Hiring Difficulties and Firm Growth

Thomas Le Barbanchon Maddalena Ronchi
Julien Sauvagnat *

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Abstract

We estimate the causal impact of hiring difficulties on firms' outcomes. Using a shift share identification strategy, we show that hiring difficulties have negative effects on firms' employment, capital, sales, and profits. Quantitatively, a one-standard-deviation change in firm exposure to hiring difficulties explains around 9% of the variation in firm size. Firms adjust to hiring difficulties by increasing wages and the retention rate of incumbent workers, and by lowering their hiring standards. The effects of hiring difficulties are larger in expanding sectors and areas, for labor intensive and financially-sound firms, and for non-routine cognitive, high-skill, high-wage, and specialized occupations.

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I. Introduction

Even within narrowly defined industries, there is massive and persistent dispersion in firm size and performance (Syverson, 2011), which contributes to significant disparities in economic growth across areas. While prior research has made progress in identifying supply-side factors driving differences in firm outcomes (Hottman et al., 2016), such as firms' production efficiency (Melitz, 2003), the quality of firm management (Bertrand and Schoar, 2003; Bloom and Van Reenen, 2007), or their access to external finance (Rajan and Zingales, 1998; Brown and Earle, 2017), much less is known about the role of local hiring difficulties in restricting the scale of firms' operations. This is surprising given the amount of anecdotal and survey evidence highlighting that firms frequently have job vacancies they could not fill.[1] In this paper, we provide novel evidence on the following questions: What is the effect of hiring difficulties on firm growth and profitability? How do firms react when it becomes more difficult to hire workers in their local labor markets?

Our empirical setting exploits a large-scale micro dataset from the French Public Employment Services that contains detailed information on job vacancies over the sample period 2010-2017, which we can link to matched employer-employee data and financial statements for the universe of French firms. The vacancy-level dataset contains information on final recruitment success/failure and the time it takes to fill vacancies, which we use to build our measure of hiring difficulties. We isolate exogenous variation in hiring difficulties at the firm level by using a shift-share design combining occupation-specific changes in the difficulty of filling job vacancies within a local labor market (the *shifts*) with variation in firms' exposure given by their pre-sampled occupation mix (the *shares*).[2] As firms differ in their baseline occupation mix even within an industry and local labor market, our approach allows us to exploit variations in hiring difficulties that are plausibly exogenous from the firm perspective in specifications in which we can in-

[1]Survey evidence from France, Denmark, and the U.S. indicate that shortages of applicants and skill mismatch are the two most frequently reported reasons for why firms experience hiring difficulties. See Terry and de Zeeuw (2020) for more details on the Federal Reserve Banks' 2017 Small Business Credit Survey in the U.S., the Danish survey designed by Bertheau et al. (2023), and the 2023 survey "*Besoins en Main-d'oeuvre*" run by Pole Emploi in France.

[2]To ensure that the shifts are indeed "exogenous" to the firm, we apply a leave-one-out correction at the industry level and instrument the difficulty of filling a vacancy for a given firm in a given occupation by using the probability and average time it takes for other firms in the same local labor market but in different industries to fill their vacancies in the same occupation.

clude granular market-level (i.e. industry $\times$ commuting zones $\times$ year) fixed-effects to absorb any other confounding shocks that could occur in the firm own product market.

In the data, we first document that there is substantial variation in year-by-year changes in hiring difficulties for a given occupation across commuting zones and time, the underlying source of identification of our empirical design. We validate our vacancy-based measure of hiring difficulties by documenting that lower hiring success and higher time-to-fill aggregated at the occupation, industry, and geography levels strongly correlate with survey-based measures of firms' perceived hiring difficulties. We then show in a first-stage specification that our firm-level shift-share measure of hiring difficulties strongly predicts the actual hiring difficulties faced by firms in filling their own vacancies.

To guide our empirical investigation on the effect of hiring difficulties for firm size, we present a simple search model of firm hiring in partial equilibrium based on Cahuc et al. (2018). We assume that firms need to post vacancies to hire workers, and interpret hiring difficulties as an exogenous decrease in the probability of filling job vacancies. We allow the flow cost of job vacancies to differ across firms, depending on the degree of specialization of their job offers. From this model, we derive the sensitivity of firm size to local hiring difficulties, and show that the negative effect of hiring difficulties is larger when production is more labor intensive and for firms hiring workers in specialized occupations.

These theoretical predictions are confirmed in the data. We start by estimating the effect of hiring difficulties on firm employment. We find that hiring difficulties explain a sizable fraction of the variation in firm size in our sample. Quantitatively, a one-standard-deviation decrease in firm exposure to hiring difficulties is associated with a 9 percentage point increase in firm employment, which amounts to 9% of the standard deviation of this variable. We assess the robustness of this result along a large series of dimensions. We experiment with alternative ways of constructing the firm-level shift-share measure of hiring difficulties. We then augment our specification with controls for pre-sample firm characteristics interacted with year fixed effects to exclude the possibility that potential differences in firm characteristics could confound our findings. We also run a battery of additional tests to ensure that our results are not biased by local business stealing effects, by sample selection on the vacancy data, by labor demand shocks correlated across industries in the production network, by shocks hitting large firms that would affect both their employment outcomes and local hiring difficulties in their occupations, and by occupation-specific productivity shocks. We find that our results remain qualitatively and quantitatively similar across all these specifications.

Next, we consider the effect of hiring difficulties on other corporate outcomes. On the one hand, the lack of suitable workers on the labor market might lead firm to operate below potential. Higher hiring difficulties might also be associated with lower production efficiency if they lead firms to hire lower-quality workers. On the other hand, firms might be flexible enough to adapt to hiring difficulties, for instance by automating some tasks, in which case the impact on their profits might be limited. We find that hiring difficulties are associated with a decline in sales, capital, value-added, and profits, of a similar magnitude as the effect on employment. Overall, our findings are consistent with prior estimates indicating low capital-labor elasticities of substitution,[3] and with the notion that hiring difficulties have a large negative impact on firms' scale of production.

We exploit the richness of our micro data to investigate the specific labor adjustments made by firms when they face higher hiring difficulties. Our analysis reveals that firms facing hiring difficulties do not adjust at the intensive margin by increasing the annual hours worked by their employees. Instead we observe a rise in hourly wages of incumbent workers coupled with a reduction in their separation rates, consistent with the idea that firms adjust at least partly to hiring difficulties internally. On the external market, we find that firms lower their hiring standards when workers are more difficult to find.

In principle, firms may experience higher hiring difficulties either because of an increase in local labor market tightness or because of a reduction in matching efficiency. For instance, firms could encounter greater difficulties in hiring for specific occupations due to a decrease in the number of workers applying for such jobs or an increase in demand for the same workers from other employers (i.e. an increase in labor tightness). Alternatively, hiring difficulties might arise from less efficient matching technologies or a higher degree of skill mismatch between job applicants and job vacancies (i.e. an increase in matching inefficiency). To capture the fact that firms may experience higher

[3]While there is a range in existing estimates, the broader consensus points to an elasticity of substitution between labor and capital that is significantly below one. See Chirinko (2008) for a meta analysis and Oberfield and Raval (2021) for recent estimates.

difficulties in hiring due to both these distinct factors, we expand our model of frictional labor markets and provide a decomposition of shocks to our measure of hiring difficulties into shocks to local labor market tightness and residual shocks to local matching inefficiency. We find that both labor tightness and matching inefficiency shocks have significant negative effects on employment. Moreover, we find a relatively large and statistically significant effect of tightness shocks on the wages of new hires, whereas the effect is small and statistically insignificant for matching inefficiency shocks. These results are consistent with the idea that raising wages for new hires is an important response to hiring difficulties, but only when they are due to higher competition for workers on the labor market.

In the last section of the paper, we look at heterogeneous effects of hiring difficulties on firms' outcomes, depending on industry, area, firm, and occupation characteristics. First, we confirm the model predictions by showing that hiring difficulties have larger impact on labor-intensive firms. Second, we show that the negative effect of hiring difficulties is larger for firms that are more likely to be actively seeking to expand their workforce, such as those in growing sectors or regions, implying that hiring difficulties can hurt precisely those segment of the economy that can contribute the most to growth. In line with this, we find that hiring difficulties tend to have larger effects for financially-sound firms, such as large firms, firms that pay dividends, low credit-risk, and low-leverage firms. Finally, we isolate in the cross-section of occupations the ones for which hiring difficulties are likely to have the highest impact on firms' outcomes. We find that firm profits are more sensitive to hiring difficulties for non-routine cognitive, high-skill, high-wage, and specialized occupations. Interestingly, consistent with the notion that these occupations are complements rather than substitutes with capital, we find that hiring difficulties for non-routine cognitive, high-skill, high-wage, and specialized occupations lead to larger declines for both firm employment and capital. These findings resonate with prior work in support of the "capital-skill complementarity" hypothesis (Griliches, 1969; Goldin and Katz, 1998; Lewis, 2011).

This paper contributes to several strands of the literature. We build on existing work showing that hiring is costly and takes time (Kramarz and Michaud, 2010; Blatter et al., 2012; Davis et al., 2013; Jäger and Heining, 2019). A number of empirical studies have delved into the reasons for why some firms have a hard time finding suitable workers for their jobs (see e.g. Haskel and Martin, 1993, 2001; Kerr et al., 2016; Weaver, 2021; Bertheau et al., 2023), but none of them estimate the impact of hiring difficulties on firms' outcomes. Related to our paper are existing studies documenting how aggregate labor market conditions affect firms' demand for skills (Modestino et al., 2016; Hershbein and Kahn, 2018; Modestino et al., 2020) and providing experimental evidence on how firms adjust vacancy wages when it is more difficult to find workers (Cullen et al., 2023). Consistent with these studies, our findings reveal that firms lower their hiring standards when confronted with hiring difficulties and that adjusting wages of new hires is not their primary response for addressing these challenges. What distinguishes our work from existing papers is our ability to extend the analysis beyond hiring policies, introducing novel evidence on the impact of hiring difficulties on firm growth and performance.

Our paper also relates to previous work studying the effects of labor supply shocks on firms and workers. While earlier studies have examined market-wide labor supply shocks - such as those from immigration or shifts in education levels (Katz and Murphy, 1992; Card, 2009; Dustmann et al., 2009) - more recent work provides micro-level evidence on the impact of specific shocks, such as the inflow of foreign workers with particular skills (Paserman, 2013; Dustmann and Glitz, 2015; Dustmann et al., 2017; Mitaritonna et al., 2017; D'Acunto et al., 2020; Orefice and Peri, 2020; Beerli et al., 2021; Doran et al., 2022). At the same time, a growing literature in finance has examined how labor market rigidities affect firm financial outcomes (Simintzi et al., 2015; Ghaly et al., 2017; Serfling, 2016; Matsa, 2018), as well as how financing frictions influence firms' employment through hiring, firing, and retention (Bernstein et al., 2024; Baghai et al., 2021; Caggese et al., 2019; Giroud and Mueller, 2017; Brown and Matsa, 2016). We contribute to these two lines of work in two ways. First, we construct a novel measure of hiring difficulties using vacancy-level data on occupation-specific job-filling rates. This measure enables us to examine how local labor market tightness and matching inefficiencies vary across firms and job characteristics. Second, whereas prior work in finance has largely examined how adverse shocks affect firm employment through financial constraints, we instead study what happens when firms face difficulties in hiring workers — thus shifting the focus to periods typically associated with economic booms or stable conditions. Our novel finding is that hiring frictions disproportionately constrain the growth of financially-sound firms. In other words, it is precisely those firms with ample financial resources - which would otherwise be best positioned to expand - that suffer the most from labor market frictions.

More broadly, we contribute to recent research providing evidence on supply-side factors that could account for the observed dispersion in firm size even within narrowly defined industries (see e.g. Bartelsman and Doms, 2000; Syverson, 2011). While a growing body of work in management and corporate finance highlights the quality and the local supply of highly ranked executives in shaping firm outcomes (Bertrand and Schoar, 2003; Bender et al., 2018; Bennedsen et al., 2020; Huber et al., 2021; Sauvagnat and Schivardi, 2020), the broader impact of hiring frictions across various job roles remains unexplored. In that respect, our results highlight the role of local hiring difficulties for a broad set of occupations as an important determinant of the growth and profitability of firms across time and space. In doing so, we provide new insights into the economic consequences of labor shortages for firms,[4] with important implications for the design of location-based policies to foster growth (e.g. Glaeser and Gottlieb, 2008; Kline, 2010; Ku et al., 2020). Specifically, our findings suggest that policies alleviating labor market tightness - such as policies promoting female employment[5] - or improving matching efficiency - such as targeted education and training programs[6] - may not only benefit individual workers, but also foster firm growth at the local level.

The remainder of this paper proceeds as follows. Section II presents a simple model of firm hiring with vacancy posting. Section III presents the data and Section IV describes our empirical strategy. Section V presents our main results on firm employment and performance, while Section VI provides evidence on firms' adjustment margins to hiring difficulties. Section VII documents the heterogeneous effects of hiring difficulties across industries, areas, firm characteristics, and occupation characteristics. Section VIII concludes.

[4]See Autor (2021); Causa et al. (2022); Forsythe et al. (2022) for discussions on the implications of labor shortages for jobs and working conditions.

[5]See Olivetti and Petrongolo (2017); Rossin-Slater (2017); Kleven et al. (2020).

[6]See Kinsler and Pavan (2015); Card et al. (2018); Grosz (2020); Guvenen et al. (2020); Katz et al. (2022); Eckardt (2023) for recent evidence on the returns to different labor market programs and the cost of occupational mismatch from the perspective of workers.

II. A Model of Firm Hiring With Vacancy Posting

To guide our empirical investigation, we present a simple search model of firm hiring based on Cahuc et al. (2018). We assume that firms need to post vacancies to hire workers, and interpret hiring difficulties as an exogenous decrease in the probability of filling job vacancies. We allow the flow cost of job vacancies to differ across firms, depending on the degree of specialization of their jobs. The model is partial equilibrium, i.e. wages and hiring difficulties are taken as given, and allows us to characterize the sensitivity of firm employment to hiring difficulties with a simple expression. From this model, we derive insights into how firm size is affected by hiring difficulties and how this relationship varies based on the labor intensity of the firm's production function and its reliance on a mix of specialized occupations. All proofs are relegated to Internet Appendix C.

The model. Time is discrete. In each market, firms produce goods using labor L only. The revenue function of the firm in period t is equal to $A_t R(L_t)$, where R is an increasing and concave function, and $A_t > 0$ is a productivity parameter. The firm needs to post job vacancies, denoted by V_t, to hire workers. Posting a vacancy costs c_v per period. Because hiring costs may differ across occupations, we allow c_v to differ across firms depending on the degree of specialization of their occupation mix. This allows us to capture the fact that hiring workers for more specialized roles, like those in engineering or IT, likely entails a more in-depth screening process, which can include technical tests, multiple interview rounds, or involve external advisors in the hiring process.[7]

In each period, the sequence of decisions is as follows: (1) an exogenous proportion q_t of workers quits the firm; (2) job vacancies are posted; (3) workers are hired; (4) production takes place and wages are paid. A job vacancy posted in period t is matched with a worker with probability $m_t \in [0, 1]$ and remains unfilled with probability $1 - m_t$. The probability to fill a job vacancy is determined by a matching function: $m_t = m_t^0 \theta_t^{-\gamma}$ where m^0 is local matching efficiency, and γ indicates the elasticity of matching to labor market tightness.

When wages are exogenous, firms maximize their profits:

[7]See Manning (2011); Blatter et al. (2012) for evidence on hiring costs being larger in specialized occupations.

$$\Pi(L_{t-1}) = \max_{L_t, V_t} A_t R(L_t) - w_t L_t - c_v V_t + \beta \mathbb{E}\left[\Pi(L_t)\right], \tag{1}$$

where β denotes the discount factor, the expectation is taken over potential shocks on future wages, job separation rates and vacancy filling rates, and the firm is subject to the law of motion of employment:

$$L_t - L_{t-1} = V_t \times m_t - L_{t-1} \times q_t. \tag{2}$$

Using the first order condition for the maximization of profits with respect to V_t, and the envelope theorem, we can derive the firm dynamic labor demand as follows:

$$A_t R_L(L_t) = w_t + \frac{c_v}{m_t} - \beta \mathbb{E}\left[\frac{(1-q_{t+1})c_v}{m_{t+1}}\right] \tag{3}$$

We interpret an increase in hiring difficulties as a decline in the vacancy filling rate m_t, or equivalently as an increase in $\tau_t = 1/m_t$, which in this model can be seen as a measure of recruiting time.

Sensitivity of firm size to hiring difficulties. Manipulating equation (3), and assuming that R is homogeneous of degree $\alpha \in (0,1)$, such that $R(L_t) = (L_t)^\alpha/\alpha$, we obtain the following expression for the semi-elasticity of firm employment to a temporary increase in hiring difficulty τ_t:

$$d \log L_t \approx \frac{c_v}{w_t} \frac{1}{(\alpha - 1)} d\tau_t \tag{4}$$

The above equation clarifies how an increase in hiring difficulties, i.e. higher recruiting time τ_t, is expected to depress firm employment. The negative effect of hiring difficulties on firm size is stronger for larger α, that is when firm production is more labor intensive, and for firms with larger flow vacancy costs c_v, i.e. those hiring workers in more specialized or skill-intensive occupations. In our empirical analysis we will test for whether these theoretical predictions are confirmed in the data.

III. Data

In what follows, we separately describe our three main administrative data sources: the vacancy-level dataset provided by the French Public Employment Service (PES), the employment registers covering the universe of the French workforce, and the financial statements covering the universe of private firms, both provided by the French Statistical Office (INSEE). These datasets are merged together using a unique firm identifier.[8] Our sample period starts in 2010 and ends in 2017, which are respectively the first and last year for which the vacancy-level dataset is available. We include in the sample all non-financial firms that were active in France in 2009, the year used for the construction of firms' pre-sample employment shares in each occupation (the *shares* in our shift-share design). We discuss the external validity of our data at the end of the section, and presents summary statistics in Table I.

A. Vacancy-level data

We follow prior work (see e.g Autor et al., 2013; Acemoglu and Restrepo, 2020), and use commuting zones as the relevant geographical unit for defining local labor markets.[9] To construct measures of hiring difficulties that vary by occupation and commuting zones, we exploit vacancy-level data from the French Public Employment Service (PES). The PES provides key intermediation services and operates *pole-emploi.fr*, the largest online job board of the French labor market.[10] On the platform, any firm (public, private) can post their job ads and any worker can search for employment opportunities free of charge.

For every vacancy posted, we observe the occupation code, the workplace location, the number of position offered, and the firm identifier. Additionally, we have access to information regarding the type of employment contract offered and any requirements

[8] The employment registers and firms' financial statements are not publicly available, but are available for academic research through a procedure similar to accessing Census data in the U.S.

[9] These areas, built by INSEE, are aggregated as clusters of municipalities that are characterized by strong within-cluster and weak between-cluster commuting ties.

[10] According to a survey conducted by the French Ministry of Labor in 2016 (the OFER survey), around 50% of firms declare using *pole-emploi.fr* for posting job offers online. *pole-emploi.fr* is also the most popular website among job seekers in France, attracting 46 million visitors per month in 2017 (source Pole Emploi website).

for education and experience specified in the vacancy listing. A unique advantage of our data is that we can observe for each vacancy its posting date and its delisting date, which we use to calculate the time it takes for firms to fill up their vacancies. Moreover, we can identify whether a vacancy is delisted because a worker has accepted the job offer, indicating a recruiting success, or whether it was removed without a successful recruitment outcome.[11]

Measuring hiring difficulties. Formally, we measure hiring difficulties in a given occupation k, commuting zone cz, and year t, using data on both the recruitment success and time-to-fill across all vacancies v posted in that occupation, commuting zone and year, as:

$$HiringDiff_{k,cz,t} = \frac{\sum_{v\in k,cz,t} Unfilled_v + \sum_{v\in k,cz,t} Filled_v \cdot min(DaysToFill_v, 365)/365}{\sum_{v\in k,cz,t} Unfilled_v + \sum_{v\in k,cz,t} Filled_v}. \quad (5)$$

$HiringDiff_{k,cz,t}$ is an index taking values between 0 and 1, and combines information on both the probability of ever filling a vacancy (through the numbers of vacancies *Filled* and *Unfilled*), and conditional on filling it, the observed time it takes (through *DaysToFill*). $HiringDiff_{k,cz,t}$ is equal to zero when the probability of filling a vacancy is 100% and vacancies are filled immediately. At the other extreme, $HiringDiff_{k,cz,t}$ is equal to one when the observed probability of filling a vacancy is either 0%, or alternatively, when it takes more than one year to fill vacancies.[12]

Occupation-level statistics. For each occupation, we present the average probability of vacancies not being filled and, for those that are filled, the time it takes to fill them, i.e. the two components that are used to build our measure of hiring difficulties defined in Equation (5). As shown in Figure A1 and A2 in the Internet Appendix, we find substantial heterogeneity in both components across the 84 2-digit occupations in our data.[13]

[11] When firms post vacancies, they are assigned to a local public employment agency. The information on whether a vacancy has been delisted due to hiring success or hiring failure is highly reliable as it is collected by the PES employees of the local agency, who, as part of their jobs, are in charge of monitoring vacancies and checking their status.

[12] We set the cutoff of 365 days to match the annual frequency of our analysis. Virtually all vacancies are filled in less than 365 days (more than 99.9%). In Table III, we also present our results when measuring hiring difficulties simply using the share of unfilled vacancies: $ShareUnfilled_{k,cz,t} = \frac{\sum_{v\in k,cz,t} Unfilled_v}{\sum_{v\in k,cz,t} Unfilled_v + \sum_{v\in k,cz,t} Filled_v}$.

[13] Unsurprisingly, occupations with a high share of unfilled vacancies also tend to have high hiring time.

In particular, across occupations the average share of unfilled vacancies is 15.9%, with a standard deviation of 3.5%, and the average time-to-fill is 39.6 days, with a standard deviation of 4.6 days.

Because our identification strategy exploits year-by-year changes in occupation-specific hiring difficulties within commuting zones (the *shifts* in our shift-share design discussed below), we report this variation for each occupation in Figure 1. We observe substantial variation in year-by-year changes in hiring difficulties for a given occupation. In particular, for all occupations, there are periods and areas in which hiring becomes more difficult (i.e. probability of filling a vacancies declines or the time it takes to fill them increases) and periods and areas in which hiring becomes easier.

Correlation with survey data. Finally, we merge our data with two surveys on firms' reported hiring difficulties in order to validate our vacancy-based measure of hiring difficulties. As discussed in more details in Appendix B, we find a strong and robust correlation between the share of unsuccessful recruiting and the average time required to fill vacancies - namely, the two components used to build our measure of hiring difficulties - and the survey-based measures - namely, the share of establishments reporting hiring difficulties at the industry $\times$ commuting-zone level in the Business Tendency Survey of the French Statistical Institute, and the fraction of difficult recruiting searches aggregated at the occupation $\times$ department level in the manpower survey from the French Public Employment Service. This evidence substantiates the reliability of our vacancy-based measure as an accurate reflection of firms' perceived difficulties in finding workers on the labor market.

B. Employment registers

Our analysis also relies on matched employer-employee data (the *déclarations administratives de données sociales*, DADS) built by INSEE from the social security contribution declarations of firms. Each year, firms declare the employment spells, the occupation code, the number of hours worked, and the associated wages for each worker. The occupations codes of each employee in each firm are crucial for our analysis, as we use them to construct the *shares* in our shift-share empirical approach presented below. From the employment registers, we also compute the following outcome variables: end-of-year firm employment, the number of new hires and total separations, as well as wages and hours worked separately for new hires and incumbents.

C. Firm-level tax filings

The third main administrative micro data we use is extracted from the universe of French firms' tax files. The data includes balance sheets as well as profit and loss statements of each firm. We track firms through time using their unique identifying number, and retrieve their three-digit level industry classification using an industry code ascribed to each firm by INSEE.

If hiring difficulties prevent firms from growing or reduce their productive efficiency, we expect this to show up in terms of sales and profits. We therefore construct from this data the following firms' outcome variables: total sales, value added, gross profits (earnings before interest, depreciation, and taxes, EBITDA), and capital (defined as the stock of tangible assets net of accumulated depreciation). We compute return on assets (ROA) as gross profits over assets. As shown in Table I, firms in our sample have on average 14 employees and ROA for the average firm is around 6.6%. Finally, we construct proxies for firm financial constraints that are widely used in the literature: credit risk, measured as the inverse of the interest coverage ratio; a dummy variable for dividend payers; and leverage.

D. External validity

One may wonder whether our empirical analysis using French data will be informative for the impact of hiring difficulties on firms' outcomes beyond the case of France. Is France an outlier in terms of the recruitment frictions faced by firms on the labor market? We can answer this question by using surveys about firms' stated hiring difficulties that available in other countries. In the 2017 wave of the U.S. National Federation of Independent Business survey, around 30% of small businesses reported that they had jobs they could not fill. This compares well with the 30% of firms declaring that they encountered recruitment difficulties in the business tendency surveys run by the French Statistical Office in 2017. Similarly, Eurostat provides information on the fraction of firms that report having hard-to-fill vacancies for jobs requiring relevant ICT skills:[14] in France, over half (54%) of all enterprises that recruited or tried to recruit ICT specialists had difficulties in filling these vacancies, a number that perfectly overlaps with the EU average (54%). Even though the survey covers only ICT occupations, the evidence suggests that France is similar to other developed countries in terms of the degree of hiring difficulties faced by firms.

A related question is how representative France is in terms of the fluidity of its labor market. While international comparisons are difficult due to data comparability issues, the existing evidence suggests that France is not an outlier in terms of job reallocation rates. Gómez-Salvador et al. (2004) compute job creation rates for 13 European countries from firm-level data, finding that France has a rate close to the average of the Euro area (5.1%, against an average of 5.6%). Bassanini and Garnero (2013) focus on worker flows for OECD countries and find that France is in the middle of the distribution for the hiring rate (16% in France against 12% in Italy, 14% in Germany, and 21% in the U.S.), and for the separation rate (16.5% in France against 12% in Italy, 15% in Germany, and 22% in the U.S.).

IV. Empirical Strategy

Our objective is to estimate the causal effect of hiring difficulties on firm outcomes. However, because firm-level shocks to demand or productivity might affect both corporate performance and hiring effort, establishing a causal link between these two variables is challenging. To address this problem, we predict hiring difficulties at the firm-level using a shift-share instrument, also called Bartik instrument, which, in general terms, can be seen as a weighted average of a common set of shocks (*shifts*) with weights reflecting heterogeneity in shock exposure (*shares*).

In practice, we follow this empirical strategy by interacting time-varying shocks to hiring difficulties that are specific to each occupation $\times$ local labor market, with the occupation-mix of a given firm. We measure shocks to hiring difficulties using variation in both the probability and the time it takes to fill a vacancy in a given 2-digit occupation

[14] For more details, see https://ec.europa.eu/eurostat/en/web/products-eurostat-news/-/ddn-20190327-1

$\times$ commuting zone. To make sure that these shocks are indeed "exogenous" from the perspective of the firm, we apply a leave-one-out correction at the industry level and include only information on hiring success and time-to-fill from vacancies posted by firms in the same occupation and commuting zone, but operating in other 3-digit industries.[15] The shares instead are specific to each firm and consist in the proportion of a firm total workforce employed in each 2-digit occupation. To avoid that shocks affecting both a firm occupational structure and firm outcomes bias our estimates, we pre-sample information on the occupation-mix and construct time-invariant shares using 2009 information on firm-level employment by occupation.[16] Finally, to obtain our firm-level shift-share measure of hiring difficulties, we multiply for each firm the shift component with the corresponding occupation share, and then aggregate these occupation-specific products at the firm-level.

Formally, denoting by $HiringDiff_{k,cz,-j,t}$ our measure defined in Equation (5) computed across all vacancies for occupation k in commuting-zone cz and year t, but excluding those posted by firms operating in industry j, and denoting by $s_{i,k,09}$ the share of firm i workforce employed in occupation k in year 2009 (with $\sum_k s_{i,k,09} = 1$), our baseline firm-level shift-share measure of hiring difficulties (indicated with the subscript ss) reads as follows:

$$HiringDiff_{ss,i,cz,j,t} = \sum_k s_{i,k,09} HiringDiff_{k,cz,-j,t} \tag{6}$$

Importantly, our shift-share measure of hiring difficulties can be computed for the universe of firms, including those that do not post vacancies on the French PES online job board. Each firm i operating in industry j and located in the local labor market cz is characterized, at baseline, by a specific production function, which is reflected by a particular occupation-mix. While "shocks" to hiring difficulties, which vary across narrowly defined occupations $\times$ commuting zone, are plausibly exogenous to any given firm i (once we remove from their computations information from job vacancies posted

[15]There are 84 distinct 2-digit occupations, 270 distinct 3-digit industries, and 322 distinct commuting zones. In robustness tests presented in Table III, we further exclude observations from local firms in connected industries, namely operating in upstream and downstream sectors.

[16]Unfortunately, we cannot use information pre-dating 2009, as the classification of occupation codes was different in earlier years. As shown in Table III, our results are robust to using shares in 2010.

by firm i and all other firms operating in the same industry as firm i), their impact may still significantly vary across firms because each of them - even *within the same local labor market and industry* - has a different occupational structure.

Our identification strategy closely approximates the following example. Take two firms, A and B, located in the same commuting-zone cz and operating in the same industry j (say the car industry). Suppose they both only employ workers in two types of occupations, mechanical engineers (k= "MECH") and IT engineers (k= "IT"), with however different occupation shares at baseline (s^A_{MECH}, s^A_{IT}) and (s^B_{MECH}, s^B_{IT}) (with $s^i_{MECH} + s^i_{IT} = 1$ for $i = A, B$). To compute *HiringDiff* as defined in Equation (5) we use data on vacancies for both occupations "MECH" and "IT" posted by firms operating in the same labor market cz as firms A and B but active in all industries other than j. We then construct our shift-share instrument for local hiring difficulties faced by firm A and firm B as:

$$HiringDiff_{ss,A,cz,j,t} = s^A_{MECH} \times HiringDiff_{MECH,cz,-j,t} + s^A_{IT} \times HiringDiff_{IT,cz,-j,t}$$

$$HiringDiff_{ss,B,cz,j,t} = s^B_{MECH} \times HiringDiff_{MECH,cz,-j,t} + s^B_{IT} \times HiringDiff_{IT,cz,-j,t}$$

Suppose that firm A relies more on occupation *IT* than firm B ($s^A_{IT} > s^B_{IT}$) in the pre-sample period, and that it becomes more difficult to hire workers for occupation *IT* in commuting zone cz. This could be the case because the current number of potential applicants for *IT* jobs declines or because more firms in other industries compete for the same *IT* workers (and therefore labor tightness increases), or because there is a higher mismatch between the skills of applicants and the skill requirements of IT vacancies (and therefore matching inefficiency increases). We will estimate whether this shock had a larger impact on the employment (or another outcome) of firm A than firm B in a specification in which we can include granular market-level (i.e. industry $\times$ commuting zones $\times$ year) fixed-effects to absorb any other confounding shocks that could occur in the firm own product market.

Specifically, we run the following OLS specification at the firm-year level:

$$Y_{i,cz,j,t} = \alpha_i + \beta HiringDiff_{ss,i,cz,j,t} + \mu_{cz,j,t} + \epsilon_{i,cz,j,t} \tag{7}$$

where $Y_{i,cz,j,t}$ is a given outcome variable of firm i (which operates in commuting zone cz and industry j) in year t, $HiringDiff_{ss,i,cz,j,t}$ is the firm-level shift-share measure for hiring difficulties defined in Equation (6), and $\mu_{cz,j,t}$ indicate industry $\times$ commuting zone $\times$ year fixed effects. Standard errors are clustered at the commuting zone level.[17]

Validity of the empirical strategy. Formally, identification rests on the assumption that shocks to hiring difficulties observed in other industries of the same commuting zone are orthogonal to the error term. Next, we discuss potential threats to this assumption and how to address them. Detailed discussions of the tests we conducted, along with further analyses for robustness, are presented in Section V.B.

One potential concern is the presence of local or industry-specific shocks that simultaneously affect firm outcomes and the hiring difficulties that they face in their local labor market.[18] Importantly, our specifications include industry $\times$ commuting zone $\times$ year fixed effects ($\mu_{cz,j,t}$ in Equation (7)) which allow us to absorb any potentially confounding product market-level shocks that could drive both changes in time-to-fill and, say, firm employment. In other words, in Equation (7), identification comes from comparing the performance of two firms within the same market and year, based only on differences in their pre-determined occupation mix.

One could still argue that the negative effect of higher hiring difficulties for the same occupations in other industries of the same local labor market on firms' employment is biased by the presence of inter-industry linkages between local firms.[19] To address this concern we perform a robustness exercise in which we remove all information on the hiring success and time-to-fill of any firm located in both upstream and downstream industries with respect to firm i when constructing the shift-share variable.

Third, the presence of firms that employ a significant portion of the workforce in a particular occupation within a local area could create a reflection problem. Specifi-

[17]This choice is more conservative than clustering standard errors at the commuting zone × industry level, and takes into account that hiring shocks for some occupations in a given commuting zone are likely to affect several industries in the same location simultaneously.

[18]Consider for instance a positive local productivity shock driving both an increase in recruiting intensity per vacancy for local firms and an increase in their employment.

[19]Consider for instance a positive productivity shock in upstream sectors driving both an increase in recruiting intensity per vacancy in upstream sectors and an increase in employment in downstream sectors. This could lead to a spurious association between our shift-share variable and employment, even in the absence of any causal effect of hiring difficulties on employment.

cally, idiosyncratic shocks affecting these large employers could simultaneously affect their employment outcomes and cause variations in their own shift-share variable for hiring difficulties by impacting local market tightness for those occupations. To address this concern, we exclude from our baseline regression all firms that represent a sizable fraction of the local labor market for any occupation.

Fourth, our shift-share variable might reflect the effects of aggregate occupation-specific productivity shocks, rather than changes in local hiring difficulties. To mitigate this concern, we will augment our baseline specification with a shift-share variable using information on filling probabilities and time-to-fill for each occupation across all commuting zones, excluding the commuting zone of the firm itself.

Finally, one might worry that firms endogenously select their location by taking into account that hiring difficulties in their most important occupations might have a negative impact on their performance. However, if anything, this should bias the results against finding any effect of hiring difficulties on firm performance, given that the most vulnerable firms to hiring difficulties are likely to endogenously select location where there is a large supply of suitable workers in the occupations for which they have a high demand.

There is a recent literature which formally derives the identification conditions of shift-share designs (e.g. Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020). As we emphasize the exogeneity of the shifts, our empirical design can be considered within the context of the framework outlined by Borusyak et al. (2021). Their framework underlines two identification conditions: quasi-random shifts and many uncorrelated shifts. As already discussed, the first condition is likely to hold because of our granular industry x commuting zone x year fixed effects, combined with the leave-one-out approach. The second condition is also likely to hold, as we leverage a large number of shocks. In particular, we leverage as many shocks as combination of 3-digit industry (250 codes), commuting zones (304 zones), 2-digit occupation (84 codes) and the seven years in our sample, which amounts to 1,883,047 shifts (after accounting for cells without any observations). In addition, we observe low intraclass correlation coefficients across shifts after we residualize them by industry x commuting zone x year fixed effects.[20]

[20] We follow Borusyak et al. (2021) and estimate a model with hierarchical random effects to compute the Intraclass Correlation Coefficients (ICC). Specifically, we proceed in two steps. To account for the fact that

Examples of identifying variation. Before proceeding to the results, we provide an informal discussion of the economic shocks that can generate identifying variations in our instrument. In principle, occupation-specific job filling rates in local labor markets can be influenced by shocks to either tightness or matching efficiency. Occupation-specific shocks to local labor market tightness may arise due to *labor supply* shocks, such as changes in the number of job applicants, or to *labor demand* shocks, which lead to an increase in vacancy posting. In contrast, matching efficiency shocks raise job filling rates for specific occupations, holding tightness constant. For example, the introduction of a job seekers' screening technology, the opening of a new local Public Employment Service agency, or the organization of a new training program that reduces skill mismatch could all create matching efficiency shocks.

In our model of firm hiring outlined in Section II, individual firms take occupation-specific job filling rates in their local labor market as given. We argue that this assumption is plausibly met in our empirical design, given the types of shocks that can determine changes in our measure of hiring difficulties. Market-level *labor supply* shocks, such as changes in recent graduate cohort size or migration flows, and *matching efficiency* shocks, such as changes in skill mismatch, can all be viewed as exogenous from an individual firm's perspective. Moreover, our industry-level leave-one-out correction enables us to leverage uncorrelated *labor demand* shocks in other industries. Thus, market-level labor supply shocks, uncorrelated labor demand shocks in other industries, and matching efficiency shocks are all likely to satisfy the exclusion restriction and can represent potential identifying sources of variation in the level of hiring difficulties that individual firms face.

In Section VI.C, we show that we can decompose shocks to hiring difficulties into shocks to labor market tightness and residual shocks to matching efficiency. This allows us to separately identify the effects of shocks to hiring difficulties on employment and wages that originate from changes in labor tightness and changes in matching in-

our baseline model includes firm fixed effects and market fixed effects, we first compute the first difference of the shifts and residualize them by the market fixed effects. This gives us the residualized first-difference $\tilde{g}_{k,cz,-j,t}$ for occupation k, in commuting zone cz, leaving out industry j, and in year t. Second, to compute the ICC, we estimate by maximum likelihood the following equation: $\tilde{g}_{k,cz,-j,t} = a_k + b_{k,cz} + c_{k,cz,j} + e_{k,cz,-j,t}$. We find that the implied ICCs are 0.004, 0.018 and 0.018, indicating that identifying shifts are mutually uncorrelated.

efficiency. We believe that our ability to estimate firms' responses to hiring difficulties arising from different types of shocks represents a key advantage of our empirical approach, particularly as previous studies have typically restricted their attention to firms' responses to specific market-level labor supply shocks, such as the inflow of foreign workers with a particular set of skills.

V. The Effect of Hiring Difficulties on Firm Outcomes

In this section, we first present the baseline effects of hiring difficulties on firms' employment, and then explore the robustness of our main findings along a large series of dimensions. Finally, we turn to the effect of hiring difficulties on other corporate outcomes.

A. Baseline results on employment

We start by assessing the internal validity of our empirical setting, and check whether there is a strong relationship between the shift-share prediction of hiring difficulties, $\textit{HiringDiff}_{ss,i}$, and the actual hiring difficulties faced by firms on their posted vacancies, $\textit{HiringDiff}_i$. By construction, in this first-stage specification, the sample is restricted to firms posting at least one vacancy in year t on *pole-emploi.fr*.

Column (1) of Table II presents the result in our baseline specification with firm fixed effects and industry $\times$ commuting zone $\times$ year fixed effects. The coefficient is positive and statistically significant at the one percent level, indicating that our shift-share instrument has predictive power for firms' hiring difficulties. In Column (2) of Table II, we then run Equation (7) where the dependent variable is the logarithm of firm employment. We find a negative relationship between the shift-share variable and log employment, statistically significant at the one percent level. This is consistent with the view that hiring difficulties have a significant adverse impact on firms' employment.

In order to interpret the magnitude of the effect of hiring difficulties on firms' employment, we perform an instrumental variable (IV) analysis, where realized hiring difficulties at the firm level ($\textit{HiringDiff}_i$) are instrumented with the shift-share variable. To maximize statistical power, we directly compute the Wald estimator, i.e. the ratio of the reduced-form estimate to the first stage coefficient. This allows us to use the whole sample for the reduced form, even if we can compute the first stage on the subsample of posting firms only.[21] As shown in Column (3) of Table II, our IV estimate is equal to -0.366. This coefficient implies that a one-standard-deviation decrease in firm exposure to hiring difficulties (0.252, see Table I) is associated with a 9 percentage point increase in firm employment, which amounts to around 9% of the standard deviation of this variable.[22] This indicates that hiring difficulties explain a sizeable fraction of the variation in firm size in our sample.

B. Robustness checks

We now explore in detail the robustness of our baseline result on employment obtained from running Equation (7), and presents the findings in Table III.

Alternative shift. Our main measure of hiring difficulties combines information on the probability of ever filling vacancies and, when filled, the time it takes to fill them. In Column (1), we check the robustness of our baseline finding to using only information on the probability of filling vacancies for a given occupation, in a given commuting zone, while using the same leave-one-out correction at the industry level. The estimate is similar to the baseline result reported in Column (2) of Table II.

Occupation shares in 2010. The year in which we measure the occupation mix of firms is the end of 2009. While occupation shares are sticky over time, one concern is that we measure them at the end of the financial crisis. We therefore check whether we find the same results when computing the shares at the end of 2010. The estimate, presented in Column (2), remains similar.

[21] The IV estimator can be computed as the Wald ratio of the reduced-form estimate ($\hat{r}$, Column (2) of Table II) and of the first-stage estimate ($\hat{f}$, Column (1) of Table II). Let us denote $se(r)$ (resp. $se(f)$) the standard errors of $\hat{r}$ (resp. $\hat{f}$). Then using the delta method, we obtain the standard errors of the Wald ratio ($\hat{w} = \hat{r}/\hat{f}$) as : $se(w) = \left(se(r)^2 / \left(\hat{f}\right)^2 + se(f)^2 \left(\hat{r}\right)^2 / \left(\hat{f}\right)^4 \right)^{1/2}$.

[22] A simple back-of-the-envelope calculation based on this estimate and equation (4) of our model delivers a magnitude for the flow vacancy costs, c_v, of around 12% of workers' annual salaries, in line with previous work (see e.g. Cahuc et al., 2018; Kramarz and Michaud, 2010). Formally, as shown in Equation (4), the ratio of the flow vacancy cost in terms of annual salaries, c_v/w_t, is equal to our estimate for the semi-elasticity of employment to hiring difficulties, $\frac{d \log L_t}{d\tau_t}$ (-0.366) multiplied by $(\alpha - 1)$, where the constant α can be approximated with standard values of the labor share, $\alpha = 2/3$.

Excluding managerial occupations. One may wonder whether our results are driven by hiring difficulties associated to managerial occupations. While this is unlikely, as managerial positions represent less than 2% of firms' workforce, we can directly test for this concern. In Column (3), we exclude managerial occupations from our measure of hiring difficulties, and find virtually identical results. This confirms that the negative impact of hiring difficulties on firm employment is not specific to managers, but applies broadly to the entire spectrum of non-managerial occupations.

Firm characteristics. One may worry that firms' occupation mix in 2009 (the *shares*) correlates in a systematic way with other initial firm characteristics that, in turn, could explain the differences in employment trends observed throughout the sample period. For example, ex-ante more productive firms might initially employ more workers in skilled occupations, and grow faster over the sample period. If this is true, and hiring difficulties decrease relatively more for skilled occupations than for unskilled occupations over the sample period, this could lead us to observe a negative relationship between hiring difficulties and employment, even in the absence of any causal relationship. To control for this possibility, we augment our specification with firm characteristics (terciles of firm size, age, and ROA, all measured pre-sample), interacted with year fixed effects. Including these controls ensures that the estimates are not driven by heterogeneous trends among large, old, or profitable firms. The result of this augmented specification is reported in Column (4). The estimate on the variable of interest remains stable, mitigating the concern that potential differences in firm characteristics that correlate with their pre-sampled occupation mix could confound our findings.

Local spillovers. Another concern is that hiring difficulties, by disrupting some firms, might benefit other less-affected firms in the same industry and area if they are competitors in local product markets. This would lead us to overestimate the causal impact of hiring difficulties on firm employment in our baseline specification. To directly address this concern, we remove non-tradable industries from our sample (e.g. restaurants), where local demand spillovers could bias our estimates upward, and present the results in Column (5). The estimate is virtually unchanged compared to our baseline result, and compared to the estimate in the subsample of non-tradable industries shown in Column (6), indicating that business-stealing effects have a negligible impact on our findings, if at all.

Sample selection on vacancy data. Even though a large fraction of French firms use the *pole-emploi.fr* online job board to post their vacancies, our results are not estimated using the universe of job posting. One possible concern is that the vacancy data we use is not representative of the whole universe of firms looking for workers. In Internet Appendix Figure A3, we first show that the industry distribution of firms that have posted vacancies on the Public Employment Service's website at least once is broadly comparable with the one of firms that never posted a vacancy (and therefore presumably use alternative means to hire workers). We then go one step further and run our baseline specification for employment separately for both sub-sample of firms. As shown in Columns (7) and (8), the estimates are virtually identical, which largely addresses the concern that potential differences in hiring difficulties across matching platforms could bias our estimates.

Input-output linkages. One may also be concerned that our results could spuriously reflect demand or productivity shocks hitting connected sectors in the supply chain, rather than the causal impact of recruiting frictions on firms' outcomes. We thus check whether our estimates are robust to removing information on filling probabilities and time-to-fill from upstream and downstream industries when computing our shift-share instrument. Specifically, we use sector-level information from the input-output matrix to compute for each industry the share of inputs that come from other industries (upstream) and the share of output bought by other industries (downstream). We tag as connected any industry that represents more than 1% of either the upstream or downstream flows. We recompute the occupation-specific shifts, with a leave-one-out correction that excludes not only the firm's own industry but also all other industries tagged as connected. Column (9) presents the results with this more conservative shift-share instrument. The coefficient on employment is slightly reduced, but remains large and statistically significant. This alleviates the concern that our result is driven by demand or productivity shocks propagating through input-output linkages in production networks.

Reflection problem. One could argue that the identifying assumption is likely to be violated for large firms on the local labor market due to a reflection problem. Consider for instance a positive demand shock that leads a large firm to hire a large number of IT engineers in a given commuting zone. To the extent that this firm represents a large share of the local market for IT engineers, that demand shock might increase hiring difficulties for other firms hiring IT engineers in other sectors in the same commuting zone (through an increase in local market tightness for IT engineers). This could in turn lead us to observe an increase in the shift-share measure of hiring difficulties for the large firm, an example of a reflection problem in our setting. Even though one can argue that examples along this line would likely lead us to underestimate the causal impact of hiring difficulties on firm employment, we can also address the reflection problem directly. To do so, we re-run our main specification after removing from the sample any firm that represents more than 1% of the local market for a given occupation in a given commuting zone, and presents the result in Column (10). The coefficient of interest remains unchanged.

Occupation-specific productivity shocks. Finally, one may worry that our shift-share variable does not capture local changes in hiring difficulties per se, but instead reflect the effects of occupation-specific productivity shocks across the French territory.[23] To tackle this issue, we augment our baseline specification with a shift-share variable using information on filling probabilities and time-to-fill for each occupation in all other commuting zones (excluding the commuting zone of the firm itself). If our baseline estimates reflect occupation-specific productivity shocks, this variable should subsume the effect of the main variable of interest, $HiringDiff_{ss}$. As shown in Column (11), the coefficient of interest remains statistically significant at the one percent level in this augmented specification, indicating that variations in our main variable of interest indeed reflect the causal impact of hiring difficulties on firms' employment.

C. Other corporate outcomes

We turn to investigate if the negative effects of hiring difficulties extend beyond firms' employment by analyzing their impact on other corporate outcomes. On the one hand, the lack of suitable workers on the labor market might lead firm to operate below potential. Higher hiring difficulties might also be associated with lower production efficiency if they lead firms to hire lower-quality workers. On the other hand, firms might be

[23] Consider for example a general labor-augmenting technology, such as specific software for IT engineers. One may worry that, across all commuting zone, the associated increase in the productivity of IT engineers might feed into changes in vacancy filling rates for this occupation and higher employment for firms hiring IT engineers, violating the exclusion restriction.

flexible enough to adapt to hiring difficulties, for instance by automating some tasks, in which case the impact on their profits might be limited. To shed light on these questions, we run the specification in Equation (7) where the dependent variable is respectively firm capital, sales, value-added, and profits. Table IV presents the results.

In Column (1), we find a negative effect on firm capital, of similar magnitude than the effect on firm employment. This is consistent with hiring frictions having a large negative impact on firm scale of production, and low degree of substitution between labor and capital. This could be due to the fact that occupations for which hiring frictions matter for firm growth are complements rather than substitutes with capital. We shed more light on this point in Section VII.

In Columns (2-4), the estimates on sales, value-added, and profits, are collectively consistent with the notion that hiring difficulties lead firms to scale down their production, which in turn leads to a reduction in value-added and profits. Quantitatively, a one-standard-deviation increase in firm exposure to hiring difficulties is associated with reductions in capital, sales, value-added, and profits of respectively around 9%, 6%, 8%, and 10%.[24] Given that profits might be negative for some firms, we check the robustness of the result on the logarithm of profits using instead ROA as an alternative measure, and find consistent effects. Taken together, our results show that firms have a hard time mitigating the negative effect of hiring difficulties on employment as they experience a reduction in their entire scale of production.

VI. Mechanisms and Adjustment Margins

We now exploit the richness of our micro data to directly investigate the adjustment margins of firms facing hiring difficulties. Specifically, we look at hours worked and wages for both new hires and incumbents in employment registers, at hiring rates and separation rates, and at changes in hiring standards. We show that hiring difficulties lead to an increase in employees' wages, an increase in incumbents' retention, and a decrease in hiring standards when measured through experience requirements. We then break

[24]For obtaining these numbers, we multiply each estimate presented in Table IV by the standard deviation of hiring difficulties in our sample (0.252, see Table I), and divide it by the first-stage estimate (0.078, Column (1) of Table II).

down shocks to hiring difficulties into shocks to local labor market tightness and shocks to local matching inefficiency, and estimate their effects on firm employment and wages. While both tightness shocks and matching inefficiency shocks have negative effects on employment and positive effects on the wages of incumbent workers, we find that firms raise wages for new hires in response to hiring difficulties only when they are due to higher competition for workers on the labor market.

A. Wages, hours worked, and retention of the workforce

Wages and hours worked. We start by investigating how firms adjust their wages when facing hiring difficulties, and present the results in Table V. In particular, firms may increase hiring wages to attract the few suitable workers available on the labor market, and/or increase wages internally to retain their existing workforce. Before looking specifically at the effect on new hires versus incumbents, we first study the effect of hiring difficulties on total payroll: as shown in the first column of Panel A of Table V, we find a negative and statistically significant effect, but smaller in magnitude compared to the baseline effect on employment (-0.015 versus -0.029, as reported in Column (2) of Table II). Consistent with this result, we find a positive effect on yearly wages per worker in Column (2), significant at the 1 percent level. In Columns (3) and (4), we decompose the yearly wages into its two components: yearly hours and hourly wages. We do not find evidence that firms compensate for hiring difficulties by increasing the hours worked by each worker. Instead, an increase in hiring difficulties is associated with an increase in hourly wages.

We then study the effects of hiring difficulties on the hours worked and wages by incumbents and new hires separately, and present the results in Panel B of Table V. As shown in Columns (1) and (2), we do not find significant effects on yearly hours for either incumbents or new hires. As for wages, Column (4) provides clear evidence that firms tend to increase wages internally when confronted with hiring difficulties. This is in line with efforts to boost retention among existing employees. The effect found on the wages of new hires instead is smaller and insignificant, although still positive (see Column (3)). This suggests that increasing the wages of new hires is not the primary response to hiring difficulties, which is consistent with recent experimental evidence by Cullen et al. (2023). We return to this finding in Section VI.C, where we show that this result masks important heterogeneity depending on the underlying factors driving hiring difficulties (i.e. shocks to labor tightness versus matching inefficiency shocks).

Workforce turnover. Finally, in Panel C of Table V, we look at hiring (in Column 1) and separation rates (Column 2), as a fraction of total employment. We find that hiring difficulties are associated with both negative effects on hiring rates and separation rates. Whereas the negative effect on hiring rates provide direct evidence that hiring difficulties lead firms to depress hiring, the negative effect on separation rates confirms an important margin of adjustment through firms' internal labor markets, which is consistent with the positive effect on incumbents' wages documented in Panel B.[25]

B. Hiring standards

Using additional information included in the vacancy-level dataset, we turn to investigate the effects of hiring difficulties on hiring standards, and present the results in Table VI. Specifically, we investigate changes in the average experience (in months) and education (in years) requirements across all job postings within a specific occupation, as well as variations in the share of vacancies offering open ended (as opposed to temporary) contracts and those offering full-time (versus part-time) contracts. By construction, in these specifications, the sample is restricted to firms posting at least one vacancy in a given year. While we do not find evidence that hiring difficulties have a discernible effect on education requirements, or changes in the type of job contract offered, there is a statistically and economically significant effect of hiring difficulties on experience requirements. Quantitatively, a one-standard-deviation increase in firm exposure to hiring difficulties is associated with more than a 6-month decrease in experience required. This represents 30% of the standard deviation of this variable.[26] This result is consistent with the notion that firms lower their recruitment standards when they struggle to find suitable candidates in their local labor markets.

[25]There are multiple channels that may explain the positive effect found on the wages of incumbents. In particular, the positive wage effects could reflect an increase in bargaining power for incumbents, or an increase in incumbents' productivity through training. Unfortunately, we do not have firm-level information on training expenses to provide direct evidence on this second margin.

[26]For obtaining this number, we multiply the estimate by the standard deviation of hiring difficulties in our sample (0.252, see Table I), and divide it by the first-stage estimate (0.078, Column (1) of Table II).

C. Labor market tightness and matching efficiency

We turn to providing a decomposition of shocks to hiring difficulties into shocks to labor market tightness and a residual component that captures shocks to matching inefficiency. We then estimate the separate effects of tightness and matching inefficiency shocks on firm employment and wages.

As in the model presented in Section II, the vacancy filling rate, $m_{k,cz,t}$, is defined at the local labor market level (occupation k, commuting zone cz and year t) and can be viewed as being the product of the following two components:

$$m_{k,cz,t} = m^0_{k,cz,t}\theta^{-\gamma_k}_{k,cz,t}\,, \tag{8}$$

where $m^0_{k,cz,t}$ is the local matching efficiency, $\theta_{k,cz,t}$ is the local labor market tightness – i.e. the ratio between the number of vacancies posted within year t and the number of unemployed for a given occupation k –, and γ_k is the elasticity of the matching function, which is bounded between 0 and 1. Equation (8) explicitly shows what can affect the difficulty of hiring for a specific occupation within a local area. Firstly, hiring becomes easier when local competition for workers (“tightness”) decreases in certain occupations. This can result from other employers decreasing their labor demand (reflected in an drop in the number of vacancies) or from an increase in the number of workers supplying labor (reflected in an increase in the number of unemployed). Secondly, improvements in ”matching efficiency” can also facilitate hiring. These shocks can be technological changes that reduce information imperfection in the labor market and mitigate coordination failures, or shocks that decrease the degree of skill mismatch between the pool of applicants and potential employers.[27]

We use the vacancy data and the unemployment registers of the French Public Employment Service, to obtain empirical counterparts for respectively the number of vacancies, and for the number of unemployed, and compute local labor market tightness $\theta_{k,cz,t}$ as the ratio between the two variables in each occupation $\times$ commuting zone $\times$ year.[28]

[27] See for example Barnichon and Figura (2015) for a discussion on how matching efficiency estimated as residuals in aggregate matching function regression captures skill mismatch, and Burke et al. (2019) for evidence on within-occupation changes in skill requirements over time using vacancy-level data.

[28] In the unemployment registers, unemployed individuals declare their preferred occupation and the local area in which they search for jobs. We do not have similar data on the industry they are searching

Separately for each occupation k, we then regress our measure of hiring difficulties on local market tightness in a 2-SLS specification where we control for both commuting-zone and year fixed effects and we instrument labor market tightness with its lagged value, $\theta_{k,cz,t-1}$, as in Borowczyk-Martins et al. (2013)[29]:

$$\log HiringDiff_{k,cz,t} = \alpha_k + \gamma_k \theta_{k,cz,t} + \mu_{cz} + \mu_t + \nu_{k,cz,t}, \tag{9}$$

As our measure of hiring difficulties can be seen as the inverse of the job filling rate $m_{k,cz,t}$, this regression provides us with an estimate for the matching elasticity γ_k in Equation (8). This allows us to compute hiring difficulties due to changes in tightness for each occupation x commuting zone x year, as: $\mathcal{T}_{k,cz,t} = 1/\left(m^0_{k,cz,2010}\theta_{k,cz,t}^{\widehat{-\gamma_k}}\right)$, and refer to the residual part, $\mathcal{M}_{k,cz,t} = HiringDiff_{k,cz,t} - \mathcal{T}_{k,cz,t}$, as matching inefficiency shocks. Finally, we construct the firm-level shift-share measure of labor tightness and matching inefficiency as: $\mathcal{T}_{ss,i,cz,t} = \sum_k s_{i,k,2009}\mathcal{T}_{k,cz,t}$ and $\mathcal{M}_{ss,i,cz,t} = \sum_k s_{i,k,2009}\mathcal{M}_{k,cz,t}$, and run a similar regression as Equation (7) where the baseline shift-share variable is replaced by $\mathcal{T}_{ss,i,cz,t}$ and $\mathcal{M}_{ss,i,cz,t}$:

$$Y_{i,cz,j,t} = \alpha_i + \beta_T \mathcal{T}_{ss,i,cz,t} + \beta_M \mathcal{M}_{ss,i,cz,t} + \mu_{cz,j,t} + \epsilon_{i,cz,j,t}. \tag{10}$$

Effect on employment. We present the results on employment in Column (1) of Table VII. We find that both β_T and β_M are negative and statistically significant, indicating that shocks to both labor tightness and matching inefficiency negatively impact firms' employment. If anything, matching inefficiency shocks tend to have larger effects than tightness shocks. Consistent with an important role played by matching inefficiencies, we show in Section VII that hiring difficulties have a stronger negative effect when they hit occupations where workers have job-specific skills that are harder to acquire or substitute away from, such as non-routine cognitive occupation or specialized occupations.

Effect on wages. We turn to the effect on hourly wages, and present the results for

into, which prevents us from making the same leave-one-out correction at the industry level as we do for the baseline shift-share variable.

[29] As discussed in Borowczyk-Martins et al. (2013), regressing recruiting time on labor market tightness in the same period would expose a simple OLS specification to simultaneity bias, because labor market tightness and job filling rates are simultaneously determined as functions of the unobserved efficiency of the matching process.

all workers in Column (2), and separately for new hires and incumbents in Column (3) and Column (4) respectively. While the aggregate effect of hiring difficulties on hourly wages of new hires was not statistically significant on average in Table V, once we look separately at shocks to tightness versus shocks to matching inefficiency, we find a relatively large and statistically significant effect of tightness shocks on the wages of new hires, whereas the effect is small and statistically insignificant for matching inefficiency shocks. These results are consistent with the notion that raising wages for new hires is an important response to hiring difficulties, but only when they are due to higher competition for workers on the labor market.[30] [31] Finally, for incumbents, we find that both tightness and matching inefficiency shocks are associated with increases in wages. Intuitively, both type of shocks can conceivably contribute to higher wages for incumbents, as increased tightness could enhance incumbents' bargaining power, while reductions in matching efficiency might result in increased productivity for existing employees if it leads firms to training their workforce.

VII. Heterogeneity Analysis

In this section, we investigate the heterogeneity of the effects of hiring difficulties on firms' employment and performance depending on firms' industry, location, and characteristics, and then turn to the heterogeneity of the effects depending on occupation characteristics and task content. In doing so, we also test the theoretical predictions presented in Section II regarding the sensitivity of firm employment to hiring difficulties depending on firms' elasticity of labor in the revenue function and flow vacancy cost.

[30] Interestingly, our findings are consistent with survey evidence in Terry and de Zeeuw (2020), where firms declare to *"increase starting pay"* as a response to hiring difficulties when they are due to *"too few applicants"* or *"competition from other employers"*, but not when they are due to *"lack of soft skills"* or *"lack of job-specific skills"*. In the same survey, firms that experience difficulties in finding candidates with *"job-specific skills, education, or experience"* were more likely to say they *"restructured existing employee responsibilities"* or *"loosened job requirements or offered more training"*.

[31] The result is also consistent with an equilibrium version of the hiring model presented in Section II. Specifically, Cahuc et al. (2018), from which we borrow our partial-equilibrium model, show that with wage posting and directed search, equilibrium wages of new hires depend on tightness, but not directly on matching efficiency.

A. Industry and firm characteristics

Expanding versus declining sectors/areas. Presumably, the negative effects of hiring difficulties on firms' employment should be stronger in expanding sectors or areas. After all, in declining sectors/areas, firms are less likely to hire new workers, and should therefore be less sensitive to hiring difficulties on the labor market. To test whether this is true, we sort sectors and areas into those in expansion and in decline, depending on their overall employment growth over our sample period (based on a median split). The results are presented in Columns (1) and (2) of Table VIII for sectors, and in Columns (3) and (4) of Table VIII for commuting zones. Overall, the sensitivity of employment to hiring difficulties is indeed larger for expanding sectors and expanding areas, implying that hiring difficulties can hurt precisely those segment of the economy that can contribute the most to growth.

Low versus high labor share. The effects should also be stronger for labor-intensive firms, whose larger weight in labor inputs make them more sensitive to hiring difficulties (see our model prediction in Section II). To check whether this is true, we sort firms into those with low and high labor-intensity, based on their ratio of employees over assets measured at baseline (i.e. 2009). The results are presented in Columns (5) and (6) of Table VIII. The negative effect of hiring difficulties on employment is indeed significantly stronger for labor-intensive firms.

Firm age, productivity, and financial constraints. One may wonder whether hiring difficulties have differential effects on firm employment depending on standard firm characteristics. For instance, young firms, for whom swift adaptation to rapidly changing economic opportunities is critical, might be more adversely affected by hiring difficulties, whereas older firms might simply postpone hiring when frictions on the labor market are less severe. The returns to hiring, and therefore the sensitivity of performance to hiring difficulties, might be larger for more productive firms. Alternatively, for not losing highly profitable matches, more productive firms might respond to hiring difficulties by increasing their recruiting efforts. Finally, financially-constrained firms might not have enough internal funds to hire workers regardless of circumstance, and therefore show a lower sensitivity of their employment to hiring difficulties. To shed light on these issues, we run our baseline specification by distinguishing firms based on whether they fall below or above the median value in terms of age, profitability, total factor productivity (TFP), size, credit risk, leverage, and their status as dividend payers. We present the findings in Table VIII.

Columns (7-12) show that hiring difficulties have a similar effect on firms employment, irrespective of firm age and productivity. Instead, when we split the sample of firms in Columns (13-20) into those that are more versus less likely to be financially constrained (small firms, those paying no dividends, with high credit risk, and high leverage versus large firms, paying dividends, with low credit risk, and low leverage), we find consistent evidence that financially constrained firms display a lower sensitivity of their employment to hiring difficulties, indicating that it is precisely those firms with ample financial resources – which would otherwise be best positioned to expand – that suffer the most from labor market frictions.

We present in Figure 2 the results of the same heterogeneity analysis by industry, geography, and firm characteristics for the other firm outcome variables presented in Table IV, namely sales, value-added, profits, and capital. Overall, the differences in the sensitivity of profits to hiring difficulties in each sub-sample reproduce the patterns in the sensitivity of employment to hiring difficulties discussed above, and confirm that the effects of hiring difficulties are heterogeneous across firms depending on the growth of their industry and location, their degree of labor-intensity, and their degree of financial constraints.

B. Occupation and task characteristics

One advantage of our data is that we can identify the occupation of each vacancy, which allows us to examine whether firms' outcomes are especially sensitive to hiring difficulties on occupations characterized by specific features. In particular, we can test our model prediction that the effects should be stronger for skill-intensive and specialized occupations (see Section II). For this, we augment our baseline specification with an interaction term representing the firm-level shift-share variable built using information on only on a subset of occupations of a given type $\mathcal{K}$:

$$Y_{i,cz,j,t} = \alpha_i + \beta HiringDiff_{ss,i,cz,j,t} + \beta_{\mathcal{K}} \sum_{k \in \mathcal{K}} s_{i,k,09} HiringDiff_{k,cz,-j,t} + \mu_{cz,j,t} + \epsilon_{i,cz,j,t}, \quad (11)$$

We consider below several types of occupations, and present the results in Table IX.

Routine, manual, cognitive and interpersonal tasks. We start by categorizing occupations into different types depending on the occupation-specific classification of tasks developed by Autor et al. (2003). Specifically, we assign to each occupation a score depending on their relative intensity in five different tasks: routine manual, routine cognitive, non-routine manual, non-routine cognitive and non-routine interpersonal tasks. Based on these scores, we then classify occupations as being routine manual intensive, routine cognitive intensive, non-routine manual intensive, non-routine cognitive intensive, and non-routine interpersonal intensive if they are in the top tercile of their respective scores.[32]

As shown in Columns (1-5) of Table IX, we find that firm employment is more sensitive to hiring difficulties in non-routine cognitive occupations (such as IT engineers), less sensitive to hiring difficulties in non-routine manual (such as vehicle drivers) and routine manual occupations (such as unskilled workers in construction), whereas the sensitivity of firm employment to hiring difficulties in non-routine interpersonal occupations (such as sales executives) and routine cognitive occupations (such as accountants) is virtually the same than for the other occupations.

High-skill and high-wage occupations. Similarly, we use information in our vacancy-level data to isolate occupations with skill requirements, and information in the employment registers to classify occupations as high-wage. High-skill occupations and high-wage occupations are those in the top tercile of their respective distribution. We then re-run the same regression as the one presented in Equation (11). As shown in Columns (8) and (9), we find that the sensitivity of firm employment to hiring difficulties is larger for high-skill and high-wage occupations.

Specialized occupations. Finally, we construct a direct measure of hard-to-substitute occupations based on the full matrix of labor flows across occupations. For this, we compute in the sample of all workers switching employers over our sample period the number of transitions from occupation O ("origin") to occupation D ("destination"). Then, for each occupation D, we compute the share of firm-to-firm transitions in which the worker was employed in their previous firm in the same occupation ($O = D$), and

[32] Specifically, we aggregate O*NET task measures available for the US into the French occupation classification at the 2-digit level using aggregate employment in each occupation as weights.

classify as specialized occupations those ranked in the top tercile.[33] We re-estimate Equation (11) for specialized occupations and present the results in Column (7). The interaction term $HiringDiff_{ss} \times Specialized$ is negative and statistically significant at the 1 percent level, consistent with the idea that it is harder for firms to redirect their hiring on other types of workers when facing hiring difficulties on specialized occupations.

One may wonder whether there is a strong overlap between our measure of specialized occupations and the other characteristics considered above. We thus present in Internet Appendix Figure A4 the list of specialized occupations as well as the list of routine manual intensive occupations, routine cognitive intensive occupations, non-routine manual intensive occupations, non-routine cognitive intensive occupations, non-routine interpersonal tasks intensive occupations, high-skill occupations, and high-wage occupations. Overall, the ranking of specialized occupations is only weakly correlated with the characteristics considered above. For instance, specialized occupations include high-wage/high-skill/non-routine analytic occupations such as IT engineers and doctors, but also low-wage/manual occupations such as cooks or skilled workers in construction. We directly test and confirm that the higher sensitivity of firm employment to hiring difficulties on specialized occupations is not explained by other occupation characteristics. For this, we re-estimate Equation (11) with the interaction term $HiringDiff_{ss} \times Specialized$, in addition to each of the previously considered interaction terms separately. Results are shown in Appendix Table A1. As shown in Columns (1-7), the negative coefficient on $Hiring\ Difficulties_{ss} \times Specialized$ remains stable across specifications and statistically significant at the 1 percent level.

Finally, we present in Figure 3 the results of the same heterogeneity analysis by task and occupation characteristics for the other firm outcome variables namely sales, value-added, profits, and capital. As shown in Figure 3, the differences in the sensitivity of profits to hiring difficulties across occupation characteristics reproduce the patterns in the sensitivity of employment to hiring difficulties that we discussed above, and confirm that the effects of hiring difficulties are stronger for non-routine cognitive, high-skill, high-wage, and specialized occupations. Interestingly, consistent with the notion that these occupations are complements rather than substitutes with capital, we find that

[33] Our measure of specialized occupations is similar to the measure of occupational mobility used in Schubert et al. (2021) for studying the impact of employer concentration on wages.

hiring difficulties for non-routine cognitive, high-skill, high-wage, and specialized occupations lead to larger declines for both firm employment and capital. These findings resonate with prior work in support of the "capital-skill complementarity" hypothesis (Griliches, 1969; Goldin and Katz, 1998; Lewis, 2011).

VIII. Conclusion

This paper studies the causal effect of hiring difficulties on firms' outcomes. We use a shift-share identification strategy combining occupation-specific changes in the difficulty of filling job vacancies within a local labor market (the *shifts*) and variation across firms in their pre-sampled occupation mix (the *shares*). The intuition behind this methodology is that while aggregate variation in difficulty of filling job vacancies in a given occupation and local labor market can be viewed as exogenous from the individual firm perspective, their impact may vary significantly across companies precisely because each of them - even within the same industry and local labor market - has a different occupational structure.

We show that hiring difficulties have negative effects on firms' employment, capital, sales and profits. Firms partially adjust to hiring difficulties by increasing wages, the retention rate of incumbent workers, and by lowering their hiring standards. Consistent with the "capital-skill complementarity" hypothesis, we find that hiring difficulties for skilled and specialized occupations have a particularly strong impact on employment and capital. Importantly, the adverse effects are most pronounced among financially-sound firms, indicating that it is precisely those firms with ample financial resources – which would otherwise be best positioned to expand – that suffer the most from labor market frictions.

Taken together, our findings lend empirical support for business leaders' concerns that hiring difficulties pose significant constraints on firms' capacity for expansion. They suggest that targeted labor market policies (such as encouraging female labor supply or financing training programs targeted at some specific professions) can enhance capital accumulation and economic growth at the local level.

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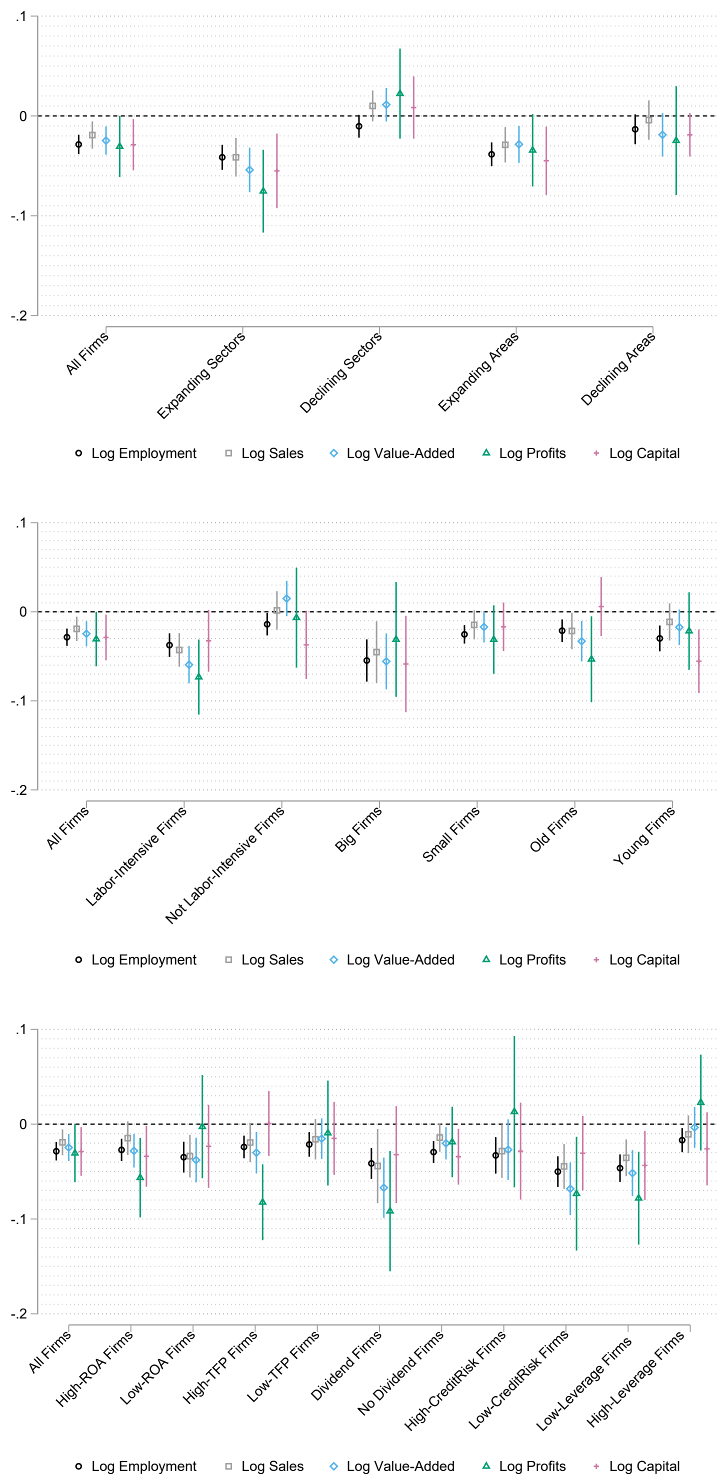
Figures and Tables

Figure 1: **Changes in Hiring Difficulties at the Occupation Level**

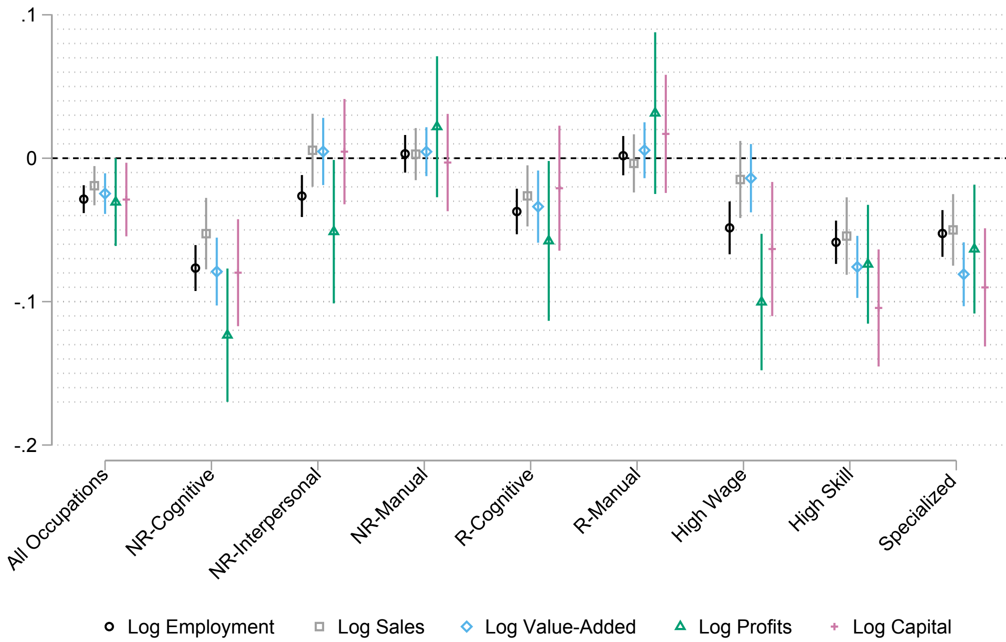
This figure presents the 25^{th} and 75^{th} percentiles of the distribution of the year-by-year changes in hiring difficulties within the 322 commuting zones in France for each 2-digit occupation. $HiringDiff_{k,cz,t}$ at the occupation X commuting-zone X year level is defined in Equation (5).

Figure 2: **Effects on Firm Outcomes - Subsample Analysis**



This figure presents the coefficient on the shift-share variable $HiringDiff_{ss,i,cz,j,t}$ in regressions of respectively log employment, log sales, log value-added, log profits, and log capital in the same sub-sample analysis presented in Table VIII. Intervals centered around each dot correspond to 95% confidence intervals. The first dot in black corresponds to the coefficients on log employment presented in Table VIII. Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level.

Figure 3: **Effects on Firm Outcomes By Task and Occupation Characteristics**



This figure presents the total effect of hiring difficulties on respectively log employment, log sales, log value-added, log profits, and log capital, for specific subset of occupations, namely the sum of coefficient on the shift-share variable $HiringDiff_{ss,i,cz,j,t}$ and $\sum_{k\in\mathcal{K}} s_{i,k,09} HiringDiff_{k,cz,-j,t}$ for different set of occupations $\mathcal{K}$ in the specification presented in Equation (11). Intervals centered around each dot correspond to 95% confidence intervals. The first dot in black corresponds to the coefficient on log employment presented in the last row of Table IX, under the label "Total Effect". Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level.

Table I: **Descriptive Statistics**

	Mean	Sd	p25	p50	p75	N
Hiring Difficulties						
Hiring Difficulties (*HiringDiff*)	0.217	0.252	0.063	0.115	0.270	647800
Hiring Difficulties$_{ss}$ ($HiringDiff_{ss}$)	0.237	0.071	0.195	0.229	0.268	3130014
Employment-Related Outcomes						
Log Employment	1.949	0.993	1.099	1.792	2.485	3130014
Yearly Wages p.w. (K €)	35.308	24.922	21.589	29.142	40.191	3130014
Yearly Hours per Worker	1381	385	1124	1420	1675	3130014
Experience Required (months)	18.239	19.165	2.000	12.000	24.000	647800
Education Required (years)	11.653	1.163	11.000	11.000	12.000	647800
Offered Contract is Open End	0.523	0.448				647800
Offered Contract is Full-Time	0.878	0.291				647800
Other Firm-Level Outcomes						
Log Capital	4.323	2.027	3.111	4.436	5.602	3130014
Log Sales	6.569	1.430	5.644	6.444	7.398	3130014
Log Value-Added	5.638	1.301	4.805	5.574	6.410	3130014
Log Profits	3.910	1.617	2.899	3.879	4.931	2495490
ROA	0.066	0.254	0.011	0.078	0.158	3130014

This table presents summary statistics for our sample, which consists of 3,130,014 firm-year observations between 2010 and 2017. There are 475,697 firms in this sample for which we observe the occupation-mix in 2009. *Hiring Difficulties* is the actual hiring difficulties faced by firms on their posted vacancies, and *Hiring Difficulties*$_{ss}$ is the firm-level shift-share prediction of hiring difficulties defined in Equation (6). Firms' employment is defined as the number of full-time employees at the end of the fiscal year. Experience required, education required, the share of vacancies for open ended contracts, and the share of vacancies for full-time contracts, are computed across all vacancies posted by each sample firm in each year. Capital is defined as the stock of tangible assets net of accumulated depreciation. Profits are earnings before interest, depreciation, and taxes (EBITDA). ROA is return on assets, defined as earnings before interest, depreciation, and taxes over assets.

Table II: **Hiring Difficulties and Firm Employment**

	(1) First Stage	(2) Reduced Form	(3) IV
	Hiring Difficulties (*HiringDiff*)	Log Employment	
HiringDiff			
$HiringDiff_{ss}$	0.078***	-0.029***	
	(0.013)	(0.005)	
HiringDiff			-0.366***
			(.087)
Firm FE	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes
Observations	647800	3130014	647800
R-Sq	0.452	0.954	

This table presents the baseline results on firm employment. Column (1) shows the results obtained from estimating Equation (7) on the sub-sample of firms posting at least one vacancy on *pole-emploi.fr* where the dependent variable is the actual hiring difficulties faced by firms on their posted vacancies. Column (2) shows the results obtained from estimating Equation (7) on the entire sample of firms where the dependent variable is the logarithm of the number of full-time employees at the end of the fiscal year. Column (3) presents an instrumental variable (IV) specification, where realized hiring difficulties at the firm level is instrumented with the shift-share variable. Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level. The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Table III: **Hiring Difficulties and Firm Employment - Robustness**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Log Employment										
	Share Unfilled$_{ss}$	Shares in 2010	Exclude Managers	Control For Firm Charact.	Tradable Industries	Non-Tradable Industries	Posting Firms	Not Posting Firms	Exclude I-O Links	Exclude Large Firms	Control For National Shift-Share
HiringDiff$_{ss}$	-0.021***	-0.024***	-0.030***	-0.034***	-0.030**	-0.028***	-0.031***	-0.028***	-0.018***	-0.031***	-0.015***
	(0.005)	(0.005)	(0.004)	(0.006)	(0.012)	(0.005)	(0.008)	(0.006)	(0.004)	(0.005)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age, Size, ROA x Year FE	No	No	Yes	No	No	No	No	No	No	No	No
Control for National Shift-Shares	No	No	No	No	No	No	No	No	No	Yes	No
Observations	3130014	3130014	3126363	2905005	312942	2814321	1787266	1342748	3126891	3063116	3130014
R-Sq	0.954	0.954	0.954	0.956	0.969	0.952	0.953	0.932	0.954	0.951	0.954

This table presents variants of the specification presented in Column (2) of Table II. Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. In Column (1), we replace the baseline firm-level shift-share variable by the same measure using only information on the probability of filling vacancies (that is replacing *DaysToFill* by 0 in Equation (5)). In Column (2), we re-compute the firm-level shift-share variable using occupation shares in 2010, instead of 2009. In Column (3), we re-compute the firm-level shift-share variable after removing managerial occupations. In Column (4), we augment our specification with firm characteristics (terciles of firm size, age, and ROA, all measured pre-sample), interacted with year fixed effects. Column (5) (respectively Column 6) restricts the sample to tradable industries (non-tradable industries). Tradable industries are agriculture, forestry, and fishing; mining and quarrying; manufacturing; and information and communication. Columns (7) (respectively Column 8) restricts the sample to firms that posted at least one vacancy on *Pole-emploi.fr* (respectively never posted a vacancy on *Pole-emploi.fr*). In Column (9), we re-compute the firm-level shift-share variable also applying the leave-one-out correction to upstream and downstream sectors with respect to each firm (using a 1% cutoff on input-output linkages at the industry level). Column (10) re-run the baseline specification after removing from the sample any firm that represents more than 1% of the total local market for any occupation in any year. In Column (11) we add as control a shift-share variable using information on filling probabilities and time-to-fill for each occupation in all other commuting zones (excluding the commuting zone of the firm itself). The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Table IV: **Hiring Difficulties and Other Firm Outcomes**

	(1) Log Capital	(2) Log Sales	(3) Log Value-Added	(4) Log Profits	(5) ROA
$HiringDiff_{ss}$	-0.029**	-0.019***	-0.025***	-0.031**	-0.009***
	(0.013)	(0.007)	(0.007)	(0.016)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3130014	3130014	3130014	2455320	3130014
R-Sq	0.927	0.940	0.927	0.819	0.533

This table presents the results obtained from estimating Equation (7) in specifications in which the dependent variable is respectively the logarithm of capital, the logarithm of sales, the logarithm of value-added, the logarithm of profits, and return on assets. Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level. The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Table V: **Wages, Hours Worked, and Turnover**

Panel A: Hours and Wages	(1) Log Total Payroll	(2) Log Yearly Wages p.w.	(3) Log Yearly Hours p.w.	(4) Log Hourly Wages
$HiringDiff_{ss}$	-0.015**	0.019***	0.005	0.032***
	(0.006)	(0.005)	(0.005)	(0.006)
Firm FE	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes
Observations	3130014	3130014	3130014	3130014
R-Sq	0.941	0.810	0.683	0.890

Panel B:	(1) Log Yearly Hours	(2)	(3) Log Hourly Wages	(4)
New Hires vs Incumbents	New Hires	Incumbents	New Hires	Incumbents
$HiringDiff_{ss}$	0.015	-0.004	0.011	0.034***
	(0.015)	(0.005)	(0.009)	(0.006)
Firm FE	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes
Observations	1959616	3017697	1959616	3017697
R-Sq	0.423	0.656	0.619	0.876

Panel C:	(1) Workforce Turnover	(2)
Hiring vs Separation Rates	New Hires (%)	Separations (%)
$HiringDiff_{ss}$	-0.048**	-0.029*
	(0.022)	(0.016)
Firm FE	Yes	Yes
Ind-Cz-Year FE	Yes	Yes
Observations	3130014	3130014
R-Sq	0.844	0.836

This table presents the results obtained from estimating Equation (7) in specifications where the dependent variable is respectively total payroll (Column 1 of Panel A), yearly wages per worker (Column 2 of Panel A), yearly hours per worker (Column 3 of Panel A), hourly wages (Column 4 of Panel A), yearly hours per worker within the subset of new hires (Column 1 of Panel B), yearly hours per worker within the subset of incumbents (Column 2 of Panel B), hourly wages within the subset of new hires (Column 3 of Panel B), hourly wages within the subset of incumbents (Column 4 of Panel B), the ratio of new hires over the number of firm employees (Column 1 of Panel C), and the ratio of separations over the number of firm employees (Column 2 of Panel C). Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level. The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Table VI: **Hiring Standards**

	(1) Experience	(2) Education	(3) Open End Contract	(4) Full-Time Contract
HiringDiff$_{ss}$	-1.963**	0.061	-0.008	-0.011
	(0.828)	(0.059)	(0.019)	(0.011)
Firm FE	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes
Observations	647800	647800	647800	647800
R-Sq	0.635	0.698	0.638	0.667

This table presents the results obtained from estimating Equation (7) on the sample of firms that have posted at least one vacancy in a given year for vacancy standards. The dependent variable is the average experience required expressed in months computed over all vacancies posted by each firm in each year in Column (4), average education required expressed in years in Column (5), the fraction of vacancies for open end contracts in Column (6) and the fraction of vacancies for full-time contracts in Column (7). Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level. The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Table VII: **Market Tightness vs. Matching Efficiency**

	(1) Log Employment	(2) Log Hourly Wages	(3) Log Hourly Wages New Hires	(4) Log Hourly Wages Incumbents
Tightness Frictions$_{ss}$	-0.014*	0.048***	0.028*	0.054***
	(0.007)	(0.010)	(0.015)	(0.010)
Matching Inefficiency	-0.028***	0.036***	0.006	0.039***
Frictions$_{ss}$	(0.007)	(0.008)	(0.011)	(0.008)
Firm FE	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes
Observations	3058786	3057384	1947665	2944634
R-Sq	0.965	0.878	0.641	0.870

This table presents the results obtained from estimating Equation (10) in specifications in which the dependent variable is the logarithm of respectively firm employment (Column 1), hourly wages (Column 2), hourly wages within the subset of new hires (Column 3), hourly wages within the subset of incumbents (Column 4). Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level. The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Table VIII: **Heterogeneity by Industry, Geography, and Firm Characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log Employment									
	Sector		Area		Labor Intensive		Age		ROA	
	Expanding	Declining	Expanding	Declining	Yes	No	Old	Young	High	Low
$HiringDiff_{ss}$	-0.041***	-0.010*	-0.038***	-0.013*	-0.037***	-0.014**	-0.021***	-0.030***	-0.027***	-0.035***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1742397	1381914	2264603	865411	1468744	1487611	1523121	1546086	1438137	1405957
R-Sq	0.958	0.951	0.953	0.958	0.958	0.954	0.967	0.935	0.957	0.956
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Log Employment									
	TFP		Size		Pay Dividend		Credit Risk		Leverage	
	High	Low	Large	Small	Yes	No	Low	High	Low	High
$HiringDiff_{ss}$	-0.024***	-0.021***	-0.055***	-0.025***	-0.041***	-0.029***	-0.050***	-0.033***	-0.046***	-0.017***
	(0.006)	(0.007)	(0.012)	(0.005)	(0.008)	(0.006)	(0.008)	(0.010)	(0.007)	(0.006)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1425925	1351034	1390436	1682279	703943	2253368	1020037	837442	1414925	1429075
R-Sq	0.954	0.960	0.943	0.833	0.966	0.948	0.956	0.961	0.953	0.959

This table presents the results obtained from estimating Equation (7) in specifications in which the dependent variable is the logarithm of firm employment for different sub-samples. The sample is restricted to expanding versus declining industries (Columns 1 and 2), expanding versus declining areas (Columns 3 and 4), low versus high labor share firms (Columns 5 and 6), old versus young firms (Columns 7 and 8), low versus high ROA firms (Columns 9 and 10), low versus high TFP firms (Columns 11 and 12), large versus small firms (Columns 13 and 14), firms paying versus not paying dividends (Columns 15 and 16), high versus low credit risk firms (Columns 17 and 18), low versus leverage firms (Columns 19 and 20). Firm size, firm age, ROA, TFP, dividend payments, credit risk - defined as the inverse of the coverage ratio - and leverage - defined as total debt over total assets - are all measured in 2009. Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level. The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Table IX: **Heterogeneity by Task and Occupation Characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Employment							
HiringDiff$_{ss}$	0.008	-0.030***	-0.047***	-0.025***	-0.041***	-0.016***	-0.006	-0.012**
	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
HiringDiff$_{ss}$ × NR Cognitive	-0.085***							
	(0.009)							
HiringDiff$_{ss}$ × NR Interpersonal		0.004						
		(0.008)						
HiringDiff$_{ss}$ × NR Manual			0.050***					
			(0.010)					
HiringDiff$_{ss}$ × R Cognitive				-0.012				
				(0.009)				
HiringDiff$_{ss}$ × R Manual					0.043***			
					(0.008)			
HiringDiff$_{ss}$ × High Wage						-0.032***		
						(0.011)		
HiringDiff$_{ss}$ × High Skill							-0.052***	
							(0.010)	
HiringDiff$_{ss}$ × Specialized								-0.041***
								(0.009)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Cz-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3130014	3130014	3130014	3130014	3130014	3130014	3130014	3130014
R-Sq	0.954	0.954	0.954	0.954	0.954	0.954	0.954	0.954
Total Effect	-0.077***	-0.026***	0.003	-0.037***	0.002	-0.049***	-0.059***	-0.052***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)

This table shows the results obtained from estimating Equation (11) in specifications in which the dependent variable is the logarithm of firm employment. Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level. The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Internet Appendix

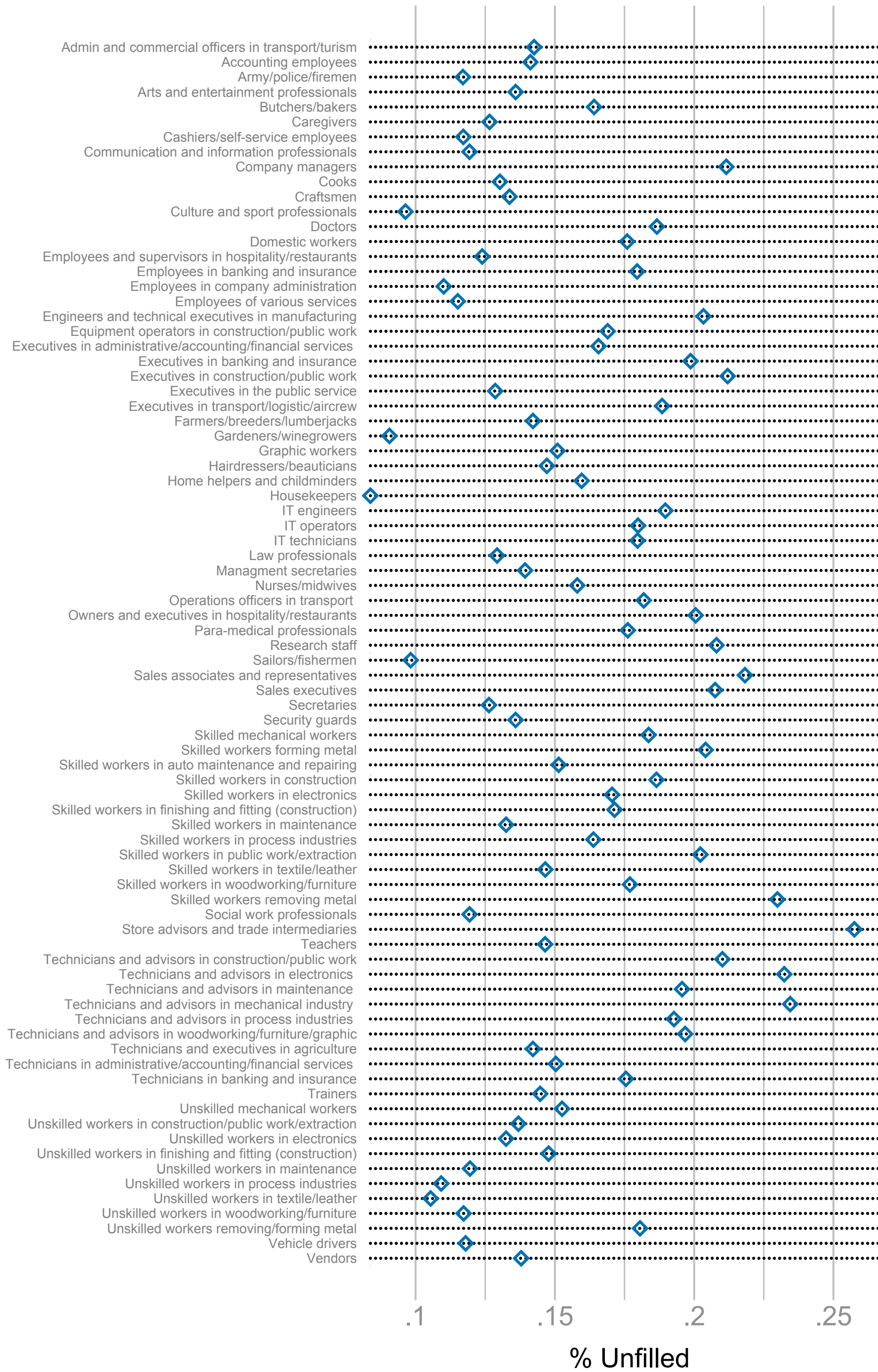
Hiring Difficulties and Firm Growth

Thomas Le Barbanchon (Bocconi)
Maddalena Ronchi (Northwestern University)
Julien Sauvagnat (Bocconi)

This Internet Appendix has several parts. Appendix A includes additional figures and tables. In Appendix B, we correlate our measure of hiring difficulties based on vacancy data with survey answers by firms on hiring difficulties. In Appendix C, we provide the proofs of the theoretical model presented in Section II.

Appendix A. Appendix Figures and Tables

Figure A1: **Share of Unfilled Vacancies by Occupation**



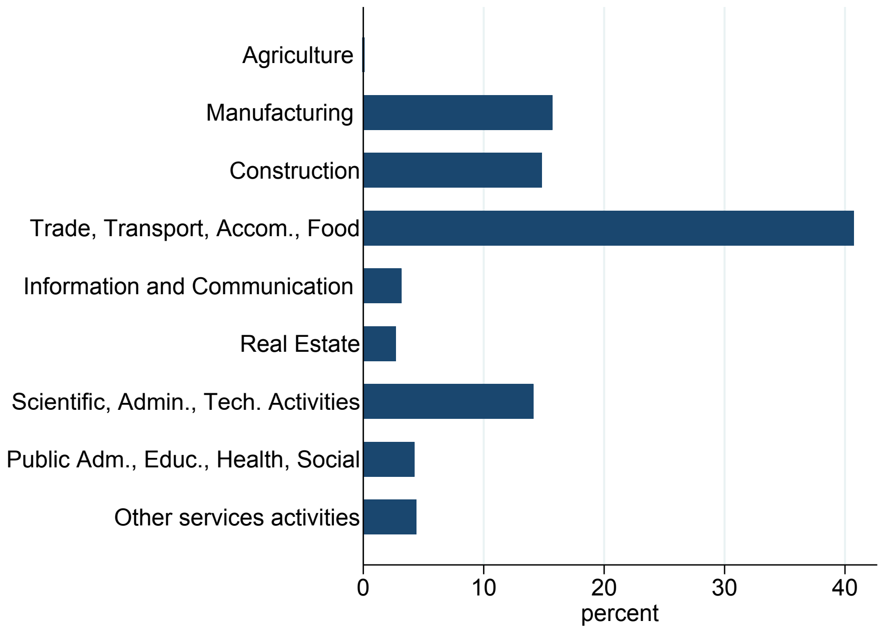
This figure presents the share of unfilled vacancies by 2-digit occupation across all vacancies posted on the online job board *pole-emploi.fr* over the sample period.

Figure A2: **Average Time-to-fill Vacancies by Occupation**

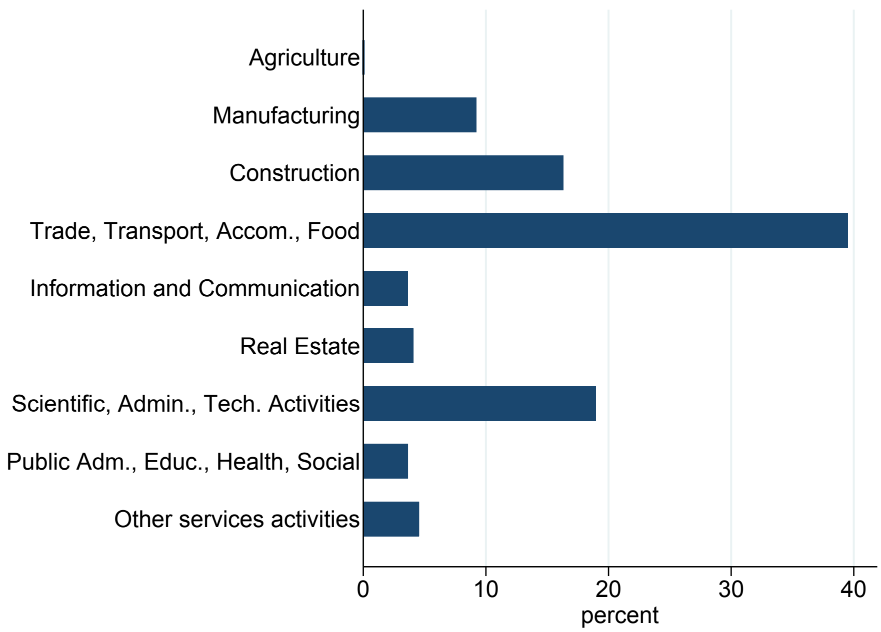
This figure presents average time-to-fill, measured in days, for each 2-digit occupation, across all vacancies eventually filled posted on the online job board *pole-emploi.fr* over the sample period

Figure A3: **Industry Distribution Depending on Whether Firms Post Vacancies on pole-emploi.fr**

(a) Firms posting at least once on pole-emploi.fr



(b) Firms never posting on pole-emploi.fr



This figure shows the distribution of firms' industry separately for firms posting at least one vacancy on pole-emploi.fr over the sample period (Upper panel a) or none (lower panel b) across our sample of 3,130,014 firm-year observations between 2010 and 2017.

Figure A4: **Ranking of Occupations by Type**

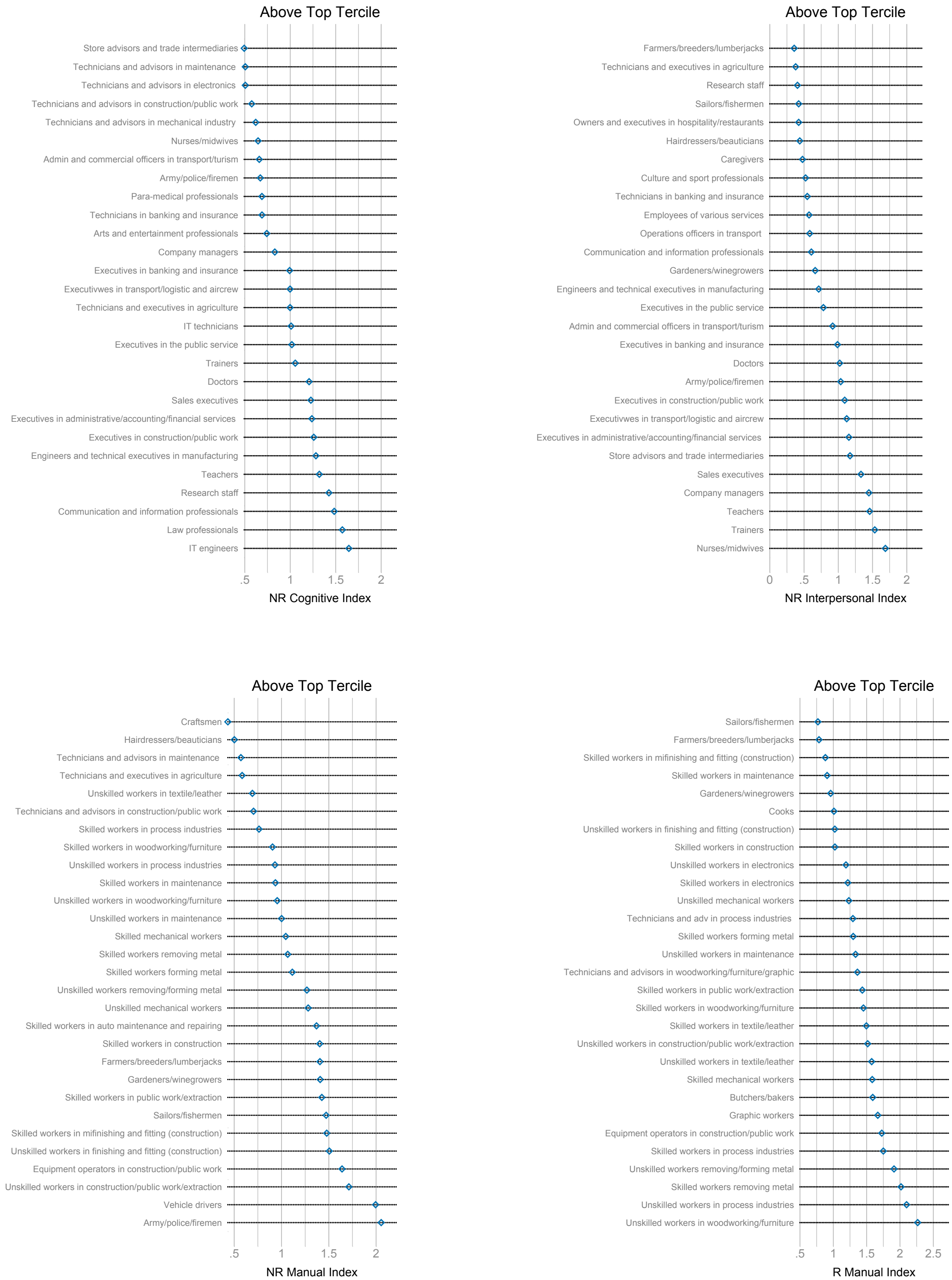
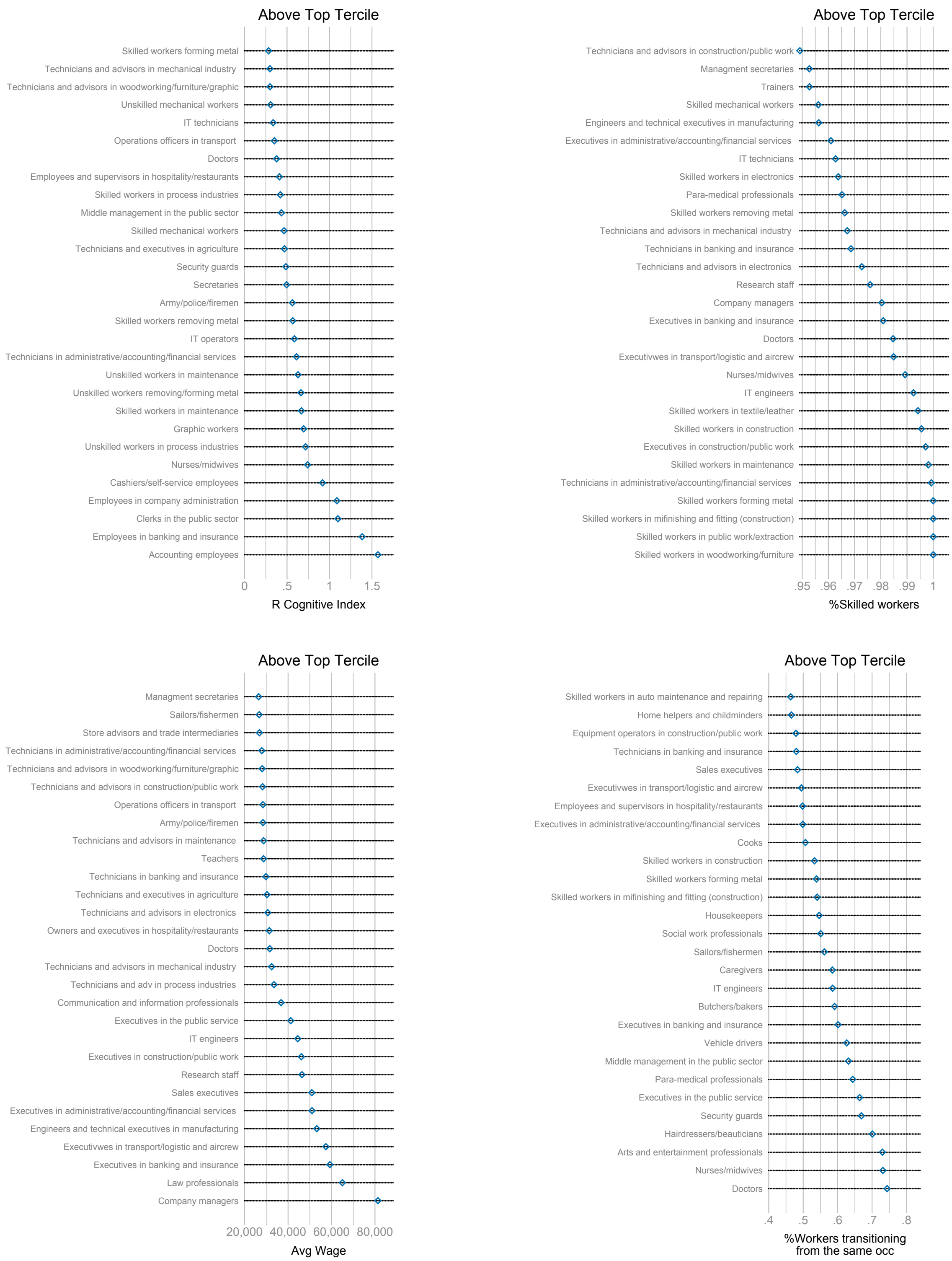


Figure A4 **(Continued)**



This figure presents the respective scores of the set of occupations defined as respectively non-routine cognitive intensive, non-routine interpersonal intensive, non-routine manual intensive, routine manual intensive, routine cognitive intensive, high-skill, high-wage, specialized.

Table A1: **Employment Effects: Specialized Occupations**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log Employment						
$HiringDiff_{ss}$	0.019***	-0.014**	-0.030***	-0.006	-0.024***	0.002	0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
$HiringDiff_{ss}$ × Specialized	-0.031***	-0.042***	-0.044***	-0.042***	-0.040***	-0.042***	-0.029***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$HiringDiff_{ss}$ × NR Cognitive	-0.081***						
	(0.009)						
$HiringDiff_{ss}$ × NR Interpersonal		0.008					
		(0.008)					
$HiringDiff_{ss}$ × NR Manual			0.053***				
			(0.010)				
$HiringDiff_{ss}$ × R Cognitive				-0.017*			
				(0.010)			
$HiringDiff_{ss}$ × R Manual					0.042***		
					(0.009)		
$HiringDiff_{ss}$ × High Wage						-0.034***	
						(0.011)	
$HiringDiff_{ss}$ × High Skill							-0.045***
							(0.010)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind*Cz*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3130014	3130014	3130014	3130014	3130014	3130014	3130014
R-Sq	0.954	0.954	0.954	0.954	0.954	0.954	0.954

This table presents the results obtained from estimating variants of Equation (11) in specifications with three firm-level shift-share variables in which the dependent variable is the logarithm of firm employment. Each regression includes firm fixed effects and industry × commuting zone × year fixed effects. Standard errors are clustered at the commuting-zone level. The sample period is 2010-2017. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Appendix B. Hiring Difficulties Measured in Vacancy Data vs. Firm Surveys

In this section, we correlate the two components of our measure of hiring difficulties from vacancy data, share unfilled and time-to-fill, with survey answers from firms on the hiring difficulties they face. We use firm answers in two surveys: the Business Tendency Survey (BTS) from the French Statistical Institute (Insee) and the Workforce Firm Survey from the French Public Employment Service (Pole Emploi). The BTS surveys a panel of French establishments every month in order to forecast economic growth (*Enquête de conjoncture*). The Workforce survey also surveys firms to assess manpower needs in the French labor market (*Besoin de Main d'oeuvre*).

In the BTS, firms are asked whether they currently encounter recruiting difficulties (yes/no question). The question is ventilated across three types of labor: executives, skilled workers, and unskilled workers. We have access to the BTS data covering manufacturing firms. We aggregate their answers at the year X industry level, where industries are within the 5-digit classification (NAF-5d). We restrict the period to 2010-2017 over which we have the vacancy data. Similarly, we collapse the share of unfilled vacancies and time-to-fill at the same year X 5-digit industry level, both across all vacancies, and separately for the sub-samples of vacancies for executives, for skilled workers and for unskilled workers. Figure A7 (resp. A8) plots binscatters of share of unfilled vacancies (resp. time-to-fill) against the average share of establishments reporting hiring difficulties. Each Year X Industry cell is weighted by the number of firms surveyed. We find a positive and significant correlation between the survey measures and our measures of hiring time / share of unfilled vacancies. The slope of each binscatter plot is statistically significant at the one percent level.

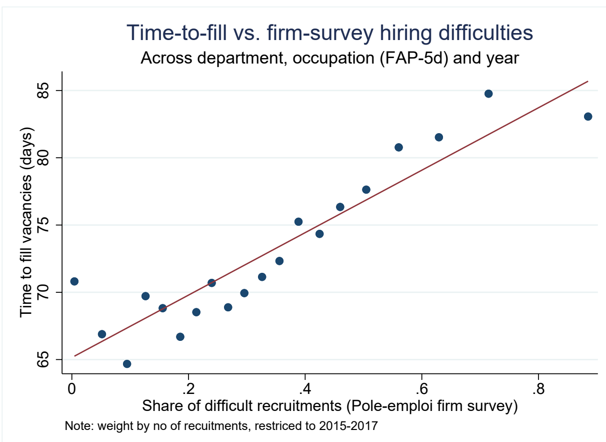
The PES manpower survey is instead available at the occupation level, and covers firms in all industries. It asks every firm in which occupation(s) they intend to hire, and for each of these occupations, the number of workers to be hired, and the number of difficult searches. We have access to aggregate counts by occupation (5-digit level, denoted FAP-5d), year and department for the period 2015-2017. The French metropolitan territory is partitioned in 100 departments. This geographical unit is less disaggregated than the set of commuting zones used in the main analysis. We collapse the vacancy data at the same level (occupation X department X year) and over the same period. Figure A6 reports binscatters of share unfilled and time-to-fill against the reported share of difficult recruiting processes. We weight cells by the overall number of intended hires.

Again, we find a significant and positive correlation between the survey-based measures and the vacancy-based measures of hiring difficulties. The slope of each binscatter plot is statistically significant at the one percent level.

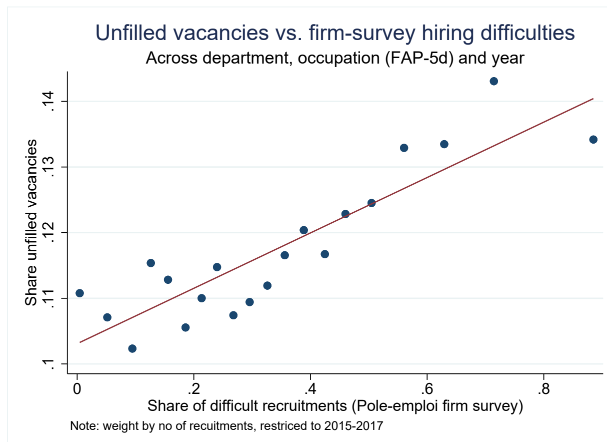
We conclude that our main measure of hiring difficulties based on the expected probability of filling a vacancy and the average time it takes to hire a worker indeed strongly correlates with firms' own-assessment in surveys of the difficulty they face for finding suitable workers on the labor market.

Figure A6: **Time-to-fill and Share Unfilled vs. Hiring Difficulties in *Pole Emploi* Firm Survey**

(a) Time-to-fill



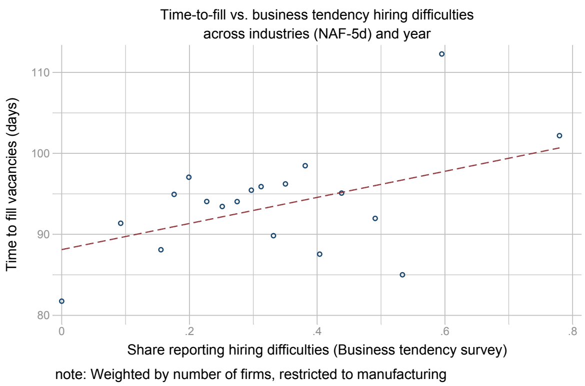
(b) Unfilled Vacancies



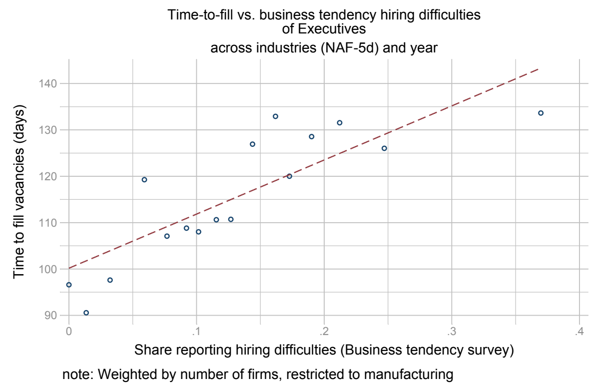
This figure presents scatter plot of the relationship between the average time-to-fill expressed in number of days (respectively share of unfilled vacancies) and the share of difficult recruitments in the Pole Emploi survey across each occupation X department X year cell. Each cell is weighted by the number of firms surveyed. The sample period is 2010-2017.

Figure A7: **Time-To-Fill vs. Hiring Difficulties in Business Tendency Survey**

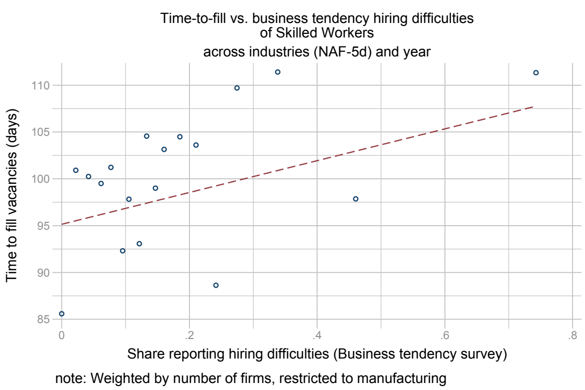
(a) All occupations



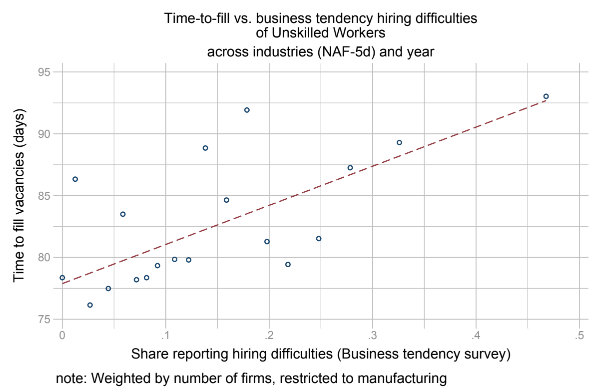
(b) Executives



(c) Skilled workers



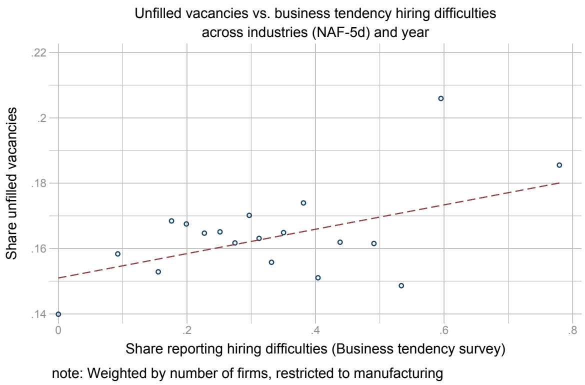
(d) Low-skill Workers



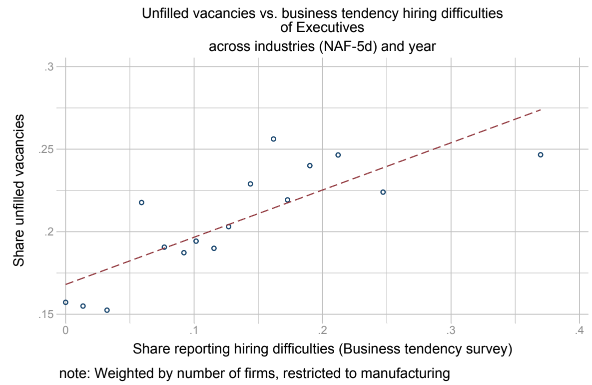
This figure presents scatter plot of the relationship between average time-to-fill (respectively across all vacancies in Panel A, for the sub-samples of vacancies for executives in Panel B, for skilled workers in Panel C, and low-skill workers in Panel B) expressed in number of days and respectively the share of firms reporting that they faced hiring difficulties in the Business Tendency Survey (across all occupations (respectively across all vacancies in Panel A, for the sub-samples of vacancies for executives in Panel B, for skilled workers in Panel C, and low-skill workers in Panel D) across each industry X year cell. Each cell is weighted by the number of firms surveyed. The sample period is 2010-2017.

Figure A8: **Share of Unfilled Vacancies vs. Hiring Difficulties in Business Tendency Survey**

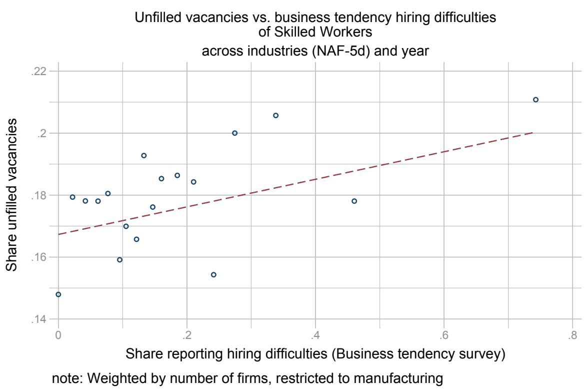
(a) All occupations



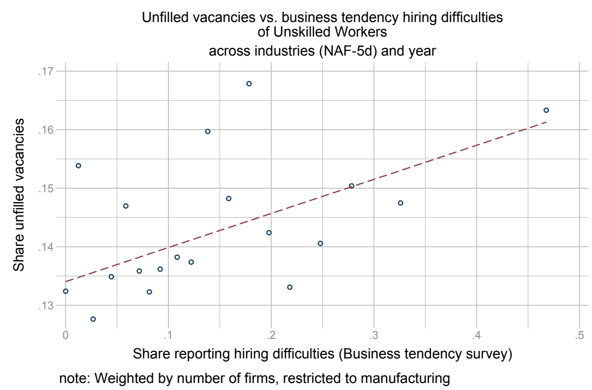
(b) Executives



(c) Skilled workers



(d) Low-skill Workers



This figure presents scatter plot of the relationship between the share of unfilled vacancies (respectively across all vacancies in Panel A, for the sub-samples of vacancies for executives in Panel B, for skilled workers in Panel C, and low-skill workers in Panel B) expressed in number of days and respectively the share of firms reporting that they faced hiring difficulties in the Business Tendency Survey (across all occupations (respectively across all vacancies in Panel A, for the sub-samples of vacancies for executives in Panel B, for skilled workers in Panel C, and low-skill workers in Panel D) across each industry X year cell. Each cell is weighted by the number of firms surveyed. The sample period is 2010-2017.

Appendix C. Theoretical Model: Proofs

In this section, we derive the theoretical results from the model of firm hiring presented in Section II.

As explained in the main text, firms' profits are:

$$\Pi(L_{t-1}) = \max_{L_t, V_t} A_t R(L_t) - w_t L_t - c_v V_t + \beta \mathbb{E}\left[\Pi(L_t)\right]. \tag{C1}$$

Firms maximize their profits subject to the employment law of motion:

$$L_t - L_{t-1} = V_t \times m_t - L_{t-1} \times q_t. \tag{C2}$$

Taking the first order condition of the maximization program of the firm with respect to vacancies V_t, we obtain:

$$A_t R_L(L_t) = w_t + \frac{c_v}{m_t} - \beta \mathbb{E}\left[\Pi_L(L_t)\right]. \tag{C3}$$

Using the envelope theorem, we obtain:

$$\Pi_L(L_t) = (1 - q_{t+1})\left(A_{t+1} R_L(L_{t+1}) - w_{t+1} + \beta \mathbb{E}\left[\Pi_L(L_{t+1})\right]\right), \tag{C4}$$

where we used that $L_{t+1} = V_{t+1} \times m_{t+1} + L_t \times (1 - q_{t+1})$.

Using the first order condition (C3) in period $t+1$, we simplify Equation (C4) as:

$$\Pi_L(L_t) = \frac{(1 - q_{t+1}) c_v}{m_{t+1}}. \tag{C5}$$

We can then write the dynamic labor demand equation:

$$A_t R_L(L_t) = w_t + \frac{c_v}{m_t} - \beta E\left[\frac{(1 - q_{t+1}) c_v}{m_{t+1}}\right]. \tag{C6}$$

Sensitivity of firm size to hiring difficulties. We now derive an approximation for the labor demand semi-elasticity with respect to the expected average recruiting time $\tau_t = 1/m_t$. Let us take the logarithm of the labor demand Equation (C6) assuming that $R(L_t) = \frac{(L_t)^\alpha}{\alpha}$:

$$\log A_t + (\alpha - 1)\log L_t = \log(w_t) + \log\left(1 + \frac{c_v \tau_t}{w_t} - \frac{\beta}{w_t} E\left[(1 - q_{t+1}) c_v \tau_{t+1}\right]\right). \tag{C7}$$

We consider a deviation $d\tau_t$, holding fixed all future values, contemporaneous wages and productivity. The change in employment writes as follows:

$$(\alpha - 1) d\log L_t = \frac{c_v}{w_t} \frac{d\tau_t}{\left(1 + \frac{c_v \tau_t}{w_t} - \frac{\beta}{w_t} E\left[(1 - q_{t+1}) c_v \tau_{t+1}\right]\right)}. \tag{C8}$$

Assuming that total hiring costs as a fraction of annual wages, $\frac{c_v \tau}{w}$, which appears on the second and third terms of the denominator, can be neglected with respect to 1, we obtain the following approximated expression of Equation (C8):

$$d \log L_t \approx \frac{c_v}{w_t} \frac{1}{(\alpha - 1)} d\tau_t \tag{C9}$$