Hire from Anywhere:
Work-from-Home Offering and Firms' Labor Market Access

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Abstract

Firms often face the difficult task of finding available workers to fill their open positions, particularly when they face tight labor markets or when relevant workers are geographically distant. One way for firms to remedy this problem is to offer work-from-home contracts that give them access to a geographically broader labor market. In this paper, I explore the extent to which firms utilize work-from-home positions as a means of attracting more workers. I outline a theoretical model where firms choose which contract type to offer – in-person or work-from-home. This model predicts that firms in relatively tighter labor markets should be more willing to offer work-from-home positions. I test the model predictions empirically and provide evidence on how job seekers value WFH in job ads and how firms use WFH to offset negative labor market conditions. I find that work-from-home job ads get more attention and applications from job seekers, particularly in occupations with high work-from-home potential. I then investigate if firms are leveraging work-from-home signaling when they face difficult hiring conditions. I find there is a relative increase in the number of work-from-home job ads posted in local labor markets that were tighter in the previous month suggesting that firms are strategically offering the working-from-home amenity.

1 Introduction

A perennial problem firms face is finding good and available workers to hire. As the European Employment Services report, "85% of all available 4-digit ISCO '08 occupations were identified as a shortage" by at least one European country (European Labour Authority 2024). Similar patterns exist in the US with consistently low ratios of unemployed workers to open vacancies since the COVID-19 pandemic (Handel 2024). In Sweden, "41% of private employers reported that they had experienced a skills shortage when recruiting in the past 6 months. Among public employers, 60% experienced a recruitment shortage over the same period" based on responses about the fall 2022 Swedish labor market (European Employment Services 2024). According to these reports, issues with hiring shortages and difficulty finding workers is pervasive across many countries and occupations. One potential contributor to this problem is that traditional labor markets are geographically confined by how far away a worker can practically commute and how far they are willing to travel in order to get to the office. This is particularly constraining when workers are expected to be at the workplace five or more days per week. With commuting constraints and a general resistance to and high costs of worker relocation for new jobs, firms are generally restricted to hiring workers in their immediate geographic vicinity.

If the geographic constraint is binding for many firms, then one potential solution to this worker shortage is for firms to offer work-from-home (WFH) positions over traditional, in-person jobs. WFH jobs offer firms access to a broader pool of workers since they reduce (in terms of hybrid work) or remove (in terms of fully remote work) the geographic constraints placed on firms and workers in the labor market. WFH can greatly increase a firm's labor market access as they can now hire workers from much further away without having to pay high relocation costs or having to convince workers to move. Workers, on the other hand, now have greatly reduced job transition costs, as switching firms would not require moving and they also have reduced costs in terms of learning new commutes, adjusting to new working spaces, or being in a new social environment. Along with the relaxed geographic constraints, WFH positions may attract more workers even within their own labor markets. WFH is documented to be a non-wage amenity that workers value (Aksoy et al. 2022), so many workers may seek WFH jobs over in-person jobs, particularly if there is a compressed wage distribution.

In this paper, I investigate the question: to what extent are firms using working from home as a tool to alleviate negative labor market conditions and how much does WFH broaden their labor market access. To answer this, I exploit unique data covering the vast majority of vacancies in the Swedish labor market linked to registry data on worker and firm characteristics as well as data on job seekers' application behavior in order to offer new evidence on how labor market conditions affect firm decision making in offering WFH. In order to capture WFH characteristics in the vacancy data, I employ a three step categorization process that utilizes OpenAI's GPT-4 Turbo, a large multimodal model. With this, I am able to correctly identify the vast majority of job ads that explicitly offer WFH as well as distinguish between hybrid and fully remote jobs.

To the best of my knowledge, this is the first paper to estimate the causal relationship of labor market tightness on WFH offering by firms. In addition, it is the first paper to provide estimates of the effect of offering WFH on the attention and number of applications a vacancy receives from job seekers. Using a combination of a general equilibrium model, the unique job ads and application data, and different reduced-form methods, I am able to generate theoretical predictions and quantitative estimates for these effects. Along with the specific estimation of these effects, the analysis in this paper also provides more general insights on labor supply effects related to changes in search behavior due to job amenities and labor demand considerations of firms when facing difficult labor market conditions.

In order to understand the underlying decision-making process and generate theoretical predictions that I can test in my empirical analysis, I develop a search-and-matching model rooted in the Diamond-Mortensen-Pissarides framework. In the model, firms can choose whether to post a WFH or in-person vacancy based on the trade-off between matching faster with WFH vacancies (due to access to more workers) and paying a randomly drawn expected productivity cost due to WFH. Firms then match to workers with a randomly-drawn productivity and decide whether to hire the worker or continue the vacancy. Workers decisions are optimal based on the trade-offs between the unemployment value and working value and are used to clear the markets and pin down the wage. This model generates several theoretical predictions including that firms which face tighter labor markets should be more willing to offer WFH and that firms which offer WFH should receive more applications and have higher match quality with their hires.

These theoretical predictions motivate the hypotheses I test in the empirical part of the paper. I begin by exploring if WFH job ads are attracting more workers using data on job search behavior. I define job attractiveness using behavior on two different search margins – (i) the number of "views" a vacancy has from job seekers, which measures the amount of attention job seekers give to that vacancy, and (ii) the number of "applications" a vacancy gets, which is proxied for by using the number of times job seekers initiate the application process for that ad. I find that, when comparing similar WFH and non-WFH job ads, WFH ads tend to receive more attention. I estimate that WFH job ads receive about 9.7% more views than in-person ads and those results are statistically significant even when controlling for local labor markets, differential time trends of commuting zones and occupations, and a rich set of vacancy-level characteristics. These results are qualitatively similar, although less precise, when looking at the number of applications for the ad. One potential issue is that a small number job ads may be classified as WFH in occupations where WFH is less likely or less feasible, which may affect the estimates. To remedy this, I restrict the analysis to occupations with high WFH potential, defined using the share of workers within 3-digit occupation categories that report WFH in the 2021 Labor Force Survey. I consider an occupation "high potential" if over 75% of the respondents report some WFH, but my analysis is robust to alternative definitions. Running the same analysis on this subsample, I find similar effects for both views and applications. WFH vacancies in these occupation groups receive, on average, 6.6% more views and 1.6% more applications than similar in-person vacancies, although the application estimates are still imprecise. These results suggest that job seekers are more favorable towards WFH vacancies than in-person vacancies, so firms may be able to offset some hiring issues due to labor market tightness by shifting to WFH.

This initial evidence suggests that firms can exploit WFH as a means of accessing more workers, which can be particularly important when they face adverse labor market conditions. To test this, I look at the extent to which firms utilize WFH when they face tighter labor markets. Here, I leverage the application and vacancy data I have to construct labor market tightness measures of number of unique vacancies over number of unique applicants per month for a local labor market (defined at the 3 digit occupation level). The application data allows me to get a better estimate of labor supply as I can include on-the-job searchers as well as the unemployed, which is different from much of the literature that relies on using only unemployed workers. The expectation is that tighter labor markets would have more WFH vacancies, ceteris paribus, because the firms in those local labor markets have greater incentives to offer WFH due to the higher competition for workers. The evidence suggests that firms are behaving in this strategic manner. Using fixed effects regressions that control for the local labor market and differential time trends, I find that local labor markets that were tighter in the previous month saw an increase in WFH vacancies. I estimate a positive and significant effect of 0.056, which corresponds to an increase in the number of WFH vacancies of 15.7% of the sample mean between the 10th and 90th percentiles of labor market tightness. The results are similar if we restrict to just the occupations with a large number of WFH vacancies. These results suggest that firms are strategically offering WFH as a mechanism to reduce their labor market tightness when hiring is difficult.

The remainder of the paper is structured in the following way. Section 2 discusses WFH more generally as well as the context and contributions of this paper. Section 3 outlines the theoretical model and discusses the predictions that motivate the empirical hypotheses. Section 4 discusses the data used, the data collection process, and provides descriptive evidence. Section 5 discusses the attractiveness of WFH job ads relative to other job ads and presents the methodology and results related to this analysis. Section 6 then includes my empirical strategy and results for the effect that labor market tightness has on WFH offering. Finally, Section 7 concludes.

2 Context

2.1 Working from home

Working from home is one of the most prominent shifts in the labor market in recent years and it has been propelled by technological developments, which made remote work easier, and the COVID-19 pandemic, which altered social stigma and preferences about this work practice (José María Barrero, Bloom, and Steven J. Davis 2021; Gill and Skans 2024b). *Working from home* (WFH) is the term commonly used today to discuss the alternative working arrangement where a worker spends at least some of their working time and performs at least some work tasks away from their workplace, often at or near their residences.[1] Some form of WFH has been around since at least as early as 1965, and technological improvements over the years has led to slow but steady growth, particularly since the turn of the century (José María Barrero, Bloom, and Steven J. Davis 2023). However, stigma around WFH remained and employees who had WFH often faced negative outcomes with respect to wages, promotions, and employment opportunities (Mas and Pallais 2020). All of this changed with the COVID-19 pandemic, which forced as many workers and firms as possible to shift to remote work in most developed countries. From this, workers discovered they liked working from home, employers realized that WFH was not a detrimental as previously believed, and firms invested in WFH-related technology (Gill and Skans 2024b).

When discussing WFH, there are important distinctions between the different forms this work structure can take. There are primarily two kinds of working from home that are discussed in the literature: *fully remote WFH*, where workers spend all (or almost all) of their time away from the workplace, and *hybrid WFH*, where workers spend a part of the time working from home (usually 2-3 days) and the rest at their workplace. The distinction between these types is important in some settings since there are different preferences surrounding them and they correspond to different consequences and policy recommendations. For example, during the peak of the COVID-19 pandemic, fully remote work structures were the norm for occupations and industries that could transition to work from home as it helped minimize the spread of the virus, but these levels fell as the virus became less prominent (Figure C.2). In the post-pandemic period, workers and employers alike report much stronger preference for hybrid work than fully remote work (Aksoy et al. 2022; Gill and Skans 2024b). In this paper, I generally combine both fully remote and hybrid work structures together into "WFH" for the main analysis, but I also run heterogeneity analysis looking at WFH type where I distinguish between these two types of work structures.

2.2 Preferences for working from home

This paper relates to two main strands of the WFH literature. First, it adds additional insights into the understanding of preferences for WFH. Most of the WFH literature focuses on worker-side preferences and they generally use survey responses of workers to try to directly elicit their preferences or measure an individual's willingness to pay for WFH. Aksoy et al. (2022) run a global survey across 27 countries during the peak COVID-19 period and find that workers in most countries want a positive number of days WFH. While it varies a lot across countries, they find that workers, on average, reported wanting 1.7 more days of WFH in the post-pandemic period. They also find that, on average, workers are willing to give up around 5% of their wages in order to have the option to WFH. They also find that a large share of workers indicate that they would quit there jobs and look for new ones if employers forced their employees to work in-person everyday. These results mirror the survey results discussed in José María Barrero, Bloom, and Steven J. Davis 2021, which is focused on workers in the US. In that

1. Alternatives nomenclature for the same or similar practices include teleworking, remote work, and working from anywhere.

paper, they find that US workers are willing to take a 7% pay cut on average for the WFH option. Nagler, Rincke, and Winkler (2022) also find a similar trend when looking at German workers. They use a stated-preference experiment to show that workers are willing to forgo 7.7% of their earnings in order to WFH. However, they also point out that workers are willing to pay even more for other non-wage amenities than they are willing to pay for WFH, suggesting that the workplace flexibility may not be the largest priority for workers. Despite these effects, all of these studies find large heterogeneity in worker preferences with women, people with children, and more educated workers reporting stronger preferences for WFH (Aksoy et al. 2022). Looking at the pre-pandemic period, the literature finds analogous trends to the more recent literature. Earlier researchers find that workers report that they are more satisfied when they WFH (Bloom et al. (2015)) and that workers state they are willing to give up some of their wages in order to have workplace flexibility (Maestas et al. 2023; Mas and Pallais 2017). For a more extensive discussion of the pre-pandemic literature about preferences regarding WFH and other workplace flexibilities, see Mas and Pallais (2020).

Another, smaller strand of this literature explores how firms and managers feel about working from home. Along with their discussions about how workers feel about working from home, José María Barrero, Bloom, and Steven J. Davis 2021 and Aksoy et al. 2022 discuss how firms feel about this work arrangement for the US and cross-country, respectively. They find high variance in employer attitudes, but find on average they are positive towards it and were willing and expecting to offer more WFH in the post-pandemic period. However, they also find that there is a sizable gap between the number of WFH days per week that firms are willing to offer and the number that workers would like to work. The high variance in firms' expectation in how much WFH they will offer also relates to a growing literature looking at firm decision making regarding removing WFH. The so called "return to office" (RTO) policies have caught recent media and researcher attention as large firms roll back previous WFH permissions. The debate around the impacts of these policies remains, but recent research has begun to shine some light on it. One recent working paper, Ding and Ma 2023, looks at firm decision to force workers back into the office and find that it has to do with firms wanted to regain control over their workers and want to use WFH as a scapegoat for poor performance. They find no change in worker performance when they return to the office, suggesting that RTO does not improve productivity. Instead, they find that it lowers the job satisfaction of workers.

While there is some discussion in the literature worker and firm preferences towards WFH, this is primarily focused on workers and firms after a position has been filled and has switched to WFH or on hypothetical scenarios. None of this discussion is focused on the attitudes of job seekers towards WFH jobs or on differential search behavior of job seekers for this amenity. In this paper, I fill this gap in the literature by cataloging the difference in job seekers preferences for WFH at the search margin. To the best of my knowledge, it is the first paper that discusses the relative attractiveness of work-from-home job ads compared to in-person job ads by estimating the the differential interest in WFH vacancies by job seekers. In addition, I estimate WFH preferences in a natural setting using a direct measure of revealed preference – job ad views and applications. This allows me to get a direct measure of job seeker preferences for WFH without needing to use self-reported surveys or more distant proxies which may generate more measurement error. The results of this paper empirically show that there are potential search-related gains that firms can get by offering WFH due to job seekers preference for these job types.

2.3 Determinants of working from home

The main question of this paper also relates to the motivation that firms have in offering WFH. Along with overall changes in preferences, there is a literature discussing some other potential causes of WFH, but it is mainly focused on structural and social conditions that promote WFH.

One of the early and most rigorously investigated determinants of WFH relates to the composition of jobs in the labor market both along the industry and occupation dimensions. Early in the pandemic, Dingel and Neiman (2020) quantified the absolute potential in transitioning to WFH that various economies across the world had based on their occupational composition. Using O*NET task data, they classified whether or not an occupation could be fully remote based on what workers were usually asked to do. They find that there is much heterogeneity in WFH feasibility across occupations that translates to differences across geographic areas due to occupational structure. Adams-Prassl et al. (2022) find a similar pattern when looking at industries. They find that the industry composition of an area has a large impact on the WFH take-up since there is large WFH differences across industries, even within similar occupations.

The technological infrastructure of an area and the digital competencies of the residents has also been shown to play a role in predicting WFH take-up. Gill and Skans (2024b) show in a cross-country analysis that there are strong correlations between the percentage of household with broadband access and the percentage of WFH. Similarly, equally an equally strong relationship exists between the digital skills of a population and WFH. Using survey data on self-reported WFH and in-person productivity and internet access, Jose Maria Barrero, Bloom, and Steven J Davis (2021) find a positive relationship between reporting having better internet at home and perceived WFH productivity relative to in-person productivity. While these relationships are not causal, they do point to a likely relationship. This is further supported by evidence of changes in technological research since the COVID pandemic with a documented increase in research (in terms of patents) into WFH related technologies (Bloom, Davis, and Zhestkova 2021) and an increase in firm investment into those technologies (Barth, Bryson, and Dale-Olsen 2022).

There is also a small literature discussing how different cultural aspects of a region affects WFH uptake. Gill and Skans (2024a) look at how aggregate managerial trust impacts the WFH offering of a region. They find a consistently positive relationship indicating that areas where managers trust that people will not take advantage are offering more WFH. This remains strongly positive even after controlling for a battery of potential covariates. Along similar lines, Zarate et al. (2024) and Bietenbeck, Irmert, and Nilsson (2024) explore the relationship between regional "individualism" and WFH. Zarate et al. (2024) look at how many factors affect WFH offering across countries and find that individualism seems to explain a large share of the differences. Bietenbeck, Irmert, and Nilsson (2024) looks within regions and compares immigrants with different cultural backgrounds. They find that immigrants that come from countries that are culturally more individualistic are more likely to WFH than immigrants from less individualistic countries of origin.

Despite this research on the determinants of WFH, the literature is still lacking in discussion about firm decision making regarding offering WFH. A notable exception to this lack of research on labor market conditions and WFH is Autor, Dube, and McGrew (2024). In their paper, they present correlative evidence suggesting there is a relationship between WFH and labor market tightness in the US which matches the correlative evidence for Sweden presented in Section 6. Their paper, however, has a different focus and does not dig deeper into the causality or extent of this relationship and merely presents the basic correlations.

This paper adds to this scarce literature by investigating how firms use WFH to recruit more workers, especially when facing differing labor market conditions. To the best of my knowledge, this is also one of the first papers investigating firm decision making about WFH and the first to explicitly look at WFH's role in alleviating labor market tightness and worker shortage issues from a causal perspective. These results can provide useful insights into the decision making process of firms, particularly with respect to WFH and non-wage amenities. In addition, it helps explain at least some of the variation in WFH across similar labor markets and can be an important channel to keep in mind when considering some labor market policies such as those aimed at reducing hiring shortages.

3 Theoretical Framework

In order to motivate the empirical analysis, I look at the theoretical expectations of firm behaviors in selecting into WFH based on labor market conditions. For this purpose, I employ a random job search model with heterogeneous productivity across workers and where firms can select into offering a WFH vacancy or an in person (IP) vacancy. The model starts from the baseline Diamond-Mortensen-Pissarides framework with this additional inclusion of different types of vacancies and jobs that firms and workers can select into. Time is continuous and workers live forever. Firms pay an entry cost k to enter the market and post a vacancy. They exist for the duration of a single job – they are created upon paying a market entry cost and are destroyed upon separating with the worker after hiring. Firms and workers both discount the future at rate r. Unemployed workers search for jobs for free and receive benefits b. There is no on-the-job search and once workers and firms accept a match, they remain matched until there is an exogenous separation. There is an endogenous finding rate based on the labor market tightness, which can differ between in-person and WFH vacancies. [*For this vesion of the draft, the model is incomplete as I have solved part of the firm side problem, but I have not solved the workers side.*]

3.1 Firm Problem

In this model, firms are profit maximizing entities that make their decisions based on the expected value and length of their vacancy posting and filled position. After entering the market (by paying the entry cost, k), firms decide whether to post a WFH vacancy or an IP vacancy by weighing the relative lifetime value of each after receiving a random WFH productivity cost draw ($z \sim G(z)$). Therefore, firms make their vacancy-posting decision based on:

$$\max\{V^{WFH}(z), V^{IP}\}, \text{ where } z \sim G(z)$$

Since the WFH productivity cost (z) is monotonically decreasing $V^{WFH}(z)$, there is a reservation productivity cost (z_R) where firms are indifferent between posting a WFH and IP vacancy. All the cost draws less than this value ($z \leq z_R$) results in the firm offering a WFH vacancy[2] and all the cost draws greater than this ($z > z_R$) results in an IP vacancy. This means that the probability that an individual firm offers a WFH position can be written as the probability that the productivity cost draw is less than or equal to the reservation cost:

$$Pr(V_i = V^{WFH}) = \int_{z \leq z_R} dG(z) = G(z_R)$$

The reverse of this is thus equivalent to the probability that a firm offers an IP vacancy:

$$Pr(V_i = V^{IP}) = \int_{z > z_R} dG(z) = 1 - G(z_R)$$

With enough firms in the market, the expected share of WFH and IP firms can be written the same way.

We can also back out our entry condition. Firms will enter the market as long as there is positive expected profit. The ex-ante expected profit of the firm is the value of the WFH vacancy and IP vacancy (which internalizes the value of the job) and the probability that the firm chooses each. At equilibrium, this profit must be equal to the cost of entering the market, making firms indifferent between entering and staying out. The entry condition can then be written as:

$$k = \int_{z \leq z_R} V^{WFH}(z) dG(z) + (1 - G(z_R)) V^{IP}$$

After drawing the WFH productivity cost and deciding which vacancy to post, a firm maximizes the following value functions based on the vacancy type. Random variables (z and ψ) are indicated by just the letter/symbol while realizations of the random variables are denoted with *.

Vacancy value equations:

$$rV^{IP} = -c + \lambda_v(\theta^{IP}) \left[\int_{\boldsymbol{\Psi}} \max\{J^{IP}(\psi), V^{IP}\} dP(\psi) - V^{IP} \right]$$

2. I assume that firms offer a WFH vacancy when they are indifferent.

$$rV^{WFH}(z^*) = -c + \lambda_v(\theta^{WFH})\left[\int_{\mathbf{\Psi}} \max\{J^{WFH}(\psi, z^*), V^{WFH}(z^*)\}dP(\psi) - V^{WFH}(z^*)\right]$$

Job value equations:

$$rJ^{IP}(\psi^*) = \psi^* - w^{IP}(\psi^*) + \sigma[0 - J^{IP}(\psi^*)]$$

$$rJ^{WFH}(\psi^*, z^*) = \psi^* - w^{WFH}(\psi^*, z^*) - z^* + \sigma[0 - J^{WFH}(\psi^*, z^*)]$$

Because productivity enters monotonically into the vacancy value equations, there is an individual reservation productivity for each equation at which firms will accept all workers at or above this productivity and reject all workers below this productivity. for all in-person vacancies, this reservation productivity is consistent and is defined as ψ^{IP}. For the WFH vacancies, the reservation productivity depends of the ex-ante draw of the expected productivity loss due to WFH (z). Therefore, I define the reservation productivity for WFH vacancies as dependent on this parameter: ψ^{z^*}. The simplified versions of the vacancy value equations are:

$$rV^{IP} = -c + \lambda_v(\theta^{IP})\int_{\psi \geq \psi^{IP}} J^{IP}(\psi) - V^{IP}dP(\psi)$$

$$rV^{WFH}(z^*) = -c + \lambda_v(\theta^{WFH})\int_{\psi \geq \psi^{z^*}} J^{WFH}(\psi, z^*) - V^{WFH}(z^*)dP(\psi)$$

There are also a few more assumptions we can make based on the definition of reservation productivity and reservation WFH cost. First, firms are indifferent at the reservation WFH cost between posting an IP or WFH vacancy.

$$V^{WFH}(z_R) = V^{IP}$$

Second, at the associated reservation productivities, firms are indifferent between hiring the worker or continuing the vacancy.

$$V^{IP} = J^{IP}(\psi^{IP})$$

$$V^{WFH}(z^*) = J^{WFH}(\psi^{z*}, z^*)$$

These conditions can be combined to give an additional equation.

$$J^{IP}(\psi^{IP}) = J^{WFH}(\psi^{z_R}, z_R)$$

3.2 Solution to Firm Problem

The first question I am interested in is to look at the relationship between reservation WFH productivity cost (z_R), which governs the number of firms that offer WFH compared to in-person firms, and labor market tightness. To do this, I begin by solving for solutions to the job value functions. I begin with the IP job.

$$rJ^{IP}(\psi^*) = \psi^* - w^{IP}(\psi^*) - \sigma J^{IP}(\psi^*)$$

$$J^{IP}(\psi^*) = \frac{\psi^* - w^{IP}(\psi^*)}{r+\sigma}$$

I solve the WFH job in the same way.

$$J^{WFH}(\psi^*, z^*) = \frac{\psi^* - w^{WFH}(\psi^*, z^*) - z^*}{r+\sigma}$$

which will be true for all values of z^* including z_R.

I can similarly solve for the value of the IP and WFH vacancies, beginning with the IP vacancy.

$$V^{IP} = -c + \lambda_v(\theta^{IP}) \int_{\psi \geq \psi^{IP}} J^{IP}(\psi) - V^{IP} dP(\psi)$$

$$rV^{IP} = -c + \lambda_v(\theta^{IP}) \int_{\psi \geq \psi^{IP}} J^{IP}(\psi) dP(\psi) - \lambda_v(\theta^{IP}) V^{IP} \int_{\psi \geq \psi^{IP}} dP(\psi)$$

$$(\lambda_v(\theta^{IP})(1 - P(\psi^{IP})) + r)V^{IP} = -c + \lambda_v(\theta^{IP}) \int_{\psi \geq \psi^{IP}} J^{IP}(\psi) dP(\psi)$$

$$V^{IP} = \frac{-c + \lambda_v(\theta^{IP}) \int_{\psi \geq \psi^{IP}} J^{IP}(\psi) dP(\psi)}{\lambda_v(\theta^{IP})(1 - P(\psi^{IP})) + r}$$

Similarly, we can solve for the WFH vacancy value.

$$rV^{WFH}(z^*) = -c + \lambda_v(\theta^{WFH}) \int_{\psi \geq \psi^{z^*}} J^{WFH}(\psi, z^*) dP(\psi) - \lambda_v(\theta^{WFH}) V^{WFH}(z^*) \int_{\psi \geq \psi^{z^*}} dP(\psi)$$

$$V^{WFH}(z^*) = \frac{-c + \lambda_v(\theta^{WFH}) \int_{\psi \geq \psi^{z^*}} J^{WFH}(\psi, z^*) dP(\psi)}{\lambda_v(\theta^{WFH})(1 - P(\psi^{z^*})) + r}$$

which will be true for all values of z^* including z_R.

I can then use the definition of reservation productivity cost to set the IP and WFH vacancy value functions equivalent.

$$V^{WFH}(z_R) = V^{IP}$$

$$\frac{-c + \lambda_v(\theta^{WFH}) \int_{\psi \geq \psi^{z_R}} J^{WFH}(\psi, z_R) dP(\psi)}{\lambda_v(\theta^{WFH})(1 - P(\psi^{z_R})) + r} = \frac{-c + \lambda_v(\theta^{IP}) \int_{\psi \geq \psi^{IP}} J^{IP}(\psi) dP(\psi)}{\lambda_v(\theta^{IP})(1 - P(\psi^{IP})) + r}$$

Then, I substitute in the solutions to the job value functions and reduce.

$$\frac{-c + \lambda_v(\theta^{WFH}) \int_{\psi \geq \psi^{z_R}} \frac{\psi - w^{WFH}(\psi, z_R) - z_R}{r+\sigma} dP(\psi)}{\lambda_v(\theta^{WFH})(1 - P(\psi^{z_R})) + r} = \frac{-c + \lambda_v(\theta^{IP}) \int_{\psi \geq \psi^{IP}} \frac{\psi - w^{IP}(\psi)}{r+\sigma} dP(\psi)}{\lambda_v(\theta^{IP})(1 - P(\psi^{IP})) + r}$$

$$\frac{-c + \frac{\lambda_v(\theta^{WFH})}{r+\sigma} \int_{\psi \geq \psi^{z_R}} \psi - w^{WFH}(\psi, z_R) dP(\psi) - z_R \frac{\lambda_v(\theta^{WFH})}{r+\sigma} \int_{\psi \geq \psi^{z_R}} dP(\psi)}{\lambda_v(\theta^{WFH})(1 - P(\psi^{z_R})) + r} = \frac{-c + \frac{\lambda_v(\theta^{IP})}{r+\sigma} \int_{\psi \geq \psi^{IP}} \psi - w^{IP}(\psi) dP(\psi)}{\lambda_v(\theta^{IP})(1 - P(\psi^{IP})) + r}$$

Now I solve for z_R.

$$\begin{aligned} -z_R \frac{\lambda_v(\theta^{WFH})}{r+\sigma}(1 - P(\psi^{z_R})) = &\frac{-c + \frac{\lambda_v(\theta^{IP})}{r+\sigma} \int_{\psi \geq \psi^{IP}} \psi - w^{IP}(\psi) dP(\psi)}{\lambda_v(\theta^{IP})(1 - P(\psi^{IP})) + r} (\lambda_v(\theta^{WFH})(1 - P(\psi^{z_R})) + r) \\ &+ c - \frac{\lambda_v(\theta^{WFH})}{r+\sigma} \int_{\psi \geq \psi^{z_R}} \psi - w^{WFH}(\psi, z_R) dP(\psi) \end{aligned}$$

$$\begin{aligned} z_R = &\frac{c(r+\sigma) - \lambda_v(\theta^{IP}) \int_{\psi \geq \psi^{IP}} \psi - w^{IP}(\psi) dP(\psi)}{\lambda_v(\theta^{IP})(1 - P(\psi^{IP})) + r} \left(1 + \frac{r}{\lambda_v(\theta^{WFH})(1 - P(\psi^{z_R}))}\right) \\ &- \frac{c(r+\sigma)}{\lambda_v(\theta^{WFH})(1 - P(\psi^{z_R}))} + \frac{1}{(1 - P(\psi^{z_R}))} \int_{\psi \geq \psi^{z_R}} \psi - w^{WFH}(\psi, z_R) dP(\psi) \end{aligned}$$

From this, we can get the derivatives of the reservation productivity cost (z_R) w.r.t. the matching rates for in-person ($\lambda_v(\theta^{IP})$) and WFH ($\lambda_v(\theta^{WFH})$) labor markets.

$$\frac{\partial z_R}{\partial \lambda_v(\theta^{IP})} < 0$$

$$\frac{\partial z_R}{\partial \lambda_v(\theta^{WFH})} > 0$$

Since the matching rates are inversely related to the tightness of that labor market, then these derivatives suggest that if the labor market tightness of the IP labor market increases, then the reservation productivity cost increases, which increases the number of firms willing to offer WFH. The reverse is true for the WFH labor market – if the labor market tightness increases, this decreases the reservation productivity cost, which decreases the number of firms willing to offer WFH. This prediction suggests that if firms face tighter labor markets (or expect to face tighter labor markets), more firms should be willing to offer WFH in order to alleviate some of the hiring difficulty if the expected cost of a WFH job relative to an in-person job is not too high.

4 Data and General Descriptives

In order to investigate the role of WFH in firm recruitment, I use various data sources within the Swedish context. I begin by using Swedish vacancy ads and categorizing them as WFH or in-person jobs. This data is then matched to unique data on job seeker behavior, specifically views and applications at the job-ad level. This allows me to estimate both the labor demand and labor supply. To enrich the data further, I connect the job ads to firm information in the Swedish registry data including data on the workers employed at the firm. I also connect unemployed workers in my applications/views data to their (anonymized) individual registry information.

4.1 Swedish job ads and WFH classification

In order to investigate the relationship between WFH offering and labor market tightness, I need a measure of WFH at the job specific level. To do this, I utilize the entirety of Swedish vacancies posted on the Swedish Employment Agency's job portal *Platsbanken*, the largest job board in Sweden. *Platsbanken* also accounts for the vast majority of job ads posted in Sweden with a comparable number of job ads posted in this portal as the number of vacancies that were estimated to be in Sweden by Eurostat in 2019-Q4 (Hensvik, Le Barbanchon, and Rathelot 2021). I remove vacancies that state they are located outside of Sweden and I focus on the period of 2016-2023, which gives me 7,053,457 vacancies (Table A.1). That is an average of about 880,000 vacancies per year, however there is some heterogeneity across years. There is a noticeable dip in the number of vacancies in 2020 (due to the COVID-19 pandemic) as well as large jumps in the number of vacancies in 2022 and 2023 (Figure C.1).

The job ads contain rich data on the type and nature of the job, employer information, location that the job is located, and the text describing the job. One notable absence, however, is there is no indicator about whether a job offers WFH. To remedy this, I classify whether or not each job ad states if the position can be WFH with the help of OpenAI's GPT-4-turbo large language model.[3]

The classification is a three-step process based off a method used by Boehnke et al. (2024). First, I use a random sample of vacancies to extract WFH-related phrases from the text of the job ads. To do this, I begin by randomly selecting vacancies from each year of 2006-2022, over sampling the later years, which gives us a total of 19,000 vacancies in this sample. I then use the text of these vacancies and ask the GPT-4-turbo model (using OpenAI's API) to categorize the vacancies as fully remote WFH, hybrid WFH, in person, "traveling" positions[4] or "WFH NA" (cannot determine). For vacancies that were classified as "fully remote" or "hybrid", I asked the model to extract the phrases from the job ad that relate to WFH.

I subsequently use the extracted phrases to filter the full sample of vacancies to a set of vacancies that could plausibly offer WFH. I create a "bag-of-words" of the extracted texts by dropping duplicates

3. I use the main text of the job ad as the input to GPT-4-turbo model. For an example of the job ad, see Figure A.2.

4. *Traveling positions* are defined as positions where an individual does not work at their workplace often because they have to travel a lot for work. This category is included separately in order to reduce the number of false positives in the WFH sample, as early tests of this method led to these jobs often (erroneously) being categorized as WFH.

and then manually pruning the list to remove non-relevant phrases, longer phrases that contained shorter phrases already in the list (since they will not be filtered out anyway) and extremely vague terms, so as to subset to only a meaningful group of vacancies. Even with the manual pruning, I kept the terms as broad as possible to prevent filtering out actual WFH vacancies. The initial extract left me with a list of 1,530 entities which was pruned down to 496 entities. These entities contain both Swedish and English phrases related to WFH, the two most common languages for the vacancies (95.1% and 4.5%, respectively).[5] I then use the bag-of-words to filter out all the vacancies that do not contain at least one of the phrases from the list for vacancies from 2016-2023. This leaves me with 507,012 (7.2%) vacancies remaining. All of the vacancies that have been filtered out are classified as "in person."

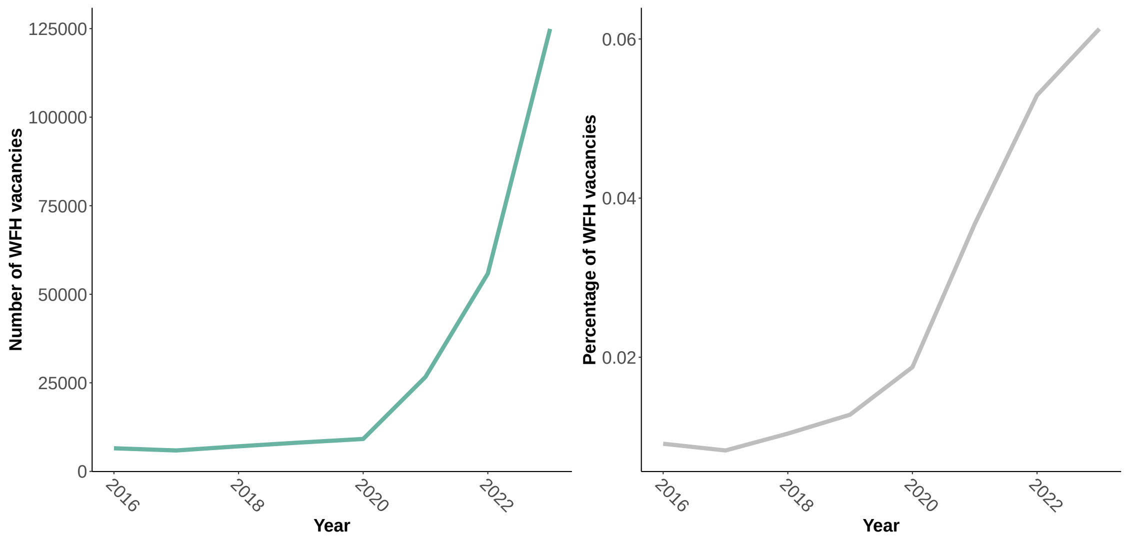
In the final step, I prompt the GPT-4-turbo model to classify all of the remaining vacancies into the same five categories asked previously (without any extraction of phrases). All vacancies that are classified by the model as "traveling" or as "WFH NA" are reclassified as "in person" vacancies. I keep the categories of "fully remote" and "hybrid work" as separate for some analyses, but they are grouped together as "WFH" vacancies for my main analysis. This gives me my final classification of vacancies, where 3.5% of the vacancies over 2016-2023 are classified as WFH (see Table A.1 for yearly breakdown).

Looking at the overall trend of WFH in the vacancies, we see that, prior to the COVID-19 pandemic, the percentage of vacancies that explicitly offered WFH was low and with only very small growth (Figure 1). This growth jumps dramatically with the onset of the pandemic with large and continual increase in the number of WFH vacancies through the pandemic and into the post pandemic period. WFH vacancies jumped from less than 1% of all vacancies in 2016 to over 6% of all vacancies in 2023. Similar trends can be seen for hybrid vacancies (Figure C.3) while we see a dip in the percentage of fully remote vacancies in the post-pandemic period (Figure C.4), but this could be due to the relatively small percentage of fully remote vacancies overall. Of the WFH vacancies, the vast majority of them are hybrid vacancies, 89.5% per year on average, with only a very small share being fully remote, 10.5% per year on average (Figure C.5). This is true for all years and the relative shares remain fairly consistent over the years. The exception is that there is an small increase in the share of fully remote job ads during the peak COVID-19 pandemic period (2020 and 2021). Even during this period, however, fully remote job ads still constituted a small fraction of the total WFH vacancies.

These trends are roughly in line with what other vacancy extractions have found. The overall shape of the time trend seems to match Hansen et al. 2023 and Boehnke et al. 2024, who perform similar exercises on vacancies from English-speaking countries and US vacancies, respectively. Our vacancies do have a smaller percentage of vacancies that explicitly offer WFH, but this is likely related

5. The language that the vacancy is written in is determined using Google's Compact Language Detector (CLD3), which is a neural network trained for language classification. It seems to perform poorly on very short texts and it does not classify some texts. Therefore, the statistics stated here are the percentage of vacancies classified as Swedish/English from the set of vacancies that were classified (not "NA") and had a text description of at least 20 characters from 2016-2022 ($N = 4,948,386$). These percentages are likely lower bounds since almost all of the non-classified and short vacancies seem to be written in Swedish.

Figure 1: WFH Vacancy Trends



Notes: This figure plots the change in Swedish job ads that explicitly offer some form of working from home from 2016-2023. The left graph plots the change in levels in WFH job ads while the right graph plots the share of all job ads in that year that state they offer WFH. The share is out of all *Platsbanken* job ads after removing the vacancies for jobs with locations stated to be outside of Sweden. In this figure, all WFH vacancies are grouped together to show the overall trends. The trends for "hybrid" job ads and "fully remote" job ads are plotted separately in Figures C.3 and C.4, respectively.

to differences in the Swedish setting. For example, according to some survey data, there are fewer days per week of WFH in Sweden than in the English-speaking countries (Aksoy et al. 2022). If we look at the breakdown of 1-digit occupations for WFH jobs, we find that they match general expectations. Manager positions and positions that require higher education have the highest share of WFH vacancies while elementary occupations, agriculture, and mechanical manufacturing tend to have the lowest shares (Figure C.6). This is in line with classifications of WFH positions in the literature that use alternative methods to categorize WFH jobs (e.g. Adams-Prassl et al. 2022; Dingel and Neiman 2020; Hensvik, Le Barbanchon, and Rathelot 2020; Mongey, Pilossoph, and Weinberg 2021). If we look at the occupations with the highest number and highest percentage of WFH vacancies by year (Table A.2), we also get a pattern that matches the literature and general expectations.

One thing to note about this WFH classification is that it does not identify which jobs actually have WFH or which workers choose to do it. Instead, the classification only captures a firm's *signaling* of WFH by tagging only job ads that specifically mention the ability to WFH. This is not a problem for the context of this paper, however, because I am specifically interested in the effect of firm signaling of WFH and not on the actual uptake of this work arrangement. To this end, any firm difference in actual uptkae is unrelated to my analysis as long as job seekers do not have specific knowledge about firms' actual WFH offering that differ from what they state in the text of their job at the application stage. Since it seems unlikely that workers would have such inside knowledge on a mass scale, this should not be a credible threat to my identification.

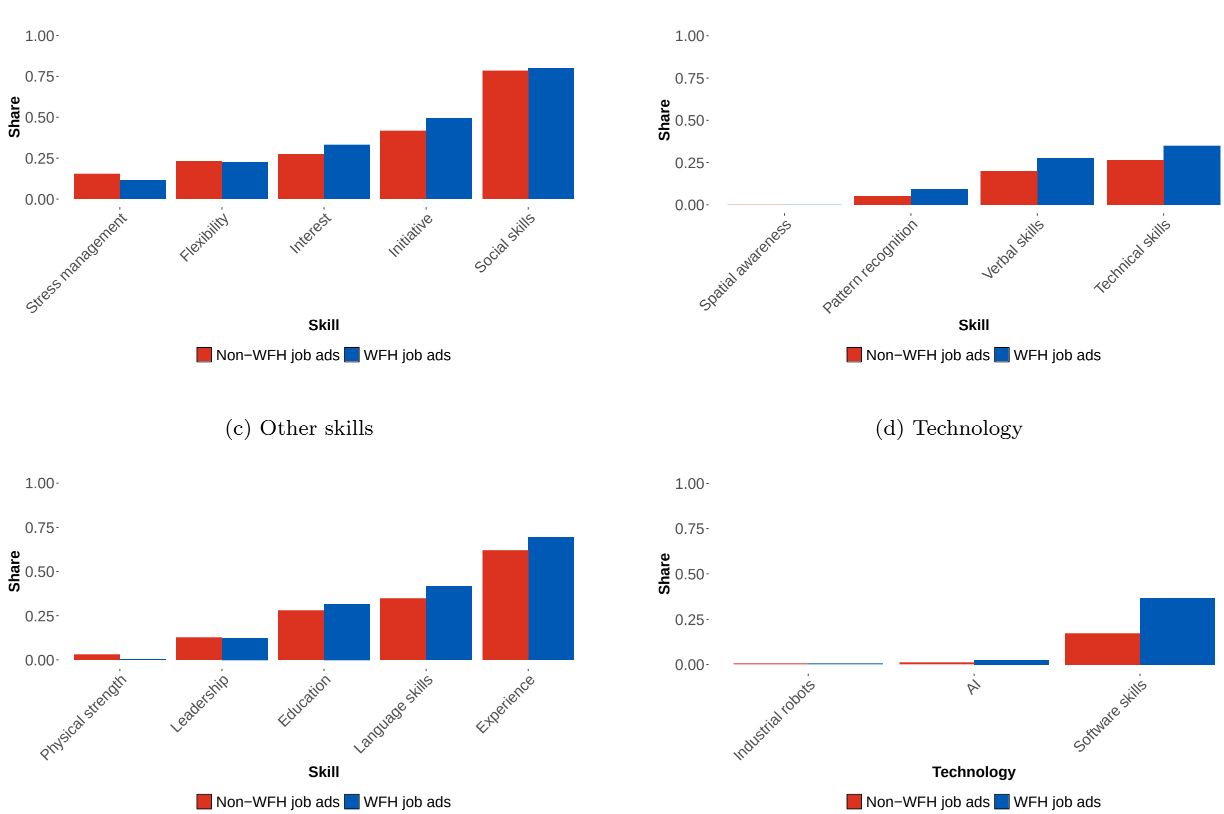
Another potential threat to my identification is that the WFH signaling I measure is actually capturing other aspects of the job ads that correlate with WFH but are unrelated. To verify the credibility of this, I look at the frequency of words that appear in the texts of the job ads between 2018 and 2022. Specifically, I look at the words that appear often in the job ads classified as "WFH" that do not appear often in the job ads classified as "non-WFH." Using all the vacancies in this time period, I subset to the 200 most frequent words for both groups and remove the words from the "WFH" list that also appear on the "non-WFH" list. Twenty-four words remain after filtering and those words are illustrated in Figure 2 with the size indicating the relative frequency. The idea here is that if non-WFH-related words have high frequency in the WFH job ads, but not in the non-WFH ads, it could suggest that job seekers are selecting these positions based on other, non-WFH related characteristics that correlate with these ads. Encouragingly, the most common word by far that appears in the WFH job ads but not commonly in the non-WFH ads is "distans" ("distance"), which is a direct reference to working from home. This is the most common "unique" word not just in the overall sample, but also for every year in this time period (Figure C.7). Another of the common words is "frihet" ("freedom," 7th most common), which is also a word commonly associated with WFH with respect to the freedom to choose the workplace. While these words suggest that the classification is successfully capturing WFH, some other, non-WFH words (and non-general words) also appear often, specifically words related to technology (e.g. "digitala," "tekniska," and "data") and social/non-cognitive skills (e.g. "support" and 'teamet").

Figure 2: High-frequency, unique words in WFH vacancy text

Notes: This figure shows the relative frequency of the top words that are "unique" to the WFH vacancies. To construct this figure, the top 200 most frequent words for the WFH and non-WFH vacancies, after filtering out "stop words," are determined separately for all of the vacancies between 2018 and 2022. The WFH words are then additionally filtered to remove any words that also appear in the top 200 words for the non-WFH vacancies. Theis figure then plot the relative frequency of the remaining WFH words. The same figure broken down by year can be found in Figure C.7.

To investigate the relationships with these potential confounders more thoroughly, I use data on the skills and the technologies mentioned in the job ads. The skills data and the technology data are both extracted using a similar method to my WFH classification. Using the job ads from 2018-2022, I compare the raw frequencies of appearance of these skills and technologies by WFH and non-WFH job ads. The share of WFH and non-WFH job ads that mention each skill or technology is illustrated in Figure 3 and differences and the p-values derived from testing the statistical significance of these differences using a t-test are found in Table 1.

Figure 3: Share of job ads asking for specific skills/technology by WFH offering



(a) Non-cognitive skills

(b) Cognitive skills

(c) Other skills

(d) Technology

Notes: These figures present the share of WFH vacancies (blue) and non-WFH vacancies (red) that ask for the specific skill (panels (a) to (c)) or technology (panel (d)) using job ad data from 2018-2022. For all four panels, the skills/technologies are sorted by share of WFH job ads that mention them. Most skills and technologies account for only a minority share of both WFH and non-WFH vacancies and the difference between these groups is quite small for almost all of them. These results are formalized in Table 1. The differences in shares broken down by year is found in Figure C.8.

There are two main takeaways from this exercise. First, the share of both WFH and non-WFH vacancies that mention these skills or technologies is generally low. None of them are mentioned in all WFH vacancies or non-WFH vacancies and all but two (social skills and experience) are mentioned in less than 50% of them. Along with the shares generally being low, the difference between the share of WFH and non-WFH vacancies mentioning the skill or technology is relatively small in almost all cases. Almost all of the shares are statistically different, but this is likely driven by the large number of observations ($N = 3,566,847$ job ads). Most of the differences themselves are economically negligible despite the statistical significance, consisting of less than 20% of the share of WFH vacancies that mention the skill or technology (10 of the 17 skills or technologies). Of the remaining ones, all but three have WFH shares less than 15%. These exceptions are software skills (difference is 53% of WFH share) and, to a lesser extent, technical skills (difference is 24% of WFH share) and verbal skills (difference is 28% of WFH share). These differences are also the raw differences and do not account for occupational differences or time trends that could also be related to WFH offering, so these differences are likely overstated. Overall, this evidence suggests that the skills and technology discussed in the job ads are not strongly predictive of WFH vacancies, implying that the results found in this paper seem to be driven by WFH, and not alternative aspects of the vacancy texts.

Table 1: Shares of job ads mentioning skills or technology by WFH offering

Skill/Technology	Share of WFH job ads	Share of non-WFH job ads	Difference	p-value
Cognitive skills				
Social skills	0.801	0.784	0.017	< 0.001
Initiative	0.494	0.418	0.076	< 0.001
Interest	0.332	0.275	0.057	< 0.001
Flexibility	0.225	0.231	-0.006	< 0.001
Stress management	0.115	0.154	-0.039	< 0.001
Non-cognitive skills				
Technical skills	0.350	0.266	0.085	< 0.001
Verbal skills	0.276	0.199	0.077	< 0.001
Pattern recognition	0.094	0.051	0.043	< 0.001
Spatial awareness	0.001	0.001	-0.000	0.445
Other skills				
Experience	0.694	0.617	0.076	< 0.001
Language skills	0.417	0.346	0.071	< 0.001
Education	0.317	0.279	0.038	< 0.001
Leadership	0.125	0.126	-0.002	0.086
Physical strength	0.005	0.029	-0.024	< 0.001
Technology				
Software skills	0.368	0.172	0.196	< 0.001
AI	0.026	0.011	0.016	< 0.001
Industrial robots	0.005	0.005	0.001	0.005

Note: This table formalizes the pattern seen in Figure 3. It presents the shares of job ads that contain different skills/technology by WFH job ads (Column 2) and non-WFH job ads (Column 3) and the differences between them (Column 4). Column 5 presents the p-values generated from t-tests testing the difference between the shares.

4.2 Views and applications data

Along with the basic vacancy information and the WFH classifications, I am also able to match the job ads to data on views data and application data for all the vacancies on the platform during a subset of months. The views and applications data is complied through a tracking cookie on the Employment Agency's job portal that recorded all interactions that devices had with the job ads. I define an "individual" in this data as a single device (recorded through an anonymized device ID). This implicitly assumes that an individual is not using multiple devices and that multiple individuals are not using the same device.

From this data, I have information on both "views" and "applications." The views data I use spans January 2019 to September 2022 and the application data spans from May 2020 to September 2022.[6] Within this data, one observation corresponds to one view or application and I have information on which vacancy it was for, the device ID that was used, and the exact time that the action was performed. One "view" is defined as a single time that a device interacts with (clicks on) a job ad. This generally

6. I also have earlier "views" data for March 2018-December 2018, but due to early bugs in the tracking software that could introduce biased measurement error, I drop it from the main results. However, including it does not qualitatively change the results (Table B.3).

occurs when an individual selects a job ad from the main page or search page, which takes them to the main description of the ad. After reaching the job ad page itself, there is an additional button that a job seeker selects in order to apply for the job. One selection of this "apply" button is one "application" in the data.[7] While I cannot see exactly who or how many job seekers actually apply, the "views" and "applications" margins provide a strong indication of search intensity and interest. The number of views and the number of applications for the job ads is also strongly and positively correlated (Pearson's $\rho = 0.63$, p-value < 0.001), suggesting that these measures are capturing similar dimensions of job search.

Along with this information on views and applications, I can match a subset of job seekers in the registry data to their application and view behavior. Unemployed workers registered with the unemployment agency, which is the majority of unemployed workers in Sweden, are required to login to the unemployment agency website and document their search behavior in order to be eligible for benefits. For most job seekers that were unemployed, I can match their views and applications data to the device ID that they used to login to the unemployment agency as long as the job seeker searches for jobs on the same device. From here, I can then connect the views and applications behavior to general characteristics of the job seeker found in the Swedish registry data, giving me richer demographic and geographic information. The geographic information is particularly important in my setting, as it allows me to investigate changes in the geographic boundary of the labor market that firms have access to based on the type of job ad they post.

4.3 Determining occupation-level WFH potential

For part of my analysis, I subset my data into occupations that have a high probability to WFH in order to remove attenuation bias caused by occupations with little-to-no chance of offering WFH.

For my main classification, I subset occupations based on the percentage of workers that report performing "at least some" of their work at home in the 2021 Swedish Labor Force Survey (LFS, Eurostat 2021). Here, I define "at least some" WFH as the union between workers who report that they "sometimes" WFH and those who report that they "usually" WFH.[8] In order to match the LFS percentages with the Swedish vacancy and registry data, I harmonize the occupations. I convert the 3-digit ISCO-08 occupation codes from the LFS to the 3-digit ssyk-12 occupation codes found in the Swedish data before generating the occupation specific WFH percentages. The ISCO-08 codes and ssyk-12 codes do not match one-to-one as some ISCO-08 codes relate to multiple ssyk -12 codes and vice versa. To remedy this, I allow the same ISCO-08 code to be counted for all connected ssyk-12 codes.

7. Prior to the main job ad page, job seekers are given limited information about the job apart from basic characteristic like the job title, location, and the employer. This provides enough information that uninterested job seekers are unlikely to view an ad they have no interest in, but it does not contain too much information that job seekers are likely to forgo viewing the ad if they are interested. Screenshots of the job portal pages at the "view" and "apply" margins can be found in Figures A.1 and A.2, respectively.

8. In the Swedish LFS, only respondents that indicate they are employed are asked a question about how much they work from home in their main job. These responses are coded into four categories: "Person mainly works at home," "Person sometimes works at home," "Person never works at home," and "Not applicable." There is also a fifth category in the data defined as "not stated," which indicates the respondent did not complete the question.

This results in some individuals being counted for multiple ssyk-12 occupations.[9] After converting the occupations to the ssyk-12 codes, I generate the percentage of respondents in each occupation that report doing some WFH and occupations where this percentage is greater than or equal to the percentage for the 75th percentile (75.1%) are classified as "high WFH" occupations.

5 Job Ad Attractiveness

The first question that comes to mind when thinking about a firm's use of WFH as a recruitment tool is whether WFH jobs are actually more attractive to workers. There is some literature discussing how workers report that they prefer WFH (Aksoy et al. 2022) and some evidence suggesting that WFH lowers turnover rates (Angelici and Profeta 2020), but the literature has been mostly quiet about the impact of WFH on job search. One notable exception is Hensvik, Le Barbanchon, and Rathelot (2021) who look at supply-side change in search behavior from pre-COVID to during COVID and find some evidence of an increase in search for job ads in high WFH potential occupations. In this section, I investigate this first-order question by estimating the impact that offering WFH has on job ad attractiveness and the search behavior of job seekers within local labor markets. I define "vacancy attractiveness" using both a measure of the number of views (attention) that a job ad receives as well as a measure of the number of applications the job ad gets. The expectation is that job ads that offer WFH should be more attractive to job seekers and thus elicit more attention from them compared to similar job ads that do not offer WFH because (i) WFH is an amenity that workers seem to want, and (ii) WFH relaxes the geographic constraint making it possible for workers further away to potentially get the job.

5.1 Methodology

In order to look at the effect of WFH on job attractiveness more rigorously, I run a fixed effects model at the vacancy level where I include local labor market fixed effects, which are defined as commuting zone by 4-digit occupation level – the most granular occupation level in the data. In the main specification, I also include controls for the commuting-zone specific time trend and the 4-digit-occupation specific time trend as well as vacancy level covariates including controls for employment type (ordinary work, summer job, on-call employment, and work abroad), salary type (fixed, variable, or hybrid salary), working hours categorization (part or full time), job duration categorization (length of the position), vacancy duration (the difference in days between the first day a vacancy was published and the last day a vacancy was published), and the length of the vacancy description (number of characters used). This specification is formalized in equation 1.

9. Since the purpose of this exercise is to categorize occupations with a higher likelihood of offering WFH, I choose to count the individuals multiple times so I do not have to make any assumptions on which occupations these individuals have. This method likely generates measurement error in the percentage of WFH calculations, but this is likely to have muted effect on the ultimate classification and any effect it would have would only attenuate my results by including low WFH potential occupations in my high potential classification. Making specific assumptions on which occupations should be connected may generate greater biases by eliminating or under-reporting percentages for certain occupations, which could have stronger effects on the results.

$$job\_attractiveness_{i,z,o,t} = \beta_0 + \beta_1 \mathbf{1}[WFH = 1]_i + \boldsymbol{\delta}\mathbf{X_i} + \theta_{z,o} + \theta_{z,t} + \theta_{o,t} + \epsilon_{i,z,o,t} \quad (1)$$

where i indexes the vacancy, z indexes the commuting zone, o indexes the occupation, and t indexes the month-year. $\mathbf{X_i}$ is the vector of vacancy-level covariates. $\mathbf{1}[WFH = 1]_i$ is the binary treatment that takes a value of 1 if the vacancy is a WFH vacancy. The fixed effects $\theta_{z,o}$; $\theta_{z,t}$; and $\theta_{o,t}$ control for the local labor market, commuting zone time trends, and 4-digit occupation time trends, respectively. The coefficient of interest is β_1 which estimates the differential level of the variable of interest that a WFH vacancy gets relative to an in-person vacancy.

I run this specification for two different outcome variables – the amount of attention a vacancy receives, proxied for by views, and the number of applications a vacancy receives, proxied for by number of initiated applications. These outcomes each represent a different stage of the job search process. The "views" outcome measures overall interest in the job ad by capturing total interaction with it. This measure captures both differences in the extensive margin (differential initial interest) and intensive margin (differential repeated interactions) jointly. The "applications" data captures those that are the most likely to want the job as it measures only those that actually attempt to apply for the job. For these two outcomes, I run this specification on two different samples. First, I run it on the entire sample of job ads that meet the inclusion criteria in order to capture the overall effect. However, because most of the WFH job ads are concentrated in a few occupation categories, these estimates are likely affected by noisy measures in primarily non-WFH occupations. I thus additionally run the analysis on only the sample of job ads in "high WFH" occupations (see Section 4.3 for the discussion of this measure). For my main analysis, I estimate both of these outcomes in logs.

With these regression results, I also include the estimates for the baseline relationship as well as the relationship within occupations. The baseline relationships are estimated using an OLS regression without any controls or fixed effects. The within-occupation relationship is estimated using just four-digit occupation fixed effects and time fixed effects. Both of these relationships are estimated for the full sample and the sample of "high WFH" occupations for both outcomes – views and applications.

5.2 Results

The main results analyzing the effect of WFH vacancies on job attractiveness can be found in Table 2 for attention and Table 3 for applications.

The baseline relationship between attention that a job ad receives and whether that job ad offers WFH shows a negative relationship. The number of views per vacancy for WFH job ads is almost always less than the views per vacancy for in-person job ads apart from two periods in the peak of the pandemic (Figure C.9). Running a raw regression of this relationship estimates that WFH vacancies receive about 23% fewer views per vacancy, on average (Column 1 of Table 2). The relationship is similar when looking at applications per vacancy (Figure C.11). The estimated relationship for the application data is that WFH vacancies receive about 34% fewer applications per ad on average

(Column 1 of Table 3).

These baseline results would suggest that WFH vacancies are less attractive in terms of job search interaction than in-person vacancies, however, they mask a lot of heterogeneity across occupations. Since WFH is not feasible for all occupations and WFH job ads are concentrated among certain occupations,[10] it is likely that the effect changes when doing within-occupation comparison as these job ads are more similar to each other. When adding 4-digit occupation and time fixed effects, there is a complete reversal of the estimated effect. WFH job ads are now estimated to receive 19.5% more views and 9.6% more applications (Column (2) of Table 2 and Column (2) of Table 3, respectively). This suggests that the initial negative relationships that were found are generated from differential job ad interaction across occupations with different WFH potential as opposed to differential preference for WFH job ads.

Table 2: WFH on attention using log total views

	All job ads			High WFH occupations		
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Baseline relationship	(5) Within occupations	(6) Main analysis
WFH offering	-0.231^{***}	0.195^{***}	0.097^{***}	-0.194^{***}	0.133^{***}	0.066^{***}
	(0.067)	(0.033)	(0.025)	(0.072)	(0.029)	(0.020)
Occupation and Time F.E.s	N	Y	N	N	Y	N
Vacancy-level Controls	N	N	Y	N	N	Y
Local Labor Market F.E.	N	N	Y	N	N	Y
Commuting Zone × month-year F.E.	N	N	Y	N	N	Y
Occupation × month-year F.E.	N	N	Y	N	N	Y
Sample mean	4.53	4.53	4.53	4.32	4.32	4.32
N	2,377,730	2,377,730	2,279,966	637,336	637,336	629,993

Note: This table presents the results of the main regression estimates for log job ad views on WFH offering using the log number of views. I present the estimates for two different job ad samples – the full sample as well as on the subsample of the "high WFH" occupations (greater than the 75th percentile as defined using the LFS data). Columns (1) and (4) correspond to the baseline (uncontrolled) regressions. Columns (2) and (5) correspond to the regressions that have only 4-digit occupation and time fixed effects. Columns (3) and (6) corresponds to the main specification outlined in equation 1. The data consists of all months from January 2019 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, and vacancies with no text written (text length = 0) are dropped from all samples. The drop-off in sample size across specifications is driven mainly by vacancies that are missing values for some vacancy control variables. Results are similar if the sample is restricted to only vacancies with no missing values in these variables (Table B.1). Sample means are presented for the unrestricted sample corresponding to that subset of the data. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: WFH on applications using log total applications

	All job ads			High WFH occupations		
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Baseline relationship	(5) Within occupations	(6) Main analysis
WFH offering	-0.344^{***}	0.096^{***}	0.025	-0.066^{**}	0.060^{***}	0.016
	(0.044)	(0.024)	(0.020)	(0.032)	(0.015)	(0.012)
Occupation and Time F.E.s	N	Y	N	N	Y	N
Vacancy-level Controls	N	N	Y	N	N	Y
Local Labor Market F.E.	N	N	Y	N	N	Y
Commuting Zone × month-year F.E.	N	N	Y	N	N	Y
Occupation × month-year F.E.	N	N	Y	N	N	Y
Sample mean	2.45	2.45	2.45	2.02	2.02	2.02
N	1,531,314	1,531,314	1,462,177	424,882	424,882	418,790

Note: This table presents the results of the main regression estimates for log job ad applications on WFH offering using the log number of applications. I present the estimates for two different job ad samples – the full sample as well as on the subsample of the "high WFH" occupations (greater than the 75th percentile as defined using the LFS data). Columns (1) and (4) correspond to the baseline (uncontrolled) regressions. Columns (2) and (5) correspond to the regressions that have only 4-digit occupation and time fixed effects. Columns (3) and (6) corresponds to the main specification outlined in equation 1. The data consists of all months from May 2020 to September 2022. Vacancies that receive only one or less total views, vacancies with no applications, and vacancies with no text written (text length = 0) are dropped from all samples. Sample means are presented for the unrestricted sample corresponding to that subset of the data. The drop-off in sample size across specifications is driven mainly by vacancies that are missing values for some vacancy control variables. Results are similar if the sample is restricted to only vacancies with no missing values in these variables (Table B.2). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

10. Figure C.10 (views) and Figure C.12 (applications) show some of the heterogeneity that exists just across coarse occupation categories.

The results using the main specification (equation 1) can be found in Column (3) of Table 2 for attention and Column (3) of Table 3 for applications. Using this specification, I control for other vacancy characteristics as well as using more specific fixed effects to ensure that the estimates are between job ads that are very similar. With this specification, I find estimates smaller effects than when just using the occupation and time fixed effects, but they are still positive and economically meaningful. I find that WFH job ads receive, on average, 9.7% more views and 2.5% more applications than similar non-WFH job ads, although the application result is noisily estimated. These effects suggest there is at least some preference for job ads that explicitly signal WFH compared to similar job ads that do not.

These results, however, may mask potential bias driven by a small number of WFH-classified job ads in otherwise non-WFH industries that are overweighted in the estimates, some of which may just be measurement error from misclassification. To remedy this, I rerun the analysis on the subset of vacancies classified in the "high WFH" occupation categories. These occupation classifications contain the majority of vacancies and the vast majority of WFH vacancies, which reduces the noise in the estimates by focusing on job ads in local labor markets that can more feasibly offer WFH and are less likely to contain misclassified job ads.

The estimates for the main specification for the "high WFH" occupations are found in Column (6) of Table 2 for the views and Column (6) of Table 3 for the applications. These results paint a similar picture to the estimates found using the full sample of job ads. Within this subsample of job ads, I estimate that WFH job ads receive 6.6% more views and 1.6% more applications, on average, than similar non-WFH job ads, however, the application results are still imprecise. These results indicate that there is a sizable increase in the amount of attention and (potentially) applications that a job ad receives when it explicitly offers WFH. If job seekers are searching rationally and viewing/applying more to job ads that they would prefer, then these results may suggest that job seekers have a stronger preference for WFH jobs over similar non-WFH jobs. On the other hand, more views/applications for WFH job ads may not be capturing stronger preferences, but may instead be capturing an increase in the number of job seekers that can reasonably access the job geographically. Either way, these results suggest that firms may increase their access to applicants by offering jobs that explicitly signal WFH.

6 Labor Market Tightness

The previous results indicate that offering WFH seems to give firms access to more workers on average which suggests that WFH could be a potential solution for firms to alleviate worker shortages. This matches with the theoretical prediction generated by the model that firms optimal behavior should be to use WFH as a way to gain access a wider labor market if the costs are low enough. Changes in the labor market tightness, either a firm's own "in-person" labor market being tighter or the wider "WFH" labor market becoming less tight, is predicted to result in more firms offering WFH. In this section, I test these theoretical predictions empirical and establish the causal link between labor market tightness and a firm's willingness to offer WFH.

6.1 Methodology

In order to look at this the relationship between labor market tightness and WFH offering, I construct a measure of labor market tightness, which is generally defined as the ratio between available jobs and available workers. In order to get a better measure of labor market tightness in my context, I exploit the unique data on job search behavior I have to proxy for the available workers. In this way, I can capture both the unemployed workers and the on-the-job workers that are actively looking for work. For my tightness measure, I use the number of unique vacancies over the number of unique job seekers, defined as the number of unique device IDs.

For my main analysis, I use the application data to proxy for available workers. I use the number of unique applicants, defined as the number of unique device IDs within a local labor market by month, as the labor market tightness denominator. I use the application data over the views data in order to get a more accurate representation of the workforce that is actively looking for work. The job seekers in the applications data have at least initiated a job application for a position in that local labor market, indicating more serious search behavior. Even so, I run the same analysis using the views data and find similar (although less precise) results.

I also use lagged labor market tightness in order to remove simultaneity bias where within period labor market tightness can be affected by contemporaneous WFH offering. Additionally, firm decision making is likely based on past realization of labor market tightness as realization of labor market tightness and decision making for hiring often has a lag. Because of this, lagged labor market tightness is the more realistic margin for firms to decide WFH offering on.

This analysis is run at the local-labor-market level where the local labor market in this analysis is defined as the CZ × 3-digit occupation. I use a broader definition of occupation in this setting both to ensure I have enough observations per cell to reasonably estimate the effects, but also because it provides a more accurate representation of the labor market competition. Firms hiring in different, but similar, positions are often competing for the same workers, who can usually switch between narrow occupation categories relatively seamlessly. By defining the labor markets more broadly, I can capture this competition in my estimates.

For my main specification, I use a fixed effects model that controls for local labor market fixed effects and differential time trends for commuting zone and 3-digit occupation. The model is formalized in equation 2.

$$WFH_{z,o,t} = \beta_0 + \beta_1 * LLM\_Tightness_{z,o,t-1} + \theta_{z,o} + \theta_{z,t} + \theta_{o,t} + \epsilon_{z,o,t} \tag{2}$$

z indexes the commuting zone, o indexes the occupation, and t indexes the month-year. *WFH* is the number (or log) of vacancies offering WFH in that LLM in that time period and *LLM_Tightness* is tightness of LLM l in the previous time period *t-1*. The coefficient of interest is β_1 which estimates the average change in the number (or log) of WFH vacancies across local labor markets due to a 1 point change in the labor market tightness.

Similar to the previous analysis, I run this specification on two different samples. First, I run it on the entire sample of job ads to capture the overall effect, but I also run it on the subset of local labor markets in the same 1-digit occupation categories I classify as "high WFH." I also include the estimates for the baseline relationship as well as the relationship with 3-digit occupation, commuting zone, and time fixed effects for both the full sample and the "high WFH" subsample.

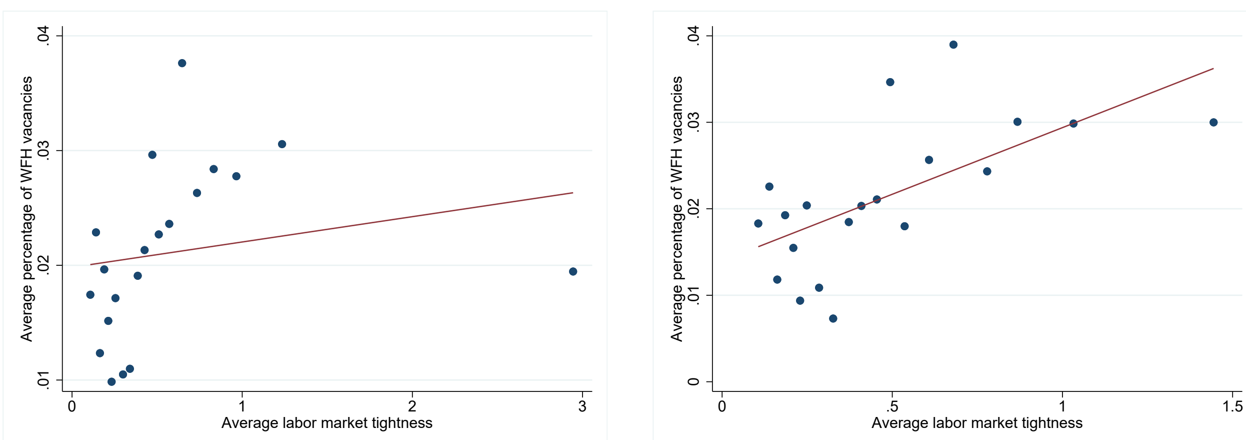
6.2 Results

When looking at the raw relationship of average labor market tightness and average share of WFH vacancies, I find correlative evidence suggesting that there is a positive relationship between labor market tightness and WFH offering. Figure 4 presents the relationship between the average monthly tightness from May 2020 to September 2022 for the local labor market (commuting zone by 3-digit occupation) and the average percentage of WFH vacancies. Panel (a) shows the relationship for the full data while Panel (b) truncates the data to remove the outlier labor markets with very high tightness measures. The figures present a strong positive relationship implying that a higher share of WFH vacancies tend to be posted in the labor markets that are tighter. These results for Sweden also match the correlative evidence for the US presented by Autor, Dube, and McGrew (2024).

Figure 4: Correlations between labor market tightness and the percentage of WFH vacancies

(a) All observations

(b) Truncated (LM tightness < 2)



Notes: These figures present the correlations between the average local labor market tightness (with the labor market defined as the 3 digit occupation by commuting zone) and the average percentage of WFH vacancies using binned scatterplots. Data consists of every labor market for every month (May 2020–September 2022) that has at least one applicant in that month. Panel (a) shows the figure for all data points. Panel (b) removes some outliers (717 observations removed) by restricting it to only observations with a labor market tightness less than 2. $N = 16,724$ in Panel (a) and $N = 16,007$ in Panel (b). the full scatterplots can be found in Figure C.13.

The results for the main analysis can be found in Table 4. Looking at the baseline regression estimates, I find that the strong, positive relationship persists even when looking over time using the lagged labor market tightness. In the full data (Column (1)), I find an estimated effect of 0.20, which corresponds to 0.32 more WFH vacancies between the 10th percentile (0.095) and the 90th percentile (1.667) of labor market tightness in the sample. This is an increase in the number of WFH vacancies of

57.1% of the sample mean (0.56). This effect remains positive and significant even when the analysis adds relevant controls and fixed effects. Using the main specification (equation 2), I estimate a positive and significant effect of 0.056, which corresponds to 0.088 more WFH vacancies between the 10th and 90th percentiles of labor market tightness, an increase of 15.7% of the sample mean (Column (3)).[11]

Table 4: Main analysis of labor market tightness on job WFH offering

	All job ads			High WFH occupations		
	(1) Baseline relationship	(2) Within occupations and CZ	(3) Main analysis	(4) Baseline relationship	(5) Within occupations and CZ	(6) Main analysis
Number of WFH job ads	0.202***	0.094***	0.056***	1.421*	0.824***	0.185**
	(0.073)	(0.027)	(0.018)	(0.732)	(0.139)	(0.092)
Occupation and Time F.E.s	N	Y	N	N	Y	N
Local Labor Market F.E.	N	N	Y	N	N	Y
Commuting Zone × month-year F.E.	N	N	Y	N	N	Y
Occupation × month-year F.E.	N	N	Y	N	N	Y
Sample mean	0.56	0.56	0.56	1.32	1.32	1.32
N	118,474	118,474	117,951	29,227	29,227	29,005

Note: This table presents the results of the main regression estimates for the number of WFH vacancies on lagged labor market tightness. I present the estimates for two different job ad samples – the full sample as well as on the subsample of the "high WFH" occupations (greater than the 75th percentile as defined using the LFS data). Columns (1) and (4) correspond to the baseline (uncontrolled) regressions. Columns (2) and (5) correspond to the regressions that have only 3-digit occupation, commuting zone, and time fixed effects. Columns (3) and (6) corresponds to the main specification outlined in equation 1. Labor market tightness here is defined using vacancies over unique applicants. Vacancies consist of all the job ads that were first posted in that month in that local labor market. Unique applicants is defined as all the unique device IDs that applied to at least one vacancy in that local labor market in that month. The data consists of all months from May 2020 to September 2022. Sample means are presented for the unrestricted sample corresponding to that subset of the data. Standard Errors are clustered at the local labor market level. The analogous table, where labor market tightness is defined using viewers instead of applicants can be found in Table B.4.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As with the previous analysis, there is concentration in WFH vacancies among certain occupations. To check that the less feasible WFH occupations are not driving the results, I re-run the analysis using the subsample of local labor markets for the "high WFH" occupation categories. I find the same general relationships in this analysis as when I use the full sample, but the effects are larger. When looking at the estimates for the main analysis (Column (6)), I find a significant effect of 0.185. This corresponds to 0.265 more WFH vacancies between the 10th percentile (0.067) and the 90th percentile (1.500) of labor market tightness in the subsample, which is an increase of 20.1% of the mean in the subsample (1.32). Overall, these results point to firms using WFH as a strategic means of relaxing the labor market tightness they face in order to hire workers easier.

7 Conclusion

Firms often struggle with hiring difficulties in tight labor markets, making any advantage in accessing potential workers strategically valuable. In this paper, I explore the extent to which WFH can be utilized as a recruitment device by firms and estimate how many firms seem are leveraging WFH to potentially gain a competitive edge. In order to answer these questions, I exploit unique vacancy data in Sweden matched to registry data on workers and firms as well as job search behavior in terms of job ad views and applications.

I find that job ads that offer WFH receive more attention and applications from job seekers when compared to non-WFH job ads in similar occupations. These effects remain even when adding a rich set of vacancy-level controls and fixed effects. These effects remain consistent even when limiting the

11. These results remain qualitatively similar if the denominator of labor market tightness is measured using the "views" data instead of the applications data (Table B.4).

sample to the occupations that are most capable of offering WFH. I estimate that WFH vacancies get, on average, 9.7% more views and 2.5% more applications than in-person vacancies. These results suggest that WFH job ads are able to attract more workers, either because job seekers prefer WFH jobs more or because WFH job ads can reach a geographically broader set of potential workers.

Since WFH job ads do tend to attract more job seekers, then firms are able to strategically use WFH to access more potential workers, especially when local job seekers are more scarce. To investigate this behavior, I estimate the relationship between labor market tightness and WFH offering. I find that local labor markets that are tighter in the previous period have more WFH vacancies in the next period. When comparing the 90th percentile labor market to the 10th percentile labor market in terms of tightness, I find that there are 0.088 more WFH vacancies opened in that month in the tighter labor market across all local labor markets in Sweden. This corresponds to an increase in the number of WFH vacancies of 15.7% of the sample mean. These results hold when looking at the effect among on the high WFH occupations as well. These results suggest that at least some firms seem to be offering WFH strategically in order to gain a hiring advantage.

Overall, this paper documents the increased attention that WFH job ads receive and the strategic utilization of WFH by firms to ease hiring difficulties. These insights in firm decision making and job seeker search behavior with respect to WFH offering add important considerations when designing policies to ease labor market shortages.

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A Additional Data Descriptions

Table A.1: Number of WFH vacancies (by year)

Year	WFH vacancies	Total vacancies	Percentage of WFH
2016	6,523	714,252	0.9%
2017	5,903	712,413	0.8%
2018	7,079	680,370	1.0%
2019	8,158	637,998	1.3%
2020	9,148	487,711	1.9%
2021	26,676	725,938	3.7%
2022	55,872	1,054,941	5.3%
2023	125,359	2,038,834	6.1%
All	**244,718**	**7,052,457**	**3.5%**

Notes: This table presents the breakdown of the vacancy data by years. The column "WFH vacancies" presents the number of vacancies that are categorized as WFH in that year and the column "Total vacancies" presents the total number of vacancies in my sample after the initial cleaning. The last column, "Percentage of WFH" indicates the share of WFH vacancies out of the total vacancies. The last row "All" presents the sum of the columns for "WFH vacancies" and "Total vacancies" and then presents the percentage of all WFH vacancies in this entire sample in the last column.

Table A.2: Most common WFH occupations

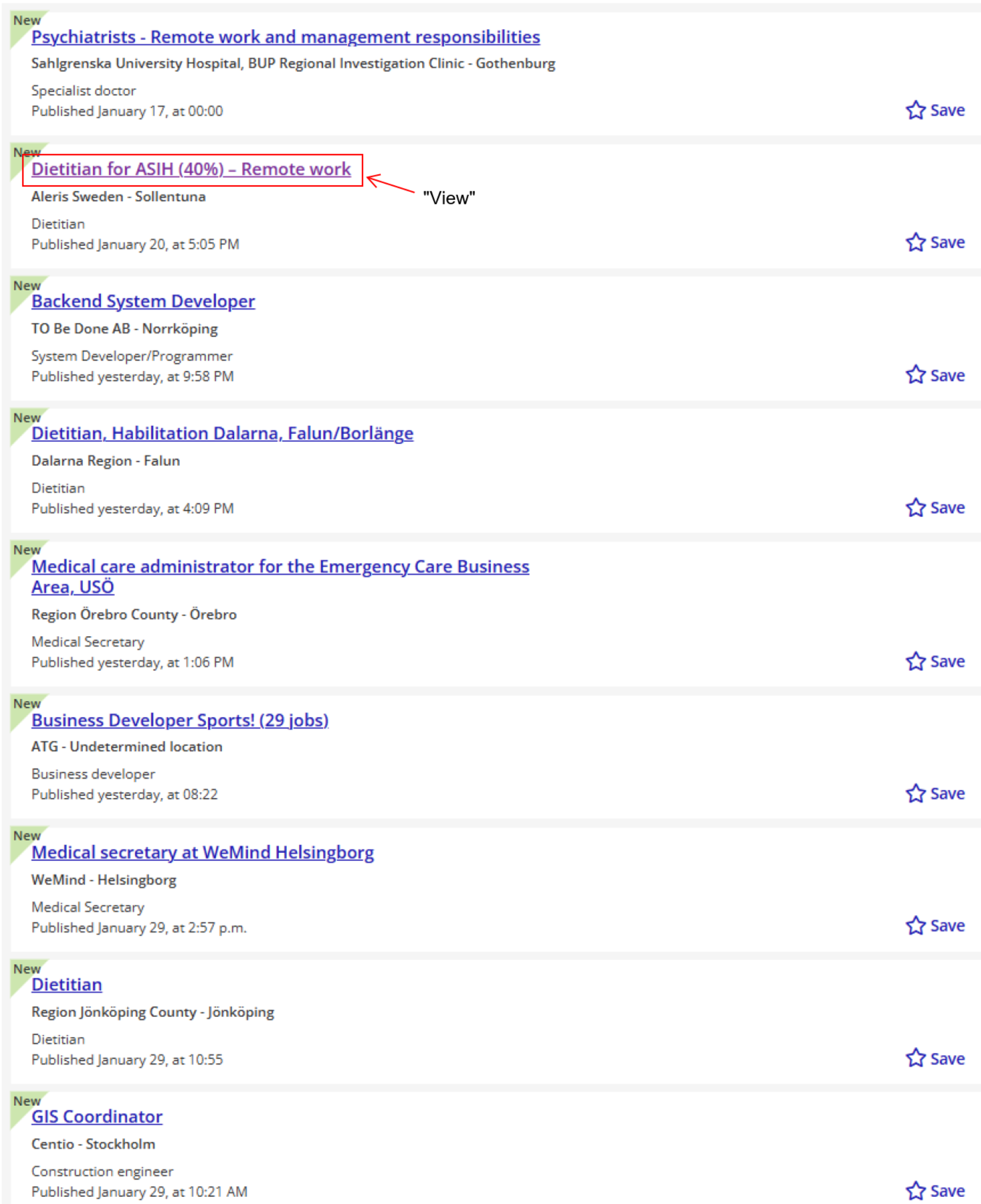
Year	Occupation (#)	Occupation (%)
	Student assistants	Social security officer
2016	Other trainers and instructors	Other trainers and instructors
	Business salesperson	Student assistants
	Business salesperson	Market researchers and interviewers
2017	Software and system developers	University and college lecturers
	Support technician, IT	Operations technician, IT
	Business salesperson	Market researchers and interviewers
2018	Software and system developers	Marketing and sales assistants
	Support technician, IT	Dietitians
	Business salesperson	Other operating technicians and process supervisors***
2019	Software and system developers	System analysts and IT architects
	System analysts and IT architects	Market researchers and interviewers
	Software and system developers	Other university teachers
2020	Business salesperson	Translators
	Telemarketers	Image and broadcasting technicians
	Software and system developers	Translators
2021	Business salesperson	Event and travel producers
	Telemarketers	Other university teachers
	Software and system developers	Dietitians
2022	Customer service staff	Developer in games and digital media
	Business salesperson	Surveyors
	Software and system developers	Employment agency
2023	Business salesperson	Administrative and organizational lawyers
	Employment agency	Managers in forestry and agriculture

Notes: Occupations are the 4 digit SSYK code. For the percentage column, does not include any occupations that have less than 5 vacancies. Exceptions were:

- 2017: Air traffic controller had highest percentage, but there was only 1 WFH vacancy

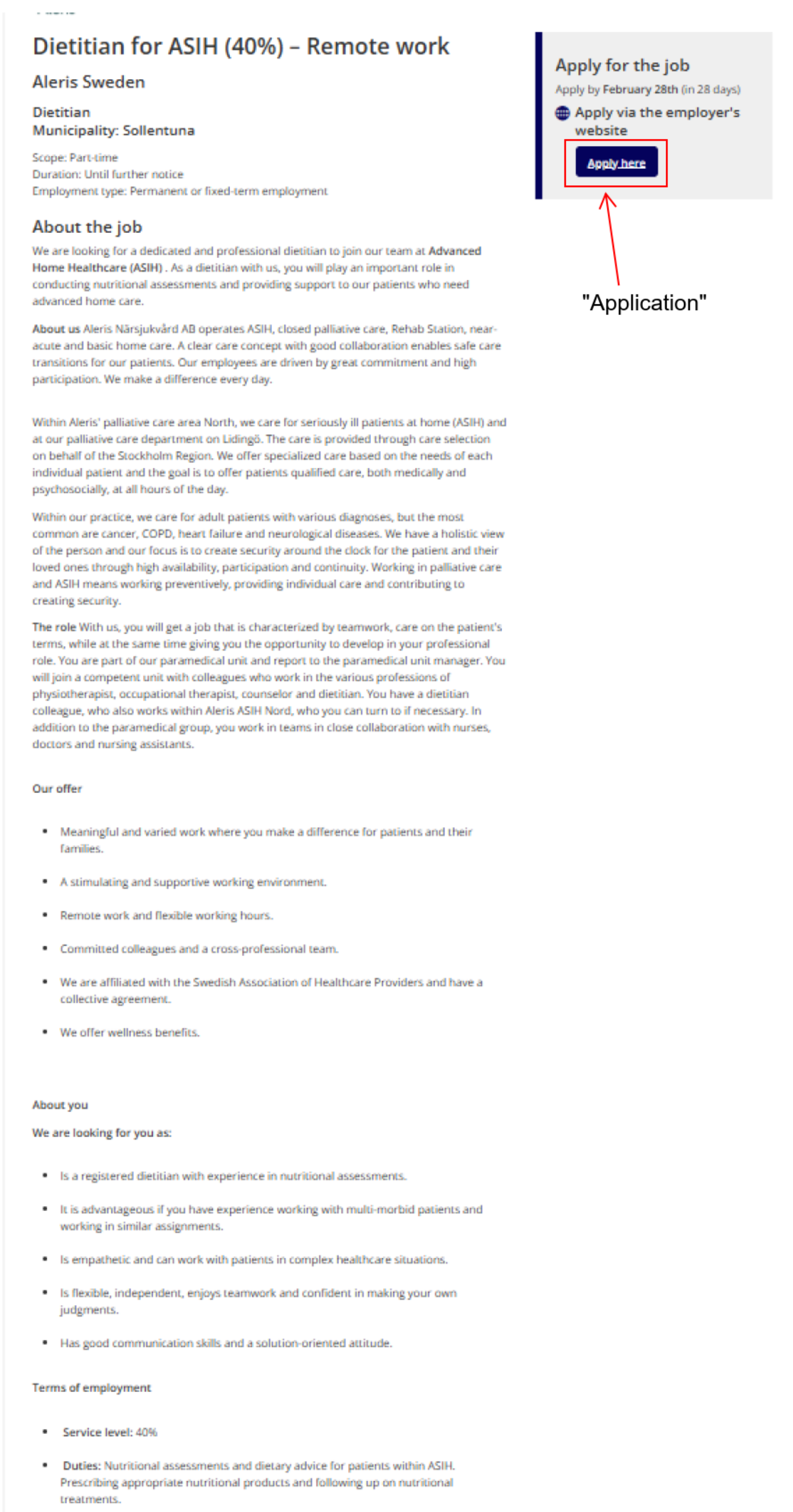
*** indicates an occupation that seems unlikely to have WFH

Figure A.1: *Platsbankan* example search page



Notes: This figure shows a snapshot of the job ads board, *Platsbanken*, at the "view" stage. Job seekers would enter search terms on the main page, and would they would be given snapshots of job ads that look like this. A "view" is counted for each time an individual clicks on one of the ads from this page to take them to the more detailed description (Figure A.2). The page (and most job ads) are in Swedish, but it has been translated into English for this figure.
Source: *Platsbanken*, https://arbetsformedlingen.se/platsbanken/ [Accessed January 31, 2025]

Figure A.2: *Platsbankan* example job ad



Dietitian for ASIH (40%) – Remote work

Aleris Sweden

Dietitian
Municipality: Sollentuna

Scope: Part-time
Duration: Until further notice
Employment type: Permanent or fixed-term employment

About the job

We are looking for a dedicated and professional dietitian to join our team at **Advanced Home Healthcare (ASIH)** . As a dietitian with us, you will play an important role in conducting nutritional assessments and providing support to our patients who need advanced home care.

About us Aleris Närsjukvård AB operates ASIH, closed palliative care, Rehab Station, near-acute and basic home care. A clear care concept with good collaboration enables safe care transitions for our patients. Our employees are driven by great commitment and high participation. We make a difference every day.

Within Aleris' palliative care area North, we care for seriously ill patients at home (ASIH) and at our palliative care department on Lidingö. The care is provided through care selection on behalf of the Stockholm Region. We offer specialized care based on the needs of each individual patient and the goal is to offer patients qualified care, both medically and psychosocially, at all hours of the day.

Within our practice, we care for adult patients with various diagnoses, but the most common are cancer, COPD, heart failure and neurological diseases. We have a holistic view of the person and our focus is to create security around the clock for the patient and their loved ones through high availability, participation and continuity. Working in palliative care and ASIH means working preventively, providing individual care and contributing to creating security.

The role With us, you will get a job that is characterized by teamwork, care on the patient's terms, while at the same time giving you the opportunity to develop in your professional role. You are part of our paramedical unit and report to the paramedical unit manager. You will join a competent unit with colleagues who work in the various professions of physiotherapist, occupational therapist, counselor and dietitian. You have a dietitian colleague, who also works within Aleris ASIH Nord, who you can turn to if necessary. In addition to the paramedical group, you work in teams in close collaboration with nurses, doctors and nursing assistants.

Our offer

- Meaningful and varied work where you make a difference for patients and their families.
- A stimulating and supportive working environment.
- Remote work and flexible working hours.
- Committed colleagues and a cross-professional team.
- We are affiliated with the Swedish Association of Healthcare Providers and have a collective agreement.
- We offer wellness benefits.

About you

We are looking for you as:

- Is a registered dietitian with experience in nutritional assessments.
- It is advantageous if you have experience working with multi-morbid patients and working in similar assignments.
- Is empathetic and can work with patients in complex healthcare situations.
- Is flexible, independent, enjoys teamwork and confident in making your own judgments.
- Has good communication skills and a solution-oriented attitude.

Terms of employment

- **Service level:** 40%
- **Duties:** Nutritional assessments and dietary advice for patients within ASIH. Prescribing appropriate nutritional products and following up on nutritional treatments.

Notes: This figure shows a snapshot of the detailed description of an arbitrary job ad on *Platsbanken*. After clicking on a job from the previous page (Figure A.1), job seekers would see a page like this that gives them the detailed description of what the employer is looking for and what the job entails. The main text found on this page is an example of the text that acts as the input for the WFH classification. This is also the point where "applications" are counted. An "application" consists of any time an individual clicks on the "apply" button located in the upper-right part of the job ad. This page (and most job ads) are written in Swedish, but this one has been translated into English for this figure.
Source: Platsbanken, https://arbetsformedlingen.se/platsbanken/ [Accessed January 31, 2025]

B Additional Results

B.1 Additional job ad attractiveness results

Table B.1: Main analysis of WFH on job attention - restricted sample

	All job ads			High WFH occupations		
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Baseline relationship	(5) Within occupations	(6) Main analysis
WFH offering	-0.241^{***} (0.067)	0.184^{***} (0.033)	0.097^{***} (0.025)	-0.196^{***} (0.072)	0.133^{***} (0.029)	0.066^{***} (0.020)
Occupation and Time F.E.s	N	Y	N	N	Y	N
Vacancy-level Controls	N	N	Y	N	N	Y
Local Labor Market F.E.	N	N	Y	N	N	Y
Commuting Zone × month-year F.E.	N	N	Y	N	N	Y
Occupation × month-year F.E.	N	N	Y	N	N	Y
Sample mean	4.53	4.53	4.53	4.32	4.32	4.32
N	2,282,765	2,282,765	2,279,966	630,700	630,700	629,993

Note: This table is related to Table 2. This table presents the results of the main regression estimates for log job ad views on WFH offering using a restricted sample. Here, the sample drops all vacancies that are missing values in any of the vacancy control variables, making the samples more comparable across specifications. I present the estimates for two different job ad samples – the full sample as well as on the subsample of the "high WFH" occupations (greater than the 75th percentile as defined using the LFS data). Columns (1) and (4) correspond to the baseline (uncontrolled) regressions. Columns (2) and (5) correspond to the regressions that have only 4-digit occupation and time fixed effects. Columns (3) and (6) corresponds to the main specification outlined in equation 1. The data consists of all months from January 2019 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, and vacancies with no text written (text length = 0) are dropped from all samples. Sample means are presented for the unrestricted sample corresponding to that subset of the data. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Main analysis of WFH on job applications - restricted sample

	All job ads			High WFH occupations		
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Baseline relationship	(5) Within occupations	(6) Main analysis
WFH offering	-0.337^{***} (0.043)	0.091^{***} (0.025)	0.025 (0.020)	-0.066^{**} (0.033)	0.059^{***} (0.015)	0.016 (0.012)
Occupation and Time F.E.s	N	Y	N	N	Y	N
Vacancy-level Controls	N	N	Y	N	N	Y
Local Labor Market F.E.	N	N	Y	N	N	Y
Commuting Zone × month-year F.E.	N	N	Y	N	N	Y
Occupation × month-year F.E.	N	N	Y	N	N	Y
Sample mean	2.45	2.45	2.45	2.02	2.02	2.02
N	1,464,939	1,464,939	1,462,177	419,476	419,476	418,790

Note: This table is related to Table 3. This table presents the results of the main regression estimates for log job ad applications on WFH offering using a restricted sample. Here, the sample drops all vacancies that are missing values in any of the vacancy control variables, making the samples more comparable across specifications. I present the estimates for two different job ad samples – the full sample as well as on the subsample of the "high WFH" occupations (greater than the 75th percentile as defined using the LFS data). Columns (1) and (4) correspond to the baseline (uncontrolled) regressions. Columns (2) and (5) correspond to the regressions that have only 4-digit occupation and time fixed effects. Columns (3) and (6) corresponds to the main specification outlined in equation 1. The data consists of all months from May 2020 to September 2022. Vacancies that receive only one or less total views and vacancies with no text written (text length = 0) are dropped from all samples. Sample means are presented for the unrestricted sample corresponding to that subset of the data. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: WFH on attention including 2018 views

	All job ads			High WFH occupations		
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Baseline relationship	(5) Within occupations	(6) Main analysis
WFH offering	-0.201^{***}	0.175^{***}	0.097^{***}	-0.164^{**}	0.118^{***}	0.067^{***}
	(0.063)	(0.032)	(0.025)	(0.065)	(0.030)	(0.021)
Occupation and Time F.E.s	N	Y	N	N	Y	N
Vacancy-level Controls	N	N	Y	N	N	Y
Local Labor Market F.E.	N	N	Y	N	N	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	N	N	Y
Occupation $\times$ month-year F.E.	N	N	Y	N	N	Y
Sample mean	4.48	4.48	4.48	4.29	4.29	4.29
N	2,915,961	2,915,961	2,805,475	776,485	776,485	767,628

Note: This table is related to Table 2. This table presents the results of the main regression estimates for log job ad views on WFH offering including the 2018 data on views. I present the estimates for two different job ad samples – the full sample as well as on the subsample of the "high WFH" occupations (greater than the 75th percentile as defined using the LFS data). Columns (1) and (4) correspond to the baseline (uncontrolled) regressions. Columns (2) and (5) correspond to the regressions that have only 4-digit occupation and time fixed effects. Columns (3) and (6) corresponds to the main specification outlined in equation 1. The data consists of all months from March 2018 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, and vacancies with no text written (text length = 0) are dropped from all samples. Sample means are presented for the unrestricted sample corresponding to that subset of the data. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Additional labor market tightness results

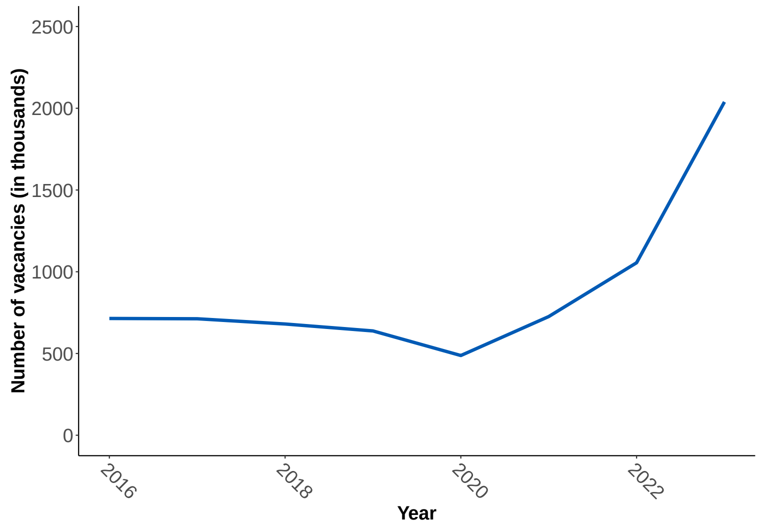
Table B.4: Main analysis of labor market tightness on job WFH offering

	All job ads			High WFH occupations		
	(1) Baseline relationship	(2) Within occupations and CZ	(3) Main analysis	(4) Baseline relationship	(5) Within occupations and CZ	(6) Main analysis
WFH offering	1.292**	0.913***	0.024	5.709*	4.404***	0.198
	(0.535)	(0.062)	(0.038)	(3.023)	(0.266)	(0.162)
Occupation, Commuting Zone, and Time F.E.s	N	Y	N	N	Y	N
Local Labor Market F.E.	N	N	Y	N	N	Y
Commuting Zone × month-year F.E.	N	N	Y	N	N	Y
Occupation × month-year F.E.	N	N	Y	N	N	Y
Sample mean	0.31	0.31	0.31	0.72	0.72	0.72
N	177,863	173,166	172,922	45,738	44,570	44,464

Note: This table presents the results of the main regression estimates for the number of WFH vacancies on lagged labor market tightness. I present the estimates for two different job ad samples – the full sample as well as on the subsample of the "high WFH" occupations (ssyk 1-digit occupation codes of 1, 2, 3, and 4). Regressions are run at the local labor market level (commuting zone × 3-digit occupation). Columns (1) and (4) correspond to the baseline (uncontrolled) regressions. Columns (2) and (5) correspond to the regressions that have only 3-digit occupation, commuting zone, and time fixed effects. Columns (3) and (6) corresponds to the main specification outlined in equation 1. Labor market tightness here is defined using vacancies over unique viewers. Vacancies consist of all the job ads that were first posted in that month in that local labor market. Unique viewers is defined as all the unique device IDs that viewed at least one vacancy in that local labor market in that month. The data consists of all months from March 2018 to September 2022. Individuals that have only one total view are dropped from all samples. Sample means are presented for the unrestricted sample corresponding to that subset of the data. Standard Errors are clustered at the local labor market level. The analogous table, where labor market tightness is defined using applicants instead of applicants can be found in Table 4.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

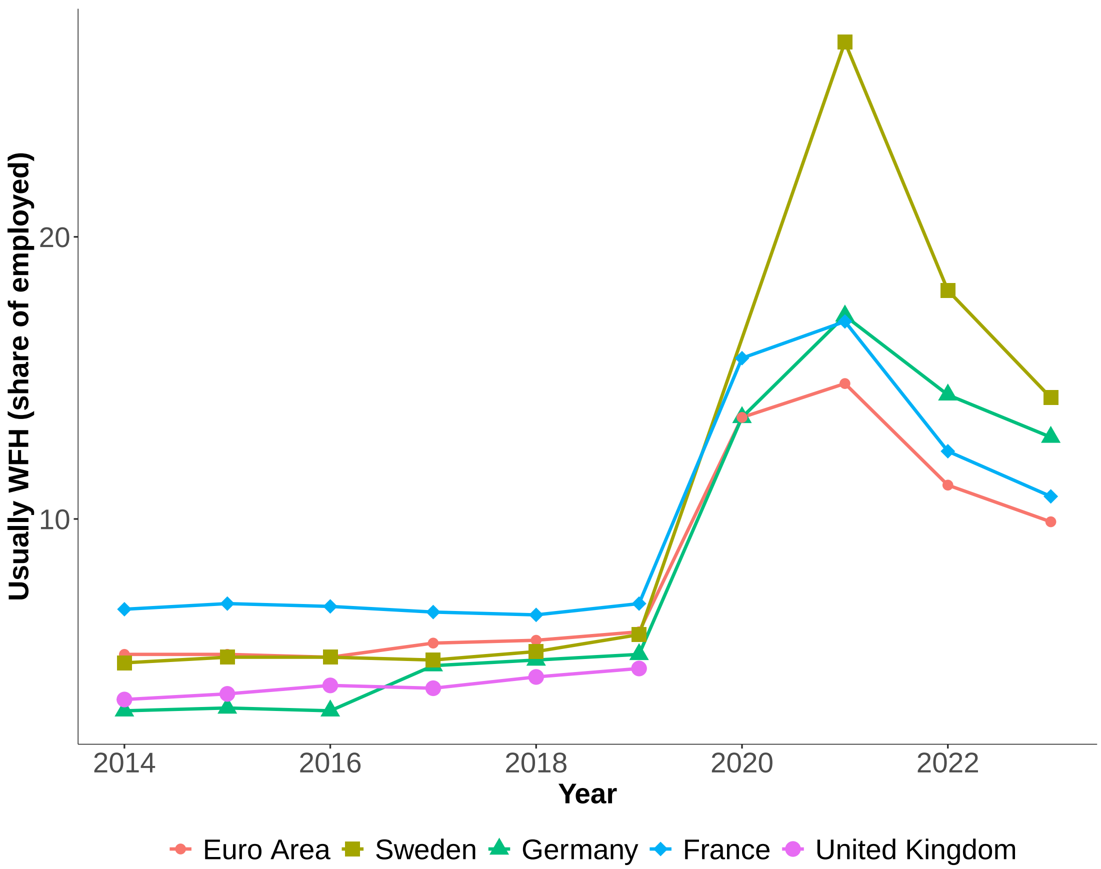
C Additional Figures

Figure C.1: Number of vacancies per year (2016-2023)



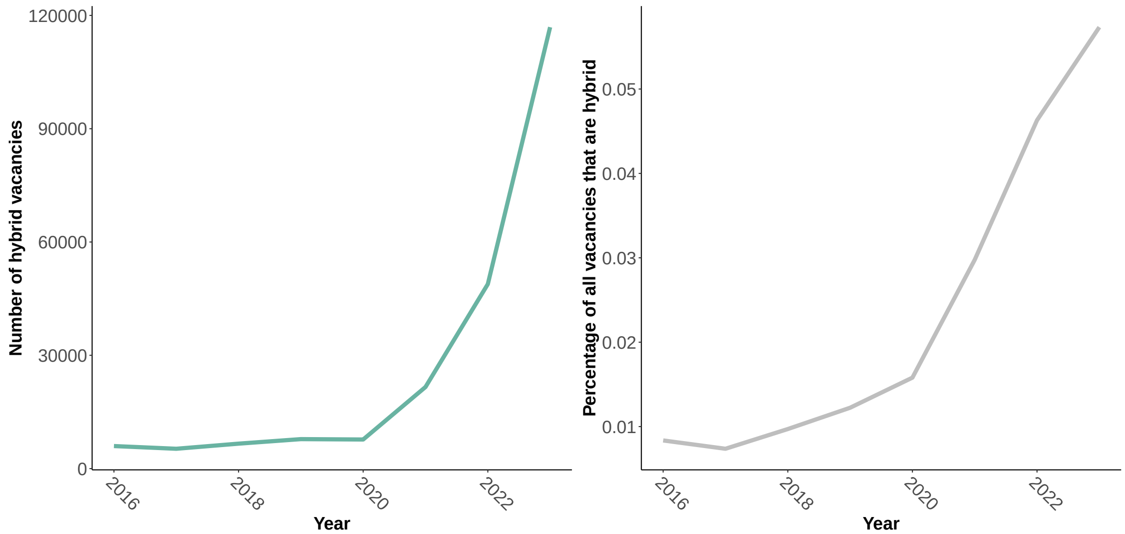
Notes: This figure plots the total number of vacancies per year (in thousands of vacancies) in the *Platsbanken* data after removing vacancies that are located outside Sweden.

Figure C.2: Share of employed that report usually WFH



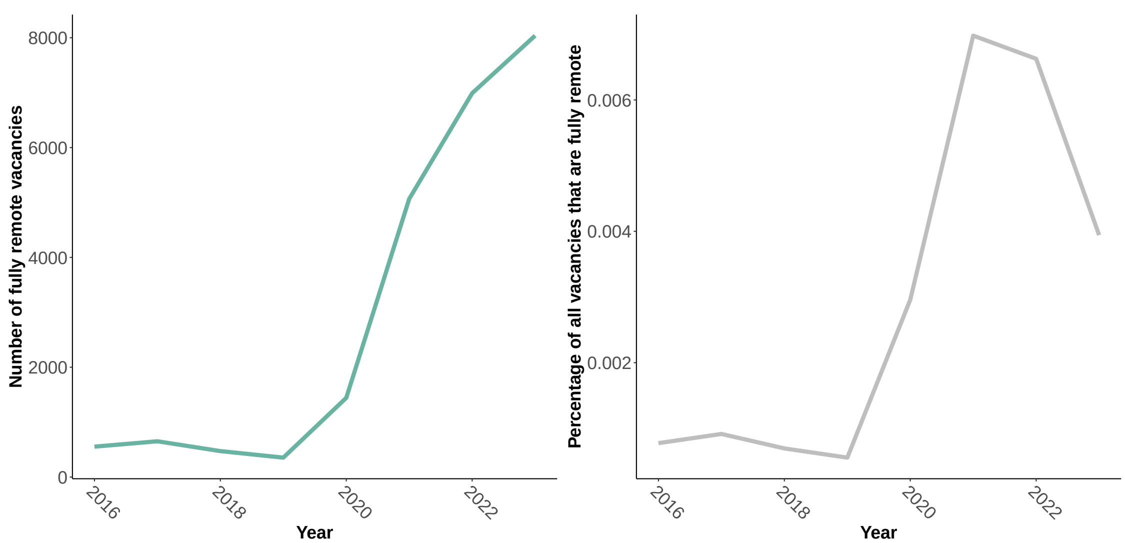
Notes: This figure plots the share of employed individuals that report that they "usually" work from home in the European Labor Force Surveys. This figure plots the shares from 2014-2023 for the average of the Euro Area (red, small circles), Sweden (olive, squares), Germany (green, triangles), France (blue, diamonds) and the United Kingdom (pink, large circles). The Euro Area is defined using from the 2023 members of the region and consists of 20 countries. WFH data is missing for Sweden in 2020.
Source: European Labour Force Surveys, 2014-2023, accessed through Eurostat.

Figure C.3: Hybrid Vacancy Trends



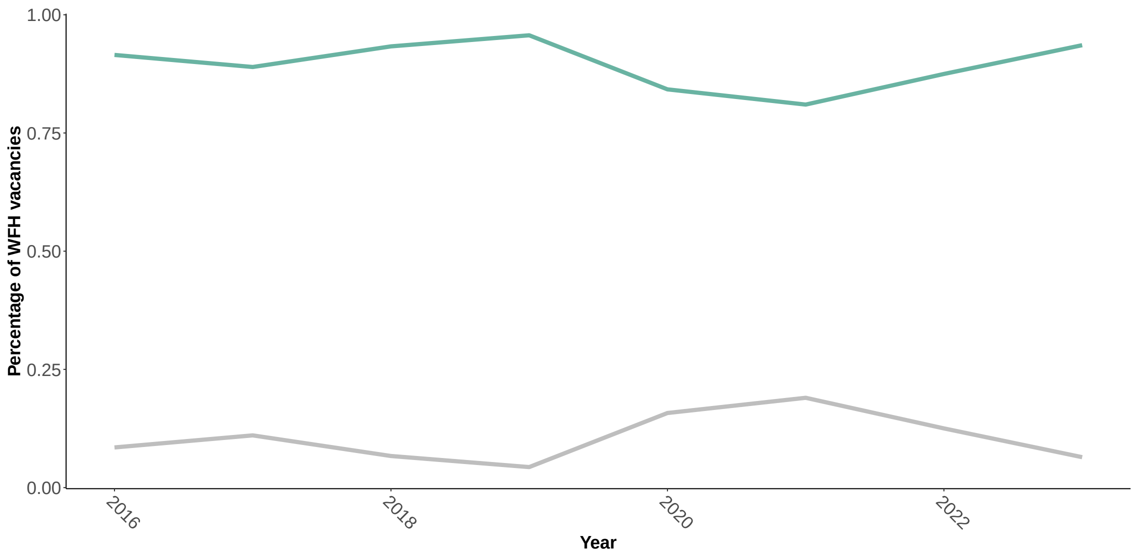
Notes: This figure plots the change in Swedish job ads that explicitly offer "hybrid" jobs from 2016-2023. The left graph plots the change in levels in hybrid job ads while the right graph plots the share of all job ads in that year that state they offer hybrid WFH. The share is out of all *Platsbanken* job ads after removing the vacancies for jobs with locations stated to be outside of Sweden. This figure corresponds to the plots that illustrate the trends for the combined WFH job ads in Figure 1.

Figure C.4: Fully Remote Vacancy Trends



Notes: This figure plots the change in Swedish job ads that explicitly offer "fully remote" jobs from 2016-2023. The left graph plots the change in levels in fully remote job ads while the right graph plots the share of all job ads in that year that state they offer fully remote work. The share is out of all *Platsbanken* job ads after removing the vacancies for jobs with locations stated to be outside of Sweden. This figure corresponds to the plots that illustrate the trends for the combined WFH job ads in Figure 1.

Figure C.5: Percentage of WFH vacancies by WFH type



Notes: This figure plots the breakdown of all working from home job ads into "hybrid" WFH jobs (green) and "fully remote" WFH jobs (gray) from 2016-2023.

Figure C.6: Percentage of WFH vacancies within occupation by year

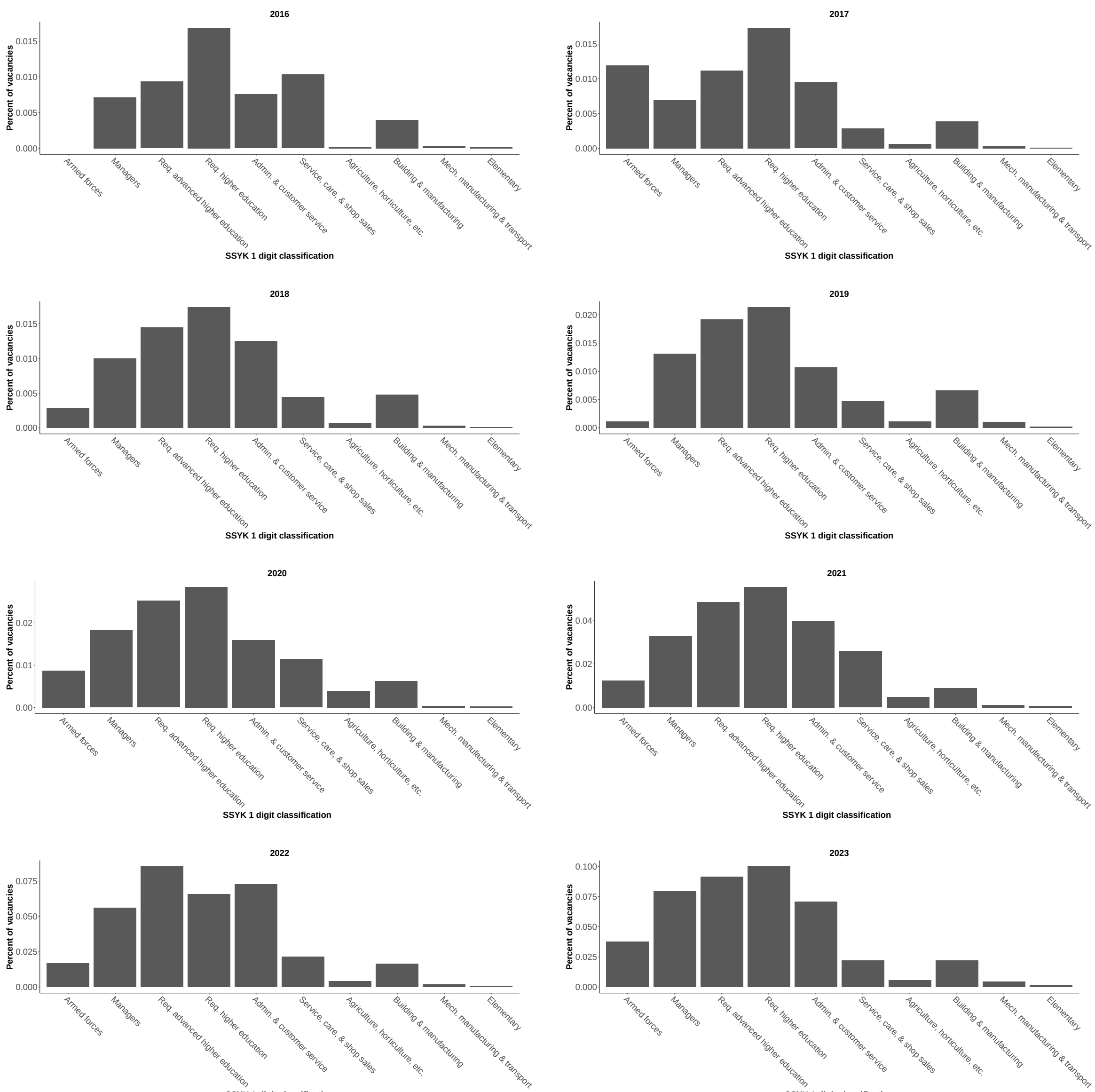


Figure C.7: High-frequency, unique words in WFH vacancy text, by year

(a) 2018

(b) 2019

(c) 2020

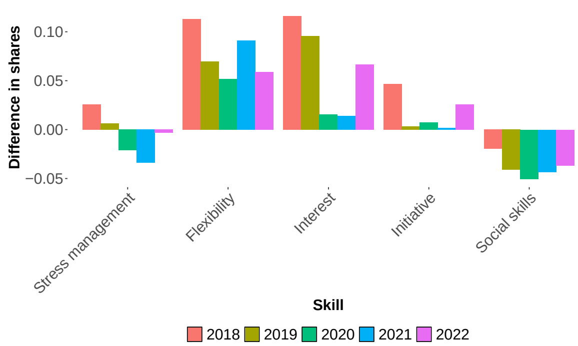
(d) 2021

(e) 2022

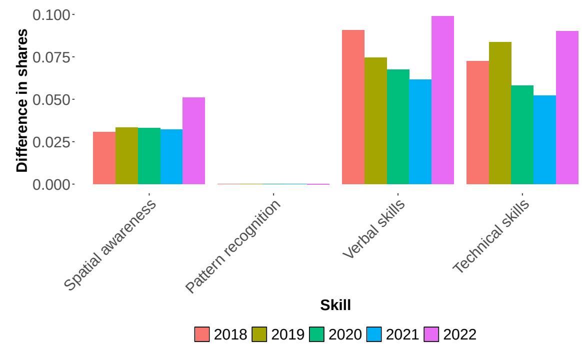
Notes: These figures present the yearly breakdown of Figure 2, using the vacancies from 2018 to 2022. Each figure shows the relative frequency of the top words that are "unique" to the WFH vacancies. To construct these figures, the top 200 most frequent words for the WFH and non-WFH vacancies, after filtering out "stop words," are determined separately for each year. The WFH words are then additionally filtered to remove any words that also appear in the top 200 words for the non-WFH vacancies. These figures then plot the relative frequency of the remaining WFH words.

Figure C.8: Differences in the share of WFH and non-WFH job ads per skills/technology by year

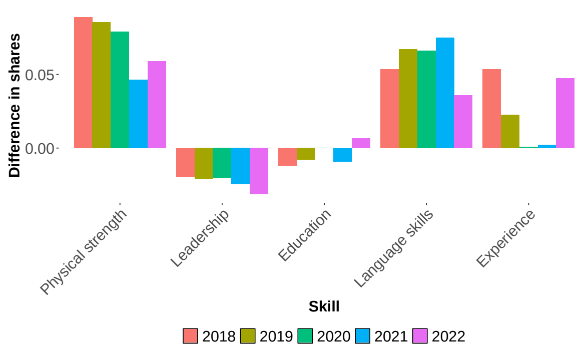
(a) Cognitive skills



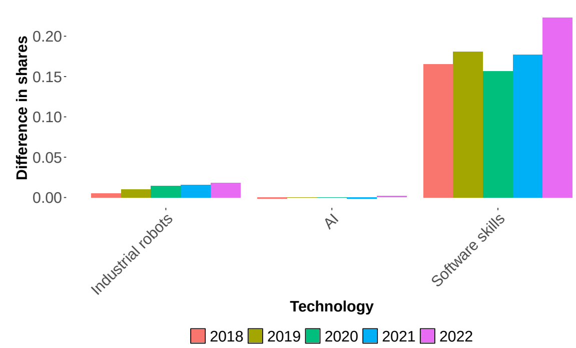
(b) Non-cognitive skills



(c) Other skills

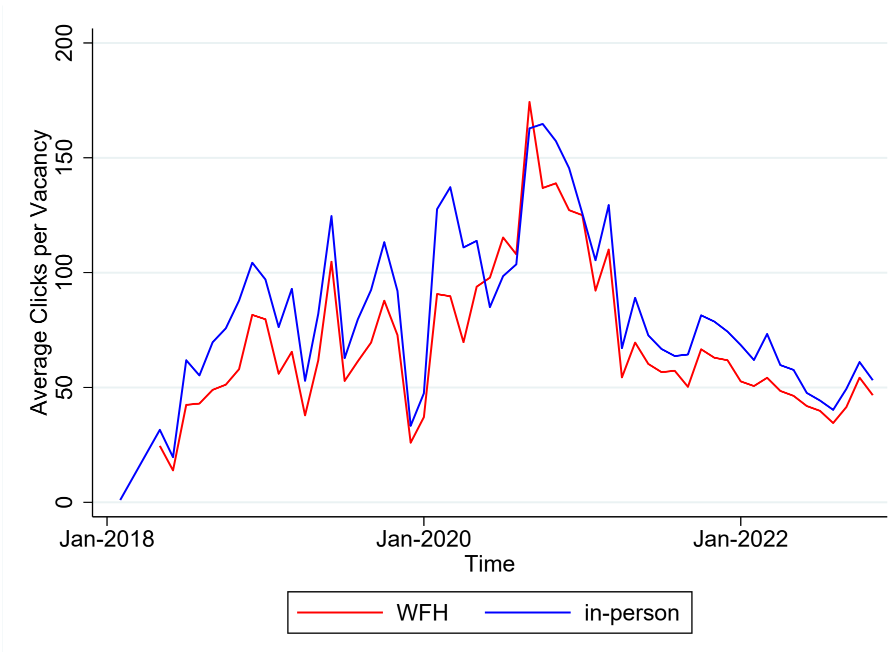


(d) Technology



Notes: These figures present the difference between WFH and non-WFH vacancies in the shares of the specific skill (panels (a) to (c)) or technology (panel (d)) that the ad asks for. The differences are plotted separately by year from 2018-2022. For all four panels, the skills/technologies are presented in the same order as in Figure 3 (sorted by overall share of WFH job ads that mention them).

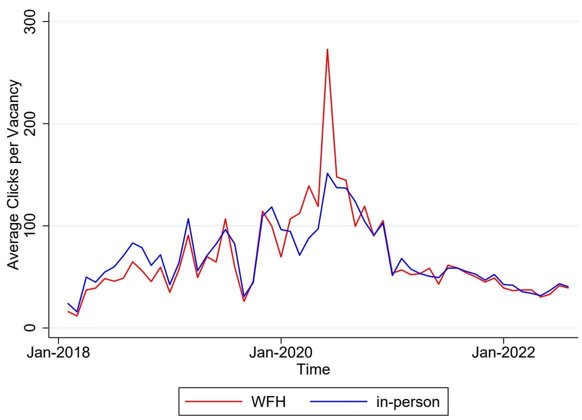
Figure C.9: Views per vacancy by WFH offering (Monthly)



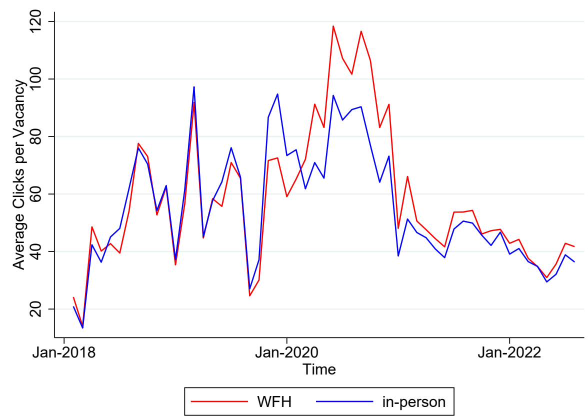
Notes: This figure presents the average number of views (clicks) per vacancy for each month by WFH type for March 2018- September 2022. Only vacancies that had at least one view in that time period are included.

Figure C.10: Views per vacancy by WFH offering for select occupations

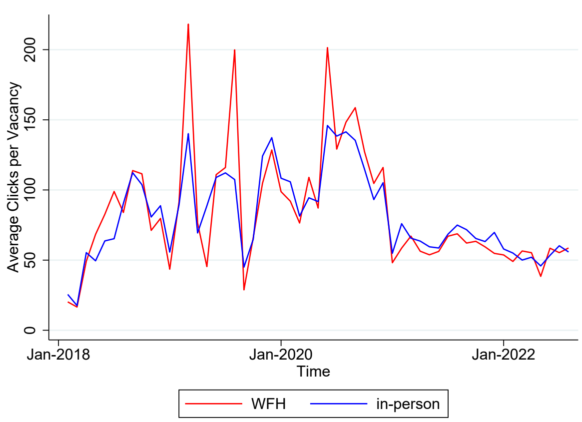
(a) "Requires higher education" job ads



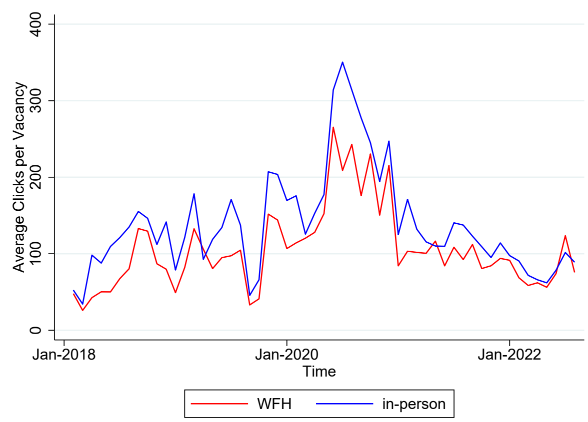
(b) "Requires advanced higher education" job ads



(c) "Manager" job ads

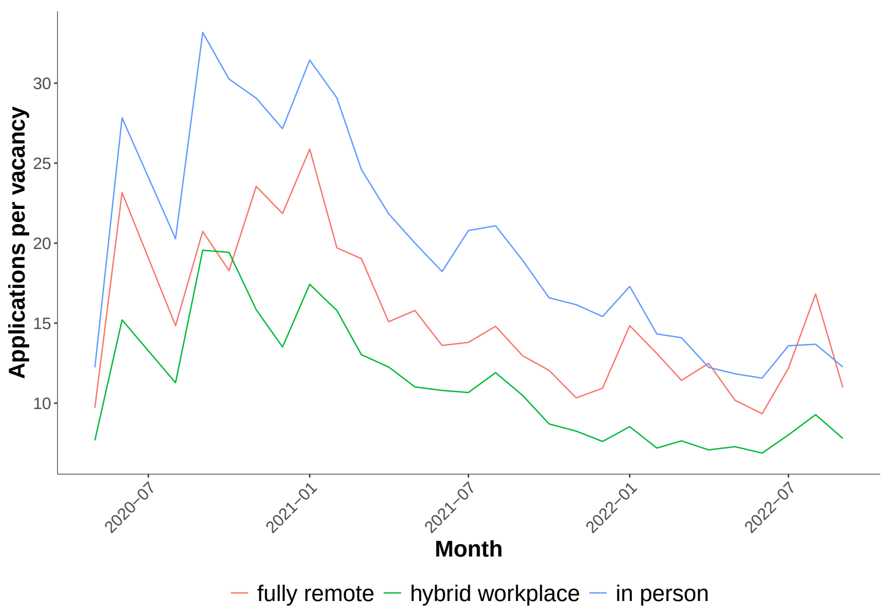


(d) "Administration and customer service" job ads



Notes: These figures present the average number of views (clicks) per vacancy for each month by WFH type for March 2018- September 2022 for the two occupation categories with the highest share of WFH vacancies. Panel (a) presents the data for the 1-digit occupation category of "requires higher education" (ssyk code 3), which has the highest share of WFH vacancies, and Panel (b) presents the data for the 1-digit occupation category of "requires advanced higher education" (ssyk code 2), which has the second highest share of WFH vacancies. Panel (c) presents the data for the 1-digit occupation category of "managers" (ssyk code 1), which has the third highest share of WFH vacancies, and Panel (d) presents the data for the 1-digit occupation category of "administration and customer service" (ssyk code 4), which has the fourth highest share of WFH vacancies. Combined, these four occupation groups account for around 64% of the job ads and around 89% of the WFH job ads. Only vacancies that had at least one view in that time period are included.

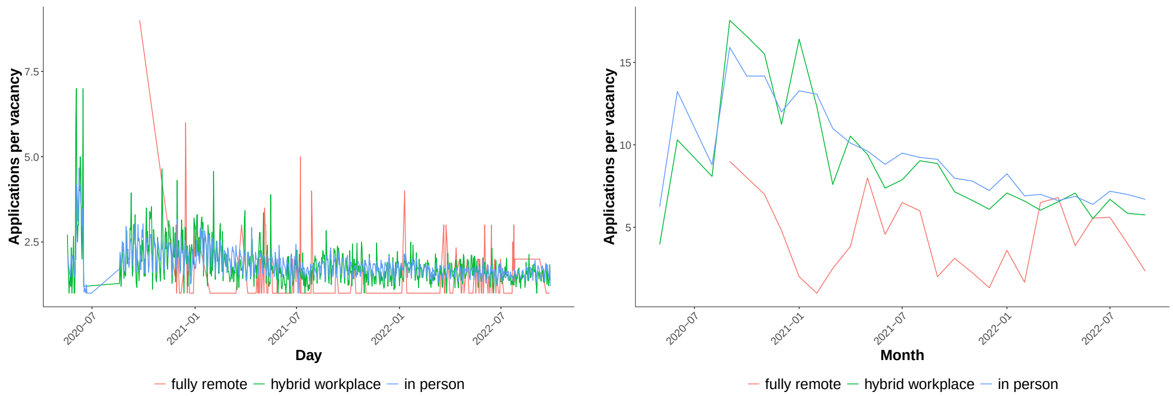
Figure C.11: Applications per vacancy by WFH type (Monthly)



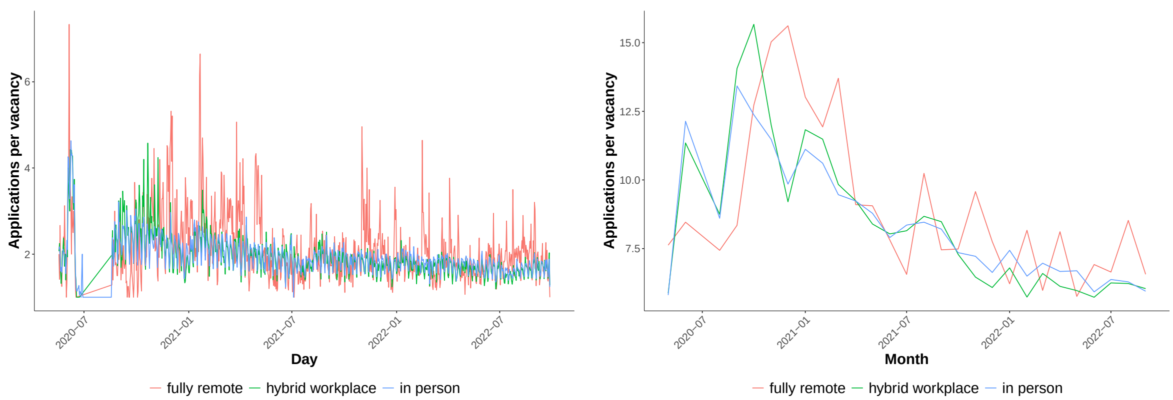
Notes: Presents average number of applications per vacancy for each month by WFH type. Only vacancies that had at least one application in that time period are included. The analogous figure but plotted at the daily level can be found as Figure **??**.

Figure C.12: Applications per vacancy by WFH type and occupation (Daily and Monthly)

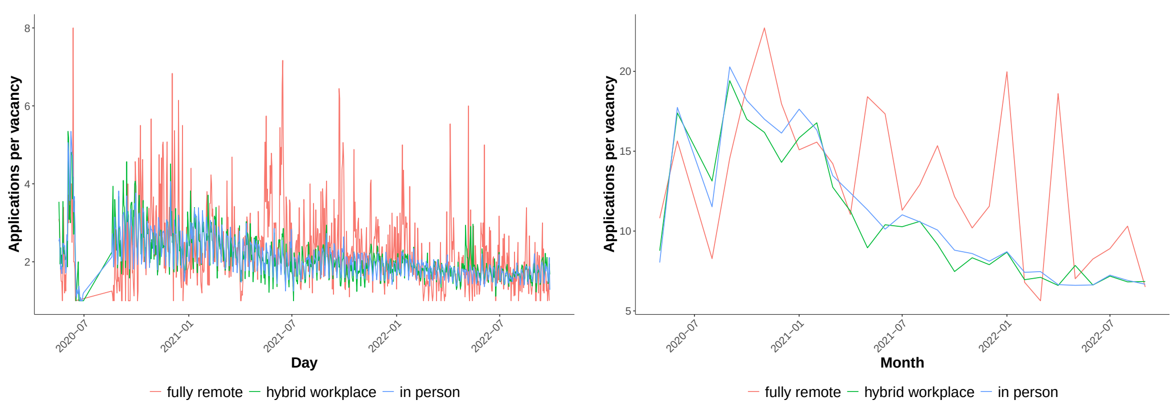
Occupation - Manager



Occupation - Requires Advanced Higher Education



Occupation - Requires Higher Education



Occupation - Administration and Customer Service

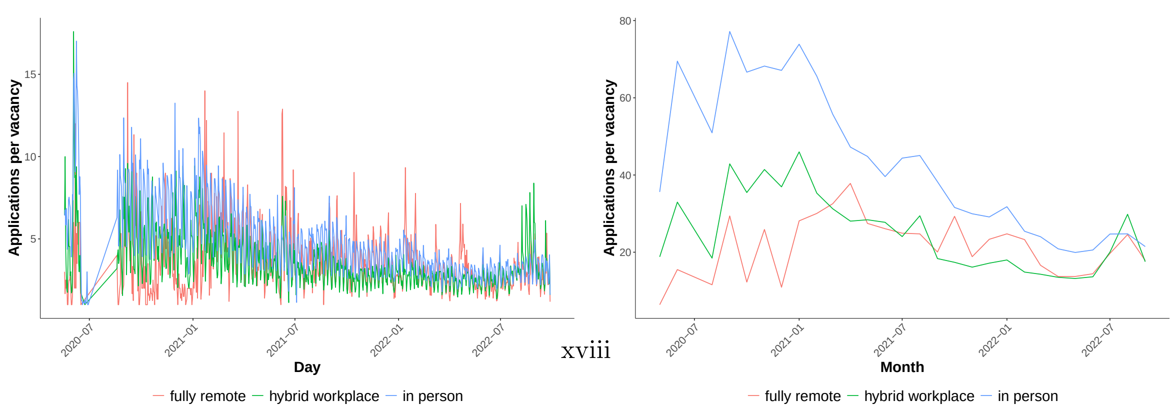
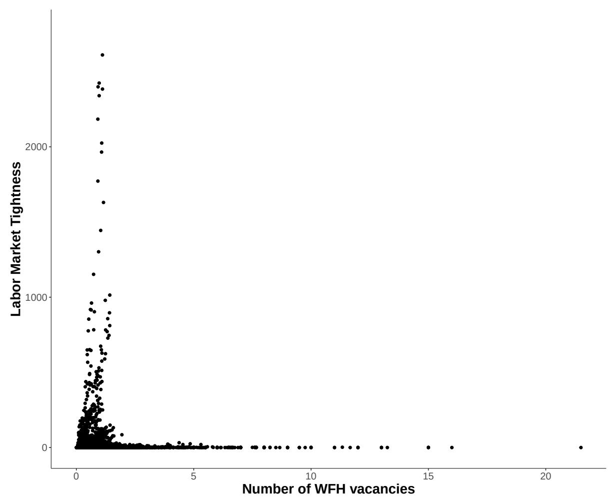
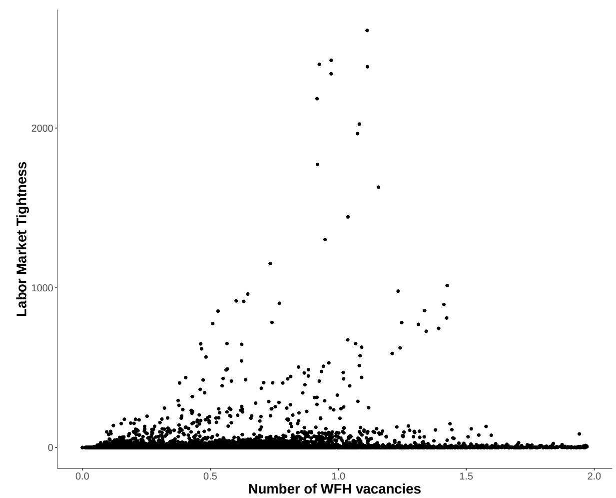


Figure C.13: Correlations between labor market tightness and the number of WFH vacancies

(a) All observations



(b) Truncated (LM tightness < 2)



Notes: These figures are the full scatterplots that relate to Figure 4. Each point represents a local labor market (defined as a commuting zone x 1 digit occupation) in a specific month. Data consists of every labor market for every month (May 2020–September 2022) that has at least one applicant in that month. Panel (a) shows the figure for all data points. Panel (b) removes some outliers (717 observations removed) by restricting it to only observations with a labor market tightness less than 2. $N = 16,724$ in Panel (a) and $N = 16,007$ in Panel (b).