and that this impacts macroeconomic fluctuations.⁷ To our knowledge, we provide the first evidence linking firms' vacancy creation and their beliefs about job seekers' abilities.

Finally, we show that a firm's misperception of its wages matters at the hiring margin. This result complements new literature documenting labor market frictions for firms (e.g., Cullen, Li, and Perez-Truglia (2023); Bertheau and Hoeck (2023)). So far the literature has focused on the effect firms' misperception of wages has on salaries. We show that it can influence a firm's hiring decision.

Overall, this paper provides a better understanding of the matching process between workers and firms by providing novel descriptive facts about firms' hiring decision processes. Also at the descriptive level, the demand side is less understood than the supply side. One reason for the lack of research on the demand side is the difficulty of collecting data. We also believe that knowledge about how beliefs explain hiring decisions is sparse compared to other topics (e.g., Jäger, Roth, Roussille, and Schoefer 2023; Mueller and Spinnewijn 2023a; Candia, Coibion, and Gorodnichenko 2023).

The paper is organized as follows. Section 2 describes the dataset and the institutional setting. Section 3 documents factors influencing hiring decisions and how they vary across firm characteristics. Section 4 documents how these factors vary across firms' subjective beliefs in our survey. Section 5 concludes.

⁷The feedback between employed workers' search effort and firms' vacancy creation incentive amplifies the economy's response to a negative productivity shock (see also Faccini and Melosi (2023)).

⁸Other studies focused on other topics, such as firms' production processes (Kuhn, Luo, Manovskii, and Qiu (2023)) or firms' inflation expectations (Andrade, Coibion, Gautier, and Gorodnichenko 2022).

2. Linked Firm-Level Survey-Administrative Data

The main dataset is a large-scale survey we conducted in 2021 among private sector firms in Denmark. We linked this survey to administrative datasets using unique firm identifiers. We subsequently collected information about each firm's financial situation, workforce characteristics, and the labor market conditions under which they operate.

2.1. Survey Overview

Sample frame. An international consulting firm (Rambøll) conducted the online survey by sending invitation emails to firms in June 2021. The target population was all private and public limited firms (ApS, Anpartsselskab and A/S, Aktieselskab) in Denmark, excluding the agricultural and mining sectors. The coverage error, i.e., the difference between the potential pool of respondents and the target population, should be negligible, since all firms in Denmark must be able to receive emails from the authorities (e.g., the tax authority). The international consulting company has access to a dataset that links legal firm identifiers to company email addresses. The survey closing date was at the beginning of August 2021, and reminders were sent in July to increase the response rate.

Invitation letter. The email contained an invitation letter stating that Rambøll was surveying on behalf of the University of Copenhagen. The invitation letter was designed to recruit as many respondents as possible to minimize selection bias. It provided useful information to respondents: the deadline for completing the survey and that it could be completed using mobile-friendly devices. The actual topic of the survey was kept vague and used simple language to minimize selection bias. The University of Copenhagen logo was visible, and we explained that the data generated would comply with data protection rules (see Figure A.10). An invitation letter containing this information increases the response rate (Stantcheva 2023).

Question ordering. The questionnaire starts with background questions about respondents and firm characteristics. Respondents must state their role in the firm, their knowledge of pay and employment policies, the number of employees, and the change in revenue in 2020 compared to 2019. We thereby demonstrate that the respondents know the economic situation of the firm (see Figure A.2). The survey also asks questions about firm characteristics that are unavailable in administrative data sets. We

ask whether one person or a family owns the company and whether it subcontracts for other firms. The next part of the questionnaire asks questions about layoffs and wages. Using these questions, Bertheau, Kudlyak, Larsen, and Bennedsen (2023b) and Bertheau and Hoeck (2023) study why firms lay off workers instead of cutting wages, and firms beliefs about wage setting. This study mainly focuses on the second part of the questionnaire, which asks questions about firms hiring decisions (Appendix B.2 reports the questionnaire).

Types of questions. Qualitative questions are reported in five answer categories to make the Likert scale manageable following common practice (Dillman, Smyth, and Christian 2014). The five categories are as follows: "Strongly agree", "Agree", "Neutral", "Disagree", and "Strongly disagree". The odd number of categories ensures that there is a middle option.

2.2. Administrative Data on Firms and Workers

We link our data to eleven additional datasets to collect information on firm-specific and market-specific characteristics that can explain responses in our survey. We report the main characteristics of the administrative data for firms and workers in this section. Appendix B.1 reports additional information.

Firm and worker characteristics. We use the dataset FIRM (Generel firmastatistik) which contains annual financial statements for private sector firms (excluding the agricultural and financial sectors) up until 2020. Nonfinancial information, such as firm age and industry codes, is also extracted from this dataset. Workforce characteristics are obtained from various administrative registers and are averaged at the firm level. We measure whether an employee belongs to a union, her education level, age, sex, and job tenure. In addition, we have access to a dataset that indicates whether a wage floor applies to each occupation (1-digit level) by industry (3-digit level). When at least 50% of a firm's employees are subject to wage floors, we classify this firm as being covered by wage floors. We measure the extent of non-wage job amenities using a mandatory employer survey (LONN, Lønstatistikken).

Aggregate labor market conditions. We use a dataset containing the universe of job vacancies posted online. We calculate the tightness of the labor market that applies to a firm, given its workforce composition. The tightness for firm j, denoted by θ_j , is the weighted sum of the two-digit occupation-specific (o = 1....O) labor market tightness ($\theta_0 = \frac{V_0}{U_0}$).

(1)
$$\theta_j = \sum_{o=1}^O w_{oj} \theta_o,$$

where V_0 and U_0 are the number of vacant jobs and the number of unemployed in an occupation o. $w_{oj} = \frac{N_{oj}}{N_j}$ is the number of workers in an occupation (N_{oj}) over the number of workers in the firm in 2019 (N_j) . We complement this measure with the percentage of unfilled vacancies and the percentage of new hires who are unqualified. Both measures are estimated from a firm-level survey (*Rekrutteringssurvey*) that asks about the hiring outcomes for a specific job vacancy four months after the vacancy is posted on a job board. Therefore, we calculate the job (un)filling rate at the occupation level, and then construct the firm level filling rate weighted by the share of each occupation in each firm. Overall, our administrative data enable us to link hiring decisions to firm characteristics, controlling for the workforce characteristics of firms and labor market conditions.

2.3. Institutional Setting and Economic Context

Institutional setting. Hiring and layoffs are not subject to stringent regulations. Denmark ranks 26 out of 36 countries on the OECD employment protection index. The US is ranked 36 (Kreiner and Svarer 2022). For 80 percent of private sector workers, the wages are set at the firm level, and wage floors apply to the other 20 percent (Dahl,

⁹Most vacancies are scraped from the two largest job board platforms in Denmark (Jobnet and Jobindex). In Denmark, workers must file their occupation at the start of an unemployment spell.

¹⁰Hoeck (2023) is the first to use a firm-specific tightness measure. We use national level tightness as the labor market in Denmark is relatively small, and dividing it into regional level would increase the variation in our measure.

¹¹We link these measures to our survey using the share of employment in each occupation. The matching rate between the survey we conducted in 2021 and this repeated survey is too low to be used directly. The survey is conducted by the National Employment Policy Agency (STAR). This survey is used to describe the aggregate labor market conditions in each quarter.

¹²Danish firms adjust at hiring and separations when they face shocks (e..g, Bonin (2023); Bertheau and Vejlin (2023).

Le Maire, and Munch 2013). Wage floors are minimum wages a firm must pay in an occupation and industry for workers who do not have experience. However, firms usually deviate from it by paying higher hourly wages. Employment clauses through which firms attempt to prevent employees from being employed by other firms are prohibited.

Economic context. Figure A.1 measures hiring difficulties in Europe and the United States. These figures show that the hiring difficulties were not as high in 2021 as in 2022 (see also Figure A.9). June 2021 was an opportune time to ask about human resources strategies because the world economy and the Danish economy were on the recovery track.

2.4. Sample Characteristics

Sample restriction. We impose the following sample restrictions. Firms and the respondents had to i) employ at least five employees in 2019, ii) operate in the private sector, iii) have financial information, and iv) (the respondents) have sufficient knowledge of the human resources policy of the firm.¹³

Sample representativeness. Table 1 reports descriptive statistics for the dataset for different samples. Column 1 and column 2 show the mean of the population of firms under study and the mean in our sample, respectively. The sample overrepresents larger (33 vs. 39 employees), older (18 vs. 21), and more productive firms (EUR 88,000 vs. EUR 95,000 value added per worker). The characteristics of the employees who work for the firms we surveyed are mostly similar. We reweight our sample so that it is more similar to the population reported in column 1. We construct weights using the entropy-balancing method (see Hainmueller and Xu 2013) to match the firm size, firm age, industry composition, and region. We use these weights throughout the paper. In our reweighted sample (column 3), the differences between the sample and the population are small. Overall, our final sample has a response rate of about 9.44% (2059/21797) and is relatively representative of the population.¹⁴

¹³Specifically, we delete respondents who respond "I only know a little about pay and employment conditions" to the question "In the following questions, we ask about pay and employment practices. How close are you to such decisions?" The two other choices for this question are: "I am responsible for pay and employment conditions". and "I am not responsible, but I know about pay and employment conditions".

 $^{^{14}}$ A response rate close to 10% is not rare in non-mandatory firm survey data. Scur et al. (2021) report that response rates range from 0.1% to 13% in recent firm surveys.

TABLE 1. Descriptive Statistics Across Samples of Firms

	Firm Population (Admin. data)	Linked Survey-Admin. (Unweighted)	•	
Firm characteristics				
Number of employees	32.79	38.86	32.79	
Firm age	18.05	20.70	18.05	
Productivity	88.09	95.13	88.09	
Wage premium	-0.01	0.00	-0.01	
In manufacturing (%)	14.50	18.75	14.50	
In services (%)	60.00	58.77	60.00	
In other sectors (%)	25.50	22.49	25.50	
In Copenhagen (%)	27.66	25.69	27.66	
Covered by wage floor (%)	16.20	17.24	17.10	
Employee characteristics				
Female (%)	28.63	28.39	29.06	
Age	40.24	42.12	40.89	
Tenure (years)	4.74	5.40	4.97	
Bachelor's degree and above (%)	18.94	22.46	20.83	
Unionized workers (%)	55.83	60.79	57.90	
Observations	21797	2059	2059	

Note: This table compares firm characteristics of the sample to the population of firms. Column 1 reports the mean characteristics of the population, i.e., firms with at least five full-time employees in 2019 with financial data. Columns 2 and 3 report the mean of the unweighted and the weighted sample, respectively. See Section 2 for more information about the variables and the weights.

Validating our survey. We use two questions from our survey to validate a respondent's attention to and knowledge of the economic situation of the firm. The question on firm size is "How many employees were in the firm on May 1, 2021?" We compare the reported number to the number of employees in March 2021 in the matched employer-employee dataset (BFL). Figure A.2, Panel (a) shows that the results are similar. The second question concerns the revenue change from 2019 to 2020. We classify firms, both in our survey and in firms' financial account data (FIRM), as unchanged, increased, and decreased. Figure A.2, Panel (b) shows that the administrative data and the survey responses align well. The figure shows that most participants know the firm's economic situation. We also use other available sources to verify specific survey questions, which we will discuss in the following sections.

2.5. Regression Models

We use ordered probit models to test the relevance of several hiring obstacles. The outcome variable reports the response to our main question "What factors can discourage the firm from recruiting despite the potential need?". The outcome variable takes five different values: Strongly agree, agree, neutral, disagree, strongly disagree.

$$y_i^* = \beta \mathbf{x}_i' + \gamma_{\text{region}} + \eta_{\text{industry}} + \varepsilon_i$$

The ordered probit model includes region and industry fixed effects. We report marginal effects (multiplied by 100) where covariates are evaluated at their mean values. Therefore, estimates reported in tables are interpreted as percentage point changes. We report the baseline probability of agreeing with the outcome variables, to enable us to measure the magnitude of the effects.

Wage premiums. To estimate firm and worker fixed effects, we estimate an AKM model (Abowd, Kramarz, and Margolis 1999) using the following specification:

$$Y_{it} = X'_{it}\beta + \alpha_i + \psi_{i(i,t)} + \varepsilon_{it},$$

where Y_{it} is the log of hourly wages of worker i in period t, X_{it} are exogenous covariates, α_i is the unobserved worker effect, j (i, t) is the firm where i works at t, $\psi_j(i,t)$ is the unobserved firm effect, and ε_{it} is an idiosyncratic error term. We include in X_{it} an

¹⁵Manning (2003, Chapter 10) also uses ordered probit models in its analysis of the job-filling rate.

unrestricted set of year dummies, as well as quadratic and cubic terms in age fully interacted with educational attainment. The model is estimated using data from 2008 to 2019. The firm-specific wage premium $\psi_{j(i,t)}$ is reported in Table 1 (labeled "wage premium"). It represents the proportional wage premium (or discount) paid by firm j to all employees. Such a premium is typically interpreted as rent-sharing, efficiency-wage, or strategic wage posting behavior to attract and retain employees. The worker effect is typically interpreted as a combination of skills and other factors that are rewarded equally across firms (Card, Cardoso, Heining, and Kline 2018).

Additional controls. We include the firm ownership type (family-owned firm), capital stock, liquidity, the change in revenue and employment, educational attainment of new hires (as a proxy for upskilling), subcontracting to other companies, and the presence of a representative worker as additional controls in our regressions. The rich firm-level financial account data available for all firms enable us to control for heterogeneity in firm performance. Our regressions also include the average of the following employee characteristics: percentage unionized, percentage of women, average age, job tenure, percentage of workers with at least a bachelor's degree, and an index of the intensity of routine tasks. See Section B.1 for further information. We include a dummy indicating the respondents' knowledge of HR policy and their occupations. We also include labor market concentration at the industry-region level. We show that our main results are not affected by these additional controls.

3. The Determinants of the Hiring Decision

Posting a job vacancy, i.e., the hiring decision, can be influenced by several factors, such as labor costs, uncertainty, or different forms of labor market friction. This section first documents the obstacles discouraging firms from hiring despite potential needs. We then show how these obstacles vary across firms using rich administrative data on firms, their employees, and the labor market in which they operate.

Survey question on hiring decisions. The wording of the survey question on hiring decisions is: "What factors can discourage the firm from recruiting despite the potential need?" Respondents must report their perceptions about five possible factors. To ensure

¹⁶We estimate the model using a matched employer-employee dataset (IDAN) containing information about the universe of jobs, including information about total earnings and total hours worked for each employment relationship at the yearly frequency.

that we did not leave out any important factors, there is an additional category that asks firms to provide details of "other" factors. ¹⁷ This question is directly related to the canonical Diamond-Mortensen-Pissarides (DMP) model of the labor market. When the value of recruiting is above a threshold, firms engage in searching for a worker. ¹⁸ However, empirical evidence about firm's decision to open a vacancy is rare, even though vacancy creation is key to explaining labor market fluctuations (e.g., Mercan and Schoefer (2020), Qiu (2023)).

3.1. The Relative Importance of Different Hiring Obstacles

Figure 1 reports the responses to the survey question. The most prevalent hiring obstacle is the lack of qualified candidates, which more than 70% of the firms agree with. This is the most popular answer and is almost twice as popular as the second most popular one. A significant share of the firms also agree that other factors discourage them from hiring. Around 38% of the firms agree that the jobseekers' wage expectations are too high. Around 36% of the firms agree that searching for the right employee is too time-consuming, while around 35% of the firms agree that training employees in firm-specific skills is too time-consuming. Around 37% of the firms say that uncertainty about economic activity discourages them from hiring. Figures A.3 displays the responses by industry. It affects more firms in the construction and hospitality sectors than in the other sectors (Figure A.3). This figure shows that the training time for new employees is a key concern for firms.

To better understand the role of training time, we ask two additional questions. First, we ask: "When recruiting an employee, which part of the hiring process is most costly in time or money?" Firms can either select "Search for candidates, conducting interviews" or "Training of new employees (either by his /her manager or colleagues). Sixty percent of firms declare that training costs more than search. For the subsample of firms that hire in 2020, we ask: "When will the newly hired employee achieve/have achieved the same productivity as an average employee in a similar position? Please indicate the estimate in months." Respondents can choose options from zero month up to eighteen months. Around 35% of firms think it will take from zero to three months, while 25% of

¹⁷We find that the majority of the "other" factors are similar to or are variants of the five categories we provided in the survey.

¹⁸Pissarides (2011) writes: A job is an asset owned by the firm: if it is vacant it has some value because it can expect to recruit a worker and yield some profit in the future; if it is filled it is producing for profit. Vacant jobs are like nascent investment projects that have not started yielding a return yet. If their net value is positive, the firm can create them for profit; if it is negative, it is losing money from them, so it makes sense to close them down.

firms believe it will take at least one year. This additional evidence is consistent with Figure 1. Search and training frictions are factors that can alter firms' hiring decisions.

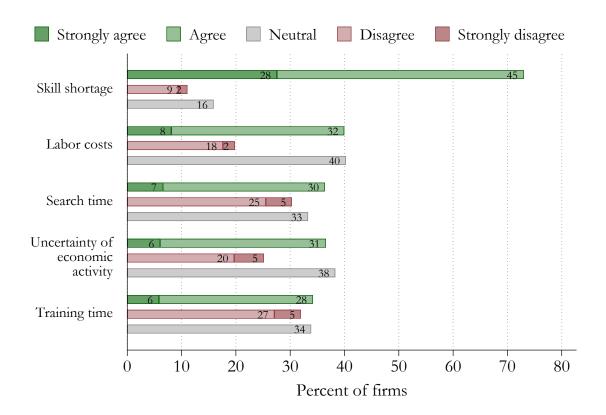


FIGURE 1. Factors Altering Firms Hiring Decisions

Note: The figure reports responses to the question: "What factors can discourage the firm from recruiting despite the potential need?" The hiring obstacles are: The lack of qualified candidates (Skill shortage); Job seekers want a higher wage than the firm can offer (Labor costs); Finding and choosing the right employee is too time-consuming (Search time); Training employees in firm-specific skills is too time-consuming (Training time); The uncertainty of economic activity.

Association between hiring obstacles. Table 2 shows the Spearman correlation between the different statements responding to this question. The most correlated factors are search and training time, with a correlation of 0.59. This correlation shows that these two non-wage labor costs will likely affect hiring decisions. Interestingly, most other difficulties are loosely correlated. For example, the correlation between labor costs and search and training costs is between 0.23 to 0.27. Other correlations vary from 0.14 to 0.29. The factor that stands out most from the others is economic uncertainty. This

factor is uncorrelated with skill shortage (-0.03). Overall, the correlation matrix analysis shows that firms distinguish different components of hiring difficulties. It also implies that the survey results are unlikely to be driven by single underlying factors.

TABLE 2. Association Between Hiring Obstacles

Hiring obstacles	Skill shortage	Labor costs	Search	Training	Uncertainty
Skill shortage	1.00				
Labor costs	0.29	1.00			
Search	0.19	0.27	1.00		
Training	0.14	0.23	0.59	1.00	
Uncertainty	-0.03	0.16	0.20	0.26	1.00

Note: This table reports the correlation matrix of hiring difficulties. Hiring difficulties are the responses to the question "What factors can discourage the firm from recruiting despite the potential need?" Figure 1 shows the distribution of each response.

Association with labor market conditions. To show that the responses concerning hiring obstacles are more than just cheap talk or do not just reflect respondents' misperceptions, we compare survey responses to aggregate measures of hiring difficulties. We measure objective benchmarks of hiring difficulties common to a similar set of firms given their occupation mix. We consider three measures of hiring difficulties: labor market tightness (defined in Section 2.5), the percentage of unfilled vacancies (labeled "unfilled vacancies"), and the percentage of new hires who are unqualified (labeled "unqualified hires"). ¹⁹

Table A.1 reports the results of the univariate regression of our measure of hiring obstacles on aggregate labor market conditions. Estimates are all positive, but the magnitude differs across aggregate labor market conditions measures. Reassuringly, the skill shortage estimate is three times as large as the training estimate. Meanwhile, none of these measures are correlated with economic uncertainty. This further reassures us since the current labor market conditions would have little impact on firms' hiring decisions if they are discouraged by future economic uncertainty. These results show that our survey responses indeed capture firms' hiring situations.

¹⁹Unfilled vacancies and unqualified hires are estimated from a firm-level survey (*Rekrutteringssurvey*) described in Section 2.2.

Additional analysis. Another concern regarding the survey question is that we ask firms to respond to a potential scenario in which they need to hire. Firms with an actual need to hire in recent periods might have different experiences or concerns regarding hiring decisions than firms without such a need. To address this, we use another question in our survey, which asks firms if they had plans to hire new employees in 2020. A total of 1072 firms answered yes to this question (52% of the baseline sample). The answer does not specify whether firms successfully hired new employees or only put an effort into recruiting people. Hence, the design of the question ensures that all firms that intended to hire, regardless of whether they were discouraged by the aforementioned factors or not, would be identified in the response. In Figure A.4, we show the responses to the hiring difficulties question but only include the firms that planned to hire in 2020. We find that the responses are virtually the same for the full sample. This result shows that firms that planned to hire people in 2020 do not differ systematically in their responses from the firms that did not hire, which reduces the concern that the survey responses could be different due to the actual hiring behaviors of the firms.

Theoretical framework. We use a search and matching model (see Appendix C) to guide our empirical analysis. In this model, we examine the impact of a change in skill shortage, labor costs, search and matching friction, and uncertainty of economic activity. We report some results here, and all the results are presented in the Appendix. Higher labor costs imply a lower vacancy supply as the expected value of a job falls. We find a similar negative effect on job openings if search time increases or training time increases. All the results are consistent with our empirical results.

Relationship to other work. Haskel and Martin (2001) use UK representative establishment data and report that 35% of employers report skill shortages. Bergeaud, Cette, and Stary (2022) show that French manufacturing firms believe that labor shortage is a more prominent obstacle than labor costs. Terry and De Zeeuw (2018) examine hiring difficulties in the US and also highlight skill shortages. However, these papers do not document the extent of search and matching frictions as we do. Hence, a key takeaway from our analysis is that search and training frictions are relevant factors that typically make hiring difficult.

These results align well with and complement empirical evidence of the expected time a new employee will take to reach their *maximal* productivity (and not average, as in this paper). Caplin et al. (2022) shows that one year of tenure is enough for about

half of the jobs. On the other hand, at least three years of experience is required in more than 30% of firms. It also relates to Bertheau et al. (2022), where they show that unexpected worker death has sizeable consequences for firm outcomes.

These results also support labor market models that show how predictions differ when hiring costs include both vacancy posting and training costs. Pissarides (2009) shows that the Diamond-Mortensen-Pissarides model can predict the US economy's labor market dynamics if hiring costs include a fixed component. Faccini and Yashiv (2022) show that hiring costs lead to a strong propagation of macroeconomic variables in response to technology shocks. Finally, our evidence shows that the uncertainty of economic activity discourages firms from hiring, as predicted by Den Haan, Freund, and Rendahl (2021). Overall, our analysis shows that search and training frictions are relevant factors in firms hiring decisions.

3.2. Hiring Obstacles, Firm and Labor Market Characteristics

Our results so far suggest that there are several factors that can influence firm's hiring decisions. The next step is to document how these factors vary across firms. The characteristics of interest are firm size, age, wage premium, labor productivity (value added per worker), and the firm's employment share in its local labor market. For easier interpretation, we normalize the characteristics of interest (i.e., we convert them to a *Z*-score). Table 3 shows the marginal effects from the ordered probit models discussed in the previous section. We estimate the probability that firms will agree or strongly agree with each hiring obstacle. Table 3 reports the selected firm characteristics, but all models include additional controls as well as regional and industry fixed effects. ²⁰ Our results are as follows.

Firm size and firm age. Some hiring obstacles are less prevalent in larger and older firms. A one standard deviation (SD) decrease in firm size is associated with a 2.97 percentage point (pp) increase in the probability that search time will be considered a hiring obstacle. Smaller firms are also more concerned about training time (3.85 pp). Similarly, younger firms are more likely to be discouraged by these two obstacles. The estimates range from -2.89 pp for search time to -3.51 pp for training time, even after controlling for wages and productivity. Our results are consistent with and complement

²⁰Specifically, the firm-specific tightness, the firms' ownership, task-contents of jobs, capital, cash, revenue, and employment growth, hiring upskilling, a subcontractor to other companies, the respondent and the workforce characteristics. Table A.10 shows the definition of each variable.

studies that characterize young firms.²¹

While our survey does not provide direct channels that explain why these young firms are more impacted by search and training frictions, one plausible explanation is that referrals and networks are less available to younger firms due to their smaller pool of employees. Indeed, a large body of literature shows that employee referral is one of the most used hiring methods (Topa 2011). A theoretical literature shows how social networks impact worker outcomes (e.g., Fontaine (2008), Arbex, O'Dea, and Wiczer (2019)). Firms use these networks to attract workers of better quality in hard-to-observe dimensions (Hensvik and Skans 2016).

Another possible explanation for our estimates is that it is difficult for job seekers to determine whether younger firms are good employers (i.e., they offer stable or high-quality jobs), given the lack of employment history in these firms. Using a search and matching model, Kim (2023) shows that this uncertainty affects young firms' hiring and ultimately dampens the growth of high-potential young firms. Since young firms play a key role in employment growth (Decker et al. 2014), and the quality of the initial workers plays a significant role in young firm's long-term success (Babina et al. 2019), our results suggest that employment policies that help firms hire should potentially place more emphasis on younger and smaller firms.

Firm-specific wage premiums and firm productivity. Next, we document the role of firms' wage policy. In labor market models with search frictions, firms can attract more job seekers (either already employed or unemployed) by setting a higher wage than their competitors. Does a higher wage premium reduce hiring obstacles? Table 3 shows that this is partly true. Indeed, high-productivity and high-wage firms are less concerned about labor costs. A one SD increase in firm productivity (wage premium) decreases the probability that the labor costs will be considered a hiring obstacle by 3.62 pp (3.94pp). Importantly, it is worth noting that the wage premium and productivity are not associated with other obstacles, such as skill shortages, search, and training frictions. This implies that the labor market is not perfectly competitive, and that firms cannot overcome labor market frictions and fill their vacancies solely by increasing their wages. Similar insights can be drawn from Table 2, which also shows that skill shortage and labor cost difficulties are only loosely correlated. These results complement the work by Mueller et al. (2023), who find that, in Austria, the duration of a vacancy negatively

²¹Studies of administrative data show that young firms are matched with lower-quality workers despite being generally high-wage firms (Babina et al. 2019; Sorenson et al. 2021).

TABLE 3. Factors Altering Firms Hiring Decisions and Firm Characteristics

Question: What factors can discourage the firm from recruiting despite the potential need?

Hiring obstacles:	Skill shortage (1)	Labor costs (2)	Search (3)	Training (4)	Uncertainty (5)
Size	1.25	-2.15	-2.97**	-3.85***	-1.79
	(1.27)	(1.31)	(1.40)	(1.45)	(1.21)
Age	-2.13*	-1.94	-2.89**	-3.51***	-1.66
	(1.19)	(1.27)	(1.29)	(1.25)	(1.24)
Productivity	1.10	-3.62***	-0.86	-2.06	-5.03***
	(1.20)	(1.32)	(1.32)	(1.29)	(1.38)
Wage premium	0.20	-3.94***	-0.93	0.74	-2.17*
	(1.18)	(1.19)	(1.15)	(1.09)	(1.17)
Local empl. share	-1.18	0.75	-5.43***	-1.06	-2.50**
	(1.55)	(1.51)	(1.88)	(1.78)	(1.18)
Wage floor	-7.39**	-9.40**	-0.92	0.02	4.02
	(3.58)	(3.93)	(3.90)	(3.74)	(4.04)
N	2059	2059	2059	2059	2059
Probability	.73	. 37	.35	.33	.36
Additional controls	Yes	Yes	Yes	Yes	Yes

Note: The table shows ordered probit marginal effects of firm characteristics on the probability of agreeing with different hiring obstacles. The exact wording of the hiring obstacles is reported in Section 3.1. Firm characteristics are measured using administrative data and are normalized (i.e., convert to a *Z*-score), except for whether the firm is covered by wage floors (indicator). Additional controls include firm, workforce, and respondent characteristics, as well as 59 industry- and 5 region-fixed effects, and firm-specific labor market tightness (see Section 2.4). Asterisks show statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

correlates with the starting wage, although the effect is small in magnitude. Therefore, while more desirable employers are probably less affected by hiring obstacles, the variation does not seem to be so large that other hiring frictions do not impact those firms. One implication of our results is that high-quality firms could potentially create more jobs and increase labor demand if there were less labor market friction.

Finally, we find that higher productivity significantly reduces the impact of economic uncertainty (5.03pp). This is consistent with Den Haan, Freund, and Rendahl (2021), who show that volatility increases the option value of waiting. It deters low-productivity firms from posting vacancies and leads to lower job creation.

Firm monopsony power. Theories suggest that the labor market in which firms operate should also impact their decisions (Manning 2021). In a more concentrated market, employer search time decreases as employers have fewer competitors. We proxy firm-level monopsony power as its employment share in its local labor market. Firms are assigned a given local labor market within a given region (5 regions) and industry (at the two-digit level).²² Firms with higher monopsony power are less likely to consider search friction. The association is also strong in magnitude, as the estimates are larger than the role of firm age or firm size. Interestingly, we do not find that firms with high monopsony power are less likely to consider training time or skill shortages as hiring obstacles (consistent with our results as regards wage premiums).

Minimum wages. In Denmark, employment protection is low and does not significantly impact hiring decisions.²³ However, in our sample, 17% of firms are covered by wage floors that set minimum wages for most of their employees. This institutional setting could lead to firms being more discouraged from hiring. However, we do not find this to be the case. Interestingly, being covered by wage floors reduces the probability of firms reporting that labor cost is a hiring obstacle by 7.39 percentage points.²⁴ One explanation is that wage floors provide information about the market wage, which reduces the likelihood of firms misperceiving the market wage. This result is consistent with Cullen (2023). We discuss this further in Section 4.2.

²²This monopsony power measure differs from the firm size (or productivity) as this margin takes into account the competitiveness of the local labor market.

²³Our open-ended text, where employers describe other hiring obstacles, shows this.

²⁴This result is less robust than other findings. Table A.5 restricts our sample to firms with at least ten employees, and the magnitude of this effect is similar (-8.50 pp vs. -7.39 pp), but standard errors are larger.

Heterogeneity analysis. We uncover how the average marginal effects vary with firm size, age, productivity, wage premium, and monopsony power. Figure A.5 shows the results. We evaluate the marginal effects of each individual firm and plot the average marginal effect of each decile. We show the results only when the effect of the variable is statistically significant in Table 3. Overall, the average marginal effects are larger for smaller, younger, less productive, lower wage, or lower labor market power firms. These results indicate that the chance of encountering hiring obstacles decreases faster when firms at the lower end of the distribution move up. These results suggest that policies that target firms at the lower end of the distribution could be more effective.

Additional analysis. We carry out additional analyses to ensure that our results are robust across specifications. First, we find similar results using OLS instead of ordered probit (see Table A.2).²⁵ Remember that all regressions are weighted to ensure comparability to the firm population under study. Regressions without weights also yield similar results (see Table A.3). The main results discussed are quantitatively similar. We also address the concern that the hypothetical nature of our question could potentially bias the results, by running the main ordered probit model with only the subsample of firms that indicate that they planned to hire in 2020 (see Table A.4). We obtain similar results in all the robustness tests mentioned above.

We also test whether different job amenities explain our results. Firms with negative job traits might have different firm characteristics (e.g., low productivity) and this can partially drive our results. We do not find this to be the case. To control for these characteristics, the regressions include the fraction of the firm's wage bill devoted to paying for non-standard working conditions. Non-standard working conditions are defined as irregular work schedules (such as night work, work on public holidays, delayed lunch, on-call and relocation) and irregular working conditions (such as outdoor work and extreme weather) in our data. We also measure the positive non-wage amenities (labeled "employee benefits"). They are defined as the value of free cars, meals, lodging, multimedia, taxable health insurance and treatments, canteen arrangements, and work clothes. We do not include these variables in our main analysis because data on wage conditions (LONN) are only available for firms with at least ten employees, and including them would cut our sample size by half. The estimates are reported in Table A.5. Non-standard work conditions are positively associated with reporting that search is a

²⁵Instead of predicting the probability of agreeing, we use a quantitative scale ranging from 1 (strongly disagree) to 5 (strongly agree).

hiring obstacle (2.46 pp). This result is consistent with studies showing that unfavorable job amenities are associated with a lower labor supply (e.g., Maestas et al. 2023). Despite having a much smaller sample size, how hiring obstacles vary across firms is similar in this specification. Younger firms are still more likely to be affected by similar hiring obstacles. Higher wage premiums still reduce the likelihood of reporting labor costs being an issue (-3.55 pp vs. -3.94 pp in the main specification). Taken together, these additional results provide support for our main results.

4. Subjective Beliefs and Firms Hiring Decisions

The previous section documents the factors that influence hiring decisions and their variation across firms using firm characteristics from matched employer-employee, vacancy, and financial account data. This section complements the analysis by investigating how the factors influencing hiring decisions vary across firms' subjective beliefs in our survey. Our analysis focuses on subjective beliefs about hiring workers with different employment statuses (either employed or unemployed) and subjective beliefs about their firm's position on the wage distribution relative to other firms.

4.1. Firms' Beliefs about Unemployed Job Seekers and Hiring Decisions

The analysis in this section is motivated by one recent empirical finding by Faberman, Mueller, Sahin, and Topa (2022). Among other findings, they showed that the employed are much more effective than the unemployed in terms of job search. However, the reasons why on-the-job search is more effective than job search while unemployed is still poorly understood. One explanation for this fact is that some firms prefer to hire employed rather than unemployed workers.²⁶ This preference may impact the job-finding rate of workers depending on their employment statuses, and also firms' hiring decisions. If some firms prefer to hire already employed workers, this will leave out an important share of job seekers. Forty percent of applications are sent by *non-employed* workers in the US (Faberman et al. 2022). We proceed in steps to provide evidence relating to this question. First, we document firms' beliefs about the unemployed and the employed. Then, we show that firms that prefer to hire already employed workers typically hire more employed workers from other firms. Finally, we report results linking hiring decisions to firms' beliefs about the unemployed.

²⁶See, among others, Kroft, Lange, and Notowidigdo (2013), Eriksson and Rooth (2014), Farber, Herbst, Silverman, and von Wachter (2019), Cohen, Johnston, and Lindner (2023).

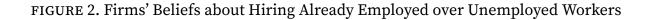
Survey question. It is widely documented that across labor markets, as workers remain unemployed, they see their prospects for earnings and reemployment fall. This tendency is called duration dependence. Guided by a large body of literature, we distinguish between the two main economic motives that can make the unemployed unfavorable.²⁷ One potential explanation is that the level of skills differs between two groups before the unemployment episode (i.e., negative selection on the pool of unemployment). The other popular explanation is that, after being unemployed for some time, skills deteriorate. To test the relevance of these two ideas, we asked firms to state their views about the following statements: "We prefer to hire employed candidates as the unemployed lose their skills." This statement relates to the literature that evaluates the depreciation of skills during an unemployment period. Evidence in this literature is mixed. Cohen, Johnston, and Lindner (2023) find a near-zero effect of skill depreciation, while Arellano-Bover (2022) and Dinerstein, Megalokonomou, and Yannelis (2022) find a sizeable impact. The second statement refers to skills before an unemployed episode: "We prefer to hire employed candidates because unemployed workers have lower skills than those employed." This statement relates to the literature on adverse selection and layoffs (e.g., Gibbons and Katz 1991).²⁸

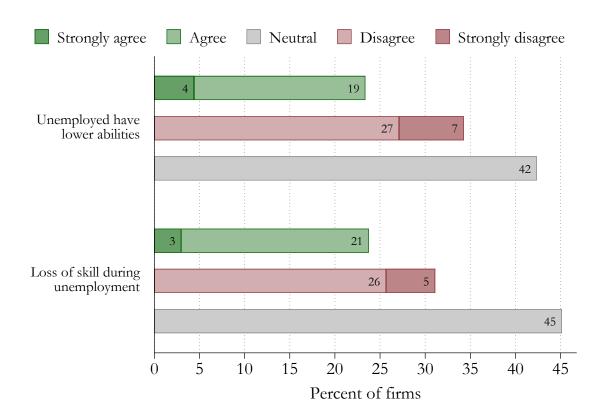
Firms' beliefs about the unemployed. Figure 2 shows firms' preferences for hiring already employed workers over unemployed workers. We find a wide variation in firm beliefs about this topic in our survey. Around 24% of the firms believe that skills depreciate over an unemployment spell, and 23% of the firms believe that the unemployed workers are negatively selected, i.e., have lower abilities. Firms' answers to these two questions are correlated but not perfectly aligned. Overall, around 31% of the respondents agree with at least one of these two statements. This shows that a significant share of firms do have some preference for already employed workers.

To our knowledge, we are the first to ask firms about their perceptions of hiring employed over unemployed workers in a large-scale and representative sample. The closest work to us is Bewley (1999). He finds that 30 out of 99 firms interviewed in 1992 in the US consider being unemployed a negative factor for job seekers. Our result, despite being from a different country setting and with a much larger sample size, is close in

²⁷A model like that of Cahuc, Postel-Vinay, and Robin (2006) predicts that firms will prefer to meet unemployed workers, as the firms have the bargaining power and can offer them their reservation wage.

²⁸We also put additional statements to respondents (see section B.2), but they do not provide additional information about the preferences to hire job seekers who are already employed.





Note: The figure shows responses to the question: Tell us your thoughts about hiring other firms' employees. Please express your opinion on the following statements: "We prefer to hire candidates who are employed as the unemployed lose their skills" (labelled "Loss of skill during unemployment"), and "We prefer to hire candidates who are employed because unemployed workers have lower abilities than those who are employed" (labelled "Unemployed have lower abilities").

terms of the share of firms with similar beliefs. ²⁹

Objective benchmark of the abilities of the unemployed. Before reporting our results on firms' beliefs about the unemployed and their hiring decisions, we first investigate whether such preferences are based on objective differences in ability between the employed and the unemployed using individual-level labor market data. Worker abilities

²⁹There might be less stigma attached to the unemployed in Denmark compared to other countries, largely due to the low employment protection. As described in Section 2.3, the level of employment protection is low, and it is closer to the level in the US than in other European countries. We therefore, expect to find less selection in workers' abilities between the unemployed and the employed.

are hard to observe. We use the worker fixed effects from an AKM model as a proxy for workers' abilities. Recall that our AKM specification includes an unrestricted set of year dummies and quadratic and cubic terms in age fully interacted with educational attainment as time-varying exogenous variables. Hence, variations in worker effects capture a combination of skills and other factors that are rewarded equally across firms, taking into consideration that different cohorts would be paid distinct wages depending on their educational attainment. To compare worker abilities by employment status, we proceed as follows. We classify workers as employed and unemployed in 2019 according to the administrative records. We assign each worker a worker effect based on the AKM specification discussed above (estimated based on data from 2008 to 2019). For the unemployed, the worker effect is estimated before the last unemployment spell. We restrict the unemployed in 2019 to those who have been employed at least once since 2015. These restrictions address the concern that previous unemployment spells can bias worker effects. 30

To quantify the difference in worker abilities, we plot the position of the worker effect percentile of the unemployed in the overall worker effect distribution. Figure 3 reports the result. Specifically, the horizontal axis shows the percentile of the unemployed worker effects, and the vertical axis shows the corresponding percentile of the unemployed worker effects in the whole workforce. The median worker effect of the unemployed is equivalent to the 32nd percentile of all workers (both employed and unemployed). Figure A.8 shows the distribution of the worker effects by employment status. These results show that firms' preference for hiring employed over unemployed workers is not unfounded. It is consistent with the study by Mueller and Spinnewijn (2023b), who show that the dynamic selection into long-term unemployment can explain half of the decline in the job finding rate, and Faberman et al. (2022), who show that 61% of the unemployed and employed wage differential can be attributed to unobserved worker heterogeneity. In the following analysis, we include the difference in worker abilities between the two groups in our regressions. This variable is constructed using the occupational level worker effect difference, weighted by the occupation share in each firm. That is, $\Delta_{E-U,j} = \sum_{o=1}^{O} w_{oj} (\bar{\alpha_o}^E - \bar{\alpha_o}^U)$. where $\bar{\alpha_o}^E$ and $\bar{\alpha_o}^U$ are the mean of AKM worker fixed effects in occupation o estimated in the AKM model, and w_{oj} is the fraction of workers employed in occupation o, in firm j.

³⁰This restriction is applied in studies on the sources of job loss (e.g., Schmieder, von Wachter, and Heining (2023); Bertheau, Acabbi, Barcelo, Gulyas, Lombardi, and Saggio (2023a)).

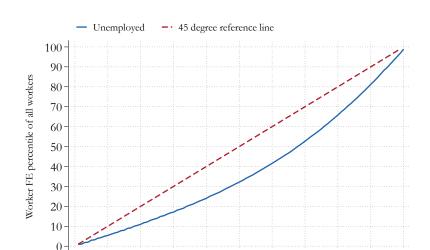


FIGURE 3. Comparing Abilities of the Employed and Unemployed

Note: The solid blue line in the figure shows the relationship between the percentile of the unemployed worker effect and the percentile of the worker effect of all workers.

Worker FE percentile of unemployed workers

Association of beliefs with firm, unemployed, and labor market characteristics. We regress whether firms prefer to hire employed over unemployed persons (for both reasons in our questionnaire) on firm, unemployed, and labor market characteristics. Our objective benchmark of the relative abilities of the employed predicts firms' preferences. Without additional control, a one standard deviation increase in the relative abilities of the employed increases the probability of reporting that the firm prefers to hire already employed workers by 2.49 percentage points. Note that the mean is 30.7%, which means that the effect is relatively large. By including additional controls (note that these also include 5 local labor market fixed effects and 59 industry fixed effects), the effect is larger (3.29 pp). This means that firms' beliefs about unemployed vs. employed workers are correlated with objective benchmarks.

The labor market tightness that firms face is also strongly correlated with prefering to hire employed workers in column (1). However, we do not find an effect when we include additional controls (and in particular industry fixed effects). Firm characteristics do not explain firms' beliefs. Firm size is weakly negatively associated with preferring hiring employed workers. ³¹

³¹The variable that has the most important explanatory power is the characteristics of the respondent. A respondent in this survey who owns a company is more likely to prefer to hire employed rather than unemployed workers. This effect can partly explain the effect of firm size. In large firms, the owner is

TABLE 4. Firms' Beliefs about the Unemployed vs. Objective Benchmark

Dep. variable: Prefer hiring employed					
	(1)	(2)			
Δ E-U abilities	2.49**	3.29**			
	(1.06)	(1.32)			
Labor market tightness	3.28***	0.20			
	(1.17)	(1.51)			
Size	-1.67	-2.14*			
	(1.03)	(1.13)			
Age	1.08	0.77			
	(1.12)	(1.39)			
Productivity	0.89	1.34			
	(1.15)	(1.28)			
Wage premium	0.65	0.16			
	(1.18)	(1.22)			
Local empl. share	0.36	1.29			
	(1.15)	(1.58)			
Wage floor	-2.28	-3 . 32			
	(2.87)	(3.99)			
\overline{N}	2031	2031			
Mean Dep. Var.	30.7	30.7			
Adj.R2	0.027	0.047			
Additional controls	No	Yes			

Note: The table shows the linear probability model estimates effects of firm and labor market characteristics on the probability of agreeing with firms' preference for hiring already employed workers over unemployed workers. The additional controls are the same as in Table 3. Table A.7 shows estimates that distinguish the motive for preferring to hire employed workers (skill depreciation and negative selection). Asterisks report statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

Table A.7 reports estimates that distinguish between motives for hiring employed workers rather than the unemployed (skill depreciation and negative selection). 32 The

less likely to respond to the survey. Typically, the HR manager will do it (see Table A.7).

³²We use a linear probability model for this analysis as the focus of these statements is on whether firms prefer to hire the employed or not.

estimates show that the results in Table 4 are driven by the statement "We prefer to hire employed candidates because unemployed workers have lower skills than those employed". We do not detect an effect for the statement about skill depreciation during unemployment. This is reassuring, since the negative selection of unemployed workers is the margin that should correlate most with objective benchmarks of unemployed workers' abilities measured using AKM worker effects. Note, however, that the adjusted R2 is low (from 4% to 7%), suggesting that beliefs are only weakly associated with objective benchmarks for firm, unemployment and labor market characteristics.

Beliefs and hiring behaviors. To ensure that our results concerning preferences for hiring already employed workers translate into actual behaviors, we ask "What percentage of your employees are recruited from other firms?" Participants have the option to choose from 0% to 100%. Figure A.6 shows the result. A third of the firms state that up to a fifth of the workers come from other firms, while a quarter say that at least 90% come from other firms. In the finance industry, almost three-quarters of employees come from other firms. Other industries poach around 50% of their workers from other firms.

We compare the poaching rate with the poaching rate in the administrative data, which is defined as the fraction of all new hires with less than a two week non-employment period between jobs. The correlation between the two measures is positive (Figure A.7), but the poaching rate in our survey has more dispersion than the poaching rate from the administrative data. This implies that the most commonly used administrative poaching rate may underestimate the extent of poaching across firms. The discrepancy between the standard registry-based employer-to-employer transitions used to measure the poaching rate and our survey may seem surprising. However, it is consistent with the evidence in Caplin, Gregory, Lee, Leth-Petersen, and Sæverud (2023), who find that Danish workers expect to be non-employed for 2.7 months after quitting and 4.4 months after being laid off. 33

We investigate whether firms' preferences for the employed over the unemployed impact their hiring behavior. The outcome variable is the poaching rate from our survey, and we include firms' preferences for hiring already employed workers as the explanatory variables. The results are shown in Table 5.

We find that preferring the employed for either reason (skill depreciation or negative selection) is associated with an increase in the poaching rate by around 10 percentage

 $^{^{33}}$ Bertheau and Vejlin (2022) document employer-to-employer and its cyclical component in Denmark.

TABLE 5. Firms' Beliefs about the Unemployed and Poaching Rate

Q: What percentage of your employees are recruited from other firms?					
	(1)	(2)			
Prefer to hire employed: loss of skill	10.41***				
	(1.95)				
Prefer to hire employed: ability		11.89***			
		(2.01)			
N	2020	2020			
Mean Dep. Var.	51.96	51.96			
Adj.R2	0.143	0.147			
Additional controls	Yes	Yes			
Δ E -U abilities	Yes	Yes			

Note: This table shows OLS estimates of the effect of firms' beliefs about hiring already employed workers over unemployed workers on their poaching rate. Column 1 includes beliefs in a loss skill during unemployment as a reason for prefering already employed workers. Column 2 includes the belief that the unemployed have lower abilities. Asterisks report statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

points (see Table A.6 for estimates of firm characteristics). These results suggest that firms' preference for the employed over the unemployed does indeed affect their actual hiring behaviors.

Beliefs and vacancy creation. Do employers who prefer to hire already employed workers experience greater hiring difficulties? We hypothesize that employers who prefer employed over unemployed workers, either due to skill depreciation or adverse selection concerns, have a more limited pool of candidates, which could increase their hiring difficulties.³⁴ To test this hypothesis, we construct a dummy variable that indicates whether the respondents agree with at least one of these two statements (labeled "prefer hiring employed"). Table 6 presents our results. The specification is the same as in Table 3. Estimates of firms' beliefs are conditional on firm and labor market characteristics as in our main regression. This reduces the concern that tighter labor market conditions induce some firms to prefer to hire employed over unemployed workers. We also control for the difference in abilities between the employed and the unemployed at the firm

³⁴Even though thoroughly understanding this relationship is beyond the scope of this paper, we nonetheless suggest a channel that can potentially explain this link.

level.

TABLE 6. Factors Altering Hiring Decisions and Firms' Beliefs about the Unemployed

Question: What factors can discourage the firm from recruiting despite the potential need?

Hiring obstacles:	Skill shortage (1)	Labor costs (2)	Search (3)	Training (4)	Uncertainty (5)
Prefer hiring employed	10.48*** (2.28)	9.00*** (2.38)	7.83*** (2.30)	7.29*** (2.21)	1.75 (2.23)
N	2031	2031	2031	2031	2031
Probability	.73	.37	. 35	.33	.36
Firm characteristics	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes
Δ E -U abilities	Yes	Yes	Yes	Yes	Yes

Note: The table shows ordered probit marginal effects of firms' preference for the employed over the unemployed on the probability of agreeing with different hiring obstacles. "Prefer hiring employed" is an indicator variable. Firm characteristics from Table 3 are included as controls and their estimates are reported in Table A.8. Asterisks report statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

We find that the preference for the already employed is strongly correlated with all the hiring obstacles except economic uncertainty. Agreeing with at least one of the two statements is associated with a 7.29 to 10.48 pp increase in the probability of reporting hiring difficulties. ³⁵

Discussion of results. Consistent with our results, Darougheh (2023) shows that a subgroup of Danish unemployed workers (the "marginal" unemployed) have much lower abilities than the majority of unemployed workers (the "stable" unemployed workers). ³⁶ Faberman et al. (2022) show that job search of the employed is more effective than that of the unemployed, which is likely to be *partially* driven by the differences between employed and unemployed workers. This fact helps us to better understand how the

³⁵For robustness, we verify that including the difference in worker abilities between employed and unemployed workers does not change our results.

³⁶He also uses administrative data and proxy worker abilities using AKM worker fixed effects. The method used to classify workers closely follows closely Gregory, Menzio, and Wiczer (2022).

labor market reacts to a change in productivity.³⁷ Our novel descriptive evidence on the firm side complements the descriptive evidence on the worker side. In a nutshell, we find that some firms prefer to hire already employed workers. While it is also possibly to some extent driven by the differences in worker abilities between these two groups, we also measure the difference in employers' preferences. An indication of this is that the measure of preferences is not associated with firm characteristics, and the effect on hiring behavior persists after including firm-level measure of worker ability differences. Overall, it is plausible that the composition of the pool of job seekers impacts the amplification of macroeconomic shocks.

4.2. Hiring Obstacles and Firms' Beliefs about Their Wages

We document that firms' beliefs about job seekers with different employment statuses impact their hiring decisions. We further investigate whether misperceptions of their own wage affect hiring difficulties. To do so, we use one survey question that asks firms about their beliefs about their wage policy relative to other firms. The wording of the question as follows: "Do you think that the company offers lower or higher salaries than competing companies in your industry? Competing companies are other employers that hire people with the same abilities in your region." The respondents have five potential options: much lower, lower, about the same, higher, and much higher. We then compare their answers to firm-specific wage premiums. Bertheau and Hoeck (2023) show that a firm's beliefs about its position in the wage distribution are correlated with its position in the firm-specific wage premium distribution. However, a substantial minority of firms misperceive their position in the wage distribution.

We define a categorical variable that measures whether a firm underestimates or overestimates its' own wage in the wage distribution. A firm overestimates its wage if it answers that it pays about the same as its peers, but its actual wage premium is below the 30th percentile of the distribution. It overestimates its wage if it answers that it pays higher or much higher than its peers, but its actual wage premium is below the 50th percentile. Based on this measure, 24 percent of the respondents underestimate their wage in the distribution, while 28 percent of the firms overestimate their wage.

³⁷Specifically, the feedback between employed workers' search efforts and firms' vacancy creation incentive amplifies the economy's response to a negative productivity shock and generates empirically plausible declines in vacancies (see also Eeckhout and Lindenlaub (2019)).

³⁸Similarly, we consider firms to be underestimating their wage if they answer that they pay about the same as their peers but their wage premium is above the 70th percentile, or if they believe that they pay lower or much lower than their peers, but their wage premium is above the medium.

Table 7 shows that wage misperceptions are associated with firms' hiring decisions. Recall that we control for firm-specific labor market tightness to alleviate the concern that a tight labor market might alter firms' beliefs about their own wage.³⁹

TABLE 7. Factors Altering Hiring Decisions and Wage Misperception

Question: What factors can discourage the firm from recruiting despite the potential need? Hiring obstacles: Skill shortage Labor costs Search Uncertainty Training (1)(2)(3) (4) (5)-5.00* 5.71* -1.95 -4.81* -0.22 Underestimates own wage (2.88)(2.94)(2.91)(2.76)(2.89)Overestimates own wage -0.37 -11.06*** 3.64 1.26 -1.40 (3.13)(3.12)(3.06)(3.00)(3.04)-8.33*** Wage premium 1.11 0.53 2.08 -2.54 (1.72)(1.64)(1.63)(1.57)(1.67)N 2059 2059 2059 2059 2059

.35

Yes

Yes

.33

Yes

Yes

.36

Yes

Yes

Note: The table reports ordered probit marginal effects of firms' misperception of their wage in the wage distribution on the probability of agreeing with different hiring obstacles. Underestimating and overestimating own wage are indicator variables. The baseline category is correctly believing how a firm's wage compares to other firms. Firm characteristics showed in Table 3 are included as controls, and their estimates are reported in Table A.9. Asterisks report statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

.37

Yes

Yes

.73

Yes

Yes

Probability

Firm characteristics

Additional controls

We find that firms that underestimate their wages are 5.71 pp more likely to agree that labor costs are a hiring obstacle. This result means that firms that believe they pay lower wages than their peers, despite the administrative data showing the opposite, are discouraged from hiring due to their perceived labor costs. On the other hand, when a firm overestimates its wage in the wage distribution, this reduces the probability that it views the expected salary as a hiring obstacle. Interestingly, once we control for the misperception, firms' wage premiums have a much stronger effect on firms' reported

³⁹The specification is the same as in Table 3 except for the misperception dummies. We also define misperception using different thresholds and find the results to be similar.

hiring difficulties as regards labor costs. A one standard deviation increase in the wage premium reduces the probability of reporting labor costs as hiring difficulties by 8.33 percentage points, in contrast to 3.94 percentage points in our main specification in Table 3. Our findings illustrate the important role played by misperception, which could have significant effects on firms and labor market outcomes. It suggests an explanation for why firms use salary benchmarking (see Cullen (2023) for a literature review). Overall, these results shed new light on the role of the demand side of subjective beliefs, complementing the literature on how supply-side subjective beliefs affect labor market outcomes.

5. Conclusion

This paper provides novel insights into the determinants of hiring decisions. We do so by designing a firm survey in Denmark that we combine with rich administrative datasets. We ask firms about the factors that can discourage them from hiring despite potential needs. We show how these factors vary with firm characteristics and how they vary with firms' subjective beliefs. Our results are useful for several reasons. Vacancies are the key equilibrium margin in canonical theories of unemployment, describing firms' job creation. Recent studies use vacancy data and have made great progress in terms of understanding hiring behaviors (see, e.g., Faberman (2020); Mercan and Schoefer (2020)). However, less is known about what factors influence hiring decisions and how they vary across firms. Beyond theoretical motivations, a better understanding of hiring decisions can help with the design of public policies that target hiring difficulties (Algan, Crépon, and Glover 2023) and understand firm dynamics (Sedláček and Sterk 2017).

Our findings are as follows. Ex-ante and ex-post matching costs (i.e., search and training time) are as important as labor costs. These frictions are larger for smaller and younger firms. A more generous pay policy reduces hiring obstacles related to labor costs but does not affect search and training frictions. Low-productivity firms are more likely to report that uncertainty alters their hiring decisions. Around 30% of firms prefer to hire already employed workers over the unemployed either due to concerns regarding negative selection of unemployed workers or skill depreciation during unemployment. Firms with such beliefs are more likely to report that labor market frictions and labor cost considerations alter their hiring decisions. This last result completes worker-side evidence (Faberman et al. 2022), suggesting that the composition of the pool of job seekers could impact the amplification of macroeconomic shocks.

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Online Appendix

A. Additional Tables and Figures

A.1. Tables

TABLE A.1. Hiring Obstacles and Aggregate Labor Market Conditions

Hiring obstacles:	Skill shortage (1)	Labor costs (2)	Search (3)	Training (4)	Uncertainty (5)
Labor market tightness	0.09***	0.07***	0.07***	0.04*	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	2059	2059	2059	2059	2059
Unqualified hires	0.06***	0.06***	0.03	0.03	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	2029	2029	2029	2029	2029
Unfilled vacancies	0.15***	0.07***	0.08***	0.05**	-0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	2029	2029	2029	2029	2029

Note: This table shows univariate OLS estimates of hiring obstacles from our survey on aggregate labor market conditions. Aggregate labor market conditions are measured at the occupational level from administrative data and are linked to our survey using the share of employment in a particular occupation at firm-level. The aggregate labor market conditions are converted to a *Z*-score. Asterisks indicate statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

TABLE A.2. Hiring Obstacles and Firm Characteristics: OLS regressions

Hiring obstacles:	Skill shortage (1)	Labor costs (2)	Search (3)	Training (4)	Uncertainty (5)
Size	0.03	-0.05**	-0.07**	-0.09***	-0.05**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Age	-0.04	-0.03	-0.06**	-0.07**	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Productivity	0.02	-0.07***	-0.02	-0.05	-0.12***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Wage premium	-0.00	-0.07***	-0.02	0.01	-0.04
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Local empl. share	-0.04	0.02	-0.09***	-0.02	-0.05**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Wage floor	-0.19**	-0.19**	-0.00	-0.00	0.06
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
N	2059	2059	2059	2059	2059
Mean Dep. Var.	3.86	3.21	3.03	2.99	3.1
Adj.R2	0.054	0.049	0.049	0.036	0.082
Additional controls	Yes	Yes	Yes	Yes	Yes

Note: The table shows OLS estimates of agreeing with different statements related to the question: "What factors can discourage the firm from recruiting despite the potential need?" The specifications are the same as in Table 3. The scale ranges from 1 (strongly disagree) to 5 (strongly agree). Asterisks report statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

TABLE A.3. Hiring Obstacles and Firm Characteristics: Unweighted Sample

Hiring obstacles:	Skill shortage (1)	Labor costs (2)	Search (3)	Training (4)	Uncertainty (5)
Size	0.73	-1.82	-2.99**	-3.61***	-1.94
	(1.26)	(1.23)	(1.27)	(1.31)	(1.20)
Age	-1.90*	-1.90	-3.68***	-3.91***	-1.62
	(1.14)	(1.20)	(1.21)	(1.17)	(1.18)
Productivity	0.76	-3.05**	-0.47	-1.79	-4.73***
	(1.13)	(1.19)	(1.22)	(1.18)	(1.28)
Wage premium	-0.05	-4.32***	-0.94	0.69	-2.53**
	(1.12)	(1.08)	(1.04)	(1.02)	(1.10)
Local empl. share	-1.05	0.36	-4.46***	-0.49	-2.16**
	(1.52)	(1.41)	(1.72)	(1.64)	(1.09)
Wage floor	-5.17	-10.30***	-1.81	-1.90	2.04
	(3.50)	(3.68)	(3.61)	(3.49)	(3.80)
N	2059	2059	2059	2059	2059
Probability	.73	.37	.35	.33	.36
Additional controls	Yes	Yes	Yes	Yes	Yes

Note: The table shows unweighted ordered probit estimates of agreeing with different statements related to the question: "What factors can discourage the firm from recruiting despite the potential need?" The specifications are the same as in Table 3. Asterisks indicate statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

TABLE A.4. Hiring Obstacles and Firm Characteristics: Firms Hiring in 2020

Hiring obstacles:	Skill shortage (1)	Labor costs (2)	Search (3)	Training (4)	Uncertainty (5)
Size	-0.62	-1.75	-3.76**	-4.09**	-1.22
	(1.33)	(1.79)	(1.86)	(1.96)	(1.45)
Age	-2.62*	-2.58	-1.22	-3.87**	-2.14
	(1.54)	(1.80)	(1.81)	(1.79)	(1.67)
Productivity	-0.37	-6.47***	-0.29	-3.57*	-6.80***
	(1.47)	(1.93)	(1.82)	(1.86)	(1.81)
Wage premium	1.94	-4.23***	-0.73	1.62	-1.19
	(1.39)	(1.63)	(1.48)	(1.44)	(1.50)
Local empl. share	0.94	1.87	-2.46	-1.11	-2.89
	(1.60)	(2.56)	(2.89)	(2.88)	(1.90)
Wage floor	-8.28*	-8.40	-2.35	-0.24	11.61**
	(4.68)	(5.77)	(5.75)	(5.28)	(5.40)
N	1072	1072	1072	1072	1072
Probability	.73	.37	.35	.33	.36
Additional controls	Yes	Yes	Yes	Yes	Yes

Note: The table shows ordered probit marginal effects of firm characteristics on the probability of agreeing with statements about different hiring obstacles. Only firms that indicate that they planned to hire in 2020 are included in the subsample. The exact wording of the hiring obstacles is cited in Section 3.1. Firm characteristics are measured from administrative data and are normalized (i.e., converted to a *Z*-score), except for whether the firm is covered by wage floors (indicator). Additional controls include firm, workforce, and respondent characteristics, as well as 59 industry- and 5 region-fixed effects, and firm-specific labor market tightness (see Section 2.4). Asterisks indicate statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

TABLE A.5. Hiring Obstacles and Firm Characteristics: Job Amenities

Hiring obstacles:	Skill shortage (1)	Labor costs (2)	Search (3)	Training (4)	Uncertainty (5)
Firm Characteristics					
Size	1.41	-1.84	-1.77	-1.81	0.27
	(1.35)	(1.38)	(1.53)	(1.46)	(1.32)
Age	-2.86*	-2.56	-4.16**	-5.14***	-1.43
	(1.52)	(1.62)	(1.70)	(1.61)	(1.59)
Productivity	1.85	-1.78	-1.42	-4.22**	-6.04***
	(1.74)	(1.89)	(1.79)	(1.91)	(2.10)
Wage premium	-3.55**	-4.02**	-2.48	-0.85	-2.81
	(1.80)	(2.00)	(1.96)	(1.91)	(1.82)
Local empl. share	0.68	1.38	-5.53**	-0.51	-2.98**
	(1.73)	(1.59)	(2.22)	(1.78)	(1.47)
Wage floor	-8 . 50 (5 . 23)	-7.42 (5.31)	-3.53 (5.45)	-2.37 (5.13)	3.80 (5.56)
Additional Pays					
Non standard condition (%)	-0.37	-0.12	2.46*	-0.30	-2.92**
	(1.25)	(1.12)	(1.38)	(1.52)	(1.38)
Employee benefit (%)	1.50	1.03	-1.21	1.85	-0.37
	(1.41)	(1.51)	(1.69)	(1.34)	(1.28)
N Probability Additional controls	1072	1072	1072	1072	1072
	.73	.37	.35	.33	.36
	Yes	Yes	Yes	Yes	Yes

Note: The table shows the marginal effects of firm characteristics on the probability of agreeing with statemtns on hiring obstacles from ordered probit models. This sample only includes firms with information on non-standard employment conditions and employee benefits. The specifications are the same as in Table 3, except for two additional variables. Non-standard working conditions are the percentage of pay for non-standard working conditions, which includes irregular work schedules (such as night work, work on public holidays, delayed lunch, on-call and relocation) and irregular working conditions (such as outdoor work and extreme weather). Employee benefits are the percentage of pay for benefits, which is defined as the value of a free car, meals, lodging, multimedia, taxable health insurance and treatments, canteen arrangements, and work clothes. Asterisks indicate statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

TABLE A.6. Firms' Beliefs about Unemployed Abilities and Poaching Rate

Q: What percentage of your employe	es are recrui	ited from other firms?
	(1)	(2)
Prefer hiring employed: loss of skill	10.41***	
	(1.95)	
Prefer hiring employed: ability		11.89***
		(2.01)
Firm Characteristics		
Size	3.67***	3.66***
	(0.87)	(0.87)
Age	-0.12	-0.03
	(0.97)	(0.95)
Productivity	3.58***	3.62***
	(0.97)	(0.97)
Wage premium	1.30	1.32
	(0.97)	(0.95)
Local empl. share	0.09	0.46
	(0.78)	(0.76)
Wage floor	-3.96	-3.70
	(3.24)	(3.19)
N	2020	2020
Mean Dep. Var.	51.96	51.96
Adj.R2	0.143	0.147
Additional controls	Yes	Yes
Worker difference	Yes	Yes

Note: This table shows OLS estimates of the effect of firms' beliefs about hiring already employed workers over unemployed workers on their poaching rate. Column 1 includes belief in the loss of skill during unemployment as a reason for preferring already employed workers. Column 2 includes the belief that the unemployed have lower abilities. Asterisks indicate statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

TABLE A.7. Firms' Beliefs about Abilities of Unemployed and Firm Characteristics

	Preferring	hiring employed	Negativel	y selected	Skill dep	reciation
	(1)	(2)	(3)	(4)	(5)	(6)
Δ E-U abilities	2.49**	3.29**	2.14**	3.71***	1.41	1.57
	(1.06)	(1.32)	(0.95)	(1.15)	(0.97)	(1.21)
Labor market tightness	3.28***	0.20	3.75***	0.01	3.00***	1.40
	(1.17)	(1.51)	(1.12)	(1.43)	(1.11)	(1.41)
Size	-1.67	-2.14*	-0.84	-1.31	-1.22	-2.13**
	(1.03)	(1.13)	(0.87)	(1.00)	(0.96)	(1.02)
Age	1.08	0.77	0.27	0.34	1.68	1.07
	(1.12)	(1.39)	(0.98)	(1.22)	(1.04)	(1.29)
Productivity	0.89	1.34	0.75	1.49	1.62	2.03*
	(1.15)	(1.28)	(1.03)	(1.16)	(1.06)	(1.17)
Wage premium	0.65	0.16	0.67	-0.37	-0.38	-0.53
	(1.18)	(1.22)	(1.05)	(1.10)	(1.08)	(1.14)
Local empl. share	0.36	1.29	0.03	-0.36	0.90	3.14**
	(1.15)	(1.58)	(1.04)	(1.49)	(1.16)	(1.35)
Wage floor	-2.28	-3.32	-2.27	-3.43	-0.38	-0.72
	(2.87)	(3.99)	(2.52)	(3.53)	(2.64)	(3.67)
Respondent: Owner	13.01***	12.75***	12.85***	12.58***	9.18***	8.73***
	(2.24)	(2.39)	(2.00)	(2.12)	(2.07)	(2.23)
N	2031	2031	2031	2031	2031	2031
Mean Dep. Var.	30.7	30.7	22.6	22.6	23.5	23.5
Adj.R2	0.027	0.047	0.033	0.067	0.017	0.028
Additional controls	No	Yes	No	Yes	No	Yes

Note: The table shows estimates of a linear probability model of the probability of agreeing with a preference for hiring already employed workers over unemployed workers on firm characteristics. Columns (1) and (2) report the estimates from Table 4. Columns (3) and (4) report estimates where the dependent variable indicates preference for employed workers due to concerns regarding the negative selection of the unemployed's abilities. Columns (5) and (6) report estimates where the dependent variable indicates preference for employed workers due to concerns regarding skill depreciation during unemployment. The additional controls are the same as in Table 3. Asterisks indicate statistical significance at the 1, 5, and 10% level (***,**,* respectively). Standard errors are in parentheses.

TABLE A.8. Hiring Obstacles, Firm Characteristics and Firm Preferences

Hiring obstacles:	Skill shortage (1)	Labor costs (2)	Search (3)	Training (4)	Uncertainty (5)
Prefer hiring employed	10.48***	9.00***	7.83***	7.29***	1.75
	(2.28)	(2.38)	(2.30)	(2.21)	(2.23)
Firm Characteristics					
Size	1.56	-1.83	-2.63*	-3.54**	-1.74
	(1.25)	(1.31)	(1.39)	(1.44)	(1.21)
Age	-2.41**	-2.08	-3.14**	-3.69***	-1.95
	(1.20)	(1.28)	(1.31)	(1.28)	(1.25)
Productivity	0.82	-3.76***	-1.18	-2.19*	-5.14***
	(1.18)	(1.36)	(1.34)	(1.30)	(1.41)
Wage premium	0.15	-4.19***	-0.84	0.61	-2.42**
	(1.19)	(1.21)	(1.17)	(1.11)	(1.18)
Local empl. share	-1.23	0.55	-5.51***	-1.35	-2.41**
	(1.57)	(1.52)	(1.85)	(1.73)	(1.18)
Wage floor	-5.95*	-8.81**	-0.08	1.38	5.31
	(3.58)	(3.97)	(3.98)	(3.81)	(4.07)
N	2031	2031	2031	2031	2031
Probability	.73	. 37	.35	. 33	.36
Additional controls	Yes	Yes	Yes	Yes	Yes
Worker difference	Yes	Yes	Yes	Yes	Yes

Note: The table shows ordered probit marginal effects of firm characteristics and firms' preferences for the employed over the unemployed on the probability of agreeing with statements about different hiring obstacles. It uses the exact same specification as Table 6 but, in addition, we report the estimates of the firm characteristics. Asterisks indicate statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

TABLE A.9. Hiring Obstacles, Firm Characteristics and Wage Misperception

Question: What factors can discourage the firm from recruiting despite the potential need? Hiring obstacles: Skill shortage Labor costs Search Training Uncertainty time time (1)(2) (3)(4) (5) Underestimate own wage -5.00* 5.71* -1.95 -4.81* -0.22 (2.91)(2.89)(2.88)(2.94)(2.76)Overestimate own wage -0.37 -11.06*** 3.64 1.26 -1.40 (3.13)(3.12)(3.06)(3.00)(3.04)Firm Characteristics Size 1.33 -2.50* -2.84** -3.74*** -1.82 (1.28)(1.34)(1.41)(1.45)(1.21)-2.11* -2.87** -3.49*** -2.03 -1.66 Age (1.19)(1.29)(1.25)(1.24)(1.27)**Productivity** 1.16 -3.40** -0.94 -2.04 -4.99*** (1.20)(1.30)(1.33)(1.32)(1.39)Wage premium -8.33*** 1.11 0.53 2.08 -2.54 (1.72)(1.63)(1.64)(1.57)(1.67)-5.37*** -2.52** Local empl. share 0.53 -0.95 -1.05(1.55)(1.54)(1.89)(1.77)(1.18)-7.37** -9.75** Wage floor 0.00 3.97 -0.83 (3.58)(3.93)(3.90)(3.76)(4.03)N 2059 2059 2059 2059 2059 **Probability** .73 .37 .35 .33 .36 Additional controls Yes Yes Yes Yes Yes

Note: The table shows ordered probit marginal effects of firm characteristics and wage misperception on the probability of agreeing with statements about different hiring obstacles. It uses the same specification as Table 7, but this table shows the estimates of the firm characteristics. Asterisks indicate statistical significance at the 1, 5 and 10% level (***,**,* respectively). Standard errors are in parentheses.

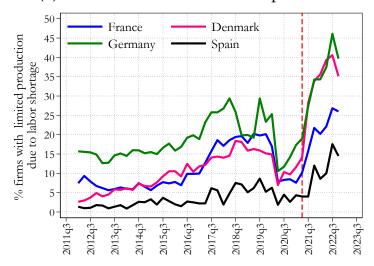
A.2. Figures

FIGURE A.1. The Prevalence of Hiring Difficulties Across Countries

Panel (a): Evidence from the United States



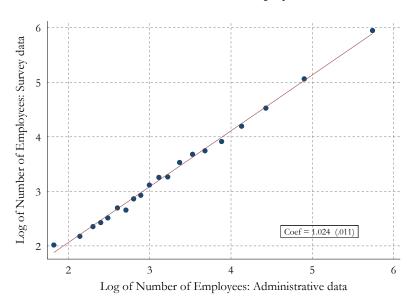
Panel (b): Evidence from Selected European Countries



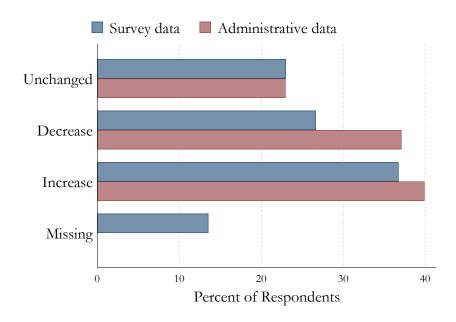
Note: The dotted red line indicates the time (June 2021) when the survey was conducted. Panel (a) reports the response to the question: Do you have any job openings that you are not able to fill right now? Source: Small Business Economic Trends, NFIB. Panel (b) reports the percentage of firms with limited production due shortage of labor in selected European countries. The question is: What main factors are currently limiting your production? Possible responses are: none, insufficient demand, shortage of labor force, shortage of material and/or equipment, financial constraints, other factors. Source: Business Survey from the DG-ECFIN 2022, i.e., the European Commission Department for Economic and Financial Affairs.

FIGURE A.2. Comparison of Survey and Administrative data

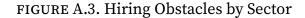
A. Panel (a): Number of Employees

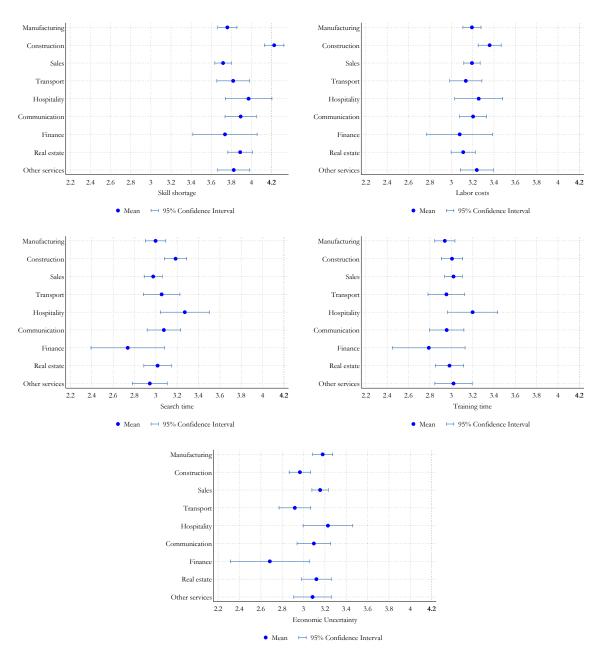


B. Panel (b): Revenue change



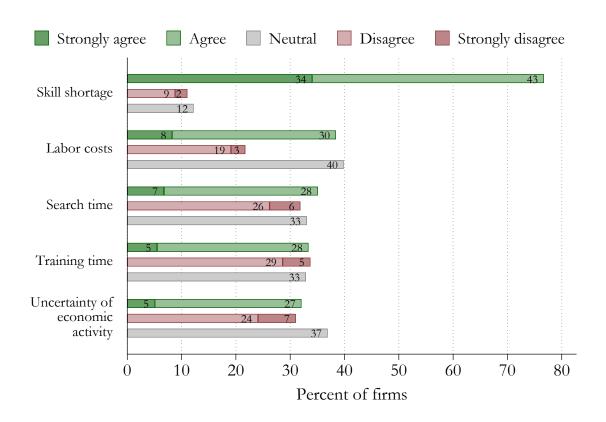
Note: Panel (a) compares the survey question, "How many employees were there in the company on May 1, 2021?" to the number of employees in March 2021 in the matched employer-employee dataset (BFL). Both variables are in logs and are winsorized. Panel (b) compares revenue changes from 2019 to 2020, in the survey and in the firm's financial data (FIRM).



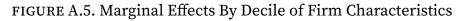


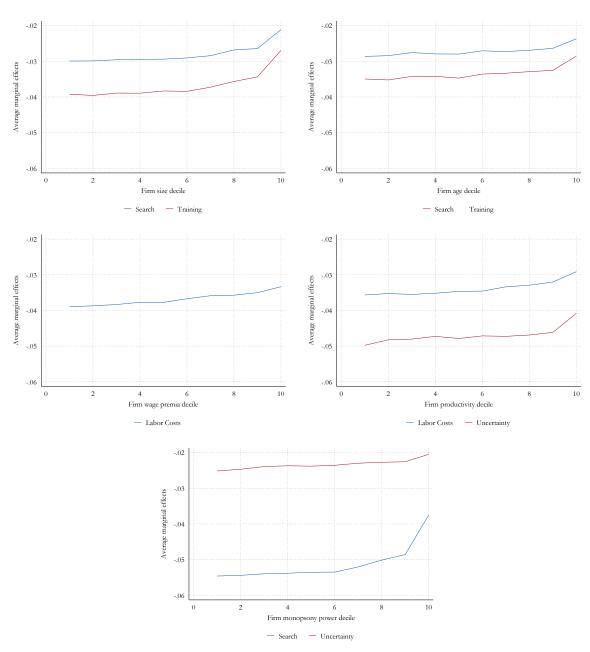
Note: These figures show how hiring obstacles (skill shortage, labor costs, search time, training time, economic uncertainty) vary by industry. The scale ranges from 1 to 5, where 5 stands for "strongly agree" and 1 stands for "strongly disagree". We report the mean responses and the 95 percent confidence intervals for each industry.

FIGURE A.4. Hiring Obstacles for Firms that Planned to Hire in 2020



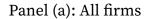
Note: The figure reports responses to the question: What factors can discourage the firm from recruiting despite the potential need? The hiring obstacles are: The lack of qualified candidates (Skill shortage); Job seekers want a higher wage than the firm can offer (Labor costs); Finding and choosing the right employee is too time-consuming (Search time); Training employees in firm-specific skills is too time-consuming (Training time); The uncertainty of economic activity. Only firms that indicate that they planned to hire in 2020 after the pandemic started are included in the sample.

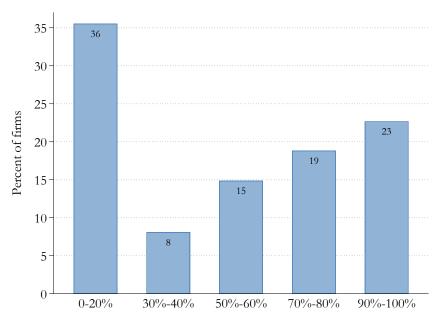




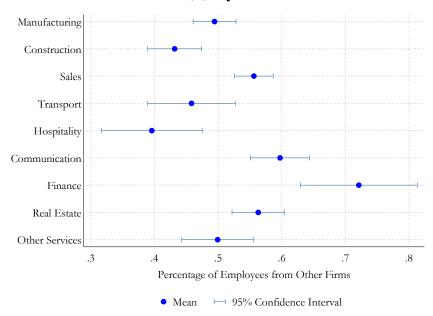
Note: These figures report the average marginal effects of firm size, age, wage premium, productivity and labor market power on firms' probability of agreeing with statements about hiring difficulties. Only statements that are strongly correlated with the specific firm characteristics are included(see Table 3). The marginal effects are the average marginal effects (evaluated at the observational level) of each decile.

FIGURE A.6. Percentage of Employees Hired from Other Firms



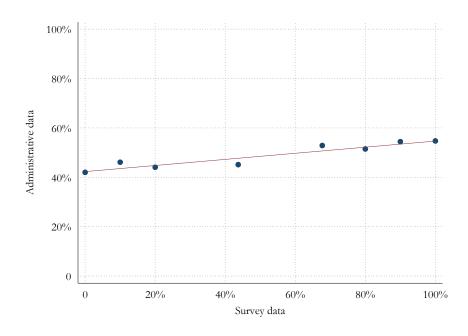


Panel (B): By sector



Note: The figure reports responses to the question: "What percentage of your employees are recruited from other firms?" The respondents have the following options: 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 100%. Panel (b) splits the sample into nine sectors.

FIGURE A.7. Poaching Rate: Our Survey vs Administrative Employer-to-Employer Rate



Note: The figure compares the survey poaching rate to the administrative poaching rate. The vertical axis shows the poaching rate from administrative data. The horizontal axis shows the poaching rate from our survey. The poaching rate from our survey is measured using the question: "What percentage of your employees are recruited from other firms?"

FIGURE A.8. Distribution of Worker Effect by Employment Status



Note: This figure shows the kernel distribution for employed and unemployed workers. Employment status is based on administrative registers. Figure 3 reports the relationship between the percentile of the unemployed worker effect and the percentile of the worker effect of all workers.

B. Additional Information on Data

B.1. Information about Administrative and Survey Data Linked to Our Survey

Most datasets can be obtained by contacting the Research service (*Forskningsservice*) of Denmark Statistics (DST henceforth). The administrative datasets come from various sources gathered by the National Statistics Agency (Statistics Denmark), the National Employment Policy Agency (STAR), and the largest employer association in Denmark (DA). To our knowledge, datasets provided by DST do not contain a DOI number, complicating replicability. The datasets that are used are recorded at a yearly frequency. Establishment identifiers are available, but our analysis focuses on the legal unit firm identifier (CVR number) as our survey asks questions about firms' practices. Individual identifiers are anonymized social security numbers (PNR number). The identifiers do not change over time. Below, we provide information about the different sources we use in this paper.

Information about workers. We use several datasets to collect information about workers. The first dataset is called IDAP (IDA persondata). IDAP contains information about the total population in Denmark. The status information for individuals mainly refers to the end of the year (31 December). From this dataset, we retrieve information about workers' age, gender, and socioeconomic status. The social economic status information allows us to delete self-employed, apprentices, and students to estimate the AKM model. It also enables to classify workers as employed or unemployed. The second dataset is called IDAN (IDA ansættelser). From this dataset, we retrieve information about occupation, earnings, hours worked, and firm identifier. Recall that hours worked are defined as paid hours (at the worker-firm frequency) that include contractual and overtime hours. Earnings are defined as the near-universe of taxable income. We use information from this dataset to define the dominant job and estimate the AKM model. Occupation classification follows the ISCO classification at 6-digit frequency.

Information about firms. We use the General Company Statistics called the FIRM dataset, which annually lists active companies in Denmark. FIRM is built from several Statistics Denmark registers. FIRM covers economic and employment information about all sectors and industries. Active companies are defined as companies with at least 0.5 full-time hours of work. The firm identifier is the CVR number, the legal firm identifier

in Denmark. We use this dataset to retrieve information about the industry classification (NACE) and the regional classification (NUTS).

The register that is used in FIRM for the value-added variable is the Accounts statistics for the Non-Agricultural Private Sector (Regnskabsstatistikken for private byerhverv), abbreviated APB. ⁴⁰ APB only includes market activity and does not contain agriculture, fishing, ports, banks, insurance, public housing companies, or public administration. There is a data break in 2014 in the population of firms included in APB. Since 2014, firms in utilities, regional and long-distance trains, and radio and TV stations have been included. Value added is defined using several items from the income statement (*Resultatopgørelse*). These items are: sales and other operating income - cost of materials and equipment - costs of energy and subcontractors - rent paid - payments to temporary workers and operational leasing of goods, and ordinary write-offs and other external charges.

Poaching rate. We use the BFL register to construct the poaching rate. BFL is a matched employer-employee data recording, at monthly frequency, the start and end dates of a job spell, as long as occupation codes, total earnings, and total hours worked in a given establishment. We measure $Poaching_j = \frac{H_{jt}^{EE}}{H_{j}t}$ where j is a firm and H^{EE} is the number of new hires coming from other firms, and H is all new hires (excluding recalls) by the firm. This definition is standard in the literature, see, e..g, Bagger and Lentz (2019).

Routine task index. We use the following categories of jobs based on tasks. We follow Acemoglu and Autor (2011) and use composite measures of O*NET Work Activities and Work Context Importance scales. Instead of using offshorability directly, we use three components of the offshorability composite measure to define "Social interaction". Below we list the definition of the variables we use.

Non-routine cognitive: Analytical.

- Analyzing data/information
- Thinking creatively
- Interpreting information for others

Non-routine cognitive: Interpersonal.

⁴⁰This register is itself built from several sources: questionnaires, official annual accounts submitted in XBRL format to the Danish Business Authority (*Erhvervsstyrelsen*), the Danish Tax Authority (SKAT), Denmark's Statistics Business Register, and the Danish Medicines Agency (*Lægemiddelstyrelsen*).

- Establishing and maintaining personal relationships
- Guiding, directing and motivating subordinates
- Coaching/developing others

Routine cognitive

- Importance of repeating the same tasks
- Importance of being exact or accurate
- Structured v. Unstructured work (reverse)

Routine manual

- Pace determined by speed of equipment
- Controlling machines and processes
- Spend time making repetitive motions

Non-routine manual: physical

- Operating vehicles, mechanized devices, or equipment
- Spend time using hands to handle, control or feel objects, tools or controls
- Manual dexterity
- Spatial orientation

Non-routine manual: interpersonal adaptability

Social perceptiveness

Social interaction

- Face-to-face discussions
- Assisting and caring for others
- Performing for or working directly with the public

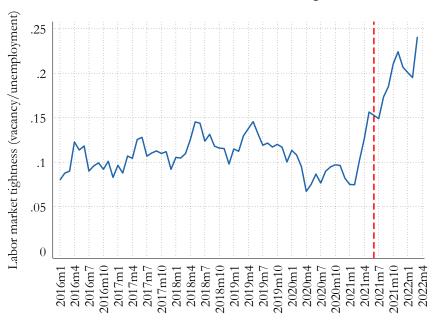
TABLE A.10. Definition of Variables

Variable:Definition and construction:Dataset:Variable name:Firm characteristicsFirm sizeNumber of employees (full-time equivalent, FTE)BFLAJO_LOENTTIMERFirm ageNumber of years since firm creationFIRMJUR_FRA_DATOProductivityValue added per firm sizeFIRMJUR_FRA_DATOWage premiumsAKM firm fixed effectsIDANLocal. emp. share within a given region-industryFIRMGF_ANSATTEWage floors=1 if at least 50% of employees are subject to a wage floor set at the industry-occupation level in the firmDA——Industry59 industries codes (2-digit NACE)FIRMGF_NACE2_DB07Region5 Danish regions codes (2-digit NUTS)FIRMJUR_BEL_REGION_KODEJob growthNet job creation rate from 2019 to 2020BFLAJO_LOENTTIMERCapital stock Liquid assets (e.g., buildings, machines, patents)FIRMGF_AATLiquidityLiquid assets (e.g., cash, bonds)FIREVKTRevenue growth Routine task in- dexRevenue growth from 2019 to 2020FIRMGF_OMSPoaching rateFraction of new hires with less than two weeks of non-employment spells between two firmsD*NETWorkforce characteritiesBFLHFAUDDEducation% of workers with at least a bachelor's degreeUDDAHFAUDDFemale% of females in the firmINDFAGFKDUpskillingMean education of new hires in 2020 / Mean educa- tion of new hires in 2019UDDAHFAUDD
Firm sizeNumber of employees (full-time equivalent, FTE)BFLAJO_LOENTTIMERFirm ageNumber of years since firm creationFIRMJUR_FRA_DATOProductivityValue added per firm sizeFIRMWage premiumsAKM firm fixed effectsIDANLocal. emp. shareFirm's employment divided by total employment within a given region-industryFIRMGF_ANSATTEWage floors=1 if at least 50% of employees are subject to a wage floor set at the industry-occupation level in the firmDA——Industry59 industries codes (2-digit NACE)FIRMGF_NACE2_DB07Region5 Danish regions codes (2-digit NUTS)FIRMJUR_BEL_REGION_KODEJob growthNet job creation rate from 2019 to 2020BFLAJO_LOENTTIMERCapital stockFixed assets (e.g., buildings, machines, patents)FIRMGF_AATLiquidityLiquid assets (e.g., cash, bonds)FIREVKTRevenue growthRevenue growth from 2019 to 2020FIRMGF_OMSRoutine task index $RTI_k = ln(T_k^R) - ln(T_k^M) - ln(T_k^A)$ O*NETdexFraction of new hires with less than two weeks of non-employment spells between two firmsBFLWorkforce characteristicsSeducation% of workers with at least a bachelor's degreeUDDAHFAUDDFemale% of females in the firmIDAPKONUnionization% unionized workers in the firmINDFAGFKDUpskillingMean education of new hires in 2020 / Mean educa-UDDAHFAUDD
Firm ageNumber of years since firm creationFIRMJUR_FRA_DATOProductivityValue added per firm sizeFIRMWage premiumsAKM firm fixed effectsIDANLocal. emp. shareFirm's employment divided by total employment within a given region-industryFIRMGF_ANSATTEWage floors=1 if at least 50% of employees are subject to a wage floor set at the industry-occupation level in the firmDA——Industry59 industries codes (2-digit NACE)FIRMGF_NACE2_DB07Region5 Danish regions codes (2-digit NUTS)FIRMJUR_BEL_REGION_KODEJob growthNet job creation rate from 2019 to 2020BFLAJO_LOENTTIMERCapital stockFixed assets (e.g., buildings, machines, patents)FIRMGF_AATLiquidityLiquid assets (e.g., cash, bonds)FIREVKTRevenue growthRevenue growth from 2019 to 2020FIRMGF_OMSRoutine task index $RTI_k = ln(T_k^R) - ln(T_k^M) - ln(T_k^A)$ O*NETdexFraction of new hires with less than two weeks of non-employment spells between two firmsBFLWorkforce characteristicsSeducationW of workers with at least a bachelor's degreeUDDAHFAUDDFemale% of females in the firmIDAPKONUnionization% unionized workers in the firmINDFAGFKDUpskillingMean education of new hires in 2020 / Mean educa-UDDAHFAUDD
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Wage premiumsAKM firm fixed effectsIDANLocal. emp. shareFirm's employment divided by total employment within a given region-industryFIRMGF_ANSATTEWage floors=1 if at least 50% of employees are subject to a wage floor set at the industry-occupation level in the firmDA—Industry59 industries codes (2-digit NACE)FIRMGF_NACE2_DB07Region5 Danish regions codes (2-digit NUTS)FIRMJUR_BEL_REGION_KODEJob growthNet job creation rate from 2019 to 2020BFLAJO_LOENTTIMERCapital stockFixed assets (e.g., buildings, machines, patents)FIRMGF_AATLiquidityLiquid assets (e.g., cash, bonds)FIREVKTRevenue growthRevenue growth from 2019 to 2020FIRMGF_OMSRoutine task index $RTI_k = ln(T_k^R) - ln(T_k^M) - ln(T_k^A)$ O*NETGF_OMSPoaching rateFraction of new hires with less than two weeks of non-employment spells between two firmsBFLHFAUDDWorkforce characteristicsEducation% of workers with at least a bachelor's degreeUDDAHFAUDDFemale% of females in the firmIDAPKONUnionization% unionized workers in the firmINDFAGFKDUpskillingMean education of new hires in 2020 / Mean educa-UDDAHFAUDD
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Age Mean age in the firm IDAP ALDERNOV
Tenure Mean tenure in the firm IDAN ANSAAR
Benefits Percentage of salary paid as personal benefits (e.g, LONN PERSGODE_PRAE car, meals, accommodation)
Non-standard Percentage of salary paid as compensation for non- LONN GENE_PRAE
work conditions standard conditions (e.g, outside working hours)
Labor market characteristics
$\Delta E - U$ Diff. in AKM worker fixed effects among employed IDAN ANSAAR
and unemployed: $\Delta_{E-U,j} = \sum_{o=1}^{O} w_{oj} (\bar{\alpha_o}^E - \bar{\alpha_o}^U)$ Tightness Firm-level labor market tightness: $\theta_i = \sum_{o=1}^{O} w_{oj} \theta_o$ STAR ——
Tightness Firm-level labor market tightness: $\theta_j = \sum_{o=1}^O w_{oj} \theta_o$ STAR —— with $\theta_o = \#V_o/\#U_o$ and $w_{oj} = N_{oj}/N_j$
Unfilled vacan- Similar to θ_j , but use % of unfilled vacancies in an Rekrutteringssurvey
cies occupation instead of θ_o
Unqualified hires Similar to θ_j , Use % of filled vacancies with "un-Rekrutteringssurvey qualified" hires in an occupation instead of θ_o
HHI index for employment at the local labor mar- FIRM GF_ANSATTE
ket level (i.e region-industry)

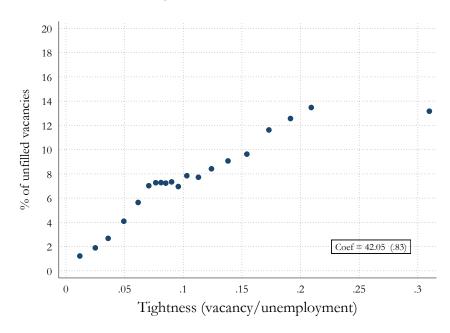
Note: The table reports the administrative datasets and the variables that we use as the firm characteristics and additional controls in our estimates. All variables are measured in 2019 unless otherwise specified.

FIGURE A.9. Labor Market Tightness in Denmark

A. Panel (a): Evolution of Labor Market Tightness



B. Panel (b): Tightness and % of Unfilled Vacancies



Note: Panel (a) reports the number of vacant positions over the number of unemployed workers in Denmark. Panel (b) links labor market tightness and the percentage of firms reporting not having filled a vacancy four months after posting it. The dotted red line indicates the time (June 2021) when the survey was conducted. Source: STAR and *Rekrutteringssurvey*.

FIGURE A.10. Invitation Letter to Participate in the Survey



Att.: Den administrerende direktør

Huardan kammar dit firma aturkat ud af krigan?

Rambøll gennemfører på vegne af Københavns Universitet en spørgeskemaundersøgelse, der skal belyse, hvordan virksomheder kan komme styrket ud af Covid19-krisen. Vi spørger om hvad du/l har gjort for at komme igennem krisen og hvilike overvejelser du gør om tiden efter Covid19.

Projektet gennemføres under ledelsen af Niels Bohr Professor Morten Bennedsen, Økonomisk Institut, og er støttet af blandt andet Industriens Fond og det Samfundsvidenskabelige Forskningsråd.

Hvis du ønsker det, vil du efter undersøgelsens afslutning modtage en anonymiseret benchmarkingsrapport, hvor du kan se dine besvarelser op mod fordelingen af andre besvarelser. Vi overholder naturligvis alle databeskyttelsesreglerne.

Det tager ca. 20 minutter at udfylde spørgeskemaet. Undervejs kan du lukke skemaet og senere genoptage besvarelsen via linket, som du har modtaget her. Husk derfor at gemme denne invitation, til du har afsluttet din besvarelse.

Sådan aar di

Spørgeskemaet besvares elektronisk via internettet. Du kan svare på alle computere, tablets (f.eks. iPad m.m.) og smartphones. Du får adgang til dit personlige spørgeskema ved at klike på nedenstående link: https://surveys.ramboil.com/answer/key=ZNEVCO9MS.ITV

Vi vil bede dig besvare spørgeskemaet senest den 27. juni 2021.

Du er sikret fortrolighed

Dine svar behandles fortroligt af Rambøll og vil kun fremgå i anonymiseret form. Du kan få mere information om behandling af personoplysninger i forbindelse med undersøgelsen på forsiden at spørgeskemaet.

Kontakt

Hvis du har yderligere spørgsmål, er du velkommen til at kontakte Rambøll på e-mail: skemasupport@ramboll.com eller tlf. 6915 8076 på hverdage i tidsrummet kl. 8.00-16.00.

På forhånd tak for din deltagelse

Med venlig hilsen Rambøll og Københavns Universitet

Note: The figure shows the invitation letter that firms received in an email asking them to participate in the survey. See an English translation of the letter below.

Att: The Administrative Director

How does your company come out of the crisis stronger?

On behalf of the University of Copenhagen, Rambøll is carrying out a survey to shed light on how firms can emerge stronger from the COVID19 crisis. We ask what you/you and others have done to get through the crisis and what thoughts you have about the time after COVID19.

The project is carried out under the leadership of Niels Bohr Professor Morten Bennedsen, Department of Economics, University of Copenhagen, and is supported by, among others Industriens Fond and the Social Science Research Council.

If you participate in the survey, we will offer you an anonymized benchmarking report that shows your responses against the distribution of the other responses. We naturally comply with all data protection regulations.

It takes approximately 20 minutes to complete the questionnaire. You can close the form and resume it later by again clicking on the link below. Therefore, please remember to save this invitation until you have completed the survey.

Here's how you do it

The questionnaire is answered electronically via the Internet. You can complete the questionnaire on any computer, tablet (e.g. iPad, etc.) or smartphone. To access your personal questionnaire, click on the link below: LINK

We ask that you complete the questionnaire no later than 27 June 2021.

You are guaranteed confidentiality

Your answers are treated confidentially by Rambøll and will only appear in anonymized form. You can find more information about the treatment of personal data in connection with the survey on the front page of the questionnaire.

Contact

If you have further questions, please feel free to contact Rambøll by e-mail: skemasupport@ramboll.com or tel. 6915 8076 on weekdays between 8.00-16.00. Thank you in advance for your participation

Yours sincerely

Rambøll and University of Copenhagen

B.2. The Survey Questionnaire

This section reports the questions from our survey we use in this paper. While some phrases can seem uncommon in English, they are perfectly understandable in Danish. Key phrases and Danish words are reported in parenthesis in Danish for Danish speakers.

Background question.

- What is your role in the company?
 - Owner manager
 - Director without ownership
 - Board member without ownership
 - Owner without being a board member
 - Other

All categories but "Other" are combined in this question to create the variable "Manager respondents".

- Does a person or family have 50% or more of the ownership?
 - Yes
 - No
 - Do not know

The category "Yes" in this question corresponds to the variable "Family-owned firm".

- How many employees were there in the company on May 1, 2021? Note: Include all employees, including full-time, part-time, furloughed and employees on apprenticeships and parental leave. Give your best estimate.
 - _ _____
- How much did revenue (*omsætningen*) change in 2020 compared to 2019? Note: If you do not know the exact change, give your best estimate.
 - Reduced by 100 percent
 - Reduced (indicate the percentage): —————
 - Unchanged
 - Increased (indicate the percentage): ----
 - Increased by 100 percent or more
- Is the company primarily a subcontractor (underlerverandør) to other companies?
 - Yes, for 90 percent or more of the revenue
 - Yes, for 50 percent to 89 percent of the revenue
 - Yes, for 25 percent to 49 percent of the revenue

- Yes, for 10 percent to 24 percent of the revenue
- Yes, for less than 10 percent of the revenue
- No
- Do not know

The categories "Yes, for 90 percent or more of the revenue" and "Yes, for 50 percent to 89 percent of the revenue in this question corresponds to the variable "Subcontractor".

- In the following questions, we ask about pay $(l \omega n)^{41}$ and hiring practices (ansæt-telsespraksis). How close are you to such decisions?
 - I am responsible for pay and employment conditions
 - I am not responsible, but I know about pay and employment conditions
 - I only know a little about pay and employment conditions
- Do you think that this company offers lower or higher salaries than competing companies in your industry? Competing companies are other employers that hire people with the same skills in your region. If you are not sure, please come up with an estimate.
 - Much lower
 - Lower
 - About the same
 - Higher
 - Much higher

Hiring question.

- What percentage of your employees are recruited from other firms? Recruited employees from other firms means people who were already employed and not unemployed or had not just entered the labor market. If you are not sure, come up with your best guess.
 - 0% from other firms
 - 10%
 - 20%
 - 30%

⁴¹In Danish, the word løn is usually translated as salary, pay or wages. The definition in the dictionary ordnet.dk is "payment that an employee receives for working".

- 40%
- 50%
- 60%
- 70%
- 80%
- 90%
- 100%, all from other firms
- Tell us your thoughts about hiring other firms' employees. Please express your opinion on the following statements. Respondents have five options (strongly agree, agree, neutral, disagree, and strongly disagree).
 - We do not necessarily prefer candidates who are employed, as there is still a need for company-specific qualities and training.
 - We do not necessarily prefer candidates who are employed as we are in doubt as to why an applicant wants to change jobs.
 - We prefer to hire candidates who are employed as unemployed workers lose their skills.
 - We prefer to hire candidates who are employed because unemployment workers have lower abilities than those who are employed.
 - Other, please write.
- When recruiting an employee, which part of the hiring process is most costly in time or money?
 - Search for candidates, conducting interviews
 - Briefing of new employees (either through his / her manager or colleagues)
- What factors can discourage the firm from recruiting despite the potential need? Please express your opinion on the following statements. Respondents have five options (strongly agree, agree, neutral, disagree, and strongly disagree).
 - The lack of qualified candidates.
 - Candidates typically want a higher salary than what the firm can offer.
 - Finding and choosing the right employee is too time consuming
 - Training (*Orientering og træning*) with company-specific skills (*evner*) and knowledge (*viden*) takes too much time
 - The uncertainty of economic activity
 - Other, please write.
- When will the newly hired employee achieve/have achieved the same productivity as an average employee in a similar position? Please indicate the estimate in months.

The possible options are from within one month up to 18 months (or more).

C. Search And Matching Model

The following model illustrates the results we derive in our empirical analysis. The model is a search and matching model that is similar in many aspects to the theoretical framework developed in Cahuc, Carcillo, and Le Barbanchon (2019). We assume that time is discrete and that firms produce differentiated products using labor as the only input factor in the production function. In period t the firm produces using the production function $A_t \frac{L_t^{1-\alpha}}{1-\alpha}$, where A_t is productivity in period t, L_t is labor in the same period and α combines both the labor elasticity of the production and the price elasticity of the production function.

For simplicity, we keep separation and the wage decisions exogenous. Posting vacancies costs c units of output per period. An exogenous fraction of workers, q_{t-1} , leaves the firm and firms post vacancies. After that, workers are hired, where matching happens with probability $m_t(\theta_t) = \bar{m}\theta_t^{-\mu}$, where $\bar{m}>0$, $\theta_t = V_t/U_{t-1}$ is labor market tightness, V_t is the number of vacancies in period t and U_{t-1} is the number of unemployed workers in period t-1. The job remains vacant at the rate $1-m_t$. Finally, production takes place.

The value of the firm is:⁴²

$$\Pi\left(A_{t}, w_{t}, m_{t}, q_{t-1}, L_{t-1}\right) = \max_{V_{t}} A_{t} \frac{L_{t}^{1-\alpha}}{1-\alpha} - w_{B}L_{t} - cV_{t} + \beta \Pi\left(A_{t+1}, w_{t+1}, m_{t+1}, q_{t}, L_{t}\right),$$

subject to the evolution of employment

$$L_t = (1 - q_{t-1}) L_{t-1} + m_t V_t$$

Consider two different states of nature, A_B when there is a boom, and A_R during a recession, hence $A_B > A_R$. The transition probability from state A_B to state A_R is denoted e_B , while the transition probability from state A_R to state A_B is denoted e_R . The separation rates potentially differ in the two states:

$$\Pi^{B}(L_{t-1}) = \max_{V_{t}} \left[A_{B} \frac{L_{t}^{1-\alpha}}{1-\alpha} - w_{B}L_{t} - cV_{t} + \beta \left(e_{B}\Pi^{R}(L_{t}) + (1-e_{B})\Pi^{B}(L_{t}) \right) \right],$$

⁴²The detailed solution of the firm's problem is available upon request.

$$\Pi^{R}(L_{t-1}) = \max_{V_{t}} \left[A_{R} \frac{L_{t}^{1-\alpha}}{1-\alpha} - w_{R} L_{t} - c V_{t} + \beta \left(e_{R} \Pi^{B}(Lt) + (1-e_{R}) \Pi^{R}(L_{t}) \right) \right],$$

subject to the evolution of employment

$$L_t = (1 - q_j) L_{t-1} + m_t V_t, j = B, R,$$

where q_i is the separation rate and we let $q_R > q_B$.

After several manipulations the first order conditions in steady state are 43

(A.1)
$$A_B L_B^{-\alpha} = w_B - \beta e_B (1 - q_R) \frac{c}{\bar{m}} \theta_R^{\mu} + \frac{c}{\bar{m}} \theta_B^{\mu} (1 - \beta (1 - e_B) (1 - q_B)),$$

(A.2)
$$A_R L_R^{-\alpha} = w_R - \beta e_R (1 - q_B) \frac{c}{\bar{m}} \theta_B^{\mu} + \frac{c}{\bar{m}} \theta_R^{\mu} (1 - \beta (1 - e_R) (1 - q_R)),$$

The law of motion equations are:

(A.3)
$$q_{j}L_{j} = \bar{m}\theta_{j}^{-\mu}V_{j}\frac{U_{j}}{U_{j}} = \bar{m}\theta_{j}^{-\mu}\frac{V_{t}}{U_{j}}U_{j} = \bar{m}\theta_{j}^{1-\mu}\left(1 - L_{j}\right), j = B, R.$$

Hence, the equations, A.1-A.3 determine labor market tightness and labour demand in booms and recessions θ_B , θ_R , L_B , and L_R . We assume that parameter values are such that labor market tightness is higher in a boom than in a recession, $\theta_B > \theta_R$ corresponding to higher employment, which is consistent with the data.

Comparative statics. We consider how labor demand and labor market tightness are affected by the variables considered in Figure 1 and Table 3. We assume that this is in a recession state (R).

First, we consider the impact of skill shortage on labor supply. We illustrate this effect by letting the productivity of workers fall corresponding to a lower productivity of the workers firms potentially hire, $\triangle A_R < 0$.

After several steps⁴⁴ we obtain:

⁴³Note that we disregard the transition periods between states. This gives two levels of employment, L_B and L_G ; and 2 levels of labor market tightness, θ_B and θ_R .

44That is, differentiation (A.2) and (A.3) with respect to θ_R , L_R and A_R , and using using equation (A.5)

(A.4)
$$dA_R L_R^{\alpha} - A_R \alpha L_R^{-\alpha - 1} \frac{dL_R}{d\theta_R} d\theta_R = \frac{c}{\bar{m}} \mu \theta_R^{\mu - 1} d\theta_R \left(1 - \beta (1 - e_R) \left(1 - q_R \right) \right),$$

(A.5)
$$\frac{dL_R}{d\theta_R} = \frac{\bar{m}\left((1-\mu)\theta_R^{-\mu}\left(1-L_j\right)\right)}{\left(q_R + \bar{m}\theta_R^{1-\mu}\right)}.$$

$$(A.6) \qquad \frac{d\theta_R}{dA_R} \triangle A_R = \frac{L_R^{\alpha}}{\frac{c}{\bar{m}} \mu \theta_R^{\mu-1} + A_R \alpha L_R^{\alpha-1} \frac{\bar{m} \left((1-\mu) \theta_R^{-\mu} \left(1-L_j \right) \right)}{\left(q_R + \bar{m} \theta_R^{1-\mu} \right)} \triangle A_R < 0,$$

where, therefore, $\frac{dL_R}{dA_R}\triangle A_R$ <0 and $\frac{d\theta_R}{dA_R}\triangle A_R$ <0. The expected sign is therefore negative, which is consistent with the findings in Figure 1 and Table 3. Hence, skill shortage implies fewer vacancies supplied and lower employment.

Second, we consider the labor costs as an impediment to hiring workers, which corresponds to a higher wage, which we observe in the second row in Figure 1. The impact on labor market tightness and employment is:

(A.7)
$$-A_R L_R^{\alpha - 1} \frac{dL_R}{d\theta_R} d\theta_R = dw_R + \frac{c}{\bar{m}} \mu \theta_R^{\mu - 1} d\theta_R \left(1 - \beta (1 - e_R) (1 - q_R) \right),$$

Using equation (A.5) we obtain

(A.8)
$$\frac{d\theta_R}{dw_R} \triangle w_R = -\frac{1}{\frac{c}{\bar{m}} \mu \theta_R^{\mu-1} + A_R \alpha L_R^{\alpha-1} \frac{\bar{m} \left((1-\mu) \theta_R^{-\mu} \left(1-L_j \right) \right)}{\left(q_R + \bar{m} \theta_R^{1-\mu} \right)} \triangle w_R < 0.$$

Hence, higher labor costs lead to fewer hirings, and labor market tightness and employment falls, $\frac{dL_R}{dw_R} \triangle w_R < 0$ and $\frac{d\theta_R}{dw_R} \triangle w_R < 0$.

Third, the third row in Figure 1, the impact of search time, can be considered through a change in the match efficiency parameter \bar{m} . We differentiate with respect to θ_R , L_R and \bar{m} . First, we obtain from equation (A.2) after using the equation to show:

in (A.4).

(A.9)
$$A_R \alpha L_R^{-\alpha - 1} dL_R + \frac{c}{\bar{m}} \mu \theta_R^{\mu - 1} \left(1 - \beta (1 - e_R) (1 - q_R) \right) d\theta_R = \frac{1}{\bar{m}} \left(A_R L_R^{-\alpha} - w_R \right) d\bar{m},$$

Then differentiating equation (A.3) gives

$$(A.10) dL_R \left(q_R + \bar{m}\theta_R^{1-\mu} \right) - \bar{m} \left((1-\mu) \theta_R^{-\mu} \left(1 - L_j \right) \right) d\theta_R = \theta_j^{1-\mu} \left(1 - L_j \right) d\bar{m},$$

These two equations have to be determined simultaneously and since the determinate is negative, D<0, if search time increases, that is, $\triangle \bar{m}$ <0, then we obtain

(A.11)
$$\frac{dL_{R}}{d\bar{m}} \triangle \bar{m} = \frac{-\bar{m}\left((1-\mu)\theta_{R}^{-\mu}\left(1-L_{j}\right)\right) - \frac{c}{\bar{m}}\mu\theta_{R}^{\mu-1}\left(1-\beta(1-e_{R})(1-q_{R})\right)}{D} \triangle \bar{m} < 0.$$

(A.12)
$$\frac{d\theta_R}{d\bar{m}} \triangle \bar{m} = \frac{-\left(q_R + \bar{m}\theta_R^{1-\mu}\right) + A_R \alpha L_R^{-\alpha-1}}{D} \triangle \bar{m},$$

Thus, longer search time leads to lower employment.

Fourth, the fourth row in Figure 1, increased uncertainty, we can illustrate by a reduction in the transition from a recession into a boom, that is, e_R falls, which means that the duration of a recession, $1/e_R$, increases. We differentiate the FOC in the recession state and get:

$$(A.13) - A_R \alpha L_R^{-\alpha - 1} \frac{dL_R}{d\theta_R} d\theta_R = \frac{c}{\bar{m}} \mu \theta_R^{\mu - 1} d\theta_R (1 - \beta(1 - e_R) (1 - q_R)) - \frac{c}{\bar{m}} \beta \left((1 - q_B) \theta_B^{\mu} - \theta_R^{\mu} (1 - q_R) \right) de_R,$$

and then use equation (A.5) to get:

$$(A.14) \qquad \frac{d\theta_R}{de_R} \triangle e_R = \frac{\frac{c}{\bar{m}}\beta\left((1-q_B)\theta_B^{\mu} - \theta_R^{\mu}(1-q_R)\right)}{\frac{c}{\bar{m}}\mu\theta_R^{\mu-1} + A_R\alpha L_R^{\alpha-1}\frac{\bar{m}\left((1-\mu)\theta_R^{-\mu}\left(1-L_j\right)\right)}{\left(q_R + \bar{m}\theta_R^{1-\mu}\right)}\triangle e_R < 0,$$

which is negative as $(1-q_B) \theta_B^{\mu} > \theta_R^{\mu} (1-q_R)$. Hirings and employment are expected to

fall.

Finally, we consider the impact of longer training time. We illustrate this by considering the impact of a higher c. We differentiate equation (A.2) and use it again to substitute to simplify to obtain:

$$(A.15) \quad -A_R \alpha L_R^{-\alpha - 1} \frac{dL_R}{d\theta_R} d\theta_R = \frac{c}{\bar{m}} \mu \theta_R^{\mu - 1} d\theta_R \left(1 - \beta (1 - e_R) \left(1 - q_R \right) \right) - \frac{1}{\bar{m}} \left(A_R L_R^{-\alpha} - w_R \right) dc,$$

and then use equation (A.5) to obtain if $\triangle c > 0$:

(A.16)
$$\frac{d\theta_R}{dc} \triangle c = -\frac{\frac{1}{\bar{m}} \left(A_R L_R^{-\alpha} - w_R \right)}{\frac{c}{\bar{m}} \mu \theta_R^{\mu-1} + A_R \alpha L_R^{\alpha-1} \frac{\bar{m} \left((1-\mu) \theta_R^{-\mu} \left(1-L_j \right) \right)}{\left(q_R + \bar{m} \theta_R^{1-\mu} \right)} \triangle c < 0,$$

Hence, hirings and employment are expected to fall when training costs increases: $\frac{dL_R}{dc}\triangle c$ <0 and $\frac{d\theta_R}{dc}\triangle c$ <0.

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