Hiring Difficulties and Firm Growth

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Abstract

This paper studies the 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*). We show that hiring difficulties have negative effects on firms' employment, capital, sales, and profits. Firms partially adjust to hiring difficulties by increasing wages and the retention rate of incumbent workers, and by lowering their hiring standards. We then document larger effects of hiring difficulties for labor-intensive firms, firms in expanding sectors, and for non-routine cognitive, high-skill, high-wage, and specialized occupations. Taken together, our findings indicate that hiring difficulties are an important determinant of the growth and profitability of firms across time and space.

Keywords: hiring difficulties, labor demand, firm growth, firm performance.

JEL Codes: J21, J63, M51.

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1 Introduction

Firms frequently report that they had job vacancies they could not fill.[1] Even though a number of empirical studies have explored 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), we know surprisingly little about the causal impact of hiring difficulties on firms' outcomes. On the one hand, hiring difficulties might lead firms to be short of essential inputs in their operations, and prevent them from growing. On the other hand, firms might be flexible enough to adapt to hiring difficulties, in which case their impact on firms' performance might be limited.[2] Providing evidence on this topic comes with data and identification challenges. In particular, one needs large-scale datasets containing linked information on firms' outcomes and measures of the hiring difficulties that they face in their local labor market, as well as an identification strategy that addresses the endogeneity of hiring difficulties to unobserved market-level and firm-level demand/productivity shocks.

In this paper we overcome both challenges and provide causal evidence on how hiring difficulties affect firms' outcomes. 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. Importantly, 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.[3] To identify the effects of interest, we construct plausibly 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*).

To guide the interpretation of our empirical findings, we first present a simple

[1] Survey evidence from France 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., and the 2023 survey "*Besoins en Main-d'oeuvre*" run by Pole Emploi in France.

[2] Hiring difficulties might also be an opportunity for the economy if they lead to an improvement in the quality of jobs, see Autor (2021).

[3] We discuss in greater detail our measure of hiring difficulties in Section 3.1.

search model of firm hiring based on Cahuc et al. (2018) in partial equilibrium. We assume that firms need to post vacancies to hire workers, and interpret hiring difficulties as an exogenous decline in the vacancy filling rate. We derive the sensitivity of firm employment to hiring difficulties, and show that the negative effect of hiring difficulties on firm labor demand is larger when production is more labor intensive and when the cost of posting vacancies is large.

We then use our vacancy-level dataset to construct plausibly exogenous measures of hiring difficulties that vary at the firm level. Taking into consideration the recent papers on shift-share instruments (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2021), there are two important clarifications to make when thinking about our empirical design. First, using pre-sampled information about the occupation mix of a firm workforce when computing the shares ensure that our estimates are unaffected by contemporaneous shocks to firms' technologies, that would affect both the types of workers required to produce and firms' outcomes. Second, 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. Overall, 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 exogenous from the firm perspective in specifications 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.

We 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 in our empirical analysis. We then 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 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. We turn to our first main result, the effect of hiring difficulties on firm employment. Quantitatively, our estimate implies that a firm facing the average degree of hiring difficulties in our sample would experience a drop in employment of around 8%, compared to a counterfactual firm that could hire workers in a frictionless way.

We assess the robustness of our result along a large series of dimensions. We experiment with alternative ways of constructing the firm-level shift-share measure of hiring difficulties. We 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 other tests to ensure that our results are not biased by local business stealing effects, sample selection on the vacancy data, labor demand shocks correlated across industries in the production network, shocks hitting large firms that would affect both their employment outcomes and local hiring difficulties in their occupations, and occupation-specific productivity shocks. We find that, despite some inherent variations, the magnitudes we obtain when estimating the effect of hiring difficulties on employment are robust, which we view as a central contribution of our paper.

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 low-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 than the effect on employment. Quantitatively, our estimates imply that a firm facing the average degree of hiring difficulties in our sample would experience a drop in capital, sales, value-added, and profits of respectively around 8%, 5%, 7%, and 9%, compared to a counterfactual firm that could hire workers in a frictionless way. Overall, this is consistent with hiring difficulties having a large negative impact on firm scale of production, and low degree of substitution between labor and capital.

We exploit the richness of our micro data to investigate specifically the labor adjustments of firms facing higher hiring difficulties. We do not find that these firms increase yearly hours per worker, not even for internal employees. Thus, firms do not seem to compensate for hiring difficulties by adjusting hours worked at the intensive margin. Instead, we find that yearly wages per worker increases. Moreover, for incumbents, we find a decrease in 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 experiencing higher hiring difficulties either because of an increase in local labor market tightness or because of a reduction in matching efficiency. For example, 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), or due to 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 difficulties in hiring due to both these distinct factors, we expand on 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' employment and performance, depending on industry, area, firm, and occupation characteristics. First, we check and confirm that the negative effects of hiring difficulties on firms' outcomes are stronger in expanding sectors and areas, and in labor-intensive firms. Second, we find that hiring difficulties tend to have smaller effects for firms that can be classified as financially-constrained – small firms, firms that do not pay dividends, high credit-risk, and high-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 employment and performance is less sensitive to hiring difficulties in manual occupations, and more sensitive to hiring difficulties in non-routine cognitive, high-wage, high-skill, and specialized occupations.

Our main contribution is to provide causal evidence showing that hiring difficulties are an important driver of firm employment and performance. In doing so, we build on existing papers documenting, either with survey measures or with indirect estimates, that hiring is costly and takes time (Abowd and Kramarz, 2003; Blatter et al., 2012; Kramarz and Michaud, 2010; Rothwell, 2014; Cahuc et al., 2018). We also build on previous studies using vacancy-level and worker-level data to provide evidence on firm's recruitment intensity and hiring behavior (Davis et al., 2013; Mueller et al., 2018; Bagger et al., 2021; Carrillo-Tudela et al., 2020; Cestone et al., 2023). Compared to these papers, we shift the focus on how exogenous variations in the difficulty of filling vacancies affect firms' outcomes. In that respect, and for what concerns our results on employment and wages, our work contributes to the labor demand literature (Hamermesh, 1993; Beaudry et al., 2018) by documenting how a direct measure of hiring difficulties affect firm employment outcomes.

Our paper also relates to previous work studying the effects of labor supply shocks on firms and workers. Earlier studies focus on large, market-wide labor supply shocks, e.g., due to immigration or changes in the college graduation rate, and their aggregate impact on employment and wages (Katz and Murphy, 1992; Card, 2009; Dustmann et al., 2009). A large body of recent work adds micro evidence on the impact of specific labor supply shocks, such as the inflows of workers with particular skills, on a series of firms' outcomes (see e.g. Moretti, 2004; Paserman, 2013; Dustmann and Glitz, 2015; Mitaritonna et al., 2017; Dustmann et al., 2017; Beerli et al., 2021; Doran et al., 2022; D'Acunto et al., 2020; Sauvagnat and Schivardi, 2020). Finally, a number of empirical studies have relied on labor supply shocks induced by the Great Recession or immigration to study how local labor market tightness affects firms' demand for skills and the quality of worker-firm matching (Hershbein and Kahn, 2018; Modestino et al., 2020; Orefice and Peri, 2020). Compared to these papers, our analysis relies on a direct and more comprehensive measure of hiring difficulties which is based on vacancy-level data. Thanks to this unique measure, we can provide novel evidence on the effects of different types of shocks that make hiring more difficult, that is not only shocks to local labor tightness but also shocks to local matching inefficiency. Moreover, we can study the effect of hiring difficulties on different dimensions of corporate behavior, as well as document their heterogeneous impact across different types of firms and occupations.

More broadly, our results highlight the role of local hiring difficulties as an important determinant of the growth and profitability of firms across time and space. Our work has important implications for the design of policies aiming at reducing the mismatch between firms' needs and the skills available in the local workforce (such as targeted education and training, relocation assistance, immigration policy), and more generally for the design of location-based policies to foster growth (see e.g. Glaeser and Gottlieb, 2008; Kline, 2010).

The remainder of this paper proceeds as follows. Section 2 presents a simple model of firm hiring with vacancy posting. Section 3 presents the data and Section 4 describes our empirical strategy. Section 5 presents our main results on firm employment and performance, while Section 6 provides evidence on firms' adjustment margins to hiring difficulties. Section 7 documents the heterogeneous effects of hiring difficulties across industries, areas, firm characteristics, and occupation characteristics. Section 8 concludes.

2 A Model of Firm Hiring With Vacancy Posting

To guide the interpretation of our empirical findings, we present a simple model of firm hiring based on Cahuc et al. (2018). A firm needs to post vacancies to hire workers. We assume that hiring difficulties are larger in labor markets in which the vacancy filling rate is lower. 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. All proofs are relegated to Online 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 to hire workers. Posting a vacancy costs c_v per period. In each period, the sequence of decisions is as follows: (1) an exogenous proportion q_{t-1} of workers quits the firm;[4] (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

[4]The assumption of exogenous job separation simplifies the analysis, and allows us to obtain a simple expression for the semi-elasticity of firm employment to hiring difficulties.

vacancy is determined by a matching function: $m_t = m_t^0 \theta_t^{-\gamma}$ where m^0 is local matching efficiency, θ the local labor market tightness, and γ indicates the elasticity of matching to tightness.

When wages are exogenous, firms maximize their profits:

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

where β denotes the discount factor, 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:

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

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 the average hiring time.

Sensitivity of firm employment to hiring difficulties. Manipulating Expression (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 that larger hiring difficulties, i.e. higher τ_t, are expected to depress firm employment. The negative effect of hiring difficulties on firm employment is stronger for larger α, that is when firm production is more labor intensive, and when the cost of posting vacancies c_v is large. In the empirical tests presented below, we will check whether, as predicted by equation (4), the sensitivity of employment to hiring difficulties is indeed larger in labor-intensive firms, and in occupations for which hiring costs are larger.[5]

[5]Intuitively, one can proxy for larger hiring costs using certain occupation characteristics such as their skill-intensity or degree of specialization.

3 Data

In what follows, we separately describe our three main administrative data sources: the vacancy-level dataset from 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 from the French Statistical Office (INSEE). These datasets are merged together using a unique firm identifier.[6] 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* below). We discuss the external validity of our data at the end of the section, and presents summary statistics in Table 1.

3.1 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.[7] 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 intermediation services on the French labor market. Specifically, the PES maintains an online job board *pole-emploi.fr*, where firms post their job ads, and workers search for employment opportunities. Any firm may post on the website (private, public firms) and the service is free of charge. The French PES provides the largest online job board of the French labor market.[8]

For every vacancy posted, we observe the occupation code, the workplace location, the number of position offered, and the firm identifier. One unique advantage of the data is that we can observe whether a given vacancy has led to recruitment or

[6]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.

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

[8]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. The PES online job board *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).

has been delisted without recruitment success, as well as the posting date and the delisting date, which we use to calculate the time it takes for firms to fill up their vacancies.[9] We also observe for each vacancy a series of job characteristics on the type of contract, as well as on education and experience requirements, if any.

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:

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

By construction, $HiringDiff_{k,cz,t}$ 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 in the counterfactual case in which the observed 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 it takes more than 1 year to fill vacancies.[10]

In our empirical analysis, we also use the vacancy-level data to construct different proxies for changes in hiring standards in terms of experience required, education required, whether the job vacancy offers an open ended contract or a temporary contract, and whether the contract is full time or not.

Occupation-level statistics. We present for each occupation, the sample average probability of not filling vacancies, and when filled, the time it takes to fill them, the two components of our measure of hiring difficulties in Equation (5). As shown in Online Figure A1 and A2, we find substantial heterogeneity in both components

[9]When firms post vacancies, they are assigned to a local public employment agency. The information on hiring success is then 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.

[10]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 3, We also present our results when simply using the share of unfilled vacancies: $ShareUnfilled_{k,cz,t} = \frac{\sum_{v \in k,cz,t} Unfilled_v}{\sum_{v \in k,cz,t} Unfilled_v + \sum_{v \in k,cz,t} Filled_v}$.

across all occupations.[11] 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, across the 84 2-digit occupations in our data.

Importantly for our identification strategy, we report year-by-year changes in hiring difficulties across the 322 commuting zones in France for each occupation, the underlying source of identification in our empirical strategy (the *shifts* in our shift-share instrument presented below). As shown in Figure 1, there is substantial variation in year-by-year changes in hiring difficulties for a given occupation across commuting zones and time. In particular, for all occupations, there are periods and areas in which hiring becomes more difficult (the expected 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 of stated hiring difficulties by firms in order to validate our vacancy-based measure. As discussed in more details in Appendix B, we find a strong and robust correlation between our vacancy-based measures of hiring difficulties - namely, time-to-fill and probabilities of unsuccessful recruitment - 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.

3.2 Employment registers

We also rely 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

[11] Unsurprisingly, occupations with a high share of unfilled vacancies also tend to have high hiring time (conditional on being filled).

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.

3.3 Firm-level tax filings

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

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 1, firms in our sample have on average 14 employees and ROA for the average firm is around 6.6%.

3.4 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? Surveys about stated hiring difficulties are 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:[12] 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 overlaps with the

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

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 also representative 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.).

4 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 $\times$ commuting zone level. To make sure that these shocks are indeed "exogenous" to 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 commuting zone, but operating in other 3-digit industries.[13] The shares instead are specific to each firm and consist in the proportion of

[13]There are 84 distinct 2-digit occupations, 270 distinct 3-digit industries, and 322 distinct commuting zones. In robustness tests, we further exclude observations from local firms in connected

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.[14] 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 we aggregate these occupation-specific products at the firm-level.[15]

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 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 in Expression (6)) reads as follows:

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

Importantly, we can compute our shift-share measure of hiring difficulties 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 × commuting zone, are plausibly exogenous to any given firm i (once we remove from their computations information from job vacancies posted 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 otherwise identical firms, A and B, located in the same commuting-zone cz and

industries, namely operating in upstream and downstream sectors.

[14]Unfortunately, we cannot use information pre-dating 2009, as the classification of occupation codes was different in earlier years. As shown in Table 3, our results are robust to using shares in 2010.

[15]When the shift for a given occupation × local labor market × year cell is missing, we adjust firms' employment by re-calculating the total number of employees over the cells with non-missing shifts and by consequentially re-calculating occupation shares over the adjusted total employment.

operating in the same industry j (say the car industry), with two types of occupations, mechanical engineers (k= "MECH") and IT engineers (k= "IT"), with however different pre-determined occupation shares (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 of firm A than firm B in a specification in which we control for any other confounding shocks that could occur at the narrowly defined market level by including industry $\times$ commuting-zone $\times$ year fixed effects.

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, and $HiringDiff_{ss,i,cz,j,t}$ is the firm-level shift-share measure for hiring difficulties defined in Equation (6) above. We include industry $\times$ commuting zone $\times$ year fixed effects ($\mu_{cz,j,t}$). Standard errors are clustered at the commuting zone level.[16]

[16]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.

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.[17] First, there might be 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 × commuting zone × year fixed effects ($\mu_{cz,j,t}$ in Equation (7)) which allows 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 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, in a robustness exercise, we will 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.

Second, idiosyncratic shocks hitting large firms on their local labor markets might drive both their employment outcomes and variations in their own shift-share variable for hiring difficulties through their potential impact on market tightness for some occupations, an example of the reflection problem in our setting. To address this concern, we will remove all firms that represent a sizeable fraction of the local labor market for any occupation.

Third, our shift-share variable might reflect the effects of 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 us-

[17] See Borusyak et al. (2021) for a formal discussion. We do not implement the shock-level representation of Borusyak et al. (2021), as it explicitly excludes leave-one-out (LOO) shocks, which our empirical design relies on.

[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.

ing information on filling probabilities and time-to-fill for each occupation across all commuting zones, excluding the commuting zone of the firm itself. We also run additional robustness checks discussed in detail in Section 5.2.

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. This is not a threat to the identification strategy: 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 their location where for instance, there is a large supply of suitable workers in the occupations for which they have a high demand.

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 a training program that reduces skill mismatch could all create matching efficiency shocks.

In our model of firm hiring outlined in Section 2, 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 6.3, 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 inefficiency. 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 only to firms' responses to market-level labor supply shocks (often driven by changes in migration flows).

5 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.

5.1 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, $HiringDiff_{ss,i}$, and the actual hiring difficulties faced by firms on their posted vacancies, $HiringDiff_i$. By construction, in this first-stage specification, the sample is restricted to firms posting at least one vacancy in year t.

Column (1) of Table 2 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 2, 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 ($HiringDiff_i$) 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.[20] As shown in Column (3) of Table 2, the result indicates that a firm facing the average degree of hiring difficulties in our sample (0.217, see Table 1) would experience a drop in employment of around 8%, compared to a counterfactual firm in the same industry and local labor market that could hire workers in a frictionless way.

While a full structural estimation of labor search models is beyond the scope of our paper, our simple model in Section 2 already exemplifies how our estimates can pin down some key structural parameters of search frictions. In a back-of-the-envelope exercise, we relate our previous estimates of employment effects to the structural semi-elasticity in Equation (4) above. Assuming that the labor share is about 2/3 ($\alpha = 0.66$), we obtain that flow vacancy costs represent 12.1% of yearly wages (c_v/w), an interesting order of magnitude for one key parameter in macro search models.

5.2 Robustness checks

We now explore in detail the robustness of the baseline result on employment, and presents the findings in Table 3.

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 the same area (using the same leave-one-out correction at the industry level). The estimate is very similar to the baseline result.

[20]The IV estimator can be computed as the Wald ratio of the reduced-form estimate ($\hat{r}$, Column (2) of Table 2) and of the first-stage estimate ($\hat{f}$, Column (1) of Table 2). 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: $se(w) = \left(se(r)^2 / \left(\hat{f}\right)^2 + se(f)^2 \, (\hat{r})^2 \, / \, \left(\hat{f}\right)^4 \right)^{1/2}$.

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.

Firm characteristics. One may worry that firms' occupation mix in 2009 (the *shares*) correlates in a systematic way with some initial firm characteristics that in turn, could explain the differences in employment trends that we observe over 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 (3). The estimate on the variable of interest remains stable, which largely mitigates 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 (4). 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 (5), indicating that business-stealing effects have, if anything, only a negligible impact on our findings.

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 strength of our approach is that, despite the selected nature of the vacancy data, we can still estimate the effects of hiring difficulties on employment for the universe of firms in the French economy, independently on whether they post job ads through the French job centers or they presumably use other means. Still, it is worth discussing whether the selected nature of our data might bias our results and, if so, in which direction.

On the one hand, the fact that we do not observe the universe of job postings might introduce noise in our occupation-level measures of hiring difficulties, and generate an attenuation bias in our results. On the other hand, there may be systematic differences in time-to-fill for a given occupation between the French job center and alternative venues for hiring workers. For instance, the French job center might be more (or less) efficient at matching workers to jobs than other online platforms for certain types of occupation, in which case the time-to-fill we observe in the data of the French job center could be on average shorter (or longer) than for the rest of the market. If this is the case, this should also lead us to overestimate (or underestimate) the true elasticity of employment to hiring difficulties.

While in most cases, the presence and nature of this type of bias cannot be directly inspected, we can take advantage of the fact that our measure of hiring difficulties can be computed for the universe of firms in the French economy and gauge the severity of this concern by running our baseline specification separately for the sample of firms posting vacancies on the French job center, and for other firms (those that never posted a vacancy on the French job center, and presumably use alternative means to hire workers). As shown in Columns (6) and (7), the estimates are virtually identical in both sub-samples, which largely addresses the concern that systematic differences in hiring difficulties across matching platforms could bias our estimates. This exercise confirms that the magnitudes we obtain when estimating the effect of hiring difficulties on employment are robust, which we view as a central contribution of our paper.

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 time-to-fill from upstream and downstream industries when computing our shift-share instrument. For this, 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, excluding not only the firms' industry but also all other industries tagged as connected. Column (8) presents the results with this more conservative shift-share instrument. The coefficient on employment is slightly smaller, 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 through 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 of the same commuting zone (through an increase in local market tightness for IT engineers), and in turn lead us, through a reflection problem, to observe an increase in the shift-share measure of hiring difficulties for the large firm. Even though one can argue that examples along this line are likely to lead us to underestimate the causal impact of hiring difficulties on firm employment, we can also address the reflection problem directly. For this, 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 (9). 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.[21] 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

[21] For instance, think about general labor-augmenting technology, such as specific softwares for clerks or IT engineers. One may worry that the associated increase in the productivity of IT engineers might feed into changes in vacancy filling rates for IT engineers and higher employment for firms hiring IT engineers across all commuting zones, violating the exclusion restriction.

variable should subsume the main variable of interest, $HiringDiff_{ss}$. As shown in Column (10), 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.

5.3 Other corporate outcomes

We turn to 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 low-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. 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 4 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 7.

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, our estimate implies that a firm facing the average degree of hiring difficulties in our sample would experience a drop in capital, sales, value-added, and profits of respectively around 8%, 5%, 7%, and 9%, compared to a counterfactual firm that could hire workers in a frictionless way.[22] Given that profits might be negative for some firms, we check the robustness of the result on the logarithm of

[22]For obtaining these numbers, we multiply each estimate presented in Table 4 by the average degree of hiring difficulties in our sample (0.217, see Table 1), and divide it by the first-stage estimate (0.078, Column (1) of Table 2).

profits using instead ROA as an alternative measure, and find consistent effects.[23]

6 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 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, 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.

6.1 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 5. 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 Panel A, Column (1), we find a negative and statistically significant effect, but smaller in magnitude compared to the baseline effect on employment (-0.015 versus -0.029 in Column 4 of Table 2). 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 their lower number of

[23] Quantitatively, the estimate implies that a firm facing the average degree of hiring difficulties would experience a drop in ROA of 2.5 percentage points compared to a counterfactual firm that could hire workers in a frictionless way, a large effect given the average ROA of 6.6% in our sample.

employees 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 wages and hours worked by incumbents and new hires separately, and present the results in Panel B of Table 5. As shown in Columns (1) and (2), we do not find significant effects on yearly hours for either incumbents or new hires. When we look at wages, we find that the magnitude of the effect is larger for incumbent workers than for new hires. While the effect of hiring difficulties on the wages of new hires is not statistically significant at conventional levels (see Column 3), we show below that this result masks important heterogeneity depending on the underlying factors driving hiring difficulties (labor tightness versus matching inefficiency shocks, see Section 6.3). For incumbents, we find clear evidence that firms raise wages internally, which is consistent with an increase in firms' effort for retaining their workers.[24]

Workforce turnover. Finally, in Panel C of Table 5, 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.

6.2 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 6. Specifically, we look at the change in the average experience required (in months) across all posted vacancies in a given occupation, in the average number of years of education required, the share of vacancies offering open ended contracts (as opposed to temporary contracts), and full-time contracts (as opposed to part-time contracts). While we do not find evidence that hiring difficulties have

[24]We do not know the exact (and potentially multiple) channels through which firms increase the retention rates of incumbent workers. 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 question.

any effect on education requirements, or changes in the type of job contract offered, there is a negative and statistically significant effect of hiring difficulties on experience requirements. This result is consistent with the idea that, when facing difficulties in finding potentially suitable workers in their local markets, firms adjust downward their hiring standards in terms of experience requirements.

6.3 Labor market tightness and matching efficiency

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

As in the model presented in Section 2, we first define the vacancy filling rate, $m_{k,cz,t}$, at the local labor market level (occupation k, commuting zone cz and year t), as being the product of two components in the following expression:

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

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 (between 0 and 1). Equation (8) indicates that hiring becomes more difficult when local competition for workers ("tightness") increases in certain occupations, either because other employers increase their labor demand (increase in the number of vacancies), or because there are fewer workers supplying labor (decrease in the number of unemployed). Shocks to "matching efficiency" instead can be thought as technology shocks that reduce the information imperfection in the labor market and mitigate coordination failures, or as shocks that decrease the degree of skill mismatch between the pool of applicants and potential employers.[25]

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 $\times$

[25]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.

commuting zone $\times$ year.[26] Separately for each occupation k, we then regress our measure of hiring difficulties on local market tightness in the following specification with both commuting-zone and year fixed effects:

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

in a 2-SLS specification where we instrument labor market tightness with its lag $\theta_{k,cz,t-1}$ as in Borowczyk-Martins et al. (2013). 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: $\mathcal{T}_{k,cz,t} = 1/\left(m^0_{k,cz,2010}\widehat{\theta^{-\gamma_k}_{k,cz,t}}\right)$, 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 labor tightness and matching inefficiency variables 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 equation 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 7. we find that both β_T and β_M are negative and statistically significant. If anything, matching inefficiency shocks tend to have larger effects on employment than tightness shocks. Consistent with an important role played by matching inefficiencies, we find in Section 7 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 all workers in Column (2), and separately for new hires and incumbents in respectively Column (3) and Column (4). While the aggregate effect of hiring difficulties on hourly wages of new hires was not statistically significant on average in Table 5,

[26] 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 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.

once we look separately at tightness versus matching efficiency shocks, 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.[27][28] Finally, for incumbents, we find that both tightness and matching efficiency shocks are associated with increases in wages, which is consistent with either an increase in their bargaining power, or an increase in their productivity through training.

7 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.

7.1 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 8 for sectors, and in Columns (3) and (4) of Table 8 for commuting zones. Overall, the sensitivity of employment to hiring difficulties is indeed larger for expanding sectors and expanding areas, than declining sectors and declining areas.

[27] 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"*.

[28] The result is also consistent with an equilibrium version of our search model in Section 2. Cahuc et al. (2018), from which we borrow our partial-equilibrium model, shows that with wage posting and directed search, equilibrium wages of new hires depend on tightness, but not directly on matching efficiency.

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 2). 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 8. The negative effect of hiring difficulties on employment is indeed significantly stronger for labor-intensive firms (Column 5) than for not labor-intensive firms (Column 6). By showing that hiring difficulties have a larger effects on firms' employment precisely for those firms relying more on labor in their production function, these results reaffirm our confidence that our baseline estimates accurately reflect the causal impact of hiring difficulties on firms' outcomes.

Other firm characteristics. One may wonder whether hiring difficulties have differential effects on firm employment depending on standard firm characteristics, such as firm size, firm age, and standard measures of firm performance and financial constraints. For instance, large firms might have more flexibility to use internal labor markets to reshuffle their workforce in order to address hiring difficulties on a given set of occupations. Young firms might need to respond to fast-changing economic opportunities by hiring quickly suitable workers in specific occupations, whereas old firms might simply postpone hiring when frictions on the labor market are less severe. The returns to hiring might be larger for more productive firms, and therefore in turn the sensitivity of their performance to hiring difficulties. 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 shows a lower sensitivity of their employment to hiring difficulties. To shed light on these issues, we run our baseline specifications in sub-samples based on firm size, firm age, firm profitability, TFP, dividend payer status, credit risk, and leverage, and report the results in Table 8.

As shown in Columns (7) and (8) the sensitivity of firm employment to hiring difficulties is significantly larger in bigger firms, maybe because small firms face financial constraints restricting their capacity to hire and grow, irrespective of the degree of hiring difficulties on external labor markets. Columns (9-14) 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 (15-20) into those that are more versus less likely to be financially constrained (those paying no dividends, with high credit risk, and high leverage versus paying dividends, with low credit risk, and low leverage), we find some evidence that financially constrained firms display a lower sensitivity of their employment to hiring difficulties.

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 4, namely sales, value-added, profits, and capital. Overall, the differences in the sensitivity of sales and 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 size, labor-intensity, and degree of financial constraints.

7.2 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' employment and profitability are especially sensitive to hiring difficulties on occupations characterized by specific features. For this, we augment our baseline specification at the firm-year level with an interaction term representing the firm-level shift-share variable based only on a subset of occupations of a given type $\mathcal{K}$:

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

We consider below a large set of different types of occupations, and present the results in Table 9.

Routine, manual, cognitive and interpersonal tasks. We start by categorizing occupations into different types depending on the occupation-specific classification of tasks initially developed in 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 this score, 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.[29]

As shown in Columns (1-5) of Table 9, 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 the 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 classify as specialized occupations those ranked in the top tercile.[30] 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

[29] Specifically, we use the mapping between tasks and occupation defined in O*NET (available for the US). We then aggregate ONET task measures originally available for the Standard Occupational Classification 2010 (SOC2010) at 6-digit level as in Acemoglu and Autor (2011). We then convert occupations in the SOC2010 into the French occupation classification at the 2-digit level using aggregate employment in each occupation as weights.

[30] 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.

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 Online Appendix Figure A3 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/low-skill/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 $HiringDiff_{ss} \times Specialized$, together with each interaction term considered above separately, and present the results 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 sales and 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 hiring difficulties for non-routine cognitive, high-skill, high-wage, and specialized occupations lead to larger declines for both firm employment and capital.

8 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*). 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. We then document larger effects of hiring difficulties in expanding sectors and areas, for labor-intensive firms, and for non-routine cognitive, high-skill, high-wage, and specialized occupations.

Taken together, our findings indicate that hiring difficulties are an important determinant of the growth and profitability of firms across time and space and they corroborate claims of business leaders that hiring difficulties represent one of their major concerns. More generally, they speak about the importance of recruitment and retention for firms' wage choices and employment outcomes. Our findings suggest that policies aimed at reducing labor market tightness (such as encouraging female labor supply) or at improving matching efficiency (such as training programs targeted at some specific professions) can significantly increase economic growth at the local level. Our results are also useful for future structural analyses relying on estimates of key hiring difficulties parameters of firm labor demand.

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Figures and Tables

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

This figure presents the 25th and 75th percentiles of the distribution of the year-by-year changes in hiring difficulties across 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 By Industry, Geography and Firm Characteristics - Subsample Analysis**

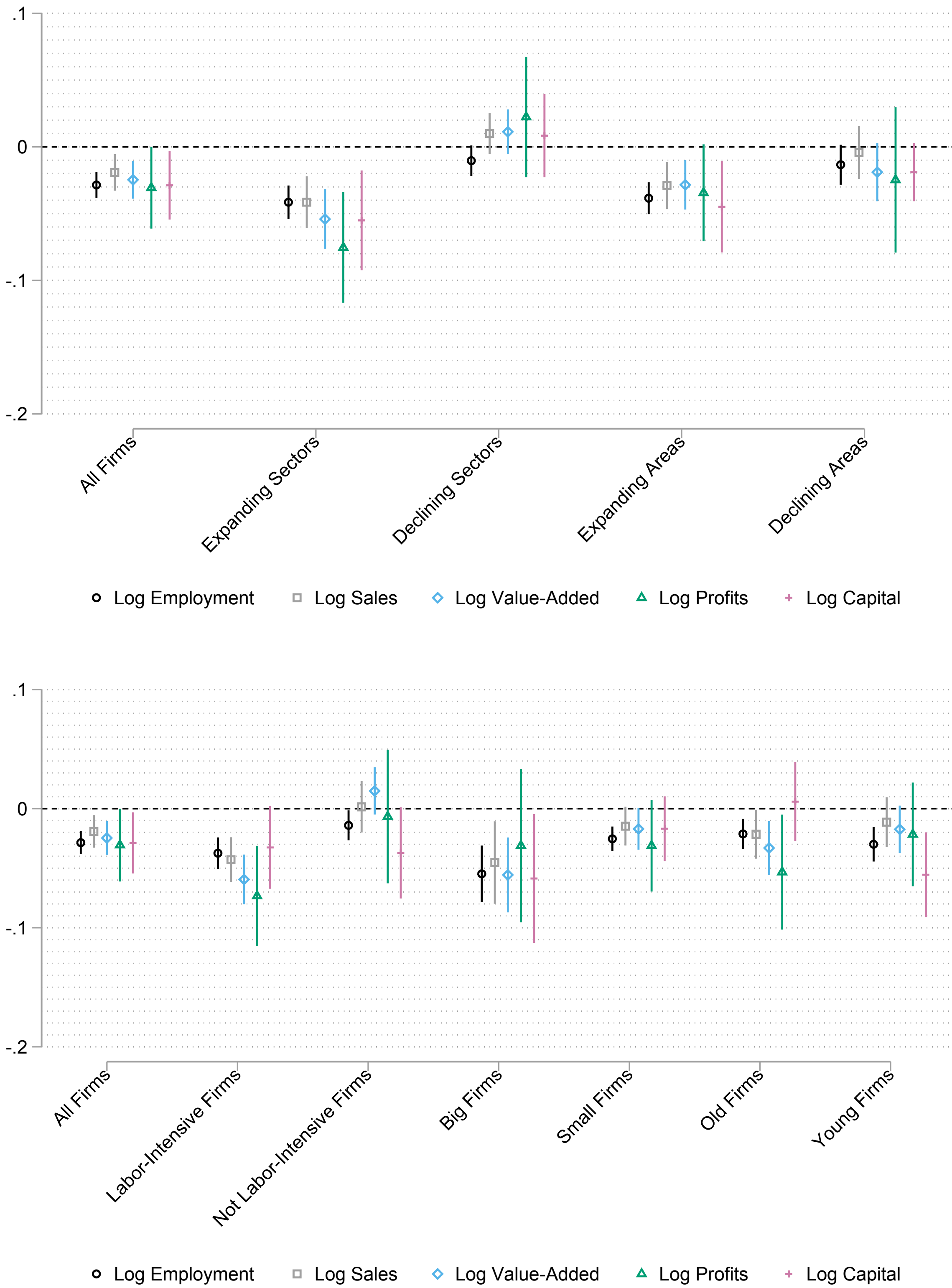
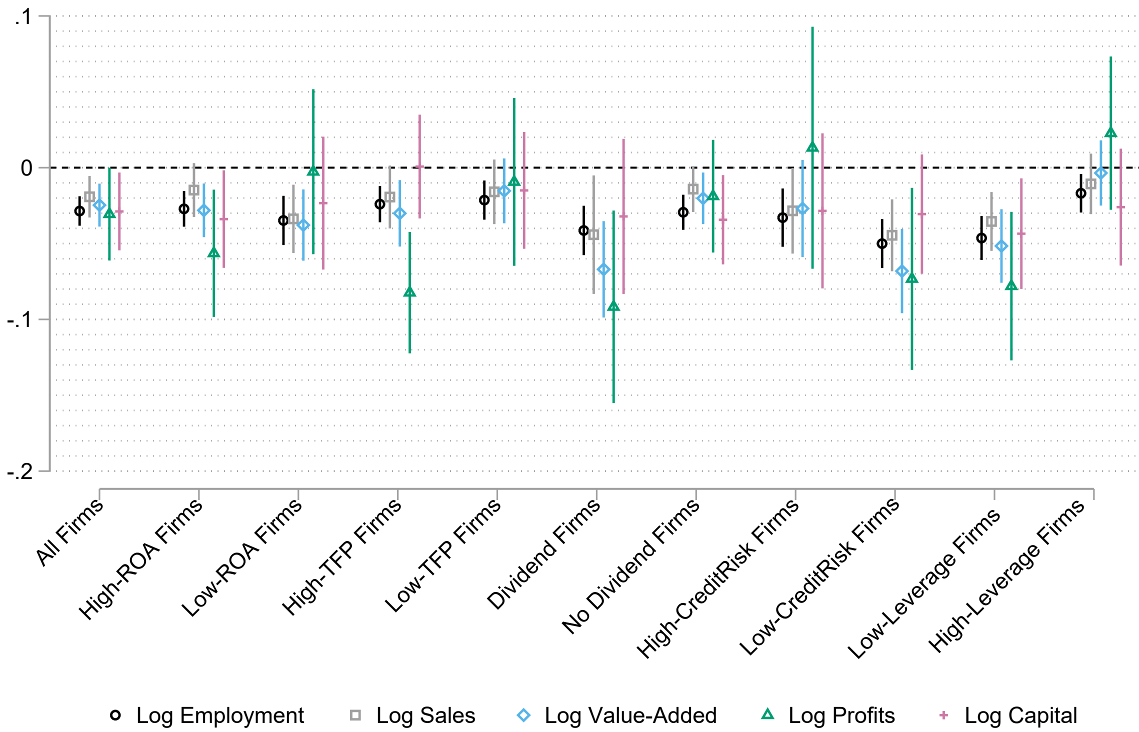
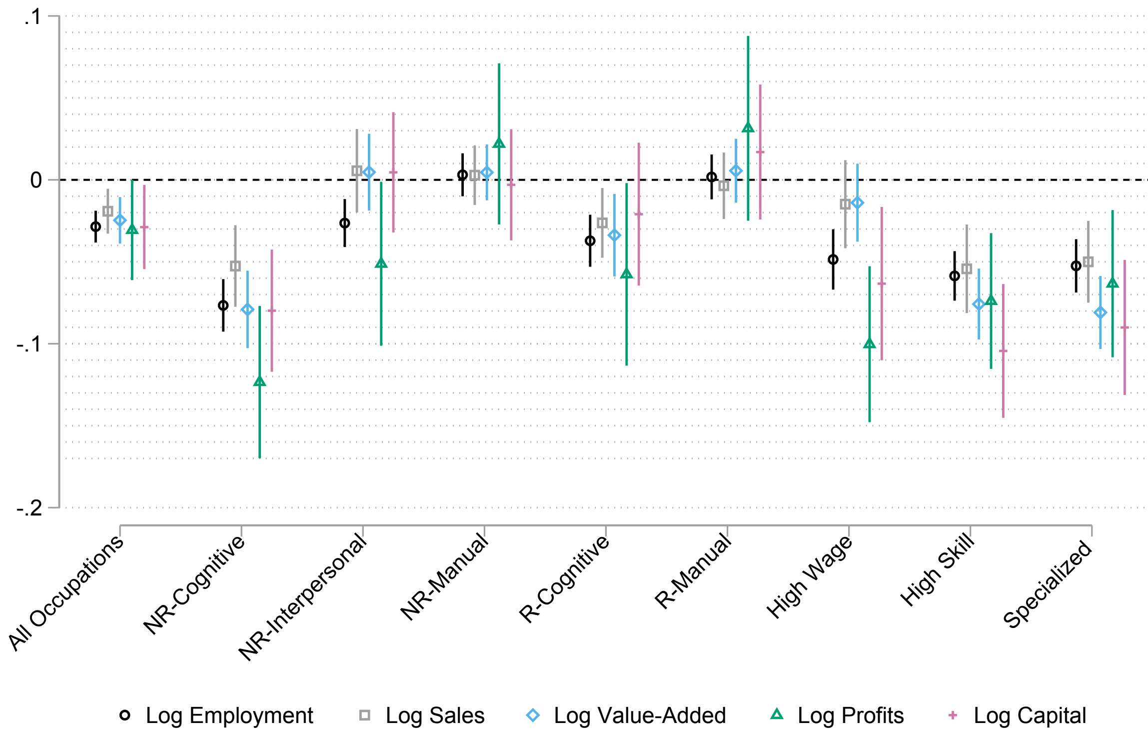


Figure 2 **(Continued)**



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 8. 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 8. 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 9, 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 1: **Descriptive Statistics**

	Mean	Sd	Min	Max	N
Hiring Difficulties					
Hiring Difficulties (*HiringDiff*)	0.217	0.252	0.000	1.000	776497
Hiring Difficulties$_{ss}$ ($HiringDiff_{ss}$)	0.237	0.071	0.000	1.000	3130014
Employment-Related Outcomes					
Employment	14.638	76.207	1.000	20350	3130014
Yearly Wages per Worker (K€)	35.308	24.922	4.919	175.498	3130014
Yearly Hours per Worker	1381	385	380	2090	3130014
Experience Required (months)	18.239	19.165	0.000	90.000	769810
Education Required (years)	11.653	1.163	11.000	17.000	769810
Offered Contract is Open End	0.523	0.448	0.000	1.000	769810
Offered Contract is Full-Time	0.878	0.291	0.000	1.000	769810
Other Firm-Level Outcomes					
Log Capital	4.323	2.027	0.000	9.582	3130014
Log Sales	6.569	1.430	0.000	10.188	3130014
Log Value-Added	5.638	1.301	-0.916	8.977	3081961
Log Profits	3.910	1.617	-1.406	7.871	2495490
ROA	0.066	0.254	-3.461	1.093	3061732

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 2: **Hiring Difficulties and Firm Employment**

	(1) First Stage	(2) Reduced Form	(3) IV
	Hiring Difficulties (*HiringDiff*)	Log Employment	
$HiringDiff_{ss}$	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 3: **Hiring Difficulties and Firm Employment - Robustness**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log Employment									
	Share Unfilled$_{ss}$	Shares in 2010	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***	-0.034***	-0.030**	-0.028***	-0.031***	-0.028***	-0.018***	-0.031***	-0.015***
	(0.005)	(0.005)	(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
Ind-Cz-Year FE	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
Control for National Shift-Shares	No	No	No	No	No	No	No	No	No	Yes
Observations	3130014	3113662	2905005	312942	2814321	1762615	1307301	3126891	3063116	3130014
R-Sq	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 2. 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 augment our specification with firm characteristics (terciles of firm size, age, and ROA, all measured pre-sample), interacted with year fixed effects. Columns (4) (respectively Column 5) 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 (6) (respectively Column 7) 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 (8), 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 (9) 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 (10) 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 4: **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	3077525	2455320	3059473
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 5: **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
	(1)	(2)	(3)	(4)
Panel B:	Log Yearly Hours		Log Hourly Wages	
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
	(1)	(2)		
Panel C:	Workforce Turnover			
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	3100276		
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 6: **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	640889	640889	640889	640889
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 7: **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 8: **Heterogeneity by Industry, Geography, and Firm Characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log Employment									
	Sector		Area		Labor Intensive		Size		Age	
	Expanding	Declining	Expanding	Declining	Yes	No	Large	Small	Old	Young
HiringDiff$_{ss}$	-0.041***	-0.010*	-0.038***	-0.013*	-0.037***	-0.014**	-0.055***	-0.025***	-0.021***	-0.030***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)	(0.012)	(0.005)	(0.006)	(0.007)
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	1390436	1682279	1523121	1546086
R-Sq	0.958	0.951	0.953	0.958	0.958	0.954	0.943	0.833	0.967	0.935
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Log Employment									
	ROA		TFP		Pay Dividend		Credit Risk		Leverage	
	High	Low	High	Low	Yes	No	High	Low	Low	High
HiringDiff$_{ss}$	-0.027***	-0.035***	-0.024***	-0.021***	-0.041***	-0.029***	-0.033***	-0.050***	-0.046***	-0.017***
	(0.006)	(0.008)	(0.006)	(0.007)	(0.008)	(0.006)	(0.010)	(0.008)	(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	1438137	1405957	1425925	1351034	703943	2253368	837442	1020037	1414925	1429075
R-Sq	0.957	0.956	0.954	0.960	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), large versus small firms (Columns 7 and 8), old versus young firms (Columns 9 and 10), low versus high ROA firms (Columns 11 and 12), low versus high TFP 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 9: **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 show 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.

Online Appendix

Hiring Difficulties and Firm Growth

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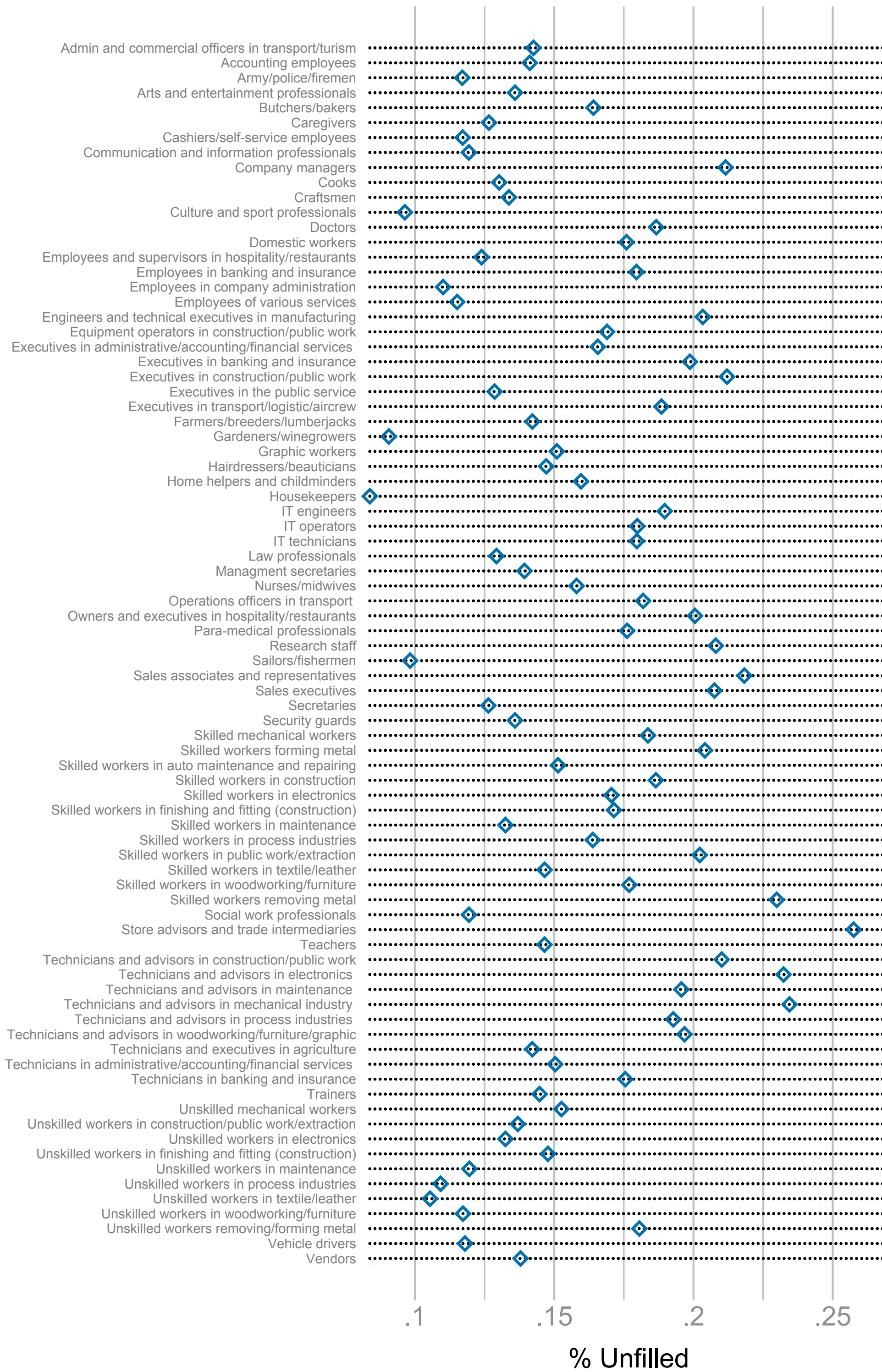
Maddalena Ronchi (Kellogg School of Management, Northwestern University)
Julien Sauvagnat (Bocconi)

The online 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 2.

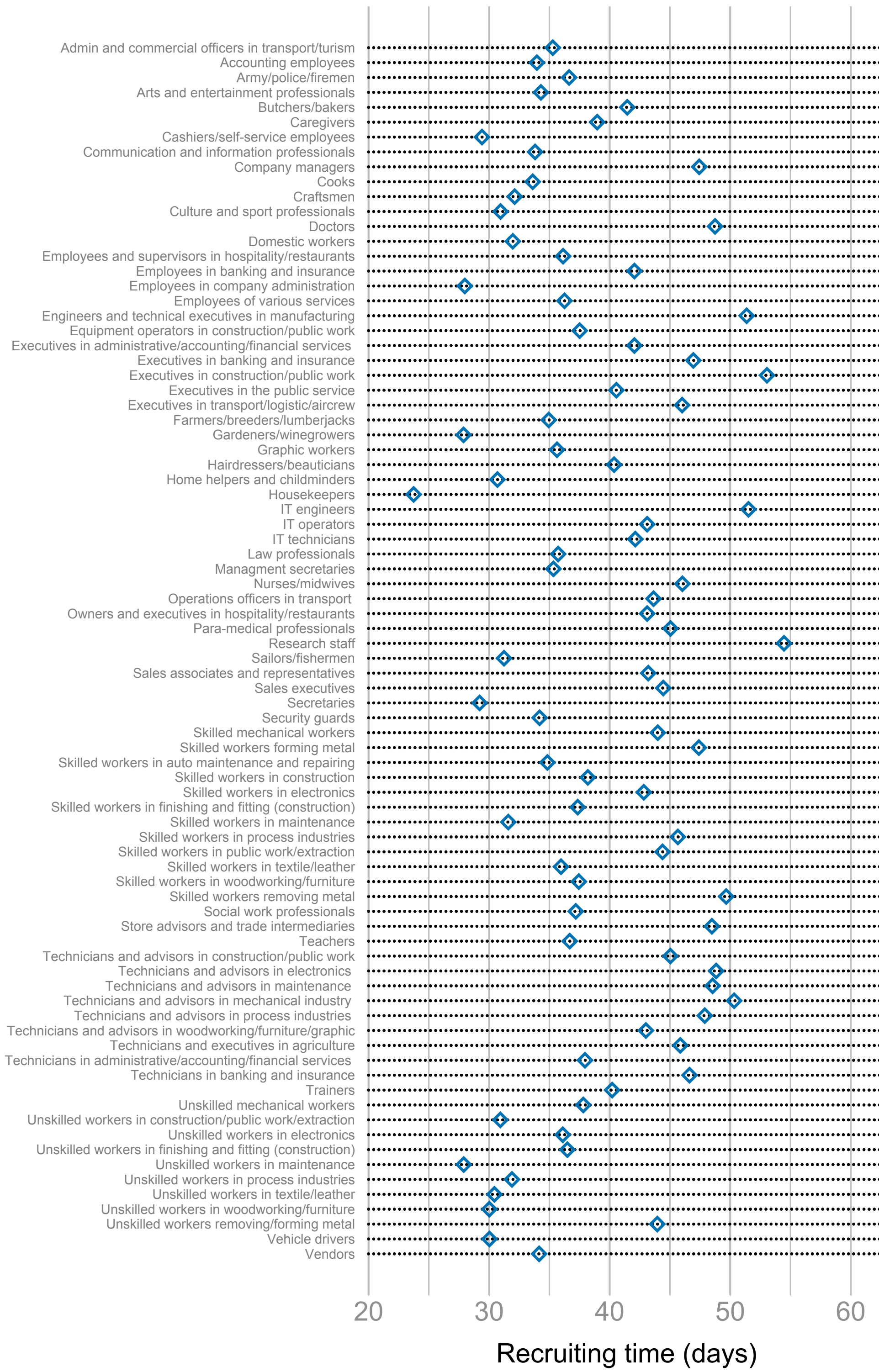
A Appendix Figures and Tables

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: **Ranking of Occupations by Type**

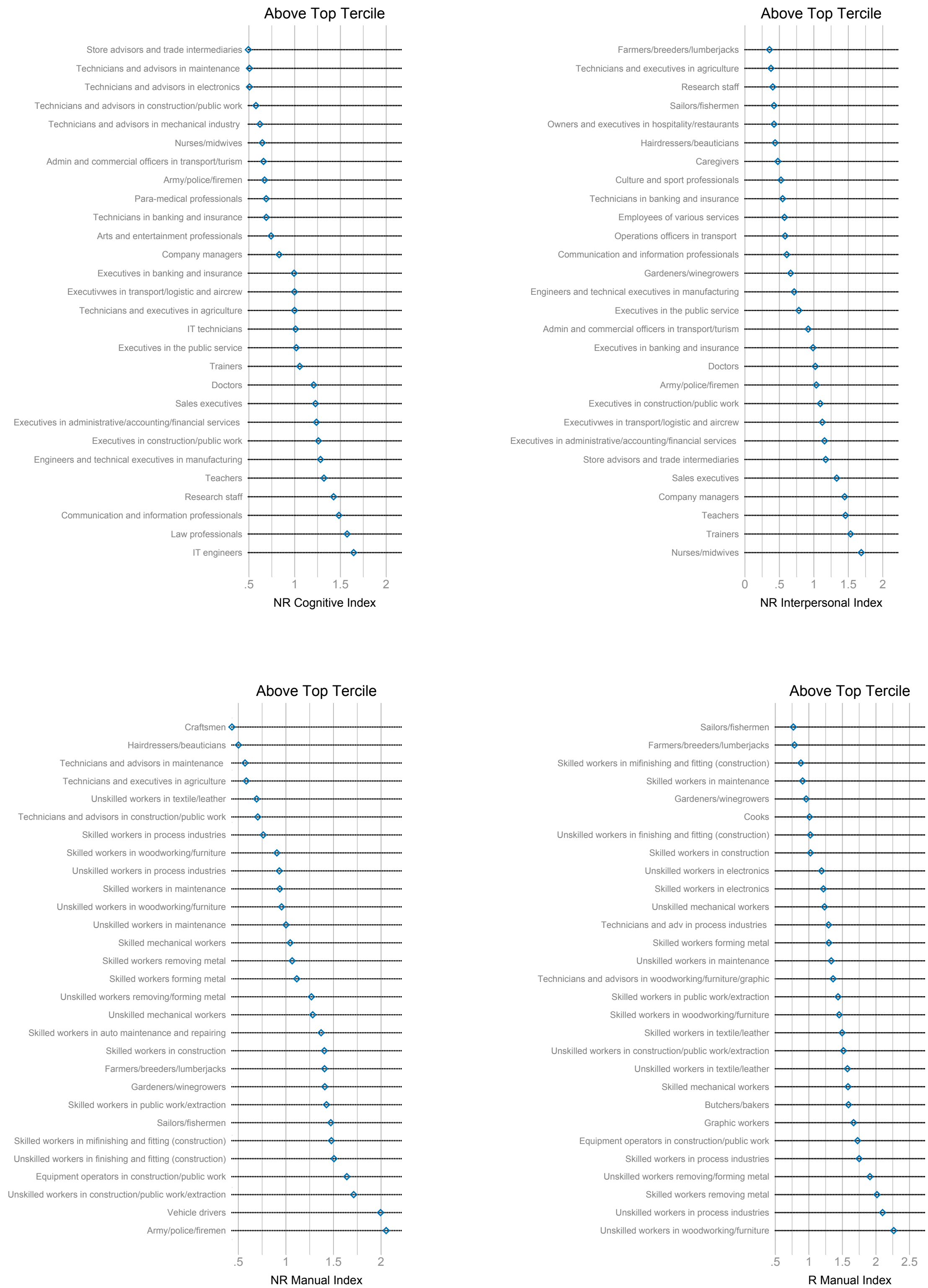
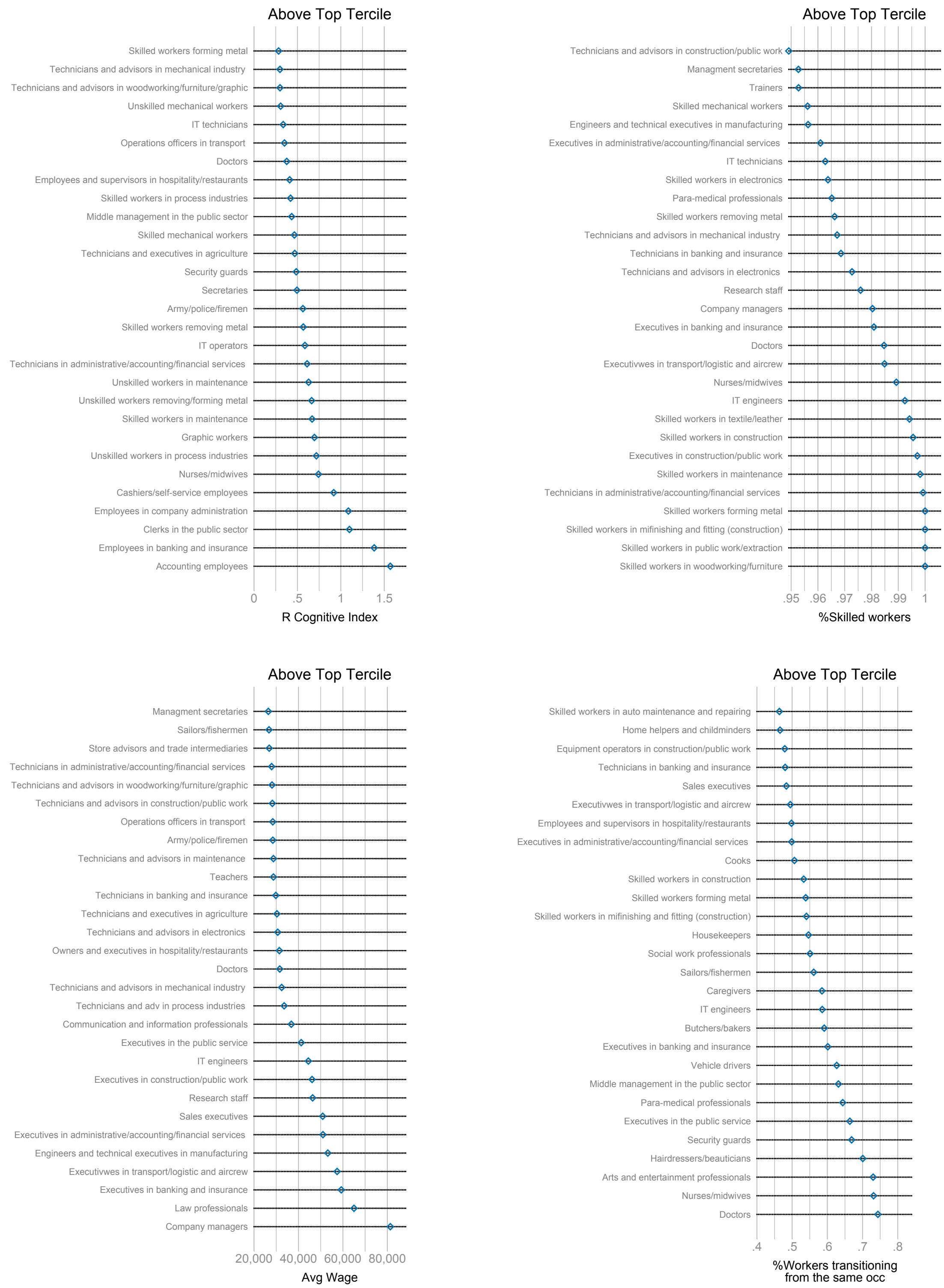


Figure A3 **(Continued)**



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.

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*).

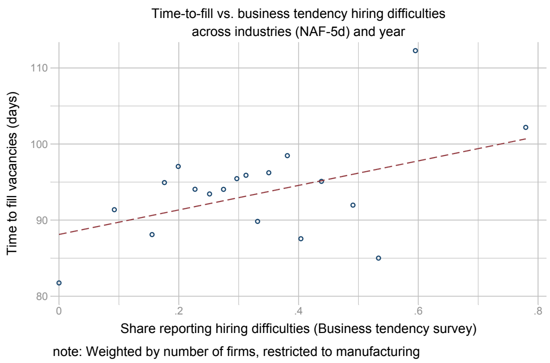
In the BTS, firms are asked whether they currently encounter recruiting difficulties (yes/no question). The question is ventilated across three types of labor: executives, skilled workers, and unskilled workers. We have access to the BTS data covering manufacturing firms. We aggregate their answers at 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 A5 (resp. A6) 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 A7 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.

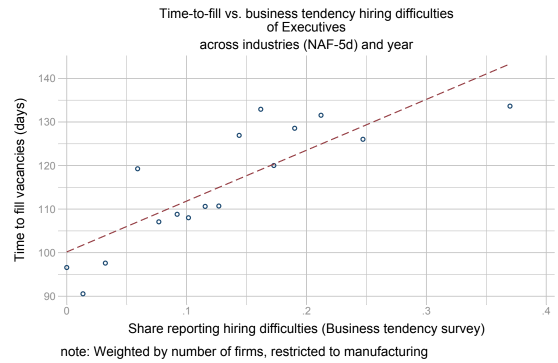
We conclude that our main measure of hiring difficulties based on the expected probability of filling a vacancy and the average time it takes to hire a worker indeed strongly correlates with firms' own-assessment in surveys of the difficulty they face for finding suitable workers on the labor market.

Figure A5: **Time-To-Fill vs. Hiring Difficulties in Business Tendency Survey**

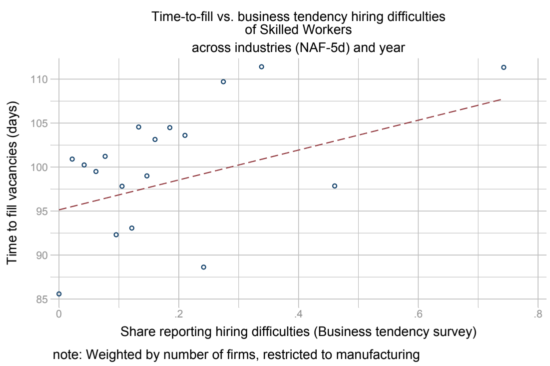
(a) All occupations



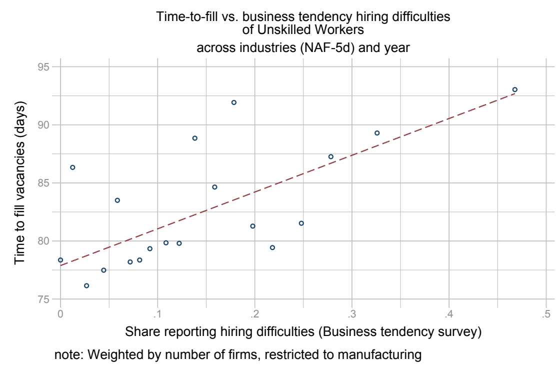
(b) Executives



(c) Skilled workers



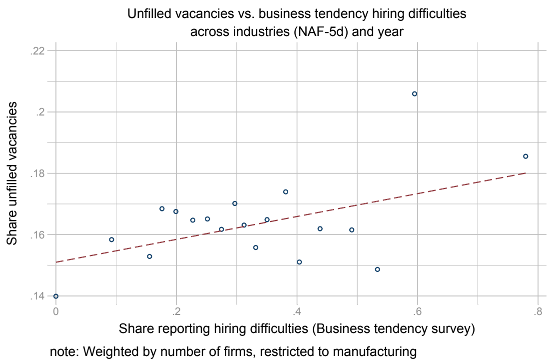
(d) Low-skill Workers



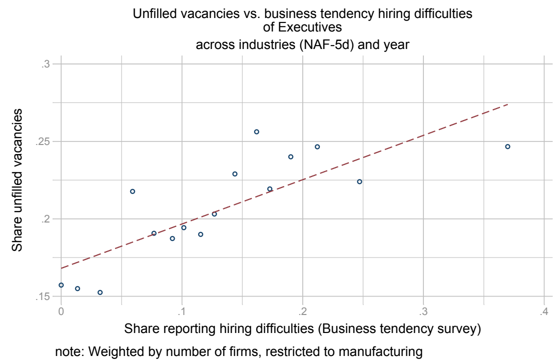
This figure presents scatter plot of the relationship between average time-to-fill (respectively across all vacancies in Panel A, for the sub-samples of vacancies for executives in Panel B, for skilled workers in Panel C, and low-skill workers in Panel B) expressed in number of days and respectively 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 A6: **Share of Unfilled Vacancies vs. Hiring Difficulties in Business Tendency Survey**

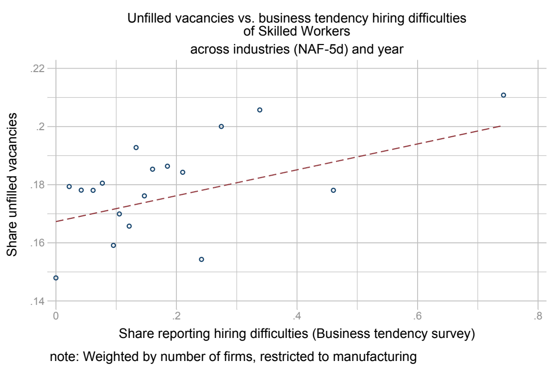
(a) All occupations



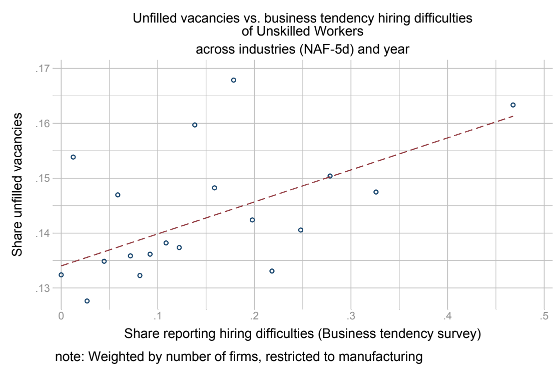
(b) Executives



(c) Skilled workers



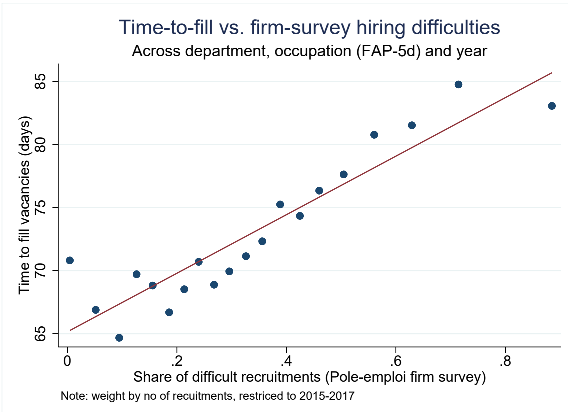
(d) Low-skill Workers



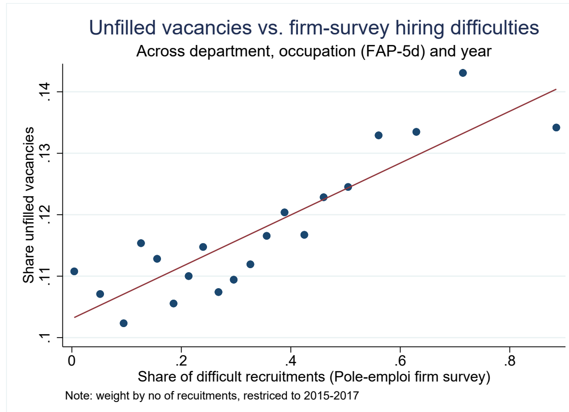
This figure presents scatter plot of the relationship between the share of unfilled vacancies (respectively across all vacancies in Panel A, for the sub-samples of vacancies for executives in Panel B, for skilled workers in Panel C, and low-skill workers in Panel B) expressed in number of days and respectively 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.

Figure A7: **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.

C Theoretical Model: Proofs

In this section, we derive the theoretical results from the model of firm hiring presented in Section 2.

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

$$\Pi(L_{t-1}) = \max_{L_t, V_t} A_t R(L_t) - w_t L_t - c_v V_t + \beta \mathbb{E}\left[\Pi(L_t)\right]. \tag{12}$$

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

$$L_t - L_{t-1} = V_t \times m_t - L_{t-1} \times q_t. \tag{13}$$

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

$$A_t R_L(L_t) = w_t + \frac{c_v}{m_t} - \beta \mathbb{E}\left[\Pi_L(L_t)\right]. \tag{14}$$

Using the envelope theorem, we obtain:

$$\Pi_L(L_t) = (1 - q_{t+1}) \left(A_{t+1} R_L(L_{t+1}) - w_{t+1} + \beta \mathbb{E}\left[\Pi_L(L_{t+1})\right]\right), \tag{15}$$

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 (14) in period $t+1$, we simplify Equation (15) as:

$$\Pi_L(L_t) = \frac{(1 - q_{t+1}) c_v}{m_{t+1}}. \tag{16}$$

We can then write the dynamic labor demand equation:

$$A_t R_L(L_t) = w_t + \frac{c_v}{m_t} - \beta E\left[\frac{(1 - q_{t+1}) c_v}{m_{t+1}}\right]. \tag{17}$$

Sensitivity of firm employment 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 (17) assuming that $R(L_t) =$

$\frac{(L_t)^\alpha}{\alpha}$:

$$\log A_t + (\alpha - 1)\log L_t = \log(w_t) + \log\left(1 + \frac{c_v \tau_t}{w_t} - \frac{\beta}{w_t} E\left[(1 - q_{t+1}) c_v \tau_{t+1}\right]\right). \quad (18)$$

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

$$(\alpha - 1) d \log L_t = \frac{c_v}{w_t} \frac{d\tau_t}{\left(1 + \frac{c_v \tau_t}{w_t} - \frac{\beta}{w_t} E\left[(1 - q_{t+1}) c_v \tau_{t+1}\right]\right)}. \quad (19)$$

We provide below a first-order approximation of Equation 19. In Cahuc et al. (2018), "the hiring cost amounts to 1.2% of the annual wage": $\frac{c_v \tau}{w} = 0.012$, which appears on both terms of the denominator, can then be neglected with respect to 1. We obtain the following approximated expression:

$$d \log L_t \approx \frac{c_v}{w_t} \frac{1}{(\alpha - 1)} d\tau_t \quad (20)$$

This expression shows that when α increases and get closer to 1, then the semi-elasticity of employment with respect to recruiting time remains negative and increases in absolute value. The parameter α is related to the employment intensity of the firm production function. The current model abstracts from capital. If we were to include the capital stock K_t, then we could assume a standard Cobb-Douglas production function: $A_t K^{1-\alpha} L^\alpha$. At equilibrium, we would obtain that the share of labor costs in firm output is equal to α, so that more labor intensive firms have higher α and a higher semi-elasticity of employment with respect to recruiting time in absolute value.