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

Adam Gill[1]

[1]*Department of Economics, Uppsala University*

August 2025

Abstract

Geographic mismatch in the labor market is a major concern for job seekers, firms, and policy makers as it leads to sub-optimal matching between job seekers and open positions. One potential remedy to this problem is increasing the number of positions that allow work from home. In this paper, I explore the extent to which working from home can help alleviate this mismatch by exploring the increased access to labor markets that firms receive if they signal work from home in their job ads using a fixed-effects framework. I find that work-from-home job ads get better access to labor markets through increased applications that come primarily from job seekers that are more geographically distant. These effects are even more prominent for workplaces in non-urban areas. These job ads that signal work from home attract more job seekers from the lower end of the distribution, but also attract higher quality job seekers at the top, particularly if the work-from-home signal is more informative. These results indicate that offering work from home can alleviate some of the mistmatch generated by the geographic frictions in the labor market.

CLICK HERE FOR THE MOST RECENT VERSION

1 Introduction

A perennial problem that plagues firms, job seekers, and policy makers is finding good matches in the labor market. However, various labor market frictions can hamper the matching process. 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 and there are high relocation costs and frictions. These issues generally restrict firms to hiring workers in their immediate geographic vicinity, even if there are good candidates in other geographic areas that struggle to find good jobs. This geographic mismatch leads to inefficiencies in the hiring process which can generate shortages of potential workers in some areas with a glut of workers in other areas.

If the geographic constraint is binding for many firms and this spatial misallocation is pervasive, one potential solution 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 prospective 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 can working from home be used as a tool to alleviate geographic frictions and spatial mismatch as well as to broaden the labor market access of firms. 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 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 mini, 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. Combining this WFH data with unique job ad and search behavior data, novel methods for measuring workplace preferences and worker quality from search behavior, and different reduced-form methods, I am able to generate quantitative estimates of the effect of WFH signaling in job ads on labor market access.

For my empirical analysis, 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 "applications" a vacancy gets, which is proxied for by using the number of times job seekers initiate the application process for that ad, and (ii) the number of "views" a vacancy has from job seekers, which measures the amount of attention job seekers give to that vacancy. I find that, when comparing similar WFH and non-WFH job ads, WFH ads tend to receive more activity from job seekers. I estimate that WFH job ads receive about 3.9% more applications 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 and firm-level characteristics. These results are qualitatively similar, when looking at the number of views for the job ads as well. While these effects are positive and significant, they are smaller than expected, which seems to be driven by noise in the WFH signal. Job ads that provide more salient signals of WFH, for example those that offer fully remote work or those that explicitly state WFH in the job ad title, see much larger effects. For example, fully remote job ads receive about 24.0% more applications, an effect that is much larger than the overall effect. Similar patterns arise when looking at the informativeness of the signal as well; occupations in the second and third quartiles of the share of workers doing some WFH see stronger effects than those in the top or bottom quartiles.

This evidence suggests that job seekers seem to prefer WFH jobs to similar non-WFH jobs, but this additional attention could come from either job seekers outside of the individual firm's geographically-constrained local labor market, or from job seekers within that local labor market who prefer the WFH amenity. To disentangle these effects, I estimate the differential distance of applicants' "preferred workplace location" (defined as the centroid of the locations for the workplaces of their in-person applications) from the location of the WFH job ads and non-WFH job ads. I find that, on average, the mean distance of an applicant's preferred commuting location to the WFH job ads is 36.7% further away than the distance from similar in-person vacancies. This translates to about 14.6 kilometers further away as the crow flies. This effect is consistent when using different definitions of the distance from job ads and workplace location preference. Job ads that signal WFH thus attract workers from further away suggesting that offering WFH does increase the geographic labor market access for firms and that it has the potential to reduce geographic mismatch in the labor market.

In order for offering WFH to be useful in reducing geographic mismatch, it not only must provide access to job seekers from more geographically distant places, but this additional access must lead to better matches. In order to investigate this, I look at the difference in quality of applicants to WFH job ads and similar in-person job ads using the leave-one-out of the firm productivity for the other jobs an applicant applied. I find that while the quality of applicants on average decreases, there is an increase in quality of the top applicant and the average of applicants in the top quartile. This suggests that signaling WFH increases the distribution of applicants by increasing applicants from both tails of the quality distribution. However, since firms generally are only hiring a limited number of positions, they benefit overall since they receive better top-end applicants which should lead to better matches. These effects are even stronger for fully remote signals and job ads that mention WFH in the title, which suggests that the salience of the signal is important in both the quantity and quality dimensions.

As a further check on the extent of geographic mistmatch WFH can help alleviate, I rerun the analysis of my main results on the subset of workplaces that have more isolated labor markets, defined as being located in more rural areas. Since these workplaces are geographically more distant and generally have access to a smaller pool of workers, these workplaces are expected to benefit even more from offering WFH if there are geographic frictions on hiring. My results suggest that this is the case. WFH job ads from these non-urban workplaces have a larger relative change in the number of applicants and the geographic distance of those applicants when compared to the effects from the entire sample of workplaces. These job ads may also see a larger increase in top-end quality, however these estimations are noisy so it is harder to draw strong conclusions. Even under the assumption that there are no quality effects, WFH signaling in job ads seems to be even more beneficial for non-urban workplaces which suggests reduced geographic mistmatch when offering this amenity.

All of these results suggest that signaling WFH can be beneficial to firms, so they could potentially use it to strategically improve their hiring. To test this, I look at the extent to which firms signal WFH when they face tighter labor markets. Here, I leverage the application and vacancy data 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. I find that local labor markets that were tighter in the previous period 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.

This paper contributes to several strands of literature. It adds insights into the the WFH literature by documenting the effects of signaling WFH on search behavior and firm incentives for offering this amenity, which has previously not been explored. Specifically, 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. This paper also contributes to the literature on firm hiring process by exploring the strategic nature of WFH in alleviating hiring difficulties and the potential unilateral advantage that offering WFH can have for firms in terms of the quantity and quality of potential hires. Finally, this paper contributes to the literature on labor market access and mismatch of job seekers and firms. This is, to the best of my knowledge, the first paper to document and estimate the effects of offering WFH on the change in labor market access and the first to estimate the potential effect WFH has on alleviating geographic mismatch in worker-firm sorting. Along with these specific analysis, this paper also provides more general insights into labor supply and search behavior effects associated with offering non-wage amenities as well as labor demand considerations of firms when facing difficult labor market conditions.

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 discusses the data used, the data collection process, and provides descriptive evidence. Section 4 outlines the empirical strategy employed. Section 5 discusses the attractiveness of WFH job ads relative to other job ads in terms of the quantity effect of offering WFH. Section 6 looks at the change in geographic access to labor markets access and discusses the geographic dispersion. Section 7 looks at the changes in the pool of applicants that apply, with a focus on the change in the quality distribution as well as changes in demographic characteristics. Section 8 discusses and analyzes the quantity, quality, and geographic effects for the subset of workplaces with more isolated labor markets. Section 9 discusses firm utilization of WFH for strategic purposes by looking at the effect of labor market tightness on WFH offering. Finally, Section 10 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 (Barrero, Bloom, and Davis 2021b; 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 (Barrero, Bloom, and 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

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

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.3). 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 and determinants of 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 Barrero, Bloom, and Davis 2021b, which is focused on workers in the US. In that 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, Barrero, Bloom, and Davis 2021b 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, Barrero, Bloom, and Davis (2021a) 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 9. 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 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.

3.1 Swedish job ads

In order to investigate the relationship between WFH offering and a firm's labor market access, I need a measure of WFH at the job 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 of the job's workplace, and the text describing the job duties and amenities.

3.2 WFH classification

One notable absence in the job ads data is there is no direct 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-mini large language model.[2]

This 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-mini model (through OpenAI's API) to categorize the vacancies as fully remote WFH, hybrid WFH, in person, "traveling" positions[3] or "WFH NA" (cannot be determined). 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 then 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 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 phrase list left me with 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).[4] 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-mini 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,

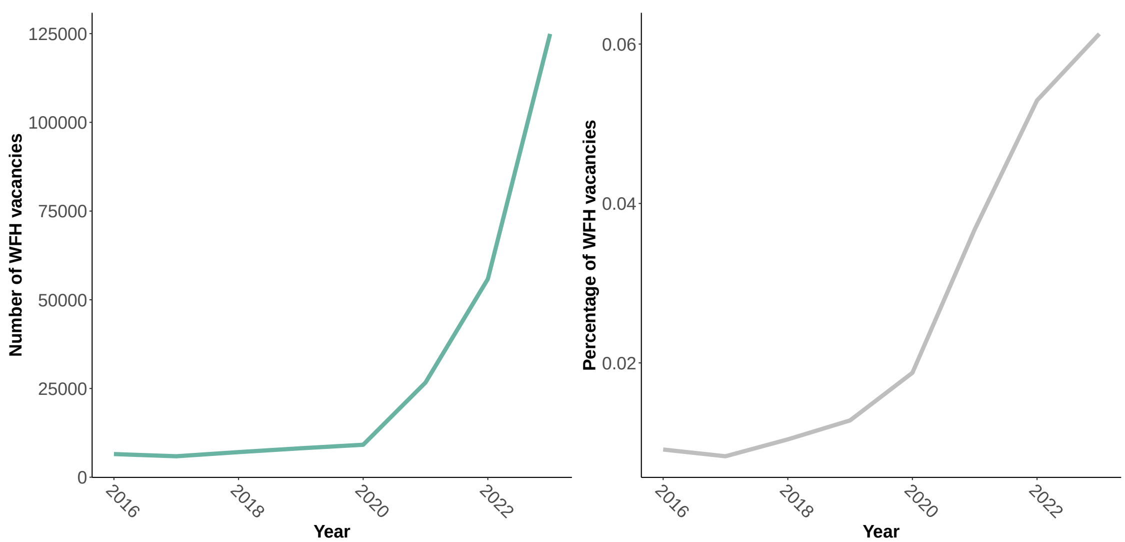
2. I use the main text of the job ad as the input to GPT-4-mini model. For an example of the job ad, see Figure A.2.

3. *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. An example of a "travelling position" would be a door-to.door salesperson.

4. 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.

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.4) while we see a dip in the percentage of fully remote vacancies in the post-pandemic period (Figure C.5). This dip is in line with the evidence of the greater popularity of hybrid structure of WFH tha fully remote work in the post-pandemic period (Barrero, Bloom, and Davis 2023). 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.6). This is true for all years and the relative shares remain fairly consistent over the years. The exception is that there is a 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.

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.4 and C.5, respectively.

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 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.7). 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 uptake 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 other job ads. To do this, I use the text of all the vacancies in this time period, separated by group, and break the text into tokens. I then subset the tokens to the 200 most frequent words for each groups and I filter out the words from the "WFH" list that also appear in 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.8). 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").

To investigate the relationships with these potential confounders more thoroughly, I use data on

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.8.

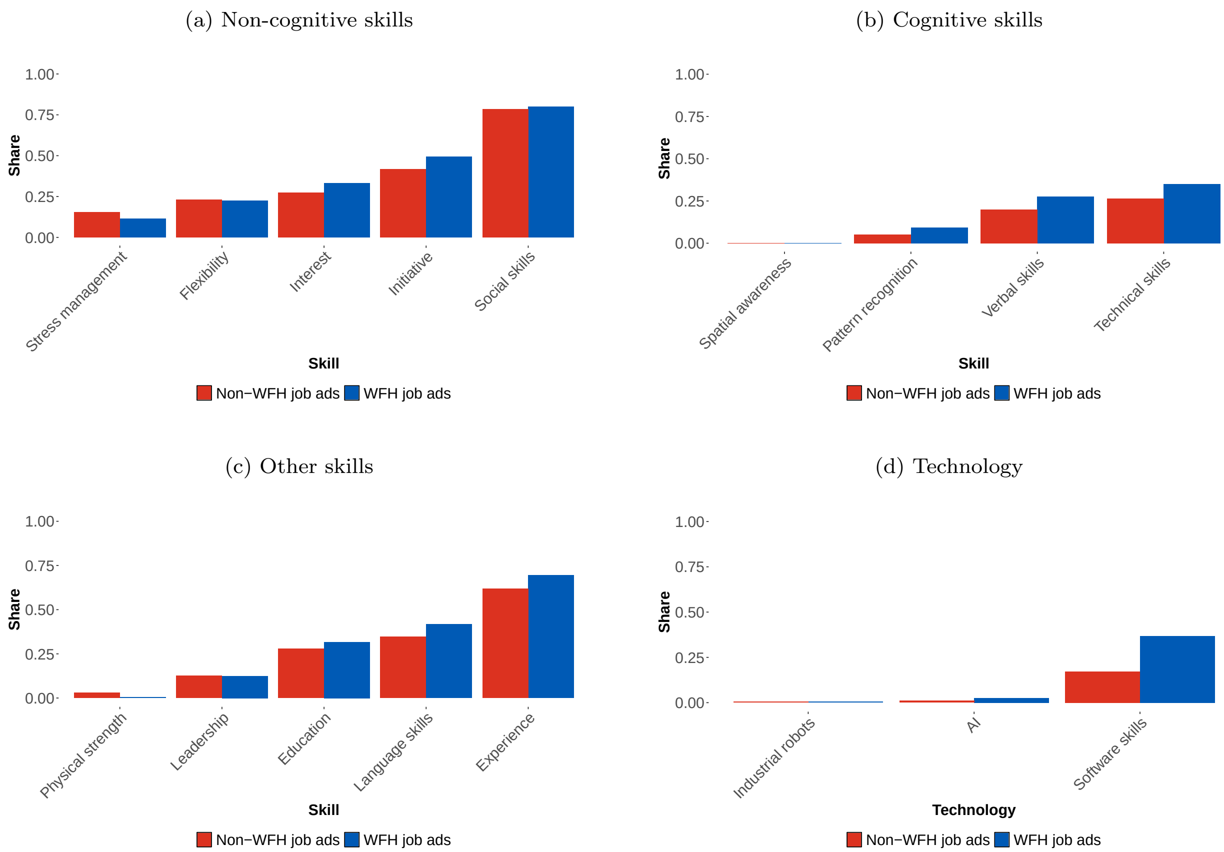
the skills and the technologies mentioned in the job ads.[5] Using the job ads from 2018-2022, I compare the raw frequencies of appearance of these skills and technologies by WFH and non-WFH job ads. The share of WFH and non-WFH job ads that mention each skill or technology is illustrated in Figure 3 and differences and the p-values derived from testing the statistical significance of these differences using a t-test are found in Table A.3.

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. Even so, I control for measures of these skills and technologies in my main analyses.

I also use an alternative classification of WFH where I only define job ads that explicitly state WFH in the job heading (which appears on the search page) as treated. For this classification, I

5. The skills data and the technology data are both extracted using a similar method to my WFH classification.

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



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 A.3. The differences in shares broken down by year is found in Figure C.9.

use a dictionary method where I tag all job ads that mention one of the following eleven key words: "distansarbete", "hemarbete", "jobba hemifrån", "fjärrarbete", "arbeta på distans", "telependling", "hemmajobb", "arbeta hemifrån", "work from home", "remote work", and "telecomut." There are 3,128 ads that explicitly state a WFH key word in job ad headline. This sample is small, but the job ads in this sample have a very strong signal that they offer WFH which is evident even before reading the job ad. Defining an alternative treatment this way, I can test the importance of the salience of the WFH signal in affecting search patterns.

3.3 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 compiled 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 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.

Prior to the job ad page with the description of the position, job seekers are given limited information about the job apart from basic characteristic like the job title, location, and the employer name. 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 an ad that they would be interested in. Although there is no information about WFH at the "view" stage and job seekers cannot filter job ads by WFH explicitly, they can search for WFH-related terms in the search bar. This allows the job seeker to find WFH-signaling positions at the point when they click to "view" an ad even without the explicit information about WFH on the page. This could explain why job seekers view WFH job ads more often as well as apply more often.

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.

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.2).

7. Screenshots of the job portal pages at the "view" and "apply" margins can be found in Figures A.1 and A.2, respectively.

3.4 Swedish registry data

These vacancies, applications, and clicks are then matched to Swedish registry data, which has firm information on wages, individual demographic information, geographic information, and firm information. The majority of the job ads are matched to firm data as the firm IDs in the job ads are linked to the IDs in the registry data. This provides information on firm wages, firm industry, firm size (defined by number of employees), and legal status of the firm. The "legal status" of the firm captures the type of entity the firm is formally registered as at the Swedish Tax Authority, which is used to determine taxation and legal liabilities among other things, and include designations like such as limited liability companies (LLC), non-profits, and natural individuals (there are 24 designations in total). Not all firms, however, have job ads connected to them during this time period. In total, 4.7% of firms are matched to at least one vacancy in this period and 72.6% of vacancies are matched to a firm in the data. The distribution of the firms by legal status is found in Figure C.2, where Panel (a) presents the distribution for firms connected to at least one job ad and Panel (b) the distribution linked to no job ad. These distributions match general expectations. The vast majority of the firms connected to job ads are LLCs and the majority of the non-connected firms are natural persons (which are non-hiring firms).

I also have demographic data from the registries that can be matched to job seekers that includes data on age, immigration status (defined by having moved to Sweden from abroad), gender, and education level. However, the search data is identified by an anonymous device ID, so I can only match this data to the sample of unemployed job seekers. This is because the unemployed job seekers need to log into the unemployment agency's website each month in order to be eligible for the unemployment benefits. That data is anonymized using the same device ID code, so all the unemployed workers that search and log in to the unemployment agency's website using the same device can be matched to this demographics data.

Finally, I have geographic data at the neighborhood level for both workplaces and individuals. The "DeSO" is a statistical area defined by Statistics Sweden that is similar to a neighborhood. The DeSO designations were created in 2018, but it has been applied retroactively and are periodically updated. In this paper, I use the original designations from 2018.[8] The DeSOs are constructed based on geographic areas with the same population, so all DeSOs in our data have roughly the same number of residents, but can vary in size of the area and in the number of individuals working in the area. The sizes can get particularly large in more rural areas. There are 5,984 DeSOs defined in 2018, each classified into one of three categories. Category "A" DeSOs are in rural areas (18.0%), category "B" DeSOs are population-concentrated areas but outside of major municipality areas (9.7%), and category"C" DeSOs are central locations within municipalities (72.3%). When I discuss the job ads from the non-urban workplaces, I am referring the job ads from workplaces in categories "A" and "B." These DeSOs are then mapped to the individuals and job ads data. The individuals can be directly mapped using the internal anonymized key. For the job ads, the DeSOs are mapped using the

8. There is an updated definition of the DeSOs from 2025, but those are not used in this paper.

coordinates for the location of the job ad compared to the polygon borders of the DeSOs assigning the job ad to the DeSO the coordinates are in.

3.5 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 or measurement error bias caused by occupations with little-to-no chance of offering WFH. I calculate this variable in multiple ways.

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.[9] 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. This results in some individuals being counted for multiple ssyk-12 occupations. [10] 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. I also run an alternative specification classifying occupations greater than the median (45.0%) as "high WFH" to check the sensitivity of this threshold.

In an alternative version of the classification, I subset the data to only the four 1-digit occupation codes that have the highest average WFH across the time period. These four 1-digit ssyk occupation classifications (in order of the share of job ads with WFH vacancies) are "requires higher education" (ssyk 3), "requires advanced higher education" (ssyk 2), "managers" (ssyk 1), and "administration and customer service" (ssyk 4). Combined, these four classifications account for about 64% of the the total job ads and about 89% of all the WFH job ads. This measuring using the 1-digit ssyk-12 occupations is also positively and significantly correlated with the LFS measures (Pearson's $\rho = 0.45$, p-value < 0.001, for subsetting at 75th percentile and Pearson's $\rho = 0.67$, p-value < 0.001, for subsetting at the median). Similarly, subsetting to 2021, the percentage of workers that can WFH at the 3-

9. 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.

10. 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.

digit occupation level from the classification generated by the GPT method in the vacancies is also positively and significantly correlated with the percentage of workers that report WFH in that LFS survey (Pearson's $\rho = 0.67$, p-value < 0.001). This suggests that these measures of WFH potential are capturing similar occupations thus showing some persistence in the WFH-ability of occupations even using different measurements. However, they are not perfectly correlated, so I still use the alternative measures as robustness checks to ensure hat the results from my preferred measure is not being driven by that specific selection of occupations.

4 Methodology

In order to look at the effect of WFH on job attractiveness, geographic dispersion, and other outcome variables, I employ a mutli-dimensional fixed effects model. In this model, I regress my outcomes on a binary indicator for whether a job ad explicitly signals that it offers WFH. To do this, I run the 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 this main specification, I also include fixed effects for the commuting-zone specific time trend as well as the 4-digit-occupation specific time trend. I also include vacancy-level and firm-level covariates to ensure I am comparing similar job ads. For the vacancy-level covariates, I control 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), posted vacancy duration (the difference in days between the first day a vacancy was published and the last day a vacancy was published), the length of the vacancy description (number of characters used), and binary measures for if the various skills/technology[11] are mentioned in the job ad text. For the firm-level covariates, I include controls for firm size (number of employees connected to that firm in that year), industry (defined at the five-digit level using the Swedish SNI classification), and the legal status of the firm (defined as the type of business the firm is registered). This fixed effects specification is formalized in equation 1.

$$Outcome_{i,f,z,o,t} = \beta_0 + \beta_1 \mathbf{1}[\text{WFH=1}]_i + \boldsymbol{\gamma}\mathbf{X}_i + \boldsymbol{\alpha}\mathbf{Z}_f + \theta_{o,z} + \theta_{o,t} + \theta_{z,t} + \epsilon_{i,f,z,o,t} \tag{1}$$

where i indexes the vacancy, f indexes the firm, 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 and $\mathbf{Z}_f$ is the vector of firm-level covariates. $\mathbf{1}[WFH = 1]_i$ is the binary treatment that takes a value of 1 if the vacancy signals that it has WFH. 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 a similar in-person vacancy.

For most of my analyses, I estimate the baseline relationship and the relationship within occupations and time along with this main regression. The baseline relationships are estimated using an OLS

11. The skills/technology measures are discussed in Section 3.2 (see, e.g. Figure 3).

regression without any controls or fixed effects. The within-occupation relationship is estimated using just four-digit occupation fixed effects and time fixed effects. Finally, to further remove any potential unobserved confounders, I run an additional regression using a similar specification to the main analysis except I drop the firm-level characteristics and instead include firm fixed effects. This regression is formalized in equation 2.

$$job\_attractiveness_{i,f,z,o,t} = \beta_0 + \beta_1 \mathbf{1}[\text{WFH=1}]_i + \boldsymbol{\gamma}\mathbf{X}_i + \theta_{o,z} + \theta_{o,t} + \theta_{z,t} + \theta_f + \epsilon_{i,f,z,o,t} \tag{2}$$

This specification uses very specific variation – differences in in-person and WFH vacancies within the same firm, occupation, and commuting zone. This limited variation thus indicates that a specific group of job ads are likely driving the results from this specification. Because of this, I do not use the firm fixed effects model as my main specification, but it provides useful robustness checks on the influence of potential unobserved confounders when comparing job ads from different firms. The results from my main regression and my firm-fixed-effects regression are generally similar, suggesting that there is limited unobserved confounding from the across-firm comparison.

5 Job Ad Attractiveness

The first-order question connected to 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 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 Main Results

To investigate the effect of WFH on job ad attractiveness, I estimate the fixed effects specification in equation 1 as my main analysis. Here, the coefficient of interest is β_1, which estimates the differential job attractiveness of the position for WFH vacancies compared to similar in-person job ads. I estimate this specification for two different outcome variables: (i) the number of applications a vacancy receives, proxied for by number of initiated applications and (ii) the amount of attention a vacancy receives, proxied for by views. For my main analysis, I estimate both of these outcomes in logs. 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. 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. In addition, I run an alternative regression using the same general specification to investigate the extensive margin of applications. Here the outcome variable is the probability that a job ad receives at least one application. For all of these outcome variables, I also estimate the baseline specification, the within occupation and time specification, and the firm fixed effects specification.

The main results analyzing the effect of WFH vacancies on job attractiveness can be found in Table 1 for applications and Table 2 for attention. The baseline relationship between applications and attention that a job ad receives and whether that job ad offers WFH shows a negative relationship (Column (1) of Table 1 and Column (1) of Table 2, respectively). This matches with the aggregate trends where 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.11). These baseline results, however, mask a lot of heterogeneity across occupations. Since WFH is not feasible for all occupations and WFH job ads are concentrated among certain occupations,[12] 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 9.6% more applications and 19.5% more views (Column (2) of Table 1 and Column (2) of Table 2, respectively). This suggests that the initial negative relationships that were found are generated primarily from differential job ad interactions across occupations as opposed to differential preference for WFH job ads.

These basic fixed effect results, however, are still capturing some omitted variable bias as other spatial, firm, and vacancy characteristics may be driving some of the effect. Thus, the main results I focus on are those from the specification outlined in equation 1. In this specification, I control for vacancy and firm characteristics as well as using more specific fixed effects to ensure that the estimates are between job ads that are very similar. These results can be found in Column (3) of Table 1 for applications and Column (3) of Table 2 for views. I find 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, 3.9% more applications when compared with similar in-person vacancies. This equates to 1.1 more applications on average for WFH job ads when compared to the sample mean of 28.78 applications. I find even larger effects when I look at the attention a job ad receives from job seekers. Here, I find that WFH job ads receive, on average, 9.9% more views than similar in-person vacancies. That corresponds to 21.7 more views for WFH job ads when compared to the sample mean of 217.54 views. These effects suggest there is at least some preference for job ads that explicitly signal WFH compared to similar job ads that do not. I find similar effects as well when

12. Figure C.12 (views) and Figure C.15 (applications) show some of the heterogeneity that exists just across coarse occupation categories.

Table 1: WFH and applications (using log total applications)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.344^{***}	0.096^{***}	0.039^{**}	0.028^{***}
	(0.044)	(0.024)	(0.017)	(0.010)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (# of applications)	28.78	28.78	28.78	28.78
N	1,531,314	1,531,314	1,060,687	1,428,685

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. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, 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 which provide the average number of applications for the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I look at the within-firm variation, with estimated effects of 2.8% more applications and 6.9% more views, on average (Column (4) of Table 1 and Column (4) of Table 2, respectively). These results suggest that job ads that signal WFH have access to a broader labor market through more views and applications, however, this effect is not especially large.

Breaking these main results down by year, I find an interesting pattern (Figure C.16). For applications, there is no effect for WFH job ads in 2020, but increasingly large effects in 2021 and 2022. This pattern likely occurred due to the normilization of WFH. Since WFH became more prevalent and less stigmatized (Barrero, Bloom, and Davis 2021b) after the pandemic, job seekers became more willing to apply to WFH jobs which explains the jump in effect size for 2021 and 2022. The null effects for 2020 likely comes from WFH being so ubiquitous during the peak of the pandemic, making the signal to offer WFH uninformative. The importance of the informativeness of the WFH signal seems to play a large role in job seekers' responses, as documented in Section 5.2. Looking at the attention that job ads received, I find no effect in 2019, but positive effects in 2020, 2021, and 2022 that remain consistent. This pattern shows that the COVID-19 pandemic really did shift preferences for WFH (like the survey evidence suggests) with large increases in the viewing of WFH job ads after the onset of the pandemic. Even including the data for 2018 views, we see a consistent, positive effect only starting with the onset of the COVID pandemic (Figure C.17).

Table 2: WFH and job ad attention (using log total views)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.231^{***}	0.195^{***}	0.099^{***}	0.069^{***}
	(0.067)	(0.033)	(0.021)	(0.013)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (# of views)	217.54	217.54	217.54	217.54
N	2,377,730	2,377,730	1,793,449	2,236,208

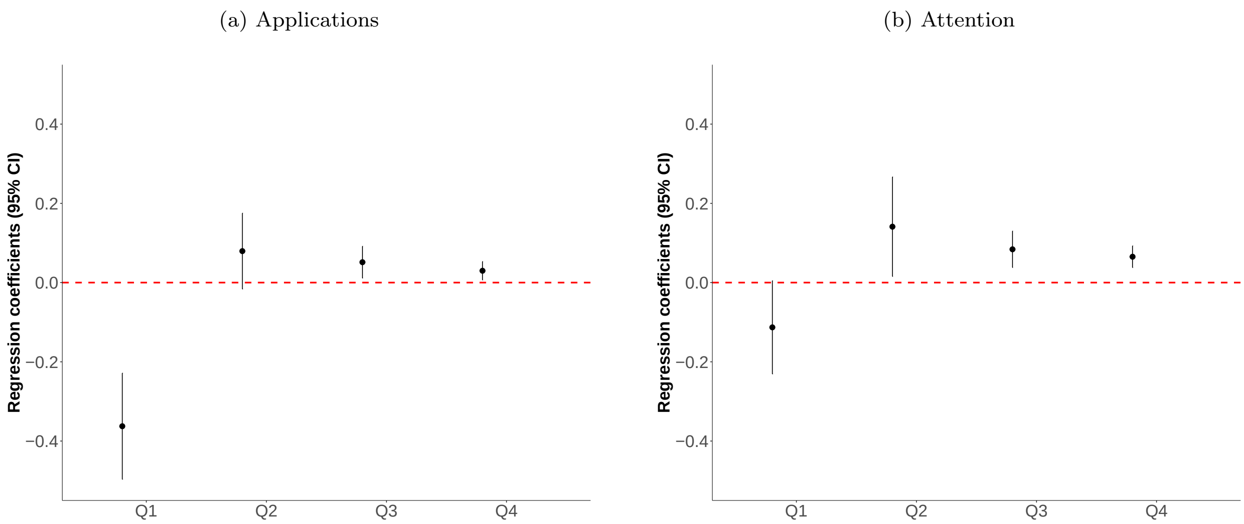
Note:This table presents the results of the main regression estimates for log job ad views on WFH offering using the log number of views. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. 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 which provide the average number of views for the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Heterogeneity

These results may mask potential occupational heterogeneity since WFH signaling likely has a non-linear relationship with respect to the likelihood that an occupation can offer WFH. Job ads that cannot or where it is very difficult to offer WFH should see small (or even negative) effects from offering WFH as it could be seen as an empty gesture or a negative signal. Similarly, for occupations where WFH is very common and there is a high potential for WFH, explicitly signaling WFH may not offer any additional information to job seekers as they may already assume that all similar jobs have a WFH option. This would suggest that higher WFH potential occupations may also see more muted effects. Where WFH signaling could be most informative is in occupations with a lot of heterogeneity in WFH offering and where job seekers may expect some, but not all, jobs to offer WFH. Therefore, the largest effects are expected to come from occupations in the middle of the WFH potential distributions.

This relationship is exactly what I find for both applications and attention when I re-run my main regressions by quartile of WFH share within the 2021 Swedish LFS. The results for these quartile regressions can be found in Figure 4 with Panel (a) the regressions for applications and Panel (b) the regressions for attention. Quartile 4 (Q4) represents the occupations with the highest share of WFH while Quartile 1 (Q1) represents the occupations with the lowest share. Looking at applications (panel (a)), I find positive and significant 3.0% relative increase in applications when looking at occupations with the highest WFH shares. However, this is a smaller effect than what I find for both the third and second quartiles of WFH shares. For quartile 3, I find a significant 5.1% relative increase in

Figure 4: Coefficient estimates by quartile of WFH share (LFS)



Notes: This figure plots the estimated coefficients for the effect of offering WFH on applications in Panel (a) and attention, proxied for by views, in Panel (b). The x-axis corresponds to the quartile of "WFH likelihood" by three-digit occupation. The quartiles are determined by ranking the occupation by the share of workers reporting that they work from home at least some of the time in the 2021 Swedish Labour Force Survey (LFS). The regression coefficients are estimated separately for each quartile. The corresponding results in table form can be found in Table B.9 for applications and Table B.10 for attention.

applications. The estimates for quartile 2 are less precise, but the magnitudes are even larger, with a 7.9% relative increase. The same pattern holds when looking at attention (ppanel (b)) with larger and significant effects for both quartile 3 (8.4%) and quartile 2 (14.1%) compared to quartile 4 (6.5%). If we look at quartile 1, we see the non-linearity in the relationship with large *negative* effects for signaling WFH in the set of occupations with the lowest share of WFH for both applications (−36.3%) and attention (−11.3%). Combined, these results suggest that the signal that a job offers WFH is strongest in occupations where WFH is possible, but less common and thus less certain. However, signaling WFH for occupations where it is very unlikely to have WFH may have the reverse effect as it may be perceived as a negative signal.

If we dig into the heterogeneity of WFH type, the main results become even more stark for fully remote job ads. For this analysis, I run the same analysis as before, but I drop all job ads that are classified as "hybrid" WFH. This allows me to compare fully remote job ads with similar in person job ads. The results for applications using this analysis can be found in Table 3.

Fully remote job ads seem to attract even more applications and attention compared to the results for the combined WFH categorization (which is dominated by hybrid job ads). Fully remote job ads are estimated to receive 24.0% more applications compared to similar in-person job ads (Column (3)). This pattern holds when looking at attention as well where fully remote job ads are execpted to receive 44.5% more views than similar in-person job ads (Column (3) of Table B.6). This corresponds to about 7 more applications and about 98 more views when these estimates are compared to the sample means.

Overall, 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

Table 3: Applications for fully remote job ads

	Fully remote job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	0.011	0.365***	0.240***	0.332***
	(0.058)	(0.124)	(0.084)	(0.055)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	29.2	29.2	29.2	29.2
N	1,480,275	1,480,275	1,028,283	1,379,066

Note: This table presents the results of the main regression estimates for log job ad applications on whether a job ad signals a fully remote position. I present the estimates for the entire sample of job ads. I present the estimates for the entire sample of job ads. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. The data consists of job ads in all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no text written (text length = 0), and job ads classified as "hybrid WFH" are dropped from all samples. Sample means are presented which provide the average number of views for the sample. Standard Errors are clustered at the local labor market level. The analogous table for attention can be found as Table B.6.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 Geographic Distribution of Job Seekers

In the previous section, I present evidence that WFH vacancies seem to attract more attention from job seekers when compared to similar in-person vacancies. However, there are two potential channels that this additional attention can arise from. First, WFH relaxes the geographic constraints on the job ads by allowing workers to live further from their workplaces due to the reduced frequency of commuting. This allows job seekers to look for jobs that are located further away from where they would search for in-person jobs. This gives firms access to workers beyond the usual geographic limits of their location, which would increase the number of potential viewers and applicants for the position. Second, WFH also offers an amenity value that job seekers often want, which would increase the value of the vacancy for job seekers even within the same local labor market that the job ad would geographically have access to if it was in person. In this section, I investigate the potential change in the geographic distance of job seekers for WFH vacancies compared in-person job ads and disentangle this effect from the WFH amenity effect.

6.1 Measurement

For the majority of the job seekers in my data, I do not have location data on where they live. Instead, I use the locations of the in-person job ads that job seekers apply to estimate the location. Using the job ads in this way, I get a revealed-preferences measure of the approximate area where that job seeker would like to work when they have to work in-person (commuting approximately 5 days per week). I likely have a location closer to the actual preferences than where the individual lives, particularly if the person does not want to work and live in the same area. This could be particularly useful for job seekers living in areas such as suburbs, where their work preference could be in the city center as opposed to where they live. To create the "workplace location preference" of the individual job seeker, I use the coordinates of all of the job ads classified as "in person" that the job seeker applies to and create a polygon of them. I then take the centroid of the those coordinates and assign that as the workplace location preference for that individual job seeker. To improve the measure of these workplace preferences, I restrict the sample to job seekers who applied to at least two in-person vacancies in my sample.

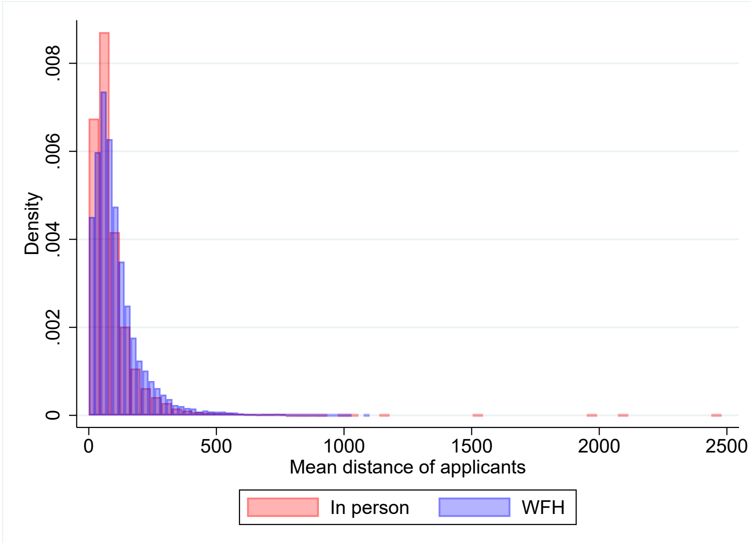
I then use the coordinates for the all the job ads (both in-person and WFH) and calculate the distances between them and the workplace location preferences (individual centroids) for all the applicants to that job ad and aggregate them to different vacancy-level measures – mean distance, maximum distance, and mean distance of those in or above the 75$^{\text{th}}$ percentile of distance for that job ad (also in logs). The overlapping distributions of mean distance for in person and WFH job ads can be seen in Figure 5.[13]

6.2 Results

To estimate the effects of WFH on the geographic distribution of job applicants, I use the fixed effects model outlined in equation 1 as my main analysis. The coefficient of interest is β_1 which estimates the differential level of the geographic dispersion that a WFH vacancy gets relative to an in-person vacancy. I also estimate the baseline specification, within occupation and time specification, and the firm-fixed-effects specification. To estimate "geographic dispersion," I use three different measures of distance that I define in Section 6.1. For my main results, I use the average distance from the job ad of the applicants workplace location preferences (in log distance). For alternative analyses, I use the maximum distance away from the job-ad location that the job seekers' workplace preference is located as well as the mean distance of those in the 75$^{\text{th}}$ percentile of distance for that job add. Due to the large right tail of the distribution for mean distance (Figure 5), I restrict the geographic measure to those applicants that are within 20km of the in-person job ads.

13. Analogous figures for maximum distance and mean distance of those in or above the 75$^{\text{th}}$ percentile of distance for that job ad can be found in Figure C.18.

Figure 5: Distributions of mean distances of applicants by whether the job ad offers WFH



Notes: This figure plots the distributions of the mean distances of applicants' "workplace location preferences" from the job ads locations. The distribution for in-person vacancies is plotted in red and the distribution of WFH vacancies is plotted in blue.

The results for the mean geographic dispersion of applicants can be found in Table 4. As expected from the distributions of the geographic dispersion, I find a positive and significant effect of WFH signaling on the mean distance of the applicants' in-person workplace commuting preference. This effect is consistent in significance and magnitude across all specifications. Looking at the main analysis (Column (3)), I find that job ads that signal WFH receive applications from job seekers whose preferred workplace location is 36.7% further from the WFH job ad than similar in person job ads). When compared to the sample mean (39.8 km), that is an average distance of approximately 14.6 km further away. This effect is also understated compared to actual commuting distance since it only measures the straight-line distance and not the actual travel routes. Running the main analysis on various thresholds from a 40 km restriction to no restriction at all estimates smaller, but still large and positive percentage effects for all thresholds (Table B.13). Interestingly, comparing the percentage change effects to the sample means (by multiplying them together) for each of these thresholds gives very similar relative distance effects in levels. All of these thresholds estimate an average effect of 14.4 to 14.9 km change, suggesting that the effect of signaling WFH on these distances is independent of the skewness of the distribution of distances.

These results remain consistent when I use alternative definitions of geographic dispersion as well. I estimate the same specifications using the distance of the furthest away applicant (maximum distance) and the mean of those applicants in the upper quartile of distance within a job ad's applicant pool in Table B.14 and Table B.15, respectively. Looking at the main specification (Column (3) of B.14), I find that the distance of the furthest away applicant is 30.9% greater for WFH vacancies than similar in person vacancies, which equates to 44.9 km when compared to the sample mean (145.3 km). When looking at the mean of the upper quartile of distances (Column (3) of Table B.15), I find that the

Table 4: WFH and geographic dispersion of applicants (using log mean distance)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	0.209***	0.366***	0.367***	0.417***
	(0.028)	(0.019)	(0.019)	(0.019)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (km)	39.8	39.8	39.8	39.8
N	1,326,144	1,326,144	927,677	1,241,048

Note: This table presents the results of the main regression estimates for the logged mean distance of applicants' "workplace location preference" and the location of the job ad on WFH offering. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0), and vacancies where the coordinates were wrong or could not be correctly matched are dropped from all samples. Job seekers with a minimum distance between their preferred location and closest job ad > 20km are also dropped from the sample (however, the results are robust to using alternative thresholds - see Table B.13). Sample means are presented as the mean average distance of job seeker "workplace location preference" and job ad location of the sample (in kilometers). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

average distance is 34.0% greater for WFH vacancies than similar in person vacancies, which equates to 27.1 km when compared to the sample mean (79.8 km).

These results suggest that there is a sizeable geographic component at play when firms explicitly signal WFH in their job ads. Job seekers seem more willing to apply to jobs further from their preferred workplace location if those jobs offer WFH. One motivation for this is job seekers are willing to commute further if they have to commute less often. If job seekers are applying from further away to WFH job ads, then offering WFH could be one mechanism for firms to use to access otherwise inaccessible potential workers which suggests that WFH can play a role in reducing geographic mismatch between workers and firms.

6.3 Decomposing the geographic effect

The results from the previous section give us an estimated effect for the change in geographic access that offering WFH provides for firms. However, the relaxing of the geographic constraint is only one potential mechanism that could play a role in the overall increase in attention that WFH job ads receive. Job seekers within the previously constrained local labor market may also be more inclined to apply to WFH job ads over similar in-person job ads due to the amenity value of WFH. Since both of these channels are likely important components in understanding the value of WFH to job seekers, it is important to understand the relative effects of these channels. In this section, I decompose the overall effect of differential applications to WFH job ads (from Section 5) into these two mechanisms by looking at the change in applications for distant and nearby applicants.

Table 5: Effect of WFH on "close" and "far" applications

	Number of applications		Log applications	
	Far applications	Close applications	Far applications	Close applications
WFH offering	0.256***	−1.840***	0.078***	−0.188***
	(0.081)	(0.173)	(0.015)	(0.015)
Vacancy Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Local labor Market F.E.	Y	Y	Y	Y
Commuting zone × month-year F.E.	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y
Sample mean (# of applications)	5.04	10.06	5.94	10.74
N	942,784	942,784	680,962	795,231

Note: This table presents the analysis looking at the differential change in applications between WFH job ads and similar in-person job ads when subsetting to applications that are "far" (Columns (1) and (3)) and "close" (Columns (2) and (4)). "Far" applications are applications that come from job seekers where the distance between the estimated workplace preference and location of the job ad is in the top quartile of distances in the local labor market (commuting zone by four-digit occupation). "Close" applications are applications that come from job seekers where the distance between the estimated workplace preference and location of the job ad is less than the median distance in the local labor market. Columns (1) and (2) present the estimates using the actual number of applications (including zeros) where columns (3) and (4) present the same estimates using log applications. Job seekers with a minimum distance between their preferred location and closest job ad > 20km are also dropped from the sample. The results for the same analysis without applying the distance threshold restriction is found in Table B.16. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results for the differential effect for far and close applications are found in Table 5. I define an application as "far" if the distance between the in-person workplace preference of the job seeker and the location of the workplace is within the top quartile of distance in the local labor market (defined as four-digit occupation by commuting zone). I define an application as "close" if the distance between the in-person workplace preference of the job seeker and the location of the workplace is below the median distance in the local labor market. I make the same 20 km restrictions on the data here so that it is comparable with the geographic results from Section 6.2, but the results are consistent if I use an unrestricted sample (Table B.16).

I find that job ads that signal WFH receive more applications from job seekers whose in-person workplace preference is further away. This is true in both levels (which include job ads with no far applications) and in percentage change (which by construction drops the job ads with no far applications). WFH-signaling job ads receive 0.26 more applications (about 5.1% more), on average, from job seekers of this type compared to similar in-person job ads. However, this increase in far away job ads come at a price. Job ads that signal WFH receive fewer close applications than similar in-person job ads. They receive 1.8 fewer applications, on average, from job seekers that are nearby. These results suggest that while offering WFH may increase the overall number of applicants, it does not do so uniformly and it does not keep the pool of applicants that were applying before fixed. Instead, it shifts the applicant pool between different groups, leading to compositional changes in the applicant pool. I explore this dimension of offering WFH more in Section 7. These results also give a possible explanation for why the general effects on applications and views is relatively small. If close applicants are applying less when offering WFH, that offsets some of the effect from the increase in the geographic size of the available labor market.

There are two potential reasons why job seekers may be disincentivized to apply to WFH job closer to their preferred workplace location. First, WFH expands the pool of applicants that can apply to the job by relaxing the geographic constraint. Nearby job seekers may internalize this increased competition so they may shy away from these job ads in favor of less competitive in-person job ads. If this is the case, we would expect lower quality job seekers to be more affected by the competition effect since high quality workers would likely be good enough to still compete. An alternative story is that WFH becomes a disamenity if the job is located near where you live or where you prefer to work in person. These job seekers may not want to WFH if the job is within close commuting distance and may not want to work at a workplace that offers a lot of WFH since the workplace is more likely to be empty. If this channel has bite, we would expect to see a greater decrease in nearby applications for higher quality job seekers, since they have stronger outside options.

7 Changes in the Applicant Pool

In the previous section,I show that offering WFH provides firms with access to a wider labor market since more job seekers apply to WFH job ads relative to in person job ads and that these applicants tend to come from further away. This suggests that offering WFH can give firms access to a geographically broader labor market and allow them to hire talent that they otherwise would not have been able. However, it is not clear that firms benefit from offering WFH by just looking at the quantity effects. If the additional job seekers that firms have access to are of low quality or if offering WFH changes the applicant pool so that worse job seekers are applying, firms would be worse off if they offered WFH from a hiring perspective. However, if the quality of the additional job seekers is better (or even the same), then firms can actually benefit from offering WFH and this workplace flexibility could help reduce spatial frictions in the labor markets.

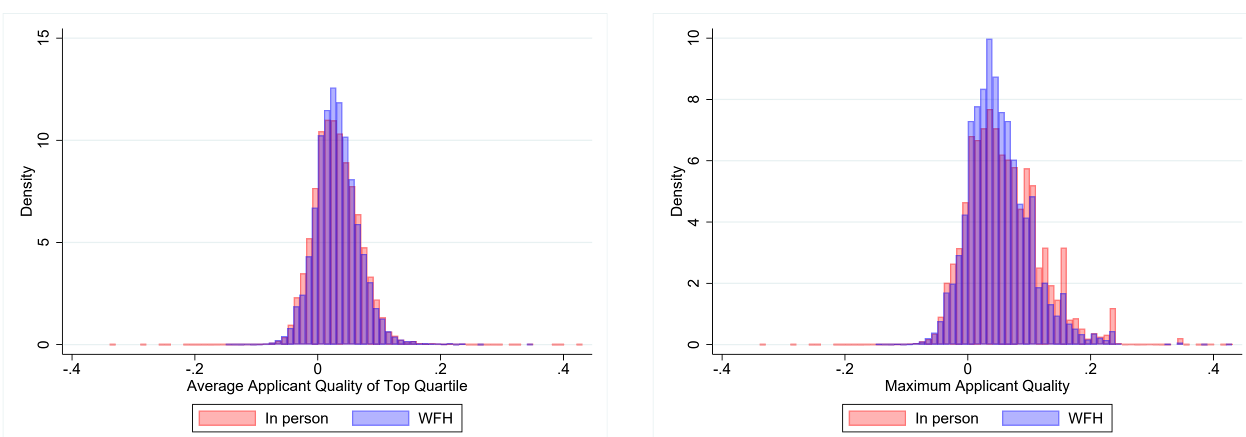
In this section, I explore how the pool of applicants changes when firms offer WFH. I focus on how the quality of the applicants change by using the average quality of the other workplaces that a job seeker applies to as a proxy for individual quality. I also look at how WFH changes the demographic characteristics of applicants focusing on the unemployed job seekers that apply for which I can match demographic characteristics.

7.1 Measurement of quality

The main problem with this analysis is defining job seeker "quality" since I have limited information on who the majority of these job seekers are beyond their search behavior. To remedy this, I leverage the variation in firms they apply to in order to construct a measure of firm quality. I begin by estimating the firm fixed effects of the potential employers in my sample based on the wages of their employees in the period of 2016-2019 (prior to my data). I construct the connected set of firms and workers during this time period and run a basic AKM model that includes firm fixed effects, worker fixed effects, and year fixed effects. Under the standard AKM assumptions, I use movement of workers between firms to estimate "firm quality" as the firm fixed effects, aka as the component of the wage that the firm contributes. I then match the firm fixed effects to the job-seeker-by-vacancy level data and compute the leave-one-out (LOO) mean of the firm effects for all the firms that job seeker applied to except the firm of the current vacancy. This provides a proxy for the job seeker under the assumption that job seekers that are higher quality workers are more likely to apply to higher quality firms (firms with higher fixed effects) on average. I leave out the current vacancy, however, in order to not bias the quality measures. Each firm is only accounted for once per job seeker in a LOO mean, even if they apply to multiple positions at the same firm. This process is done for all job-seeker-job-ad combinations. Once these job-seeker quality measures are calculated, they are averaged at the job ad level to get the average quality of applicants to the job ad. Similarly, I also construct a measure for the mean quality of the top quartile of applicants by only taking the average of the applicants in the 75^{th} percentile and above for each job add as well as constructing a measure for the applicant with the highest quality (top quality applicant). I use the same method to calculate the quality of job seekers for close and far applicants (used in Section 6.3), except the LOO means are calculated on the subset of applicants that are close or far, respectively, using the same definition as before. The distribution of the mean quality measure and the top quality applicant by WFH signal is found in Panel (a) and Panel (b), respectively, of Figure 6. From the raw distributions, WFH job ads look to attract slightly better workers on average than in-person job ads, but slightly worse top quality applicants. These distributions, however, mask occupational heterogeneity in applicant quality.

Figure 6: Distributions of applicant quality by whether the job ad offers WFH

(a) Mean quality of applicants (b) Top quality applicant



Notes: This figure plots the distributions of the mean and top quality of applicants from the job ads. "Applicant quality" is defined as the average firm fixed effects of all the other firms that applicant applied. Panel (a) plots the mean quality while Panel (b) plots the top quality. For both panels, the distributions for in-person vacancies are plotted in red and the distributions of WFH vacancies are plotted in blue. The distribution for the mean of the top quartile of applicants is found in Figure C.19.

7.2 Quality of applicants

To more rigorously investigate the quality of applicants, I regress the quality measures discussed above on an indicator for signalling WFH in the job ad using the main specification as before (equation 1). Similarly to the other analysis, I also include estimates for the baseline regression, within occupation and time regressions, and the firm FE regression. I run these regressions for all three measures of quality (average quality, top quality, and average quality of the top quartile).

The results when looking at the mean quality of applicants can be found in Table 6. Generally, I find that the mean quality of the applicant actually decreases when a job ad offers WFH. When looking at the main analysis for all WFH job ads, I find that the average quality of the job seeker decreases by 0.031 standard deviations (Column (1)). While this amount is not particularly large, it still suggests that WFH job ads attract at least some more workers of lower quality than similar in-person job ads. These results are also similar if we look at WFH job ads where the WFH amenity is more salient. I find no difference in the quality of applicants when comparing fully remote job ads to similar in person job ads (Column (2)), but I find an even larger negative effect for job ads that mention WFH in the headline (a decrease of 0.191 standard deviations, Column (3)). This reduction in average quality for WFH job ads is likely driven either by lower quality applicants feeling like they have a better chance for getting these positions or by job seekers that want to shirk at work applying to more WFH job ads.

Table 6: Mean quality of applicants by WFH offering

	All WFH job ads	Fully remote job ads	Job ads with WFH in headline
WFH offering	-0.031^{***}	0.089	-0.191^{***}
	(0.008)	(0.043)	(0.067)
Vacancy Controls	Y	Y	Y
Firm Controls	Y	Y	Y
Local labor Market F.E.	Y	Y	Y
Commuting zone × month-year F.E.	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y
Sample mean (standardized mean quality)	0.00	0.00	0.00
N	492,262	476,181	492,262

Note: This table presents the regression estimates for the main analysis (based on equation 1) for average quality of applicants on whether the job ad offers WFH. The table present the estimates for three versions of WFH, Column (1) uses all the job ads classified as WFH, Column (2) uses only the fully remote job ads (dropping the hybrid job ads), and Column (3) redefines the treatment as job ads that explicitly state WFH in the headline. 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. For the fully remote sample (Column (2)), job ads classified as "hybrid WFH" are also dropped. The quality of applicants is standardized to have mean = 0 and standard deviation = 1. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Despite the average quality of workers decreasing, employers generally only hire one or two workers per job ad so they are primarily concerned with the quality of the top candidates that apply. Therefore, I rerun the analysis looking at the differential quality of the top-quality worker that applies to these positions. These results are found in Table 7. When looking at all the job ads categorized as WFH, I find no differential effect in quality of the top applicant between WFH and similar in person job ads (Column (1)). However, I find an increase in quality if I subset to WFH job ads that have more salient

WFH offerings. The effects are positive and significant both for the fully remote job ads (an increase of 0.115 standard deviations, Column (2)) and for the job ads with WFH in the headline (an increase of 0.216 standard deviations, Column (3)), and both of these effects are economically significant. These results are qualitatively similar (although less precise) if we look at the mean quality of the top quartile of applicants, particularly for the fully remote job ads (Table B.17).

Table 7: Quality of the top applicant by WFH offering

	All WFH job ads	Fully remote job ads	Job ads with WFH in headline
WFH offering	-0.009	0.115^{***}	0.216^{**}
	(0.007)	(0.043)	(0.097)
Vacancy Controls	Y	Y	Y
Firm Controls	Y	Y	Y
Local labor Market F.E.	Y	Y	Y
Commuting zone × month-year F.E.	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y
Sample mean (standardized maximum quality)	0.00	0.00	0.00
N	492,262	476,181	492,262

*Note:*This table presents the regression estimates for the main analysis (based on equation 1) for the quality of the top applicant (maximum quality) on whether the job ad offers WFH. The table present the estimates for three versions of WFH, Column (1) uses all the job ads classified as WFH, Column (2) uses only the fully remote job ads (dropping the hybrid job ads), and Column (3) redefines the treatment as job ads that explicitly state WFH in the headline. 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. For the fully remote sample (Column (2)), job ads classified as "hybrid WFH" are also dropped. The quality of applicants is standardized to have mean = 0 and standard deviation = 1. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results suggest that offering WFH tends to attract more job seekers that are of lower quality generally, employers can get access to better top-end talent, particularly if they offer fully remote work or make the WFH offer more salient and informative. Because of this, it seems that offering WFH can be lucrative to firms in terms of getting better matches to potential workers.

7.3 Demographic composition of applicants

Along with changes in quality of applicants, there can also be a change in the types of job seekers that are applying for WFH jobs. Previous research finds that there is heterogeneity in preferences for WFH across different demographic characteristics and individuals (Aksoy et al. (2022)). This suggests that, when firms offer WFH, they should expect a different distribution of applicants than they would get for an equivalent in-person vacancy. We already see this, to some extent, when looking at the mechanisms driving the increase in applications as there is a decline in nearby job seekers towards job seekers that are further away when firms offer WFH, but this could be true across other demographic characteristics as well.

I investigate the change in the applicant pool along this dimension by looking at how the demographic structure of job seekers differs between similar WFH and in-person job ads. To investigate this, I use the same fixed effects model in equation 1, but I regress the share of job seekers for different demographic groups on the indicator for signaling WFH, controlling for the same potential confounders as before.[14] I look into potential changes of five characteristics: share of female applicants, share of

14. The results are consistent when including the share of the other demographic characteristics as controls as well.

applicants that are immigrants, share of applicants from non-urban neighborhoods (defined as applicants residing in "A" or "B" DeSOs, aka neighborhoods located outside of central metropolitan areas), share of young applicants (job seekers < 45 years old), and share of highly educated applicants (job seekers that at least have a bachelor's degree). Due to data restrictions, I can only match the demographic characteristics to the subset of unemployed job seekers and not to the entire population of applicants. The unemployed sample is an interesting but inherently different group compared to the overall population (Table A.4). Despite this, these demographic differences I find in the unemployed sample still provide interesting insights into the shifting composition of the overall applicant pool.

Table 8: Compositional changes of unemployed applicants (in shares)

	(1) Female	(2) High Education ($\geq$ bachelor's)	(3) Young (< 45)	(4) Immigrant	(5) Non-urban
WFH offering	0.018***	0.009*	0.012**	−0.005	0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
Vacancy Controls	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y	Y
Sample mean	0.461	0.263	0.601	0.489	0.167
N	397,719	398,588	398,588	398,588	398,588

Note: This table presents the results for the changes in the demographic composition of unemployed applicants by regressing the share of a specific characteristic on an indicator for if the job ad signals WFH using the main specification outlined in equation 1. The characteristics are measured as the shares of the unemployed applicants that apply to the job ad. These regressions only consider unemployed applicants since those are the only job seekers that can be matched to the demographic data. I look at five demographic characteristics: the share of female applicants (Column (1)), share of highly educated applicants (having at least a bachelor's degree, Column (2)), share of young applicants (applicants under the age of 45, Column (3)), share of applicants that are immigrants (Column (4)), and share of applicants living in non-urban neighborhoods (Column (5)). The data consists of all job ads over the months from May 2020 to September 2022 that had at least one applicant who was unemployed. 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 the sample. Standard Errors are clustered at the local labor market level. The analogous table looking at changes in attention by demographic characteristics is Table B.18.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results for these demographic changes on applicants are found in Table 8. When firms signal that they offer WFH, I find sizeable differences in the demographic characteristics of unemployed applicants for WFH job ads compared to similar in-person job ads for all these characteristics. WFH-signaling job ads attract, on average, 1.8% more applicants that are female, 1.2% more applicants that are younger, and 0.9% more applicants that are highly educated. I also find a small negative (but imprecise) effect on immigrant applicants (0.5% fewer applicants). Surprisingly, I find no differential effect on applicants that live in non-urban neighborhoods. The results are similar when looking at the change in attention when a job ad signals WFH (Table B.18) with significantly more views from female (1.2%). young (0.8%), and highly educated (0.8%) job seekers and significantly fewer views from immigrant job seekers (0.7%). The main difference is that there is a significantly positive effect on

See Table B.19 for the results for applications including these additional controls.

the number of views from job seekers living in non-urban neighborhoods (0.9%). These results suggest that not only can work from home alleviate some of the geographic frictions in the labor market, but it also changes the overall composition of the applicant pool and may be an avenue for helping job seekers from groups less attached to the labor market (e.g. women).

8 Non-Urban Workplaces

One key dimension of heterogeneity that we may expect to see differential effects is whether or not the workplace is located in a more rural or more urban area. Rural firms are more isolated from large labor markets, so they are more likely to suffer from geographic mismatch especially if they offer more specialized jobs. One example of this is a bank located on an isolated island may have trouble finding good (if any workers) to fill positions, while a bank in central Stockholm would have access to a large pool of potential workers. By offering WFH positions, that isolated bank could gain access to the same market as the centrally located bank. This provides greater incentives for rural firms to offer WFH while also helping to alleviate potential geographic mismatch. In this section, I follow much of the same analysis used before, but I specifically subset to firms in non-urban areas.[15]

8.1 Job attractiveness

The results for the differential effect of signaling WFH on applications for non-urban firms are found in Table 9. These estimations follow the same procedure as the analysis for the full sample in Section 5. In accordance with expectations, I find that non-urban workplaces benefit much more strongly from offering WFH with respect to the number of applications they receive. Looking at the results for the main specification (Column (3)), I find that non-urban workplaces receive 9.1% more applications than similar in-person job ads, which corresponds to 2.44 more applications on average when compared to the sample mean. This effect is around 2.4 times larger than the effect in the whole sample of workplaces (Section 5), both in terms of the percentage change and in terms of the number of applications.

I find a similar, but more muted pattern when looking at the effect on attention (Table B.20). Job ads at non-urban workplaces that signal WFH also receive more job ads than similar in-person job ads from non-urban workplaces. They receive 10.4% increased attention which corresponds to 23.4 more views, on average, when compared to the sample mean. This effect is also larger than the effect from the full population of workplaces, which saw a 9.9% increase in attention, but it is a relatively smaller effect increase compared to applications. Combined, these results suggest that non-urban workplaces benefit even more than urban workplaces when they signal WFH in both attention and applications, but the relative benefit is even higher for applications. This suggests that offering WFH in non-urban workplaces sees a better conversion rate of the additional views into applications.

15. "Non-urban" areas here is defined using Statistics Sweden's A and B classifications of the neighborhoods (DeSOs). These relate to neighborhoods located outside major population centers and neighborhoods located in population centers outside of the municipality's central area for A and B, respectively.

Table 9: WFH and applications (using log total applications) - non-urban firms

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.021 (0.064)	0.185^{***} (0.064)	0.091^{***} (0.032)	0.103^{***} (0.035)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (# of applications)	26.84	26.84	26.84	26.84
N	164,192	164,190	99,321	131,332

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 subset to firms in non-urban areas. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0) and vacancies from firms in urban areas are dropped from all samples. Sample means are presented which provide the average number of applications for the sample. The analogous table presenting the results for logged attention is found in Table B.20. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8.2 Geographic distances

Not only would we expect larger increases in attention and applications for job ads from non-urban workplaces when they offer WFH, but we also expect that they should receive more applications from job seekers that are further away since the local labor markets for these workplaces are much smaller and much more isolated. To investigate this, I follow the same procedure discussed in Section 6. The results for the mean distance between job seekers' in-person workplace preferences and the job ads' locations is found in Table 10.

I again find a pattern for non-urban workplaces that follows my hypothesis. When looking at the log mean distance between job applicants "in-person workplace preferences" and the location of the job ad workplace, I find that job ads that signal WFH receive applications from job seekers whose workplace preference is 44.4% further away on average. This corresponds to 27.9 km further away as the crow flies. When comparing this the the results for the entire population of job ads, the effect of signal WFH for non-urban workplaces is 1.2 times more than the overall. I find similar results if I look at the maximum distance or the average distance in the top quartile of applicant distances (Table B.22 and Table B.23, respectively) and if I look using different distance restriction thresholds (Table B.21). These results suggest that these non-urban workplaces are seeing even greater effects from the relaxation of the geographic constraint that WFH can provide, providing additional evidence that WFH could be a useful tool in reducing geographic frictions between workers and firms.

Table 10: WFH and geographic dispersion of applicants (using log mean distance) - non-urban firms

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	0.480***	0.554***	0.444***	0.413***
	(0.044)	(0.045)	(0.093)	(0.081)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (km)	62.85	62.85	62.85	62.85
N	74,894	74,885	43,971	59,607

Note: This table presents the results of the main regression estimates for the logged mean distance of applicants' "workplace location preference" and the location of the job ad on WFH offering subset to firms in non-urban areas. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0), vacancies where the coordinates were wrong or could not be correctly matched, and vacancies from firms in urban areas are dropped from all samples. Job seekers with a minimum distance between their preferred location and closest job ad > 20km are also dropped from the sample (however, the results are robust to using alternative thresholds - see Table B.21). Sample means are presented as the mean average distance of job seeker "workplace location preference" and job ad location of the sample (in kilometers). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8.3 Quality of applicants

The previous results show that the geographic and quantity effects are even stronger for workplaces that are more geographically remote. I also investigate if the effects on quality differ form non-urban workplaces. I follow the same procedure as discussed in Section 7.2. The results for this analysis are found in Table 11 for mean quality of applicants and in Table 12 for the top quality applicant.

When looking at the results for mean quality, we find similar effects as in the main sample. The overall quality of applicants that apply to WFH job ads tends to be slightly worse than similar in person jobs, although these effects are not precisely estimated. When compared to the effects of the full sample of job ads (Table 6), the effect on mean quality of applicants for job ads from non-urban workplaces is reduced, suggesting that there are fewer applicants on the low-end of the distribution that are applying to these job ads relative to applicants on the higher end of the quality distribution. The exception to this pattern is when we focus on fully remote jobs (Column (2) of Table 11). Fully remote jobs in non-urban workplaces tend to see a large jump in overall quality. This is further confirmed if we look at the results for the quality of the top applicant. Similar to the overall sample, the quality of the top applicant increases for job ads that signal WFH when the signal is salient. However, the effect is strongest for job ads that signal a fully remote structure (Column (2) of Table 12), which mimics the results from the mean quality analysis and is a larger effect than those found in the overall sample (Table 7). Similar results are found if we look at the mean quality of the top quartile of applicants

Table 11: Mean quality of applicants by WFH offering - non-urban firms

	All WFH job ads	Fully remote job ads	Job ads with WFH in headline
WFH offering	−0.027	0.602	−0.054
	(0.061)	(0.971)	(0.244)
Vacancy Controls	Y	Y	Y
Firm Controls	Y	Y	Y
Local labor Market F.E.	Y	Y	Y
Commuting zone × month-year F.E.	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y
Sample mean (standardized mean quality)	−0.10	−0.10	−0.10
N	18,260	17,872	18,260

Note: This table presents the regression estimates for the main analysis (based on equation 1) for average quality of applicants on whether the job ad offers WFH subset to firms in non-urban areas. The table present the estimates for three versions of WFH, Column (1) uses all the job ads classified as WFH, Column (2) uses only the fully remote job ads (dropping the hybrid job ads), and Column (3) redefines the treatment as job ads that explicitly state WFH in the headline. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0) and vacancies from firms in urban areas are dropped from all samples. For the fully remote sample (Column (2)), job ads classified as "hybrid WFH" are also dropped. The quality of applicants is standardized to have mean = 0 and standard deviation = 1. The sample means here deviate from the mean zero because the standardization is done on the full sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Quality of the top applicant by WFH offering - non-urban firms

	All WFH job ads	Fully remote job ads	Job ads with WFH in headline
WFH offering	−0.000	0.357	0.024
	(0.048)	(0.344)	(0.217)
Vacancy Controls	Y	Y	Y
Firm Controls	Y	Y	Y
Local labor Market F.E.	Y	Y	Y
Commuting zone × month-year F.E.	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y
Sample mean (standardized maximum quality)	−0.08	−0.08	−0.08
N	18,260	17,872	18,260

Note:This table presents the regression estimates for the main analysis (based on equation 1) for the quality of the top applicant (maximum quality) on whether the job ad offers WFH subset to firms in non-urban areas. The table present the estimates for three versions of WFH, Column (1) uses all the job ads classified as WFH, Column (2) uses only the fully remote job ads (dropping the hybrid job ads), and Column (3) redefines the treatment as job ads that explicitly state WFH in the headline. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0) and vacancies from firms in urban areas are dropped from all samples. For the fully remote sample (Column (2)), job ads classified as "hybrid WFH" are also dropped. The quality of applicants is standardized to have mean = 0 and standard deviation = 1. The sample means here deviate from the mean zero because the standardization is done on the full sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(Table B.24).

These results are also imprecisely estimated due to the limited sample size, but the signs and relative magnitudes are consistent with the expectations about job ads from more rural labor markets. These workplaces tend to be more isolated compared to the urban job ads, so offering a hybrid WFH structure likely has little effect since the workplaces are too far for even periodic commuting. However, the job ads that offer fully remote structures are more appealing and can reach beyond the limited labor market the workplace initially had access.

9 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.

9.1 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 $\times$ 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 3.

$$WFH_{z,o,t} = \beta_0 + \beta_1 * LLM\_Tightness_{z,o,t-1} + \theta_{z,o} + \theta_{z,t} + \theta_{o,t} + \epsilon_{z,o,t} \quad (3)$$

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.

9.2 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 7 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).

The results for the main analysis can be found in Table 13. 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 3), 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)).[16]

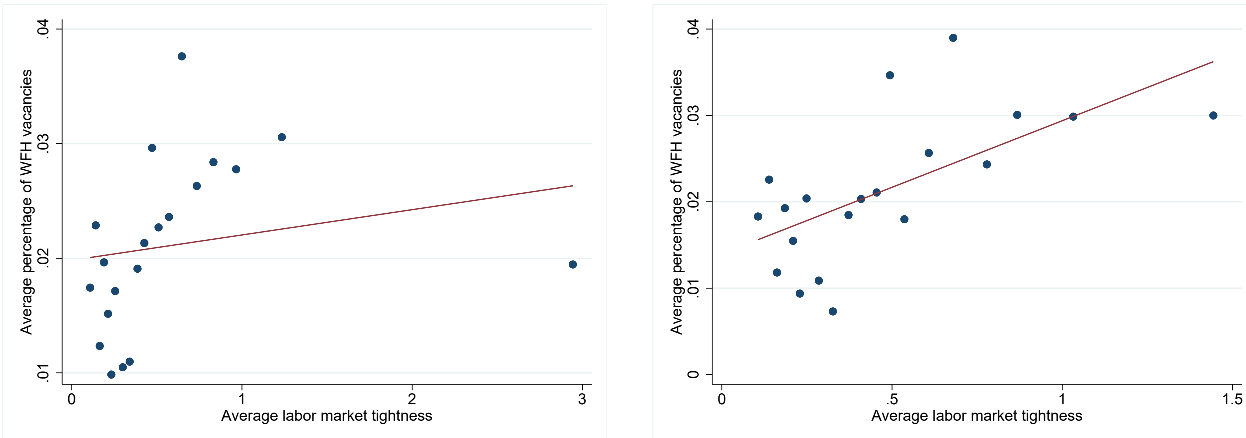
As with the previous analysis, there is concentration in WFH vacancies among certain occupations. To check that the less feasible WFH occupations are not driving the results, I re-run the analysis using

16. 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.25).

Figure 7: 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.20.

Table 13: 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*** (0.073)	0.094*** (0.027)	0.056*** (0.018)	1.421* (0.732)	0.824*** (0.139)	0.185** (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.25.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.

10 Conclusion

Geographic frictions in the labor market are one prominent source of sub-optimal matching between workers and firms. When relevant job seekers and employers are separated in space, traditional working arrangements restrict the matching between these groups because there are generally high relocation costs and there is a maximum distance that workers can or are willing to commute. In order to alleviate these frictions, firms can offer WFH positions which allow potential workers to commute less or not at all, allowing them to live further from their assigned workplace. This allows firms to gain access to geographically wider labor markets and can improve the matching between firms and job seekers, as firms have the potential to get access to better, more qualified workers.

In this paper, I explore the extent to which WFH can reduce geographic mismatch and improve the matching between job seekers and firms by altering the labor market access of firms. 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. For the quantity dimension, 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 sample to the occupations that are most capable of offering WFH. I estimate that WFH vacancies get, on average, 3.9% more applications and 9.9% more views than similar in-person vacancies. These results suggest that WFH job ads are able to attract more workers.

One potential reason for the change in applications for WFH job ads is the change in geographic access that WFH provides. I estimate the direct effect of the change in geographic dispersion by looking at the differential effect of WFH job ads and in-person job ads in the mean difference of the distances between the locations of where job seekers prefer to work when they have to commute and where they apply. I find that job seekers apply to WFH job ads that are 17.6% further from their preferred workplace location, on average, compared to similar in-person jobs. This increase in more distant workers, however, does come at the cost of workers whose workplace preferences are closer to the job ads. This suggests that there is a realized relaxation of the geographic constraint of labor markets when firms offer WFH. This relaxation points to the potential use of WFH to alleviate some of the geographic mismatch, however there is a tradeoff between types of workers that needs to be considered.

When looking at the quality dimension, I find that there is no decrease in the top-end quality of workers for general WFH offering and that there is even an improvement in the top-end quality for job ads with more salient signals. For example, fully remote job ads had top applicants with 0.12 standard deviation higher quality than similar in-person job ads. This is true despite average quality generally being slightly lower for WFH job ads. This indicates that there is movement on both sides of the distribution, but since firms usually only hire a few applicants at most, they would be primarily affected by the quality increase at the top. This quality improvement suggests that the greater labor market access can actually help improve the matches between workers and firms by giving firms access to better talent they otherwise would not have had.

While these results discuss the labor market as a whole, workplaces in more rural areas with isolated labor markets are more incentivized to offer WFH as they should have more potential benefit. Non-urban job markets likely face greater mismatch than other workplaces since there is generally concentrations of skills around cities (European Labour Authority 2024). I therefore run the same analysis on non-urban workplaces and generally even larger effects. These workplaces tend to receive relatively more applications and tend to attract job seekers that are relatively further away, with larger effects than the estimates for the whole sample of workplaces. They, on average, receive 9.1% more applications and applicants apply 44.4% further from their commuting workplace preference when compared to similar in-person job ads. In terms of quality, the estimates are imprecise, but the effects are positive. These results suggest that these more isolated workplaces receive even stronger benefits from signaling WFH, providing evidence of even broader potential benefit of using WFH to reduce geographic frictions.

All of these results suggest that offering WFH attracts more job seekers, at least in part by attracting job seekers from further away and these job seekers can be of better quality. Firm could then act strategically by using WFH to access the broader labor market particularly 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 0.056 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.

The results in this paper suggest that WFH could be a potential tool to alleviate geographic mismatch in the labor market and it is an instrument that at least some firms are beginning to strategically implement to attract more or better workers. This means that incentivizing firms to offer more WFH could be a potential low-cost intervention that policy makers can implement to improve the match quality of workers and firms if spatial frictions are significant barriers. It could act as a replacement to worker relocation programs since incetivizing WFH is likely more cost effective. Similarly, it could complement job retraining programs if skills are geographically mismatched along with the workers. However, there are a few limitations that should be considered when thinking about the role WFH can play in reducing these geographic frictions for policy and more generally. One key issue that this paper does not consider are the costs or effects of implementing WFH on the non-hiring margin. There could be several reasons why offering WFH would be sub-optimal for firms and even inefficient at the societal level despite the improved match quality. For example, there could be potential productivity effects or additional monetary costs that make WFH inefficient at either the individual firm level or the aggregate level. Exploring these costs are beyond the scope of the paper, but are a necessary element for future research in order to determine optimal policy about WFH. Similarly, WFH feasibility is restricted to specific occupations and industries, many of which are higher income, higher education jobs. This divide in WFH potential could create externalities for the non-WFH labor markets that generate or exacerbate inequalities. Even if these inequalities do not manifest, WFH can not play a role in reducing geographic frictions for low-WFH potential jobs with the current technology.

References

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh. 2022. "Work that Can be Done from Home: Evidence on Variation within and across Occupations and Industries." *Labour Economics* 74:102083. https://doi.org/10.1016/j.labeco.2021.102083.

Aksoy, Cevat Giray, José María Barrero, Nicholas Bloom, Steven J. Davis, Mathias Dolls, and Pablo Zarate. 2022. "Working from home Around the world." *NBER Working Paper Series* No. 30446. https://doi.org/10.3386/w30446.

Angelici, Martina, and Paola Profeta. 2020. *Smart-Working: Work Flexibility without Constraints.* Technical report 8165. CESifo Working Paper Series. https://doi.org/10.2139/ssrn.3556304.

Autor, David, Arindrajit Dube, and Annie McGrew. 2024. "The Unexpected Compression: Competition at Work in the Low Wage Labor Market." *NBER Working Paper Series* No. 31010. https://doi.org/10.3386/w31010.

Barrero, José María, Nicholas Bloom, and Steven J. Davis. 2021a. "Internet Access and its Implications for Productivity, Inequality, and Resilience." *NBER Working Paper Series* No. 29102. https://doi.org/10.3386/w29102.

———. 2021b. "Why Working from Home Will Stick." *NBER Working Paper Series* No. 28731. https://doi.org/10.3386/w28731.

———. 2023. "The Evolution of Work from Home." *Journal of Economic Perspectives* 37 (4): 23–50. https://doi.org/10.1257/jep.37.4.23.

Barth, Erling, Alex Bryson, and Harald Dale-Olsen. 2022. "Creative Disruption: Technology Innovation, Labour Demand and the Pandemic." *IZA Discussion Paper Series* No. 15762. https://docs.iza.org/dp15762.pdf.

Bietenbeck, Jan, Natalie Irmert, and Therese Nilsson. 2024. "Individualism and Working from Home." *IZA Discussion Paper Series* No. 17102. https://docs.iza.org/dp17102.pdf.

Bloom, Nicholas, Steven J. Davis, and Yulia Zhestkova. 2021. "COVID-19 Shifted Patent Applications toward Technologies That Support Working from Home." *AEA Papers and Proceedings* 111:263–66. https://doi.org/10.1257/pandp.20211057.

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying. 2015. "Does Working from Home Work? Evidence from a Chinese Experiment." *The Quarterly Journal of Economics* 130 (1): 165–218. https://doi.org/10.1093/qje/qju032.

Boehnke, Jörn, Richard B. Freeman, Qian Wang, Yuxi Yang, and Yang You. 2024. "COVID-19 Fiscal Spending and Job Openings."

Ding, Yuye, and Mark (Shuai) Ma. 2023. "Return-to-Office Mandates," https://doi.org/10.2139/ssrn.4675401.

Dingel, Jonathan I., and Brent Neiman. 2020. "How many jobs can be done at home?" *Journal of Public Economics* 189. https://doi.org/10.1016/j.jpubeco.2020.104235.

European Employment Services. 2024. "Labour Market Information - Sweden." Accessed: 2024-11-10, https://eures.europa.eu/living-and-working/labour-market-information/labour-market-information-sweden_en.

European Labour Authority. 2024. *EURES Report on Labour Shortages and Surpluses 2023.* Luxembourg: European Union. https://doi.org/10.2883/973861.

Eurostat. 2021. *Swedish European Labour Force Surveys, 2021.* https://ec.europa.eu/eurostat. Accessed through Eurostat.

Gill, Adam, and Oskar Nordström Skans. 2024a. "Trusted from Home: Managerial Beliefs and Workers' Spatial Autonomy." *IZA Discussion Paper Series* No. 17468. https://docs.iza.org/dp17468.pdf.

———. 2024b. "Working from home in the Nordic Region? More than a remote possibility." Chap. 7 in *Economic Policy beyond the Pandemic in the Nordic Countries,* edited by Lars Calmfors and Nora Sánchez Gassen, 230–271. Stockholm: Nordregio. https://doi.org/10.6027/R2024:121403-2503.

Handel, Michael J. 2024. "Labor Shortages: What Is the Problem." *Intereconomics: Review of European Economic Policy* 59 (3): 136–142. https://doi.org/10.2478/ie-2024-0029.

Hansen, Stephen, Peter John Lambert, Nicholas Bloom, Steven J. Davis, Raffaella Sadun, and Bledi Taska. 2023. "Remote Work across Jobs, Companies, and Space." *NBER Working Paper Series* No. 31007. https://doi.org/10.3386/w31007.

Hensvik, Lena, Thomas Le Barbanchon, and Roland Rathelot. 2020. "Which Jobs Are Done from Home? Evidence from the American Time Use Survey." *IZA Discussion Paper Series* No. 13138. https://docs.iza.org/dp13138.pdf.

———. 2021. "Job search during the COVID-19 crisis." *Journal of Public Economics* 194:104349. https://doi.org/10.1016/j.jpubeco.2020.104349.

Maestas, Nicole, Kathleen J. Mullen, David Powell, Till von Wachter, and Jeffrey B. Wenger. 2023. "The Value of Working Conditions in the United States and the Implications for the Structure of Wages." *American Economic Review* 113 (7): 2007–2047. https://doi.org/10.1257/aer.20190846.

Mas, Alexandre, and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." *American Economic Review* 107 (12): 3722–59. https://doi.org/10.1257/aer.20161500.

———. 2020. "Alternative Work Arrangements." *Annual Review of Economics* 12:631–658. https://doi.org/10.1146/annurev-economics-022020-032512.

Mongey, Simon, Laura Pilossoph, and Alexander Weinberg. 2021. “Which Workers Bear the Burden of Social Distancing?” *The Journal of Economic Inequality* 19:509–526. https://doi.org/10.1007/s10888-021-09487-6.

Nagler, Markus, Johannes Rincke, and Erwin Winkler. 2022. “How Much Do Workers Actually Value Working from Home?” *CESifo Working Paper* No. 10073. https://doi.org/10.2139/ssrn.4279162.

Zarate, Pablo, Mathias Dolls, Steven J. Davis, Nicholas Bloom, José María Barrero, and Cevat Giray Aksoy. 2024. “Why Does Working from Home Vary Across Countries and People?” *NBER Working Paper Series* No. 32374. https://doi.org/10.3386/w32374.

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:

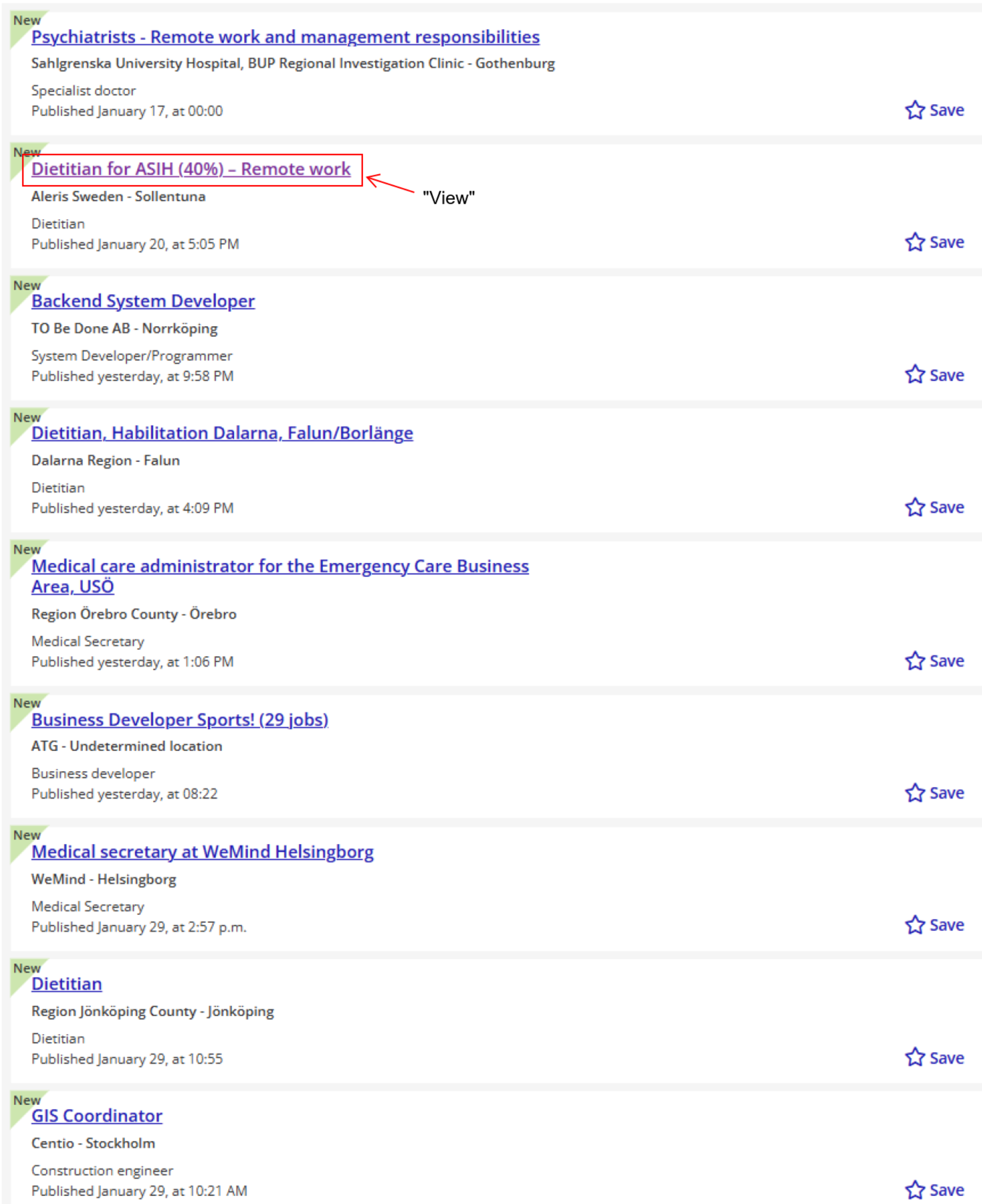
- 2017: Air traffic controller had highest percentage, but there was only 1 WFH vacancy (4 total vacancies)

Table A.3: 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

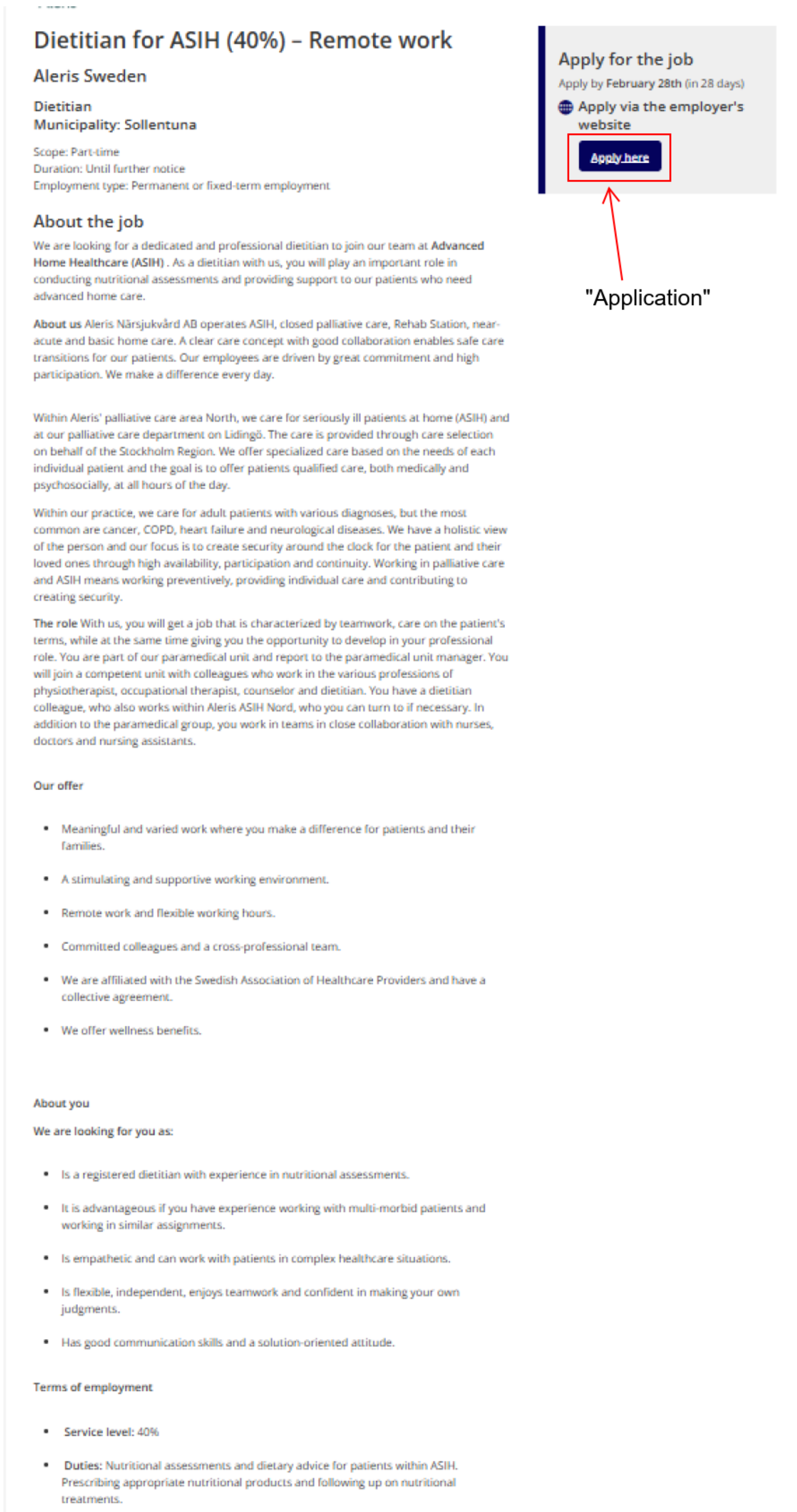
Note: This table formalizes the pattern seen in Figure 3. It presents the shares of job ads that contain different skills/technology by WFH job ads (Column 2) and non-WFH job ads (Column 3) and the differences between them (Column 4). Column 5 presents the p-values generated from t-tests testing the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

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

Apply for the job

Apply by **February 28th** (in 28 days)

Apply via the employer's website

Apply here

"Application"

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]

Table A.4: Summary Statistics for Unemployed Sample

	Unemployed applicants	Unemployed viewers	Full population
Share of female	0.479	0.491	0.500
Share of immigrants	0.486	0.471	0.252
Share of non-urban individuals	0.165	0.186	0.234
Share of highly educated ($\geq$ bachelors)	0.218	0.228	0.301
Share of young workers (< 45)	0.625	0.617	0.479
Average age	39.77	40.24	47.01
N	1,405,143	2,537,722	7,779,436

Note: This table presents the summary statistics for several demographic characteristics for the sample of unemployed applicants and unemployed viewers of job ads as well as the full population from the registry data. Specifically, I look at the share of female individuals, share of immigrants, the share of individuals living in non-urban areas, share of individuals with at least a bachelors degree, the share of workers under the age of 45, and the average age of the sample.

B Additional Results

B.1 Additional results for "Job Ad Attractiveness"

Table B.1: WFH on probability a job ad receives an application

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	0.036***	0.024***	0.011***	0.005**
	(0.008)	(0.004)	(0.002)	(0.002)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	0.881	0.881	0.881	0.881
N	1,738,379	1,738,379	1,187,663	1,615,134

Note: This table presents the results of the linear probability model estimates for the probability that a job ad receives at least one application on WFH offering. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. The data consists of all months from May 2020 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" here present the share of job ads in the sample that have at least one application. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: WFH on attention (including 2018 views)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.201^{***} (0.063)	0.175^{***} (0.032)	0.099^{***} (0.021)	0.075^{***} (0.014)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	204.88	204.88	204.88	204.88
N	2,915,961	2,915,961	1,793,449	2,752,417

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. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. 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 as the average number of views that job ads receive for the sample. 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 (subset to application time period)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.163^{**} (0.0068)	0.214^{***} (0.035)	0.111^{***} (0.021)	0.062^{***} (0.011)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	204.1	204.1	204.1	204.1
N	1,738,379	1,738,379	1,187,663	1,615,134

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 subsetting the data to the time period that I have applications for. The data thus consists of all months from May 2020 to September 2022. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. 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 as the average number of views that job ads receive for the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: WFH on applications - post-COVID period (2021-2022)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.329^{***}	0.100^{***}	0.043^{**}	0.027^{***}
	(0.044)	(0.024)	(0.018)	(0.010)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	26.3	26.3	26.3	26.3
N	1,306,978	1,306,978	854,513	1,220,373

Note: This table is related to Table 1 except it subsets the data to the post-peak-COVID period (defined as January 2021-September 2022). This table presents the results of the main regression estimates for log job ad applications on WFH offering. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. 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 as the average number of applications that job ads receive for the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: WFH on attention - post-COVID period (2021-2022)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.079	0.216^{***}	0.109^{***}	0.061^{***}
	(0.066)	(0.034)	(0.023)	(0.011)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	143.16	143.16	143.16	143.16
N	1,455,490	1,455,490	930,684	1,355,579

Note: This table is related to Table 2 except it subsets the data to the post-peak-COVID period (defined as January 2021-September 2022). This table presents the results of the main regression estimates for log job ad views on WFH offering. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. 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 as the average number of views that job ads receive for the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Attention for fully remote job ads

	Attention			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.011	0.695^{***}	0.445^{***}	0.417^{***}
	(0.063)	(0.143)	(0.103)	(0.078)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	219.5	219.5	219.5	219.5
N	2,314,163	2,314,163	1,751,107	2,174,301

Note: This table presents the results of the main regression estimates for log job ad attention (log views) on whether a job ad signals a fully remote position. I present the estimates for the entire sample of job ads. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. The data consists of job ads in all months from January 2019-September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no text written (text length = 0), and job ads classified as "hybrid WFH" are dropped from all samples. Sample means are presented which provide the average number of views for the sample. Standard Errors are clustered at the local labor market level. The analogous table looking at application is Table 3.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: WFH and applications (using log total applications) - job ads with WFH in title

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH in title	0.254^{***}	0.741^{***}	0.482^{***}	0.452^{***}
	(0.087)	(0.107)	(0.108)	(0.110)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone $\times$ month-year F.E.	N	N	Y	Y
Occupation $\times$ month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	28.78	28.78	28.78	28.78
N	1,531,314	1,531,314	1,060,687	1,428,685

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, but using whether the job ad explicitly mentions WFH in the job ad title as the treatment. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, 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 which provide the average number of applications for the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: WFH and job ad attention (using log total views) - job ads with WFH in title

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH in title	0.082	1.10***	0.748***	0.663***
	(0.101)	(0.149)	(0.156)	(0.106)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean	217.54	217.54	217.54	217.54
N	2,377,730	2,377,730	1,793,449	2,236,208

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, but using whether the job ad explicitly mentions WFH in the job ad title as the treatment. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. 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 which provide the average number of views for the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: Effect of WFH on applications by quartile of WFH share

	(1) Quartile 4 (Highest WFH share)	(2) Quartile 3	(3) Quartile 2	(4) Quartile 1 (Lowest WFH share)
WFH offering	0.030**	0.051**	0.079	−0.363***
	(0.012)	(0.020)	(0.049)	(0.068)
Vacancy Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y
Sample mean	13.6	23.2	26.7	50.0
N	312,795	233,025	242,105	272,320

Note: This table presents the results of the main regression estimates (based on the fixed effects specification from equation 1) for log applications on WFH signaling in a job ad by occupation quartile of WFH usage. To construct the quartiles, three-digit occupations are ranked by share of workers reporting they WFH "at least some of the time" in the 2021 Swedish Labour Force Survey (LFS). Separate regressions are then run, subsetting the data to the relevant quartile. The quartiles are constructed at the three-digit-occupation level, but the regressions are estimated at the four-digit-occupation level. Column (1) reports the estimates for Quartile 4 (the occupations with the highest share of WFH), Column (2) the estimates for Quartile 3, Column (3) the estimates for Quartile (2), and Column (4) the estimates for Quartile 1 (the occupations with the lowest share of WFH). The data consists of all months from May 2020 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 as the average number of applications for job ads in that quartile. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.10: Effect of WFH on attention by quartile of WFH share

	(1) Quartile 4 (Highest WFH share)	(2) Quartile 3	(3) Quartile 2	(4) Quartile 1 (Lowest WFH share)
WFH offering	0.065***	0.084***	0.141**	−0.113*
	(0.014)	(0.023)	(0.064)	(0.060)
Vacancy Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y
Sample mean	164.2	240.8	169.0	305.9
N	501,832	391,552	460,483	438,947

Note: This table presents the results of the main regression estimates (based on the fixed effects specification from equation 1) for log views on WFH signaling in a job ad by occupation quartile of WFH usage. To construct the quartiles, three-digit occupations are ranked by share of workers reporting they WFH "at least some of the time" in the 2021 Swedish Labour Force Survey (LFS). Separate regressions are then run, subsetting the data to the relevant quartile. The quartiles are constructed at the three-digit-occupation level, but the regressions are estimated at the four-digit-occupation level. Column (1) reports the estimates for Quartile 4 (the occupations with the highest share of WFH), Column (2) the estimates for Quartile 3, Column (3) the estimates for Quartile (2), and Column (4) the estimates for Quartile 1 (the occupations with the lowest share of WFH). 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 as the average number of views for job ads in that quartile. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Effect of WFH on applications by quartile of WFH share - fully remote job ads

	(1) Quartile 4 (Highest WFH share)	(2) Quartile 3	(3) Quartile 2	(4) Quartile 1 (Lowest WFH share)
WFH offering	0.177***	0.241***	0.339***	−0.743***
	(0.051)	(0.080)	(0.080)	(0.157)
Vacancy Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y
Sample mean	13.7	23.3	26.9	50.0
N	291,933	225,854	238,557	271,494

Note: This table presents the results of the main regression estimates (based on the fixed effects specification from equation 1) for log applications on signaling a "fully remote" position in a job ad by occupation quartile of WFH usage. To construct the quartiles, three-digit occupations are ranked by share of workers reporting they WFH "at least some of the time" in the 2021 Swedish Labour Force Survey (LFS). Separate regressions are then run, subsetting the data to the relevant quartile. The quartiles are constructed at the three-digit-occupation level, but the regressions are estimated at the four-digit-occupation level. Column (1) reports the estimates for Quartile 4 (the occupations with the highest share of WFH), Column (2) the estimates for Quartile 3, Column (3) the estimates for Quartile (2), and Column (4) the estimates for Quartile 1 (the occupations with the lowest share of WFH). The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no text written (text length = 0), and job ads classified as "hybrid WFH" are dropped from all samples. Sample means are presented as the average number of applications for job ads in that quartile. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.12: Effect of WFH on attention by quartile of WFH share - fully remote job ads

	(1) Quartile 4 (Highest WFH share)	(2) Quartile 3	(3) Quartile 2	(4) Quartile 1 (Lowest WFH share)
WFH offering	0.183***	0.232***	0.452***	−0.232
	(0.058)	(0.089)	(0.123)	(0.185)
Vacancy Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y
Sample mean	166.8	241.4	169.6	306.2
N	475,100	382,586	455,094	437,684

Note: This table presents the results of the main regression estimates (based on the fixed effects specification from equation 1) for log views on signaling a "fully remote" position in a job ad by occupation quartile of WFH usage. To construct the quartiles, three-digit occupations are ranked by share of workers reporting they WFH "at least some of the time" in the 2021 Swedish Labour Force Survey (LFS). Separate regressions are then run, subsetting the data to the relevant quartile. The quartiles are constructed at the three-digit-occupation level, but the regressions are estimated at the four-digit-occupation level. Column (1) reports the estimates for Quartile 4 (the occupations with the highest share of WFH), Column (2) the estimates for Quartile 3, Column (3) the estimates for Quartile (2), and Column (4) the estimates for Quartile 1 (the occupations with the lowest share of WFH). 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, vacancies with no text written (text length = 0), and job ads classified as "hybrid WFH" are dropped from all samples. Sample means are presented as the average number of views for job ads in that quartile. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Additional results for "Geographic Distribution of Job Seekers"

Table B.13: WFH and geographic dispersion of applicants (additional minimum distance thresholds)

	Minimum distance threshold			
	(1) 40 km	(2) 60 km	(3) 100 km	(4) Full data
WFH offering	0.266***	0.225***	0.201***	0.163***
	(0.015)	(0.013)	(0.012)	(0.010)
Vacancy Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y
Sample mean	55.0	63.9	74.2	88.9
N	961,288	973,521	985,609	996,813

Note: This table presents the results of the regression estimates for the main specification (equation 1) of logged mean distance of applicants' "workplace location preference" from the location of the job ad on WFH signal. The results here correspond to the estimates in Column (3) of Table 4, except in this table, I vary the threshold restriction placed on the minimum distance of an applicants' "workplace location preference" to the job ad for in person jobs. The thresholds used here are < 40 km (Column (1)), < 60 km (Column (2)), < 100 km (Column (3)), and no distance restrictions (Column (4)). The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0), and vacancies where the coordinates were wrong or could not be correctly matched are dropped from all samples. Job seekers with a minimum distance between their preferred location and closest job ad $>$ 40km (Column 1), $>$ 60km (Column 2), and $>$ 100km (Column 3) are also dropped from the relevant sample. No additional job seekers are dropped from the sample in Column (4). Sample means are presented as the mean maximum distance of job seeker "workplace location preference" and job ad location of the sample (in kilometers). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.14: WFH and geographic dispersion of applicants (maximum distance of applicants)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.073^{*}	0.332^{***}	0.309^{***}	0.352^{***}
	(0.042)	(0.025)	(0.021)	(0.020)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (km)	145.3	145.3	145.3	145.3
N	1,326,144	1,326,144	927,677	1,241,048

Note: This table presents the results of the regression estimates looking at the effect of WFH signaling on the log distance of the applicant with the greatest distance from the "workplace location preference" and the location of the job ad. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0), and vacancies where the coordinates were wrong or could not be correctly matched are dropped from all samples. Job seekers with a minimum distance between their preferred location and closest job ad > 20km are also dropped from the sample. Sample means are presented as the average maximum distance of the job seeker's "workplace location preference" from the job ad for the sample (in kilometers). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.15: WFH and geographic dispersion of applicants (mean distance of top quartile)

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	0.118^{***}	0.346^{***}	0.340^{***}	0.380^{***}
	(0.034)	(0.022)	(0.020)	(0.020)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (km)	79.8	79.8	79.8	79.8
N	1,326,144	1,326,144	927,677	1,241,048

Note: This table presents the results of the regression estimates for the logged mean distance of applicants in or above the 75^{th} percentile in terms of distance from the "workplace location preference" and the location of the job ad on WFH offering. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0), and vacancies where the coordinates were wrong or could not be correctly matched are dropped from all samples. Job seekers with a minimum distance between their preferred location and closest job ad > 20km are also dropped from the sample. Sample means are presented as the mean distance of job seeker in the 75^{th} percentile of "workplace location preference" distance for the sample (in kilometers). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.16: Effect of WFH on “close” and “far” applications (no distance restrictions)

	Number of applications		Log applications	
	Far applications	Close applications	Far applications	Close applications
WFH offering	0.243^{**}	-2.073^{***}	0.056^{**}	-0.153^{***}
	(0.095)	(0.221)	(0.012)	(0.017)
Vacancy Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Local labor Market F.E.	Y	Y	Y	Y
Commuting zone × month-year F.E.	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y
Sample mean (# of applications)	6.83	13.64	8.40	15.47
N	1,009,572	1,009,572	840,465	897,791

Note: This table is analogous to Table 5 except without restricting the distances. The table presents the analysis looking at the differential change in applications between WFH job ads and similar in-person job ads when subsetting to applications that are “far” (Columns (1) and (3)) and “close” (Columns (2) and (4)). “Far” applications are applications that come from job seekers where the distance between the estimated workplace preference and location of the job ad is in the top quartile of distances in the local labor market (commuting zone by four-digit occupation). “Close” applications are applications that come from job seekers where the distance between the estimated workplace preference and location of the job ad is less than the median distance in the local labor market. Columns (1) and (2) present the estimates using the actual number of applications (including zeros) where columns (3) and (4) present the same estimates using log applications. These results use the full sample of applicants with no restrictions on distances. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Additional results for "Changes in the Applicant Pool"

Table B.17: Average quality of the top quartile of applicants by WFH offering

	All WFH job ads	Fully remote job ads	Job ads with WFH in headline
WFH offering	-0.011	0.071^{*}	0.017
	(0.008)	(0.040)	(0.065)
Vacancy Controls	Y	Y	Y
Firm Controls	Y	Y	Y
Local labor Market F.E.	Y	Y	Y
Commuting zone $\times$ month-year F.E.	Y	Y	Y
Occupation $\times$ month-year F.E.	Y	Y	Y
Sample mean (standardized maximum quality)	0.00	0.00	0.00
N	492,262	476,181	492,262

*Note:*This table presents the regression estimates for the main analysis (based on equation 1) for the average quality of the top quartile of applicants on whether the job ad offers WFH. The table present the estimates for three versions of WFH, Column (1) uses all the job ads classified as WFH, Column (2) uses only the fully remote job ads (dropping the hybrid job ads), and Column (3) redefines the treatment as job ads that explicitly state WFH in the headline. 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. For the fully remote sample (Column (2)), job ads classified as "hybrid WFH" are also dropped. The quality of applicants is standardized to have mean = 0 and standard deviation = 1. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.18: Compositional changes of unemployed attention (in shares)

	(1) Female	(2) High Education ($\geq$ bachelor's)	(3) Young ($<$ 45)	(4) Immigrant	(5) Non-urban
WFH offering	0.012***	0.008***	0.008***	−0.007***	0.009***
	(0.003)	(0.0)	(0.0)	(0.003)	(0.002)
Vacancy Controls	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y	Y
Commuting Zone $\times$ month-year F.E.	Y	Y	Y	Y	Y
Occupation $\times$ month-year F.E.	Y	Y	Y	Y	Y
Sample mean	0.526	0.279	0.554	0.411	0.185
N	401,639	401,639	401,639	401,639	401,639

Note: This table is similar to Table 8 except these results are based on the attention that job seekers gave to the job ads. This table presents the results for the changes in the demographic composition of unemployed job seekers that viewed the job ads by regressing the share of a specific characteristic on an indicator for if the job ad signals WFH using the main specification outlined in equation 1. The characteristics are measured as the shares of the unemployed job seekers that viewed the job ad. These regressions only consider unemployed job seekers since those are the only job seekers that can be matched to the demographic data. I look at five demographic characteristics: the share of female job seekers (Column (1)), share of highly educated job seekers (having at least a bachelor's degree, Column (2)), share of young job seekers (job seekers under the age of 45, Column (3)), share of job seekers that are immigrants (Column (4)), and share of job seekers living in non-urban neighborhoods (Column (5)). The data consists of all job ads over the months from May 2020 to September 2022 that had at least one job seekers who was unemployed view the ad. 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 the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.19: Compositional changes of unemployed applications - controls for other demographics

	(1) Female	(2) High Education ($\geq$ bachelor's)	(3) Young ($<$ 45)	(4) Immigrant	(5) Non-urban
WFH offering	0.017***	0.010**	0.013**	−0.007	0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
Vacancy Controls	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y	Y
Commuting Zone $\times$ month-year F.E.	Y	Y	Y	Y	Y
Occupation $\times$ month-year F.E.	Y	Y	Y	Y	Y
Other Demographics Controls	Y	Y	Y	Y	Y
Sample mean	0.461	0.263	0.601	0.489	0.167
N	397,719	397,719	397,719	397,719	397,719

Note: This table is similar to Table 8 except the specification used here also includes the shares of the other demographic characteristics as controls. This table presents the results for the changes in the demographic composition of unemployed job seekers that applied to the job ads by regressing the share of a specific characteristic on an indicator for if the job ad signals WFH using the main specification outlined in equation 1. The characteristics are measured as the shares of the unemployed job seekers that applied to the job ad. These regressions only consider unemployed job seekers since those are the only job seekers that can be matched to the demographic data. I look at five demographic characteristics: the share of female job seekers (Column (1)), share of highly educated job seekers (having at least a bachelor's degree, Column (2)), share of young job seekers (job seekers under the age of 45, Column (3)), share of job seekers that are immigrants (Column (4)), and share of job seekers living in non-urban neighborhoods (Column (5)). The data consists of all job ads over the months from May 2020 to September 2022 that had at least one job seekers who was unemployed apply to the ad. 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 the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 Additional results for "Non-urban Workplaces"

Table B.20: WFH and job ad attention (using log total views) - non-urban workplaces

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	-0.204^{**}	0.267^{***}	0.104^{***}	0.111^{***}
	(0.089)	(0.044)	(0.032)	(0.029)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (# of views)	224.99	224.99	224.99	224.99
N	1,003,452	1,003,452	825,795	929,576

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 subset to firms in non-urban areas. It is analogous to Table 9 except using attention. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the regressions that have only 4-digit occupation and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regressions specified in equation 2. 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, vacancies with no text written (text length = 0) and vacancies from firms in urban areas are dropped from all samples. Sample means are presented which provide the average number of views for the sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.21: WFH and geographic dispersion of applicants (additional minimum distance thresholds) - non-urban workplaces

	Minimum distance threshold			
	(1)	(2)	(3)	(4)
	40 km	60 km	100 km	Full data
WFH offering	0.266***	0.225***	0.201***	0.163***
	(0.015)	(0.013)	(0.012)	(0.010)
Vacancy Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y
Sample mean	55.60	64.51	74.71	89.42
N	961,288	973,521	985,609	996,813

Note: This table presents the results of the regression estimates for the main specification (equation 1) of logged mean distance of applicants' "workplace location preference" from the location of the job ad on WFH signal for workplaces in non-urban areas. The results here correspond to the estimates in Column (3) of Table 10, except in this table, I vary the threshold restriction placed on the minimum distance of an applicants' "workplace location preference" to the job ad for in person jobs. The thresholds used here are $<$ 40 km (Column (1)), $<$ 60 km (Column (2)), $<$ 100 km (Column (3)), and no distance restrictions (Column (4)). The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0), vacancies where the coordinates were wrong or could not be correctly matched, and job ads at workplaces in urban areas are dropped from all samples. Job seekers with a minimum distance between their preferred location and closest job ad $>$ 40km (Column 1), $>$ 60km (Column 2), and $>$ 100km (Column 3) are also dropped from the relevant sample. No additional job seekers are dropped from the sample in Column (4). Sample means are presented as the mean maximum distance of job seeker "workplace location preference" and job ad location of the sample (in kilometers). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.22: WFH and maximum distance of applicants - non-urban workplaces

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	0.195***	0.488***	0.303***	0.283***
	(0.050)	(0.051)	(0.100)	(0.089)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (km)	184.27	184.27	184.27	184.27
N	74,894	74,885	43,971	59,607

Note: This table presents the results of the regression estimates looking at the effect of WFH signaling on the log distance of the applicant with the greatest distance from the "workplace location preference" and the location of the job ad for job ads from workplaces in non-urban areas. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0), vacancies where the coordinates were wrong or could not be correctly matched, and job ads at workplaces in urban areas are dropped from all samples. Job seekers with a minimum distance between their preferred location and closest job ad > 20km are also dropped from the sample. Sample means are presented as the average maximum distance of the job seeker's "workplace location preference" from the job ad for the sample (in kilometers). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.23: WFH and mean distance of top quartile - non-urban workplaces

	All job ads			
	(1) Baseline relationship	(2) Within occupations	(3) Main analysis	(4) Firm fixed effects
WFH offering	0.371***	0.526***	0.361***	0.328***
	(0.046)	(0.047)	(0.095)	(0.083)
Occupation and Time F.E.s	N	Y	N	N
Vacancy Controls	N	N	Y	Y
Firm Controls	N	N	Y	N
Local Labor Market F.E.	N	N	Y	Y
Commuting Zone × month-year F.E.	N	N	Y	Y
Occupation × month-year F.E.	N	N	Y	Y
Firm F.E.	N	N	N	Y
Sample mean (km)	113.84	113.84	113.84	113.84
N	74,894	74,885	43,971	59,607

Note: This table presents the results of the regression estimates for the logged mean distance of applicants in or above the 75^{th} percentile in terms of distance from the "workplace location preference" and the location of the job ad on WFH offering for job ads from workplaces in non-urban areas. Column (1) corresponds to the baseline (uncontrolled) regression. Column (2) corresponds to the regression that has only 4-digit occupation fixed effects and time fixed effects. Column (3) corresponds to the main specification outlined in equation 1. Column (4) corresponds to the firm fixed effects regression specified in equation 2. The data consists of all months from May 2020 to September 2022. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no applications, vacancies with no text written (text length = 0), vacancies where the coordinates were wrong or could not be correctly matched, and job ads at workplaces in urban areas are dropped from all samples. Job seekers with a minimum distance between their preferred location and closest job ad > 20km are also dropped from the sample. Sample means are presented as the mean distance of job seeker in the 75^{th} percentile of "workplace location preference" distance for the sample (in kilometers). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.24: Average quality of the top quartile of applicants by WFH offering - non-urban firms

	All WFH job ads	Fully remote job ads	Job ads with WFH in headline
WFH offering	0.013	1.037	0.036
	(0.056)	(0.748)	(0.255)
Vacancy Controls	Y	Y	Y
Firm Controls	Y	Y	Y
Local labor Market F.E.	Y	Y	Y
Commuting zone × month-year F.E.	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y
Sample mean (standardized maximum quality)	−0.07	−0.07	−0.07
N	18,260	17,872	18,260

Note: This table presents the regression estimates for the main analysis (based on equation 1) for the average quality of the top quartile of applicants on whether the job ad offers WFH subset to firms in non-urban areas. The table present the estimates for three versions of WFH, Column (1) uses all the job ads classified as WFH, Column (2) uses only the fully remote job ads (dropping the hybrid job ads), and Column (3) redefines the treatment as job ads that explicitly state WFH in the headline. Individuals that have only one total view, vacancies that receive only one or less total views, vacancies with no text written (text length = 0) and job ads for workplaces in urban areas are dropped from all samples. For the fully remote sample (Column (2)), job ads classified as "hybrid WFH" are also dropped. The quality of applicants is standardized to have mean = 0 and standard deviation = 1. The sample means here deviate from the mean zero because the standardization is done on the full sample. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.5 Additional results for "Labor Market Tightness"

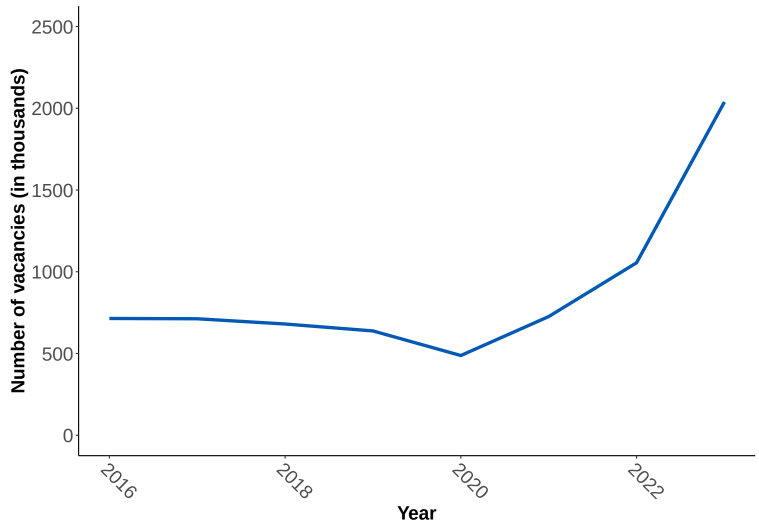
Table B.25: Main analysis of labor market tightness on job WFH offering

	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 13.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Additional Figures

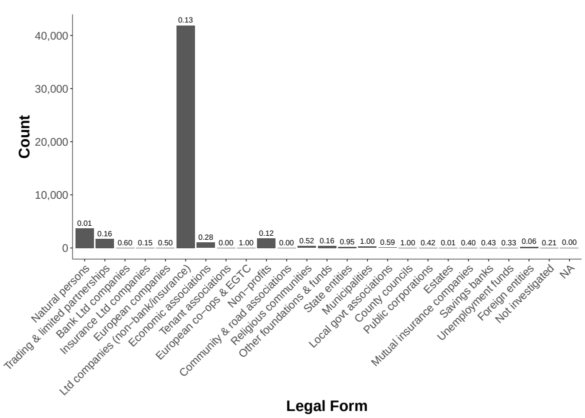
Figure C.1: Number of vacancies per year (2016-2023)



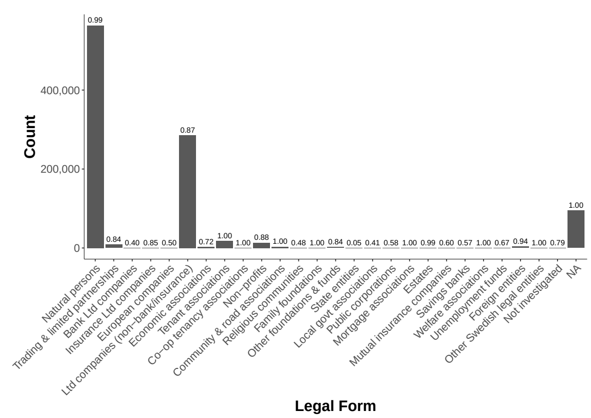
Notes: This figure plots the total number of vacancies per year (in thousands of vacancies) in the *Platsbanken* data after removing vacancies that are located outside Sweden.

Figure C.2: Distribution of Swedish firms by legal type

(a) Linked to at least one vacancy

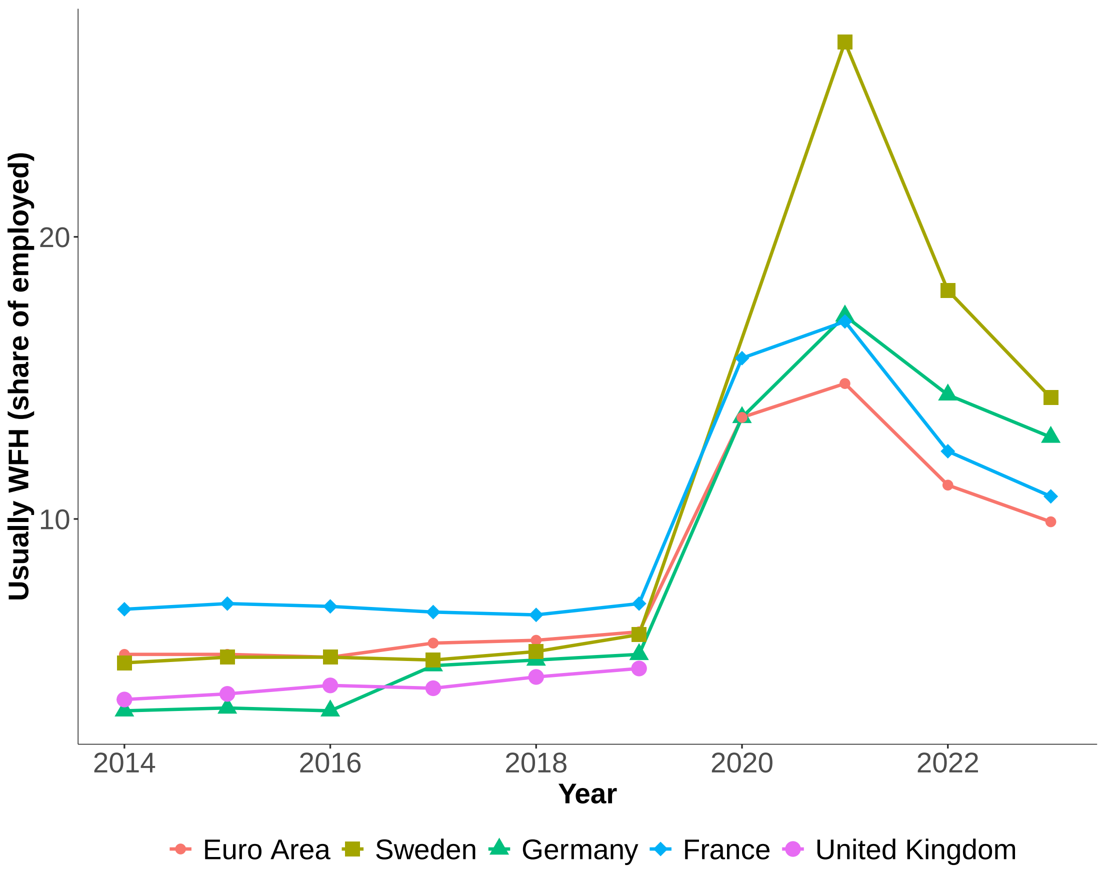


(b) Linked to no vacancies



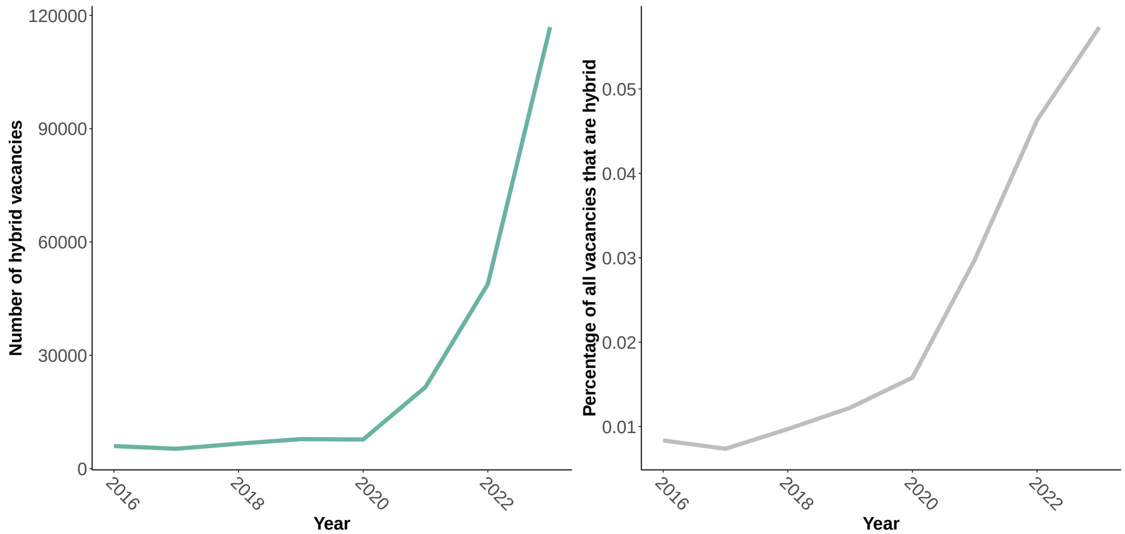
Notes: These figures present the distribution of firms by legal status based on the classification from the Swedish Tax Authority. Panel (a) presents the distributions for firms that are registered in Sweden and are connected to at least one vacancy from 2018-2022. Panel (b) presents the distributions for firms that are not connected to any vacancies. For both panels, the number of firms by type can be found on the y-axis. The numbers above the bars correspond to the share of total firms within that type that are found in that panel. In total, 4.7% of firms are matched to at least one vacancy in this period and 72.6% of vacancies are matched to a firm in the data.

Figure C.3: Share of employed that report usually WFH



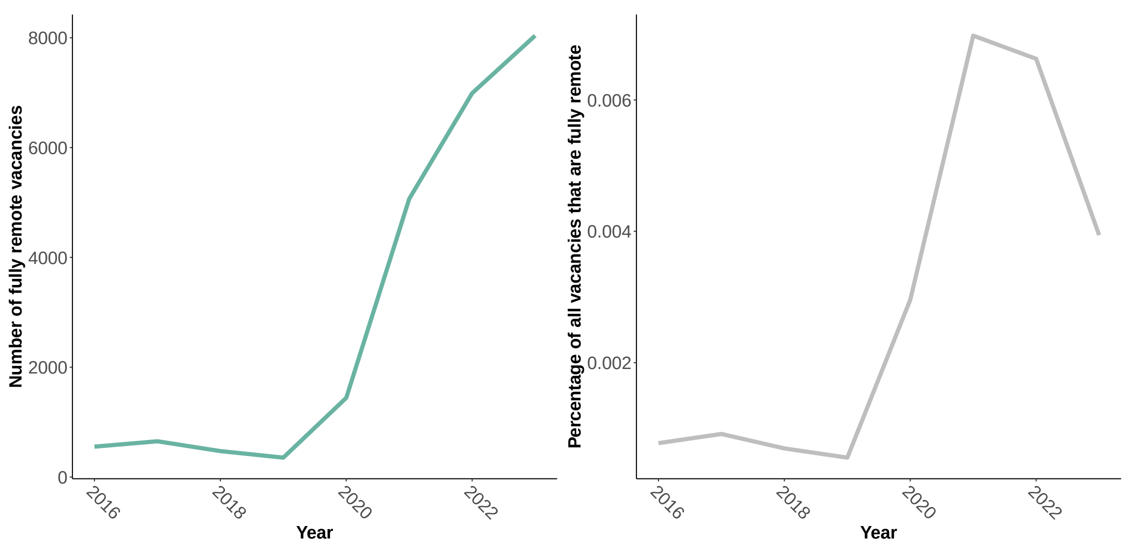
Notes: This figure plots the share of employed individuals that report that they "usually" work from home in the European Labor Force Surveys. This figure plots the shares from 2014-2023 for the average of the Euro Area (red, small circles), Sweden (olive, squares), Germany (green, triangles), France (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.4: Hybrid Vacancy Trends



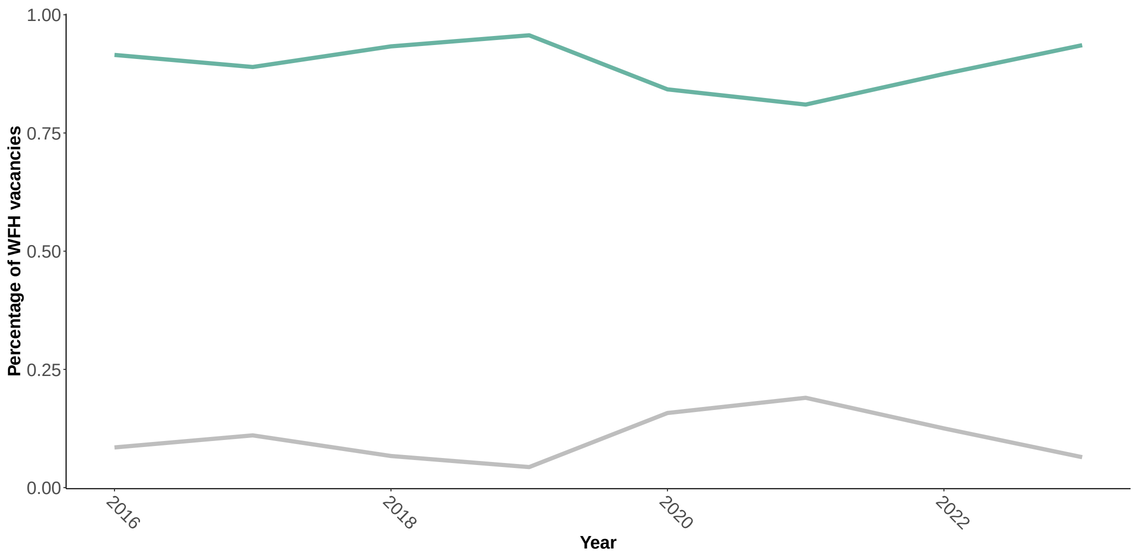
Notes: This figure plots the change in Swedish job ads that explicitly offer "hybrid" jobs from 2016-2023. The left graph plots the change in levels in hybrid job ads while the right graph plots the share of all job ads in that year that state they offer hybrid WFH. The share is out of all *Platsbanken* 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.5: Fully Remote Vacancy Trends



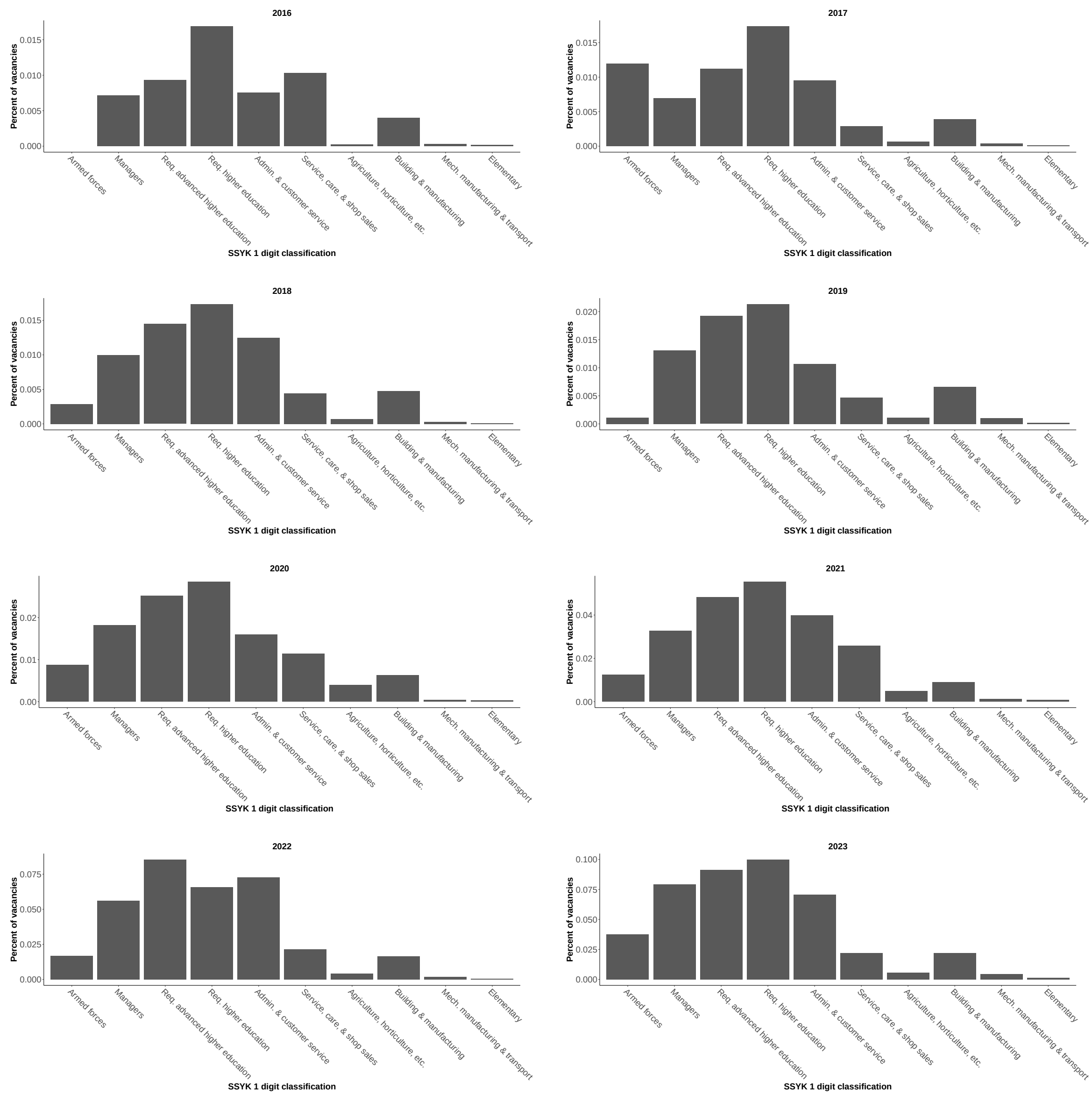
Notes: This figure plots the change in Swedish job ads that explicitly offer "fully remote" jobs from 2016-2023. The left graph plots the change in levels in fully remote job ads while the right graph plots the share of all job ads in that year that state they offer fully remote work. The share is out 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.6: 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.7: Percentage of WFH vacancies within occupation by year



Notes: These figures plot the share of job ads signaling WFH by broad, one-digit occupation categories for 2016-2023. Each figure plots the distribution by year, starting with 2016 in the upper left corner and ending with 2023 in the bottom right corner. The shares are calculated within one-digit occupation categories.

Figure C.8: 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.

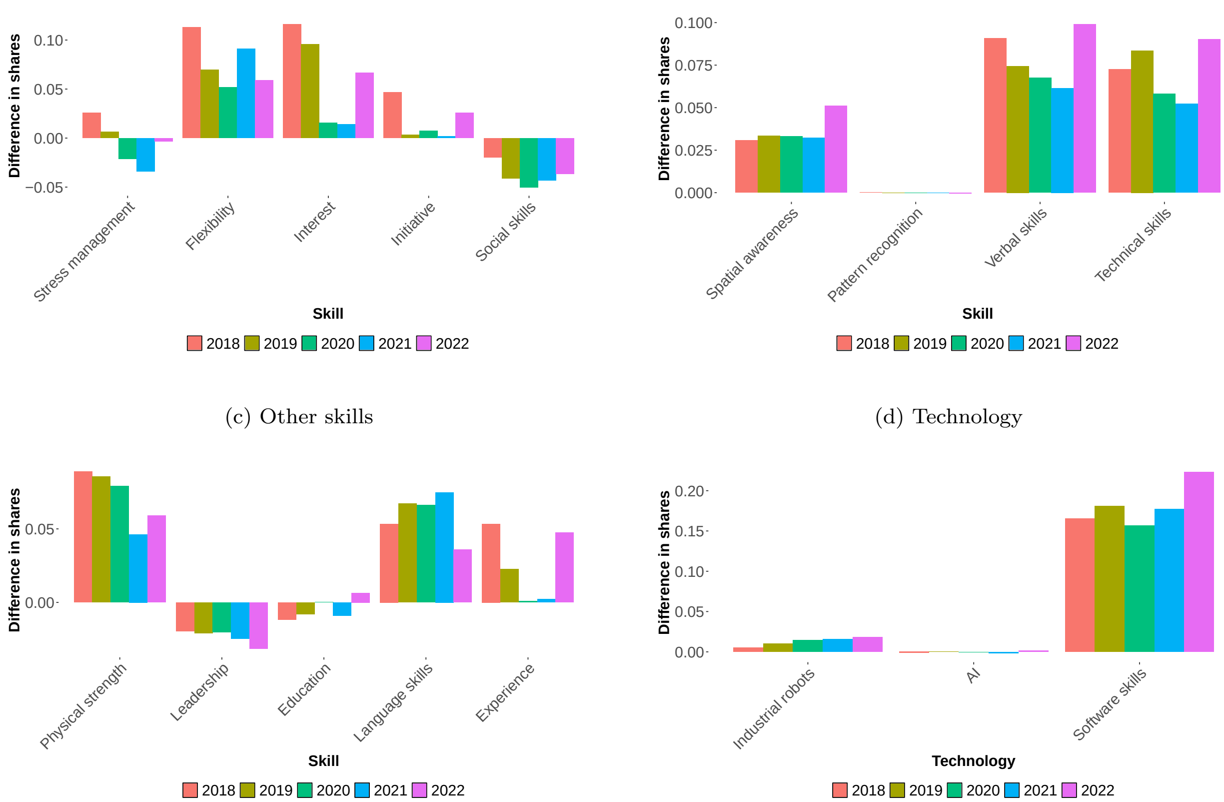
Figure C.9: Differences in the share of WFH and non-WFH job ads per skills/technology by year

(a) Cognitive skills

(b) Non-cognitive skills

(c) Other skills

(d) Technology

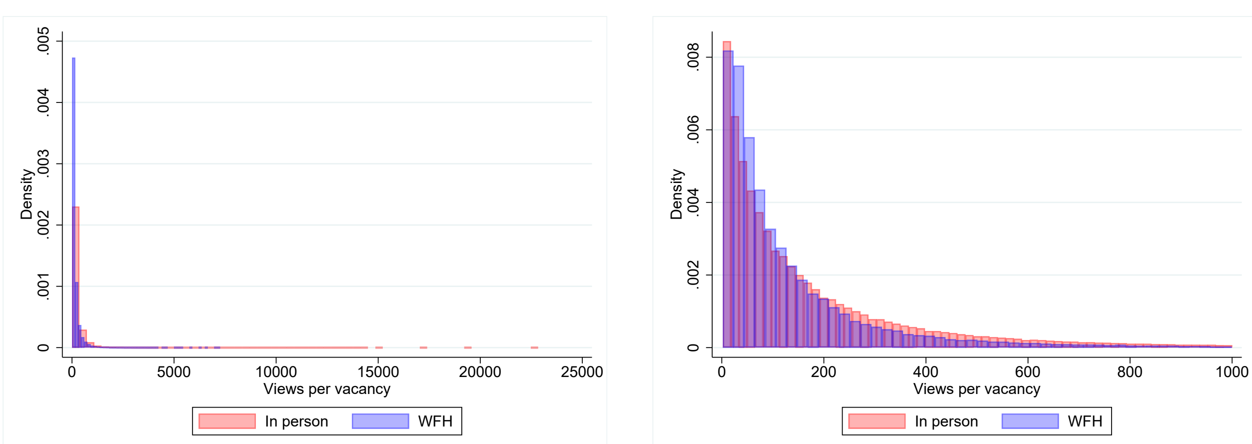


Notes: These figures present the difference between WFH and non-WFH vacancies in the shares of the specific skill (panels (a) to (c)) or technology (panel (d)) that the ad asks for. The differences are plotted separately by year from 2018-2022. For all four panels, the skills/technologies are presented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

Figure C.10: Distributions of views per job ad by whether the job ad offers WFH

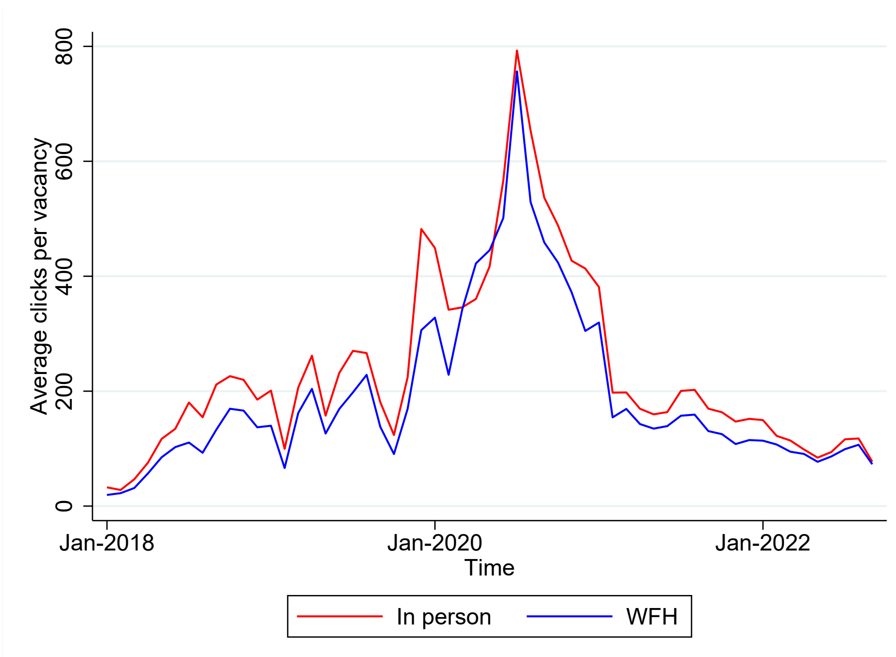
(a) Full distribution

(b) Truncated ($\leq$ 1,000 views)



Notes: These figures plot the distributions of the number of views the job ads receive by WFH offering. Panel (a) plots the distribution of the whole distribution. Panel (b) plots the distribution of the distribution truncated at job ads that received no more than 1,000 views. Only vacancies that had at least one view are included. For both panels, the distributions for in-person vacancies are plotted in red and the distributions of WFH vacancies are plotted in blue.

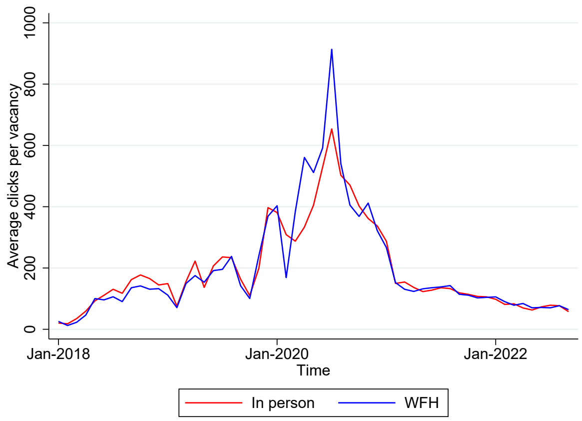
Figure C.11: Views per vacancy by WFH offering (Monthly)



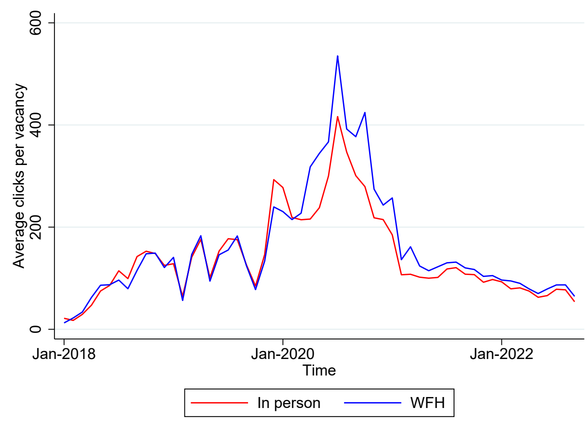
Notes: This figure presents the average number of views (clicks) per vacancy for each month by WFH type for March 2018 - September 2022. Only vacancies that had at least one view in that time period are included. The time series for in-person vacancies is plotted in red and the time series for WFH vacancies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

Figure C.12: Views per vacancy by WFH offering for select occupations

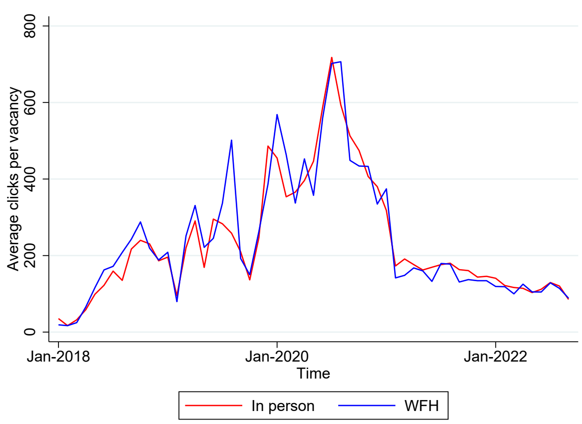
(a) “Requires higher education” job ads



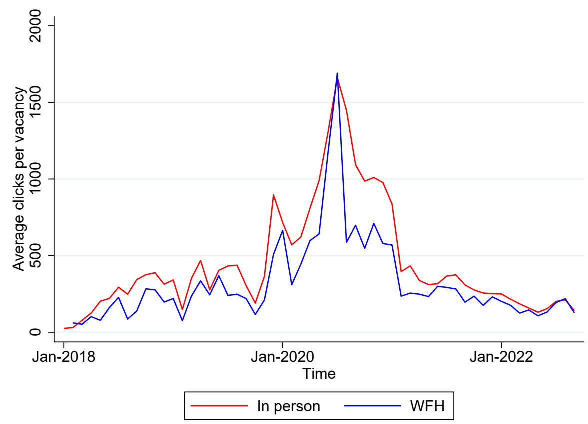
(b) “Requires advanced higher education” job ads



(c) “Manager” job ads



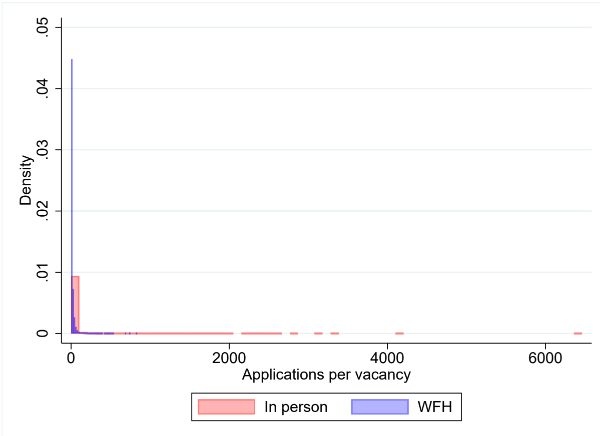
(d) “Administration and customer service” job ads



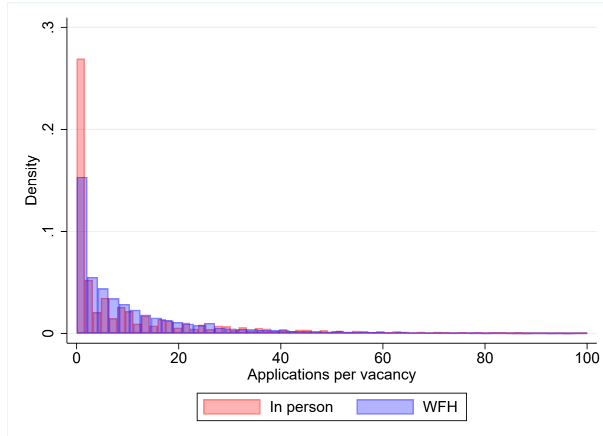
Notes: These figures present the average number of views (clicks) per vacancy for each month by WFH type for March 2018 - September 2022 for the four, 1-digit occupation categories with the highest share of WFH vacancies. Panel (a) presents the data for the 1-digit occupation category of “requires higher 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. For all panels, the time series for in-person vacancies are plotted in red and the time series for WFH vacancies are plotted in blue.

Figure C.13: Distributions of applications per job ad by whether the job ad offers WFH

(a) Full distribution

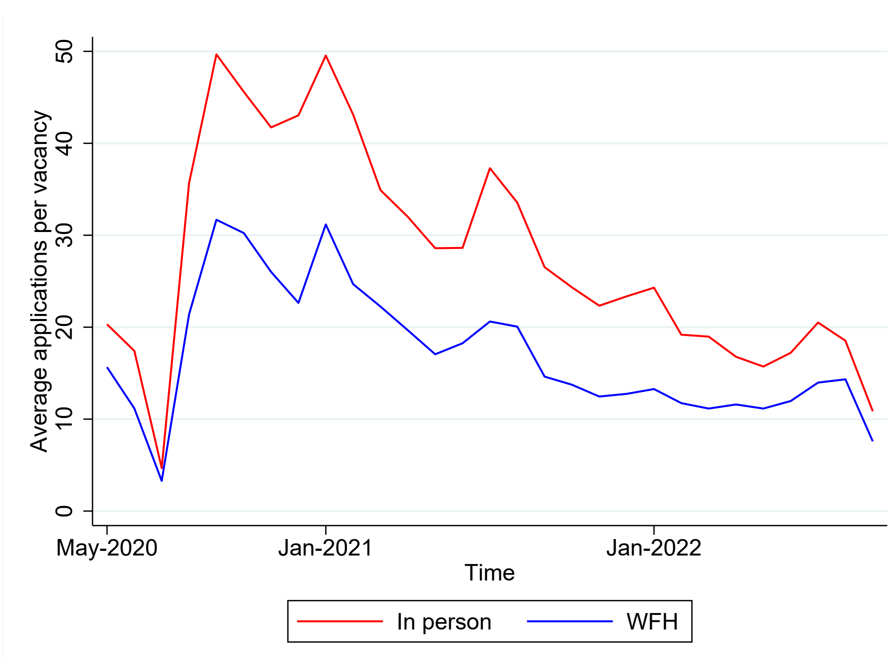


(b) Truncated ($\leq$ 100 applications)



Notes: These figures plot the distributions of the number of applications the job ads receive by WFH offering. Panel (a) plots the distribution of the whole distribution. Panel (b) plots the distribution of the distribution truncated at job ads that received no more than 100 applications. Only vacancies that had at least one view are included (but no restrictions on number of applications). For both panels, the distributions for in-person vacancies are plotted in red and the distributions of WFH vacancies are plotted in blue.

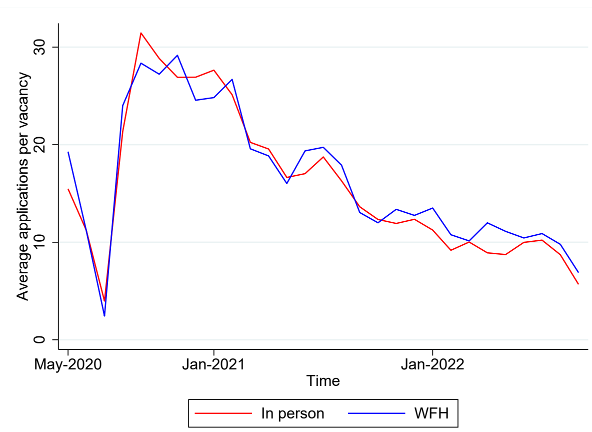
Figure C.14: Applications per vacancy by WFH type (Monthly)



Notes: This figure presents the average number of applications per vacancy for each month by WFH type for May 2020 - September 2022. Only vacancies that had at least one view in that time period are included, but there is no restrictions on the number of applications. The time series for in-person vacancies is plotted in red and the time series for WFH vacancies is plotted in blue.

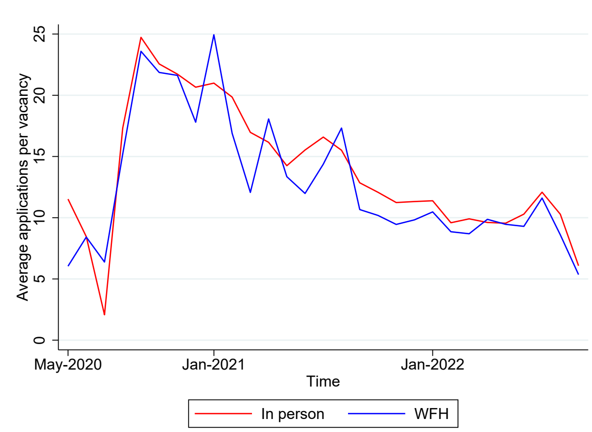
Figure C.15: Applications per vacancy by WFH offering for select occupations

(a) “Requires higher education” job ads

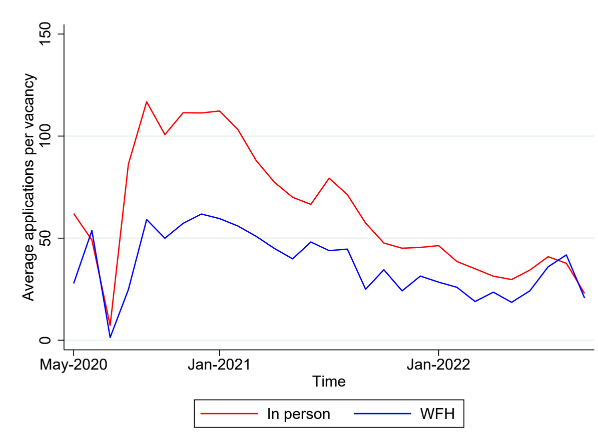


(b) “Requires advanced higher education” job ads

(c) “Manager” job ads

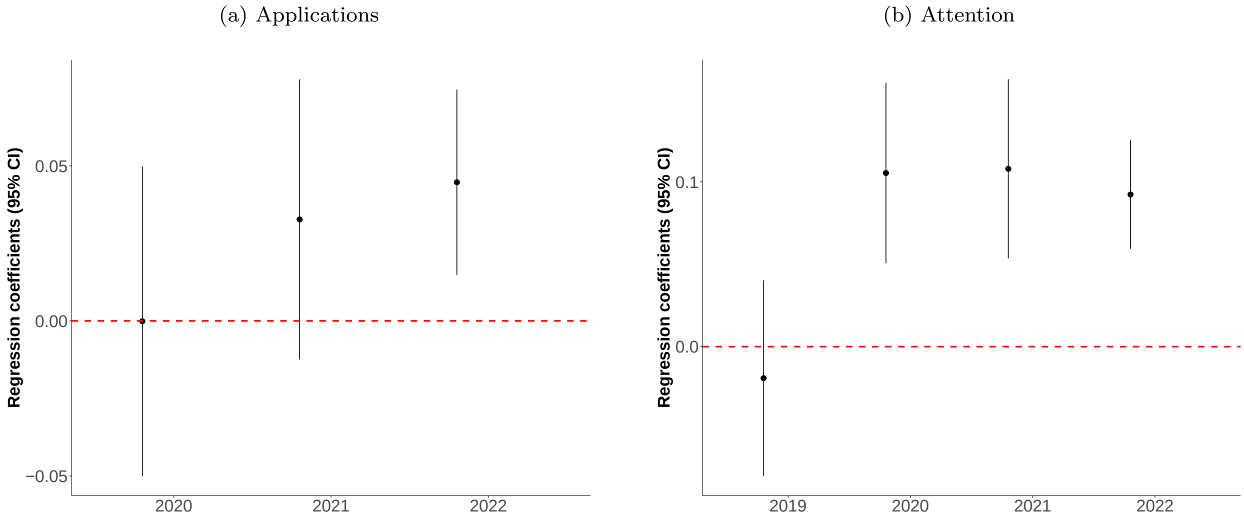


(d) “Administration and customer service” job ads



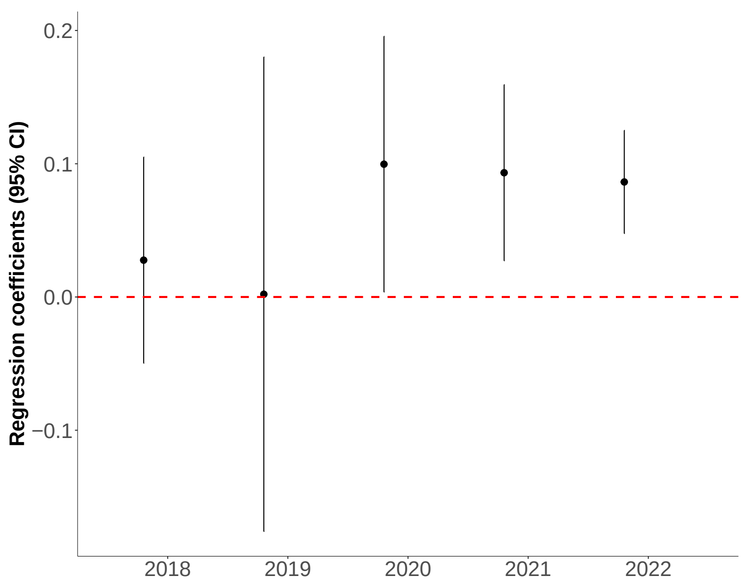
Notes: These figures present the average number of applications per vacancy for each month by WFH type for May 2020 - September 2022 for the four, 1-digit occupation categories with the highest share of WFH vacancies. Panel (a) presents the data for the 1-digit occupation category of “requires higher 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, but there are no restrictions on number of applications. For all panels, the time series for in-person vacancies are plotted in red and the time series for WFH vacancies are plotted in blue.

Figure C.16: Main results by year



Notes: These figures present the regression coefficients and 95% confidence intervals for applications (Panel (a)) and attention (Panel (b)) broken down by year. The coefficients are estimated using the main specification found in equation 1. The outcome variables for both applications and view are in logs using the full sample of job ads. 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 the sample. For applications, the data spans May 2020 through September 2022; for views the data spans January 2019 through September 2022. Standard Errors are clustered at the local labor market level.

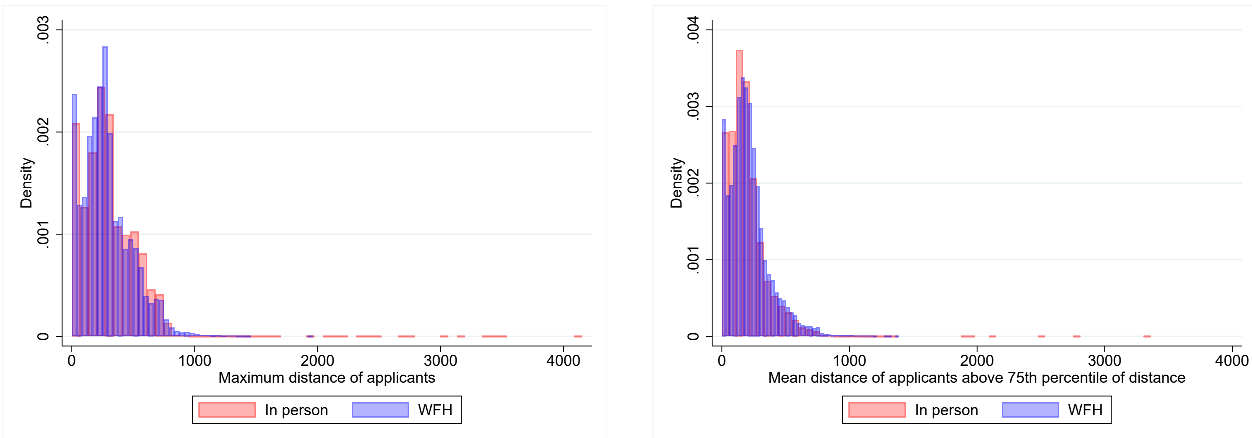
Figure C.17: Main results by year - Attention including 2018



Notes: This figure is the analogous figure to Panel (b) of Figure C.16 but including the data for 2018. It presents the regression coefficients and 95% confidence intervals for attention broken down by year. The coefficients are estimated using the main specification found in equation 1. The outcome variables are in logs using the full sample of job ads. 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 the sample. The data spans March 2018 through September 2022. Because of limitations in the data for the firm characteristics (most are missing for 2018), these regressions do not include the controls for firm industry, firm legal status, or firm size. Standard Errors are clustered at the local labor market level.

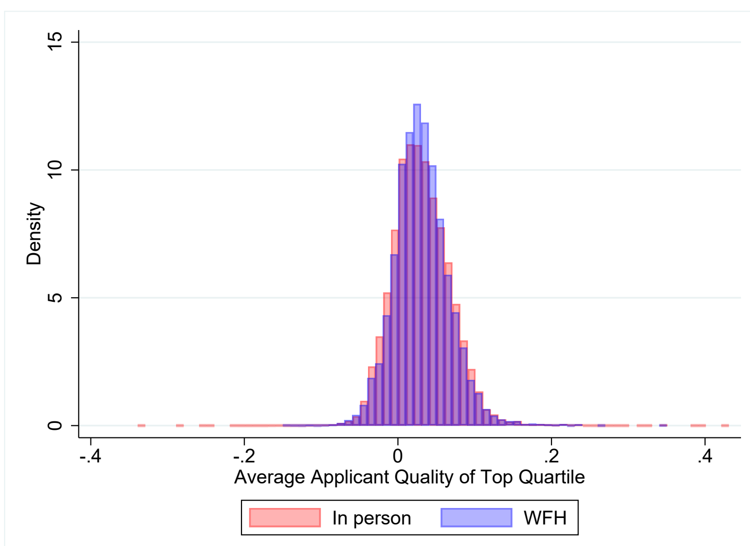
Figure C.18: Distributions of distances of applicants by whether the job ad offers WFH

(a) Maximum distance (b) Mean distance of top quartile



Notes: These figures plot the distributions of the distances of applicants' "workplace location preferences" from the job ads. Panel (a) plots the distributions of the maximum applicant distance. Panel (b) plots the distribution of the mean distance away for applicants in the 75th percentile of distance of job seekers that applied to that job ad. For both panels, the distributions for in-person vacancies are plotted in red and the distributions of WFH vacancies are plotted in blue.

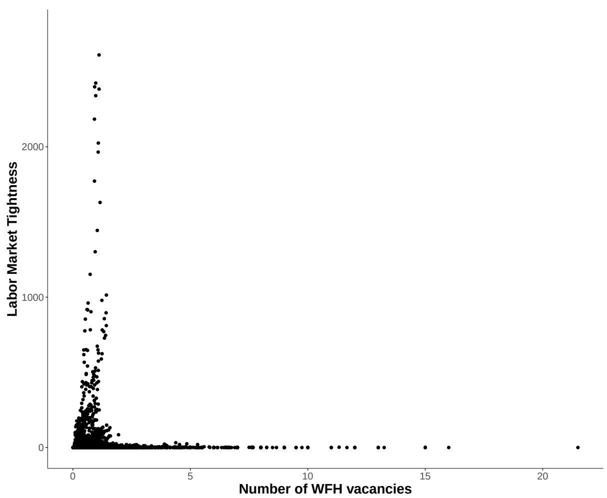
Figure C.19: Distribution of the average quality of the top quartile of applicants by WFH signal



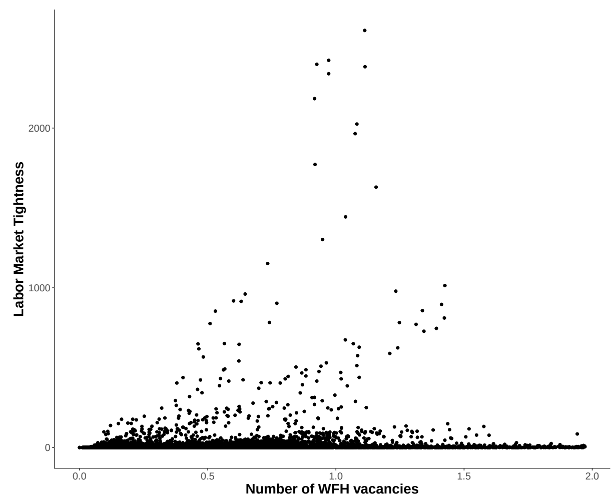
Notes: This figure plots the distributions of the average quality of the top quartile of applicants (the mean quality for applicants in the 75th percentile and above) from the job ads. "Applicant quality" is defined as the average firm fixed effects of all the other firms that applicant applied. The distributions for in-person vacancies are plotted in red and the distributions of WFH vacancies are plotted in blue. The figure plotting the distributions for the average quality and top quality is Figure 6.

Figure C.20: Correlations between labor market tightness and the number of WFH vacancies

(a) All observations



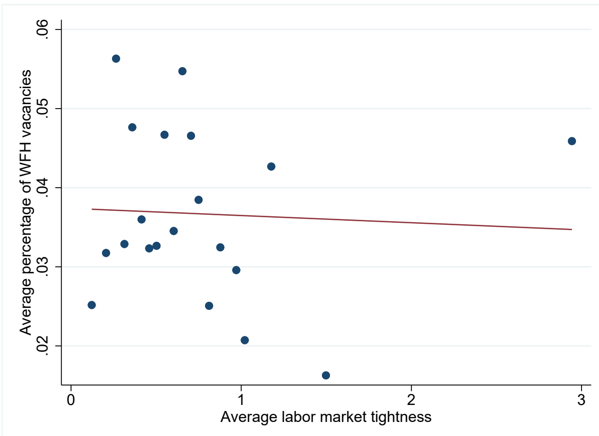
(b) Truncated (LM tightness < 2)



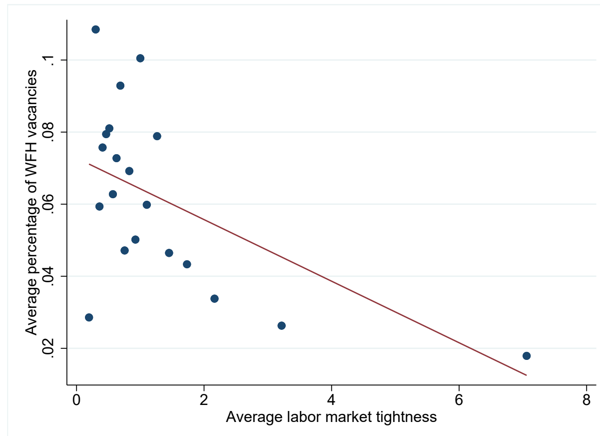
Notes: These figures are the full scatterplots that relate to Figure 7. Each point represents a local labor market (defined as a commuting zone x 1 digit occupation) in a specific month. Data consists of every labor market for every month (May 2020–September 2022) that has at least one applicant in that 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).

Figure C.21: Relationship between labor market tightness and WFH by occupation

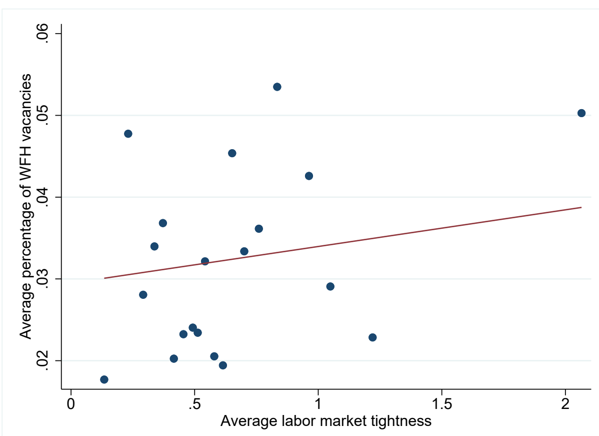
(a) "Requires higher education" job ads



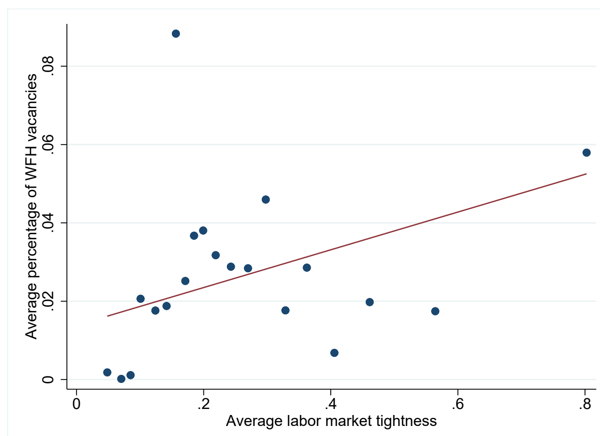
(b) "Requires advanced higher education" job ads



(c) "Manager" job ads



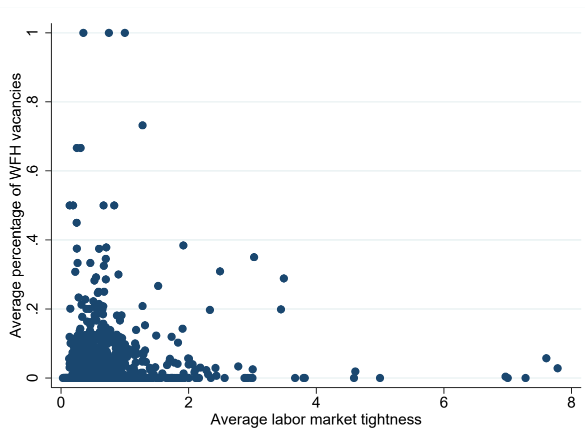
(d) "Administration and customer service" job ads



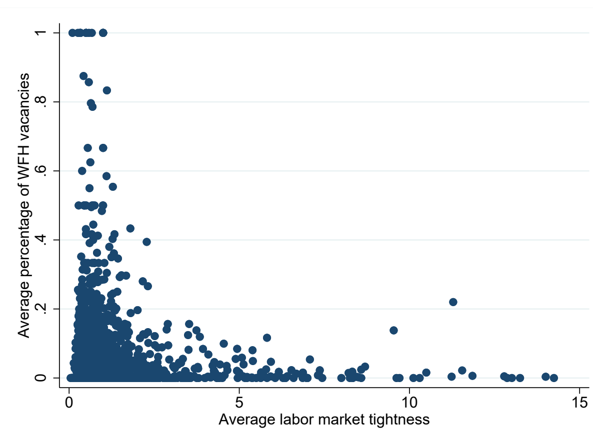
Notes: These figures present the binned scatter plot illustrating the relationship between the average local labor market tightness (with the labor market defined as the 3 digit occupation by commuting zone) and the average percentage of WFH vacancies by occupation category. Data consists of every labor market for every month (May 2020–September 2022) that has at least one applicant in that month. 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. The associated full scatter plots are found in Figure C.22.

Figure C.22: Relationship between labor market tightness and WFH by occupation - full scatter plots

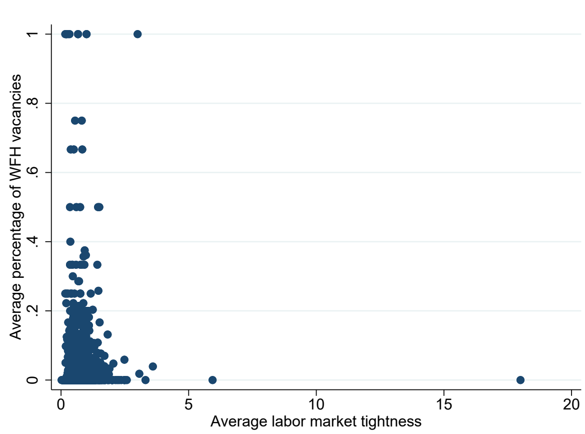
(a) "Requires higher education" job ads



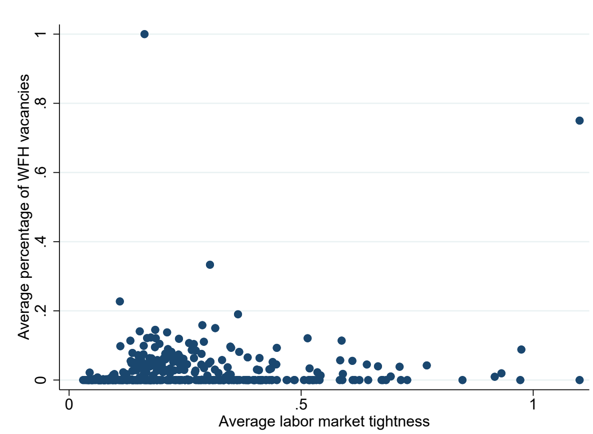
(b) "Requires advanced higher education" job ads



(c) "Manager" job ads



(d) "Administration and customer service" job ads



Notes: These figures present the full scatter plots illustrating the relationship 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 by occupation category. Data consists of every labor market for every month (May 2020–September 2022) that has at least one applicant in that month. 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. These figures are related to the binned scatter plots found in Figure C.21.