Hire from Anywhere:

Work-from-Home Offering and Firms' Labor Market Access*

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Abstract

Geographic frictions constrain hiring and worker-firm matching by limiting firms' access to workers outside their usual commuting range. Work-from-home (WFH) arrangements have the potential to relax these frictions by expanding firms' effective labor markets. Using population-level data from Sweden that link vacancy postings, employer-employee matched registry data, and data on job search behavior, I examine how signaling WFH in job ads reshapes firms' labor market access at the application and hiring stages. I identify WFH offers using a generative-AI-based text-classification procedure that distinguishes between hybrid and fully remote jobs, and I construct novel measures of revealed commuting preferences and applicant quality using job seekers' application behavior. I find that vacancies signaling WFH attract applicants from a geographically broader pool of job seekers. They also receive more applications on average and, for job ads with strong WFH signals, see an increase in quality for the top applicants. Both of these effects are driven by more distant applicants. At the hiring stage, I find that WFH-signaling vacancies hire workers from farther away, but I find no clear effect on average hire quality. By reducing the importance of commuting distance, WFH expands firms' effective labor markets, changes the size and composition of applicant pools, and widens the spatial reach of realized matches.

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1 Introduction

For many firms, the value of work from home (WFH) may lie not only in worker preferences, but in access to a broader and more distant pool of potential hires. Geographic frictions are a central source of mismatch in labor markets. When workers and firms are separated in space, traditional work arrangements limit matching because relocation is costly and commuting is feasible only over relatively short distances. By allowing workers to commute less or not at all, WFH arrangements can relax these constraints, expanding the effective geographic reach of firms and potentially improving match quality.

In this paper, I study whether WFH relaxes geographic constraints in hiring by expanding firms' effective labor markets, and how this affects applicants and hires. I find that job ads signaling WFH receive applications from a geographically broader pool of job seekers. Relative to applicants to similar in-person job ads, applicants to WFH job ads deviate 37% more from their revealed commuting preferences and apply to jobs 10% farther from where they live, consistent with WFH relaxing geographic constraints in job search. WFH job ads also receive 3.9% more applications on average, and this increase is driven by applicants applying from farther outside their usual commuting markets. At the same time, WFH reshapes the quality distribution of the applicant pool. While mean applicant quality declines slightly in some specifications, stronger WFH signals attract better applicants at the top of the quality distribution, a pattern again driven by workers with larger deviations from their commuting preferences.

These effects vary in economically meaningful ways across WFH arrangements and firms. Fully remote job ads generate geographic effects that are similar in magnitude to the main WFH results, suggesting that the broader geography effect is not driven solely by hybrid work arrangements. At the same time, fully remote vacancies exhibit large positive effects on applications, views, and top applicant quality, consistent with stronger remote-work arrangements generating larger recruitment benefits. The geographic effects are also especially pronounced for rural firms and other workplaces in thinner labor markets, where local hiring constraints are likely to be most severe. This pattern suggests that WFH is particularly valuable for relatively isolated firms because it allows them to reach workers who would otherwise lie outside their effective labor market.

These changes in the applicant pool induced by WFH signaling also have downstream effects on hiring. I find that new hires associated with WFH job ads live 6% farther from the workplace than new hires connected to similar in-person job ads. Moreover, the hiring-distance effect is larger for vacancies that attract geographically broader applicant pools, which is suggestive of some pass-through from applicant geography to the geography of realized hires. By contrast, I find no discernible effect on the average quality of hires. Taken together, these results suggest that the main downstream effect of WFH operates through geography rather than through average hire quality.

Taken together, these findings suggest that WFH affects firms by relaxing geographic frictions in hiring. By reducing the importance of commuting distance, WFH expands firms' effective labor markets and allows them to recruit from workers who would otherwise be unlikely to apply or be

hired. The results therefore suggest that WFH changes not just the size of applicant pools, but their geographic and quality composition, with some downstream consequences for realized matches. More broadly, the paper shows how a change in work organization can alter the geographic boundaries of labor markets and, in doing so, reshape firms' access to labor.

I study these questions using Swedish vacancy data linked to matched employer-worker registers and detailed search data on vacancy views and applications. These linked data make it possible to observe vacancy characteristics, applicant geography, and realized hires within the same setting. I combine these data with two novel measures derived from job-search behavior: a measure of applicants' revealed commuting preferences and a measure of worker quality based on search patterns. These measures allow me to study not only whether WFH attracts more applicants, but also whether it draws workers from beyond their usual commuting range and changes the quality of firms' applicant pools. I identify WFH offers from vacancy text using a text-classification procedure based on a generative AI model and compare outcomes across similar vacancies using rich controls and fixed effects, with identification coming from within local labor markets, occupations, and time.

This paper contributes to three related literatures: WFH, non-wage amenities and online job search, and spatial frictions in labor markets. First, the paper contributes to the literature on spatial frictions and geographic mismatch. A large literature shows that labor markets are highly local, with commuting and relocation costs limiting efficient matching between workers and firms (Manning and Petrongolo 2017; Kennan and Walker 2011; Caliendo, Dvorkin, and Parro 2019; Marinescu and Rathelot 2018; Şahin et al. 2014; Behrens et al. 2017; Bryan and Morten 2019; Heise and Porzio 2021; see also Moretti 2011 and Diamond 2016). I show that WFH can relax these frictions at the pre-hiring stage by expanding firms' effective geographic reach. WFH-signaling vacancies attract applicants whose revealed commuting-preference locations are farther from the job location and who are more willing to deviate from their usual commuting patterns. I further show that improvements in top-end applicant quality are driven primarily by these more distant applicants, with especially strong effects for rural workplaces where local labor markets are thinner. These findings suggest that WFH can reduce geographic mismatch in hiring by connecting relatively isolated firms to larger labor markets.

Second, the paper contributes to the growing literature on WFH. Existing work shows that WFH is one of the most important non-wage amenities in modern labor markets, that workers value it highly, and that its productivity effects depend on job tasks, workplace organization, and the form of remote work offered (Barrero, Bloom, and Davis 2021; Mas and Pallais 2017; Aksoy et al. 2022; Nagler, Rincke, and Winkler 2024; Barrero, Bloom, and Davis 2023; Gill and Skans 2024; Bloom et al. 2015; Angelici and Profeta 2024; Gibbs, Mengel, and Siemroth 2023; Bloom, Han, and Liang 2024; Emanuel and Harrington 2024). Relative to this literature, I shift attention away from realized WFH take-up and worker-side willingness to pay and instead study how signaling WFH in vacancy text changes firms' effective labor supply. This distinction between signaling and realized WFH is central in my setting: I document the extent to which firms explicitly advertise WFH in the vacancy text and study how that signal shapes search behavior at the application stage. I show that signaling WFH increases not

only firms' geographic reach, but also the number of applicants and parts of the quality distribution, highlighting a novel firm-side recruitment channel through which WFH can benefit firms regardless of the direct productivity effects.

Third, the paper contributes to the literature on non-wage amenities and online job-platform data. A broad literature shows that workers value non-wage job attributes and that these preferences shape search behavior, labor supply, and inequality (Mas 2025; He, Neumark, and Weng 2021; Le Barbanchon, Rathelot, and Roulet 2020; Cullen, Pakzad-Hurson, and Perez-Truglia 2025; Adams-Prassl et al. 2023; Harrington and Kahn 2025). A growing body of work then uses vacancy text and online search behavior to measure amenities and study how they affect search and matching outcomes (Alipour, Falck, and Schüller 2023; Hansen et al. 2023; Adrjan et al. 2025; Escudero, Liepmann, and Vergara 2024; Marinescu and Rathelot 2018; Teodorovicz, Choudhury, and Starr 2025; Akan et al. 2025; Hsu and Tambe 2025; Marinescu and Wolthoff 2020). I extend this literature in three ways. First, I improve on the traditional dictionary-based approach by constructing a vacancy-level measure of WFH signaling using generative-AI text-classification to distinguish hybrid from fully remote jobs. Second, I study firm-side labor-market access at the vacancy level, rather than focusing only on worker-side valuations of amenities. Third, I develop two novel measures based on search behavior: a measure of revealed commuting preferences based on the locations of workers' in-person applications, and a measure of applicant quality based on the AKM firm effects of the firms to which workers apply. These measures allow me to study how WFH signaling changes the size, composition, and quality distribution of the applicant pool using the full population of vacancies and applicants in the data.

The closest paper to mine is Akan et al. (2025), which studies how the rise of WFH has changed the spatial organization of workers and firms in the post-pandemic period. My paper complements theirs in two main ways. First, I directly observe whether vacancies explicitly signal WFH in job-ad text, rather than inferring WFH from realized worker-firm matches or occupation-industry structure. This gives me a job-level measure of WFH that is more precise than prediction-based approaches, which reduces measurement error when thinking about sorting. Second, I focus on the pre-hiring margin, which allows me to study the mechanism through which WFH reshapes geographic matching by expanding applicant pools and drawing applications from workers outside firms' usual commuting markets, especially in thinner rural labor markets.

The remainder of the paper proceeds as follows. Section 2 describes the Swedish setting. Section 3 presents the data and descriptive evidence. Section 4 provides descriptive evidence on firms' strategic use of WFH in response to labor market tightness. Section 5 outlines the empirical strategy. Section 6 examines how signaling WFH changes the geographic distribution of applicants. Section 7 studies how WFH changes the size and composition of the applicant pool. Section 8 analyzes how offering WFH affects hiring outcomes. Section 9 concludes.

2 Swedish Context

This section highlights four features of the Swedish setting that are important for interpreting the empirical results: pre-pandemic WFH prevalence, the nature of Sweden's COVID-19 response, the country's digital infrastructure, and the spatial distribution of jobs and housing. Taken together, these features make Sweden a useful setting for studying whether WFH relaxes geographic matching frictions by expanding firms' effective labor markets.

Work-from-home prevalence

Sweden had relatively high levels of WFH even before the COVID-19 pandemic. Using European Labour Force Survey (ELFS) data, Gill, Hensvik, and Nordström Skans (2025) show that Sweden ranked among the highest countries in Europe in the share of workers reporting that they "sometimes" or "usually" worked from home. Restricting to those who "usually" worked from home, Sweden appears closer to other major European countries (Figure A.1). WFH rose substantially in Sweden during the pandemic and remained elevated through at least 2023, with increases that were larger than in many other European countries. At the same time, post-pandemic survey evidence for highly educated white-collar workers suggests a more moderate pattern, although WFH remains common in Sweden. Aksoy et al. (2025), using the Global Survey of Working Arrangements (GSWA), report that workers in Sweden work from home 1.3 days per week on average, which is close to the median among European countries in their sample and slightly above the full-sample average of 1.2 days. These patterns suggest that Sweden is a useful setting for studying the effects of WFH on applicant pools and labor market access. WFH was already prevalent before the pandemic, which reduces the extent to which the analysis relies on a zero-baseline setting, but post-pandemic WFH levels are still comparable to those observed elsewhere in Europe.

COVID-19 policies

Since the setting of this analysis overlaps with the pandemic period, a second important feature is Sweden's response to the COVID-19 pandemic. Relative to many other countries, Sweden imposed comparatively limited formal restrictions (Hale et al. 2021). In particular, Sweden did not adopt widespread lockdowns or a general mask mandate. Formal interventions were concentrated instead in restrictions on amenities and public gatherings, including limits on restaurants, bars, and indoor commercial or public spaces. Schools also moved part of the instruction online at various points in order to reduce interpersonal contact. While formal restrictions were relatively limited, government recommendations were strong and appear to have been widely followed. In particular, workers whose tasks could be performed remotely were encouraged to work from home, contributing to a substantial shift toward fully remote and hybrid work during the pandemic period.

When these recommendations are incorporated alongside formal policy measures in the Oxford Coronavirus Government Response Tracker Stringency Index (Hale et al. (2021)), Sweden does not

appear markedly less stringent than many other European countries or parts of the world (Figure A.2). This suggests that Sweden's pandemic-related shift toward WFH was not uniquely weak or idiosyncratic, which strengthens the external relevance of the Swedish setting for studying how COVID-era changes in work arrangements affected labor market outcomes.

Digital infrastructure

A third relevant feature of the Swedish setting is the strength and breadth of its digital infrastructure. For WFH to be feasible, workers must have access to reliable digital tools and possess the skills required to use them effectively. Along both dimensions, Sweden stands out relative to many non-Nordic countries. According to European technology survey data, Sweden has among the highest shares of households with broadband internet access in Europe (Gill, Hensvik, and Nordström Skans 2025), an important prerequisite for WFH in many occupations. Broadband access is also close to universal, implying relatively limited differences across regions and along the rural-urban dimension. A similar pattern holds for digital skills. Sweden has a high share of residents with the baseline competencies needed for common remote-work tasks such as email and video communication, again ranking near the top of the European distribution. These features reduce the likelihood that regional differences in WFH offers or application patterns primarily reflect unequal access to technology or basic digital skills, allowing for a cleaner interpretation of geographic heterogeneity in the empirical results.

Spatial distribution and housing

Sweden's economic geography and housing market make spatial frictions particularly salient. Employment and high-skill job opportunities are concentrated in three main metropolitan labor markets (Stockholm, Gothenburg, and Malmö) with Stockholm by far the largest. These areas tend to have tight labor and housing markets, which increase the cost of relocation. Housing-market regulation adds to these frictions by making moves into, and within, high-demand urban areas more difficult. Outside the major metropolitan regions, Sweden is relatively sparsely populated, with a number of medium-sized and smaller local labor markets. As a result, many workers face a trade-off between residing in more affordable or accessible locations and maintaining access to dense urban job markets. Limited availability of centrally located housing can push households farther from major job centers, increasing commuting times and narrowing effective search radii. In this setting, WFH can relax commuting- and relocation-based constraints, thereby expanding workers' access to distant jobs and firms' access to applicants outside their traditional local labor markets.

3 Data

3.1 Swedish job ads

My main data source is vacancy postings, which provide measures of labor demand as well as rich information on job characteristics. I use the universe of vacancies posted in 2016–2023 on the Swedish Public Employment Service's job portal, *Platsbanken*, the largest job board in Sweden.[1] I exclude vacancies whose stated workplace is outside Sweden, since these cannot be linked to firm-level data. The resulting sample contains 7,053,457 vacancies (Table B.1), corresponding to roughly 880,000 vacancies per year on average.

The annual number of vacancies is fairly stable from 2016 to 2019, declines noticeably in 2020 during the COVID-19 pandemic, and then rises sharply in 2022 and 2023 (Figure B.1). The postings contain detailed information on occupation, employer, workplace location, posting date, and general job characteristics such as contract type, duration, and salary type. I complement these structured fields with information extracted from the open-text job descriptions, which contain details on job tasks, amenities, and required skills. Notably, Swedish job ads generally do not report wages or salaries even in these free-text descriptions.

Although *Platsbanken* covers most of the Swedish vacancy market, it does not cover it perfectly, and the sample is not necessarily representative of all vacancies. In particular, public-sector employers are required to advertise open positions and must post them on this platform, implying that public-sector jobs are likely overrepresented. Private-sector employers are encouraged, but not required, to use *Platsbanken*, so coverage is likely incomplete for those firms. I address part of this concern by controlling for whether the firm is public or private in the main analyses. More generally, because vacancy postings measure labor demand, firms, occupations, and industries with high turnover are also likely to be overrepresented. Extensive controls and fixed effects mitigate some of these concerns, but the results should nevertheless be interpreted with this selection in mind.

WFH classification procedure

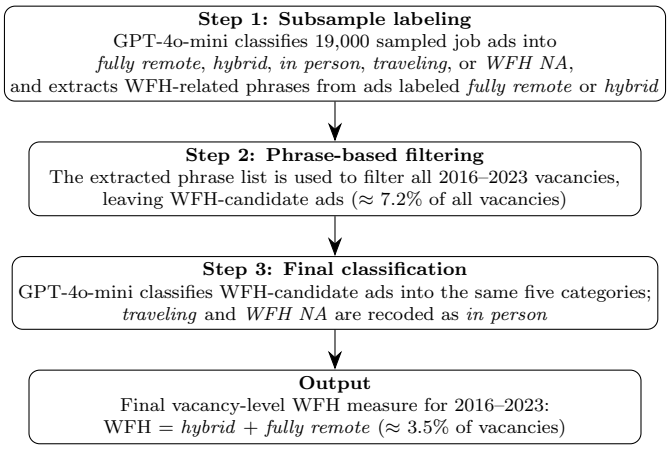
A key variable missing from the raw vacancy data is whether a job offers work from home (WFH). To address this, I classify whether each vacancy explicitly signals the possibility of WFH using a generative-AI-based text-classification procedure built on OpenAI's GPT-4o-mini model.[2] The objective is to identify whether the job ad itself signals WFH to job seekers, rather than whether the job is ex-post performed remotely. An outline of the classification procedure is found in Figure 1.

In the first step, I draw a random sample of 19,000 vacancies from 2006–2022, oversampling later years, and use GPT-4o-mini to classify each posting into one of five categories: fully remote, hybrid,

1. Compared with other major online job boards in Sweden, *Platsbanken* accounts for roughly 67% of market share based on web traffic (Figure B.2). There is also evidence that it captures the large majority of Swedish vacancy postings as the number of ads posted on the platform is comparable to the number of vacancies estimated for Sweden by Eurostat in 2019Q4 (Hensvik, Le Barbanchon, and Rathelot 2021).

2. The classification is a three-step procedure based on the approach in Boehnke et al. (2024). The main text of each vacancy is used as the input. An example of a vacancy posting is shown in Figure B.3.

Figure 1: Three-step procedure used to classify vacancies by WFH status



in person, "traveling" positions, or "WFH NA" (cannot be determined).[3] For vacancies classified as fully remote or hybrid, I also ask the model to extract the phrases in the job ad that indicate WFH.

In the second step, I use the extracted phrases to construct a filter for the full vacancy sample. I first form a bag-of-words from the extracted phrases by removing duplicates. I then manually prune the list to eliminate irrelevant terms, unnecessarily long phrases that contain shorter phrases already on the list, and overly vague expressions. The goal is to retain a broad set of WFH-related phrases while minimizing obvious false positives. The initial list contains 1,530 phrases and is reduced to 496 after pruning. These phrases are in both Swedish and English, the two dominant languages in the vacancy data (95.1% and 4.5%, respectively).[4] I then apply this dictionary to all vacancies in 2016–2023 and retain only postings that contain at least one phrase from the list. This leaves 507,012 vacancies, or 7.2% of the full sample. All vacancies removed at this stage are classified as in person.

In the final step, I reclassify all remaining postings using GPT-4o-mini, again assigning each ad to one of the five categories but without extracting phrases. Vacancies classified as "traveling" or "WFH NA" are recoded as in person. For some analyses, I distinguish between fully remote and hybrid vacancies; in the main analysis, however, I combine them into a single WFH category. Under this procedure, 3.5% of all vacancies in 2016–2023 are classified as WFH (Table B.1). As a robustness check, I also classify all vacancies directly with GPT-4o-mini, without the initial filtering step, and obtain a very similar set of WFH vacancies (Pearson's $\rho = 0.67$ for all WFH and $\rho = 0.79$ for fully remote; $p < 0.001$ in both cases).

It is important to emphasize that this measure does not identify jobs that are actually performed from home, nor does it capture whether workers ultimately choose to work remotely. Instead, it measures firms' *signaling* of WFH in the job ad text. This distinction is central for the analysis: the

3. "Traveling" positions are jobs in which work is performed away from the main workplace because the job requires frequent travel. This category is included to reduce false positives in the WFH classification, since early tests showed that such postings were sometimes mistakenly classified as remote. A typical example would be a door-to-door salesperson.

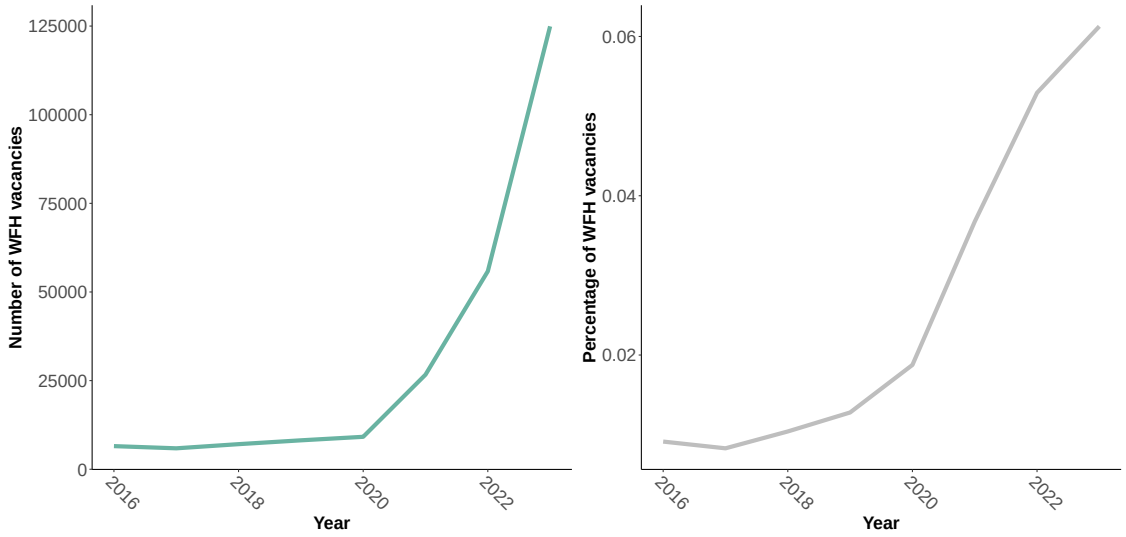
4. Vacancy language is identified using Google's Compact Language Detector (CLD3), a neural-network-based language classifier. Because CLD3 performs poorly on very short texts and leaves some texts unclassified, these shares are calculated among vacancies with non-missing language classifications and text descriptions of at least 20 characters in 2016–2022 ($N = 4,948,386$). The reported shares are therefore likely lower bounds, since most unclassified and very short postings appear to be written in Swedish.

variable captures whether job seekers observe a WFH offer at the application stage, not whether WFH is realized after hiring. As long as job seekers do not systematically possess better information about firms' true WFH policies than what is stated in the vacancy text, this measure isolates the effect of advertised WFH on search behavior.

WFH classification descriptives and validation

The time-series pattern in the WFH classification is intuitive. Before the COVID-19 pandemic, the share of vacancies explicitly offering WFH is low and grows only slowly (Figure 2). It then rises sharply with the onset of the pandemic and continues increasing through the post-pandemic period. The share of vacancies signaling WFH increases from below 1% in 2016 to more than 6% in 2023. Hybrid vacancies follow a similar pattern (Figure B.9), while fully remote vacancies rise during the pandemic but fall somewhat afterward (Figure B.10). This post-pandemic decline in fully remote postings is consistent with evidence that hybrid arrangements became more prevalent than fully remote work after the pandemic (Barrero, Bloom, and Davis 2023). On average, 89.5% of WFH vacancies are hybrid and 10.5% are fully remote (Figure B.11). This composition is fairly stable over time, although the fully remote share increases somewhat in 2020 and 2021.[5]

Figure 2: WFH Vacancy Trends



Notes: This figure plots the evolution of Swedish job ads that explicitly offer some form of work from home from 2016 to 2023. The left panel shows the number of WFH job ads, while the right panel shows their share among all *Platsbanken* job ads after excluding vacancies located outside Sweden. In this figure, hybrid and fully remote vacancies are grouped together. Separate trends for hybrid and fully remote vacancies are shown in Figures B.9 and B.10, respectively.

These trends are broadly consistent with other vacancy-based WFH measures. In particular, the overall time pattern resembles that documented by Hansen et al. 2023 and Boehnke et al. 2024, who apply similar methods to vacancy data from English-speaking countries and the United States, respectively. The level of WFH signaling is lower in Sweden, but that likely reflects institutional and

5. The geographic distribution of job ads and WFH job ads is found in Figure B.5.

cultural differences. For example, survey evidence suggests that workers in Sweden spend fewer days per week working from home than workers in many English-speaking countries (Aksoy et al. 2022).

The occupational distribution of WFH vacancies also matches prior expectations. At the 1-digit occupation level, managerial and highly educated occupations have the highest shares of WFH vacancies, while elementary occupations, agriculture, and mechanical production have the lowest shares (Figure B.12). This pattern is consistent with alternative occupation-based WFH classifications in the literature (e.g. Adams-Prassl et al. 2022; Dingel and Neiman 2020; Hensvik, Le Barbanchon, and Rathelot 2020; Mongey, Pilossoph, and Weinberg 2021). The occupations with the highest numbers and highest shares of WFH vacancies likewise correspond closely to standard notions of which jobs can be performed remotely (Table B.2).

To assess whether the classification is capturing WFH specifically, rather than other correlated features of vacancy text, I first examine words that appear frequently in WFH ads but not in in-person ads during 2018–2022. The concern is that if the WFH classification were instead proxying for unrelated job attributes, then non-WFH-specific words would dominate the set of words unique to WFH postings. Reassuringly, the most common unique word in WFH vacancies is "distans" ("distance"), which directly references remote work ("distansarbete") in Swedish, both in the pooled sample (Figure 3) and year by year (Figure B.13).

Figure 3: High-frequency, unique words in WFH vacancy text



Notes: This figure shows the relative frequency of the most common words that are unique to WFH vacancies. For the pooled 2018–2022 sample, I first identify the 200 most frequent non-stop words separately for WFH and non-WFH vacancies. I then remove from the WFH list any word that also appears among the top 200 words in non-WFH vacancies. The figure plots the relative frequencies of the remaining WFH-specific words. Year-specific versions of the figure are reported in Figure B.13.

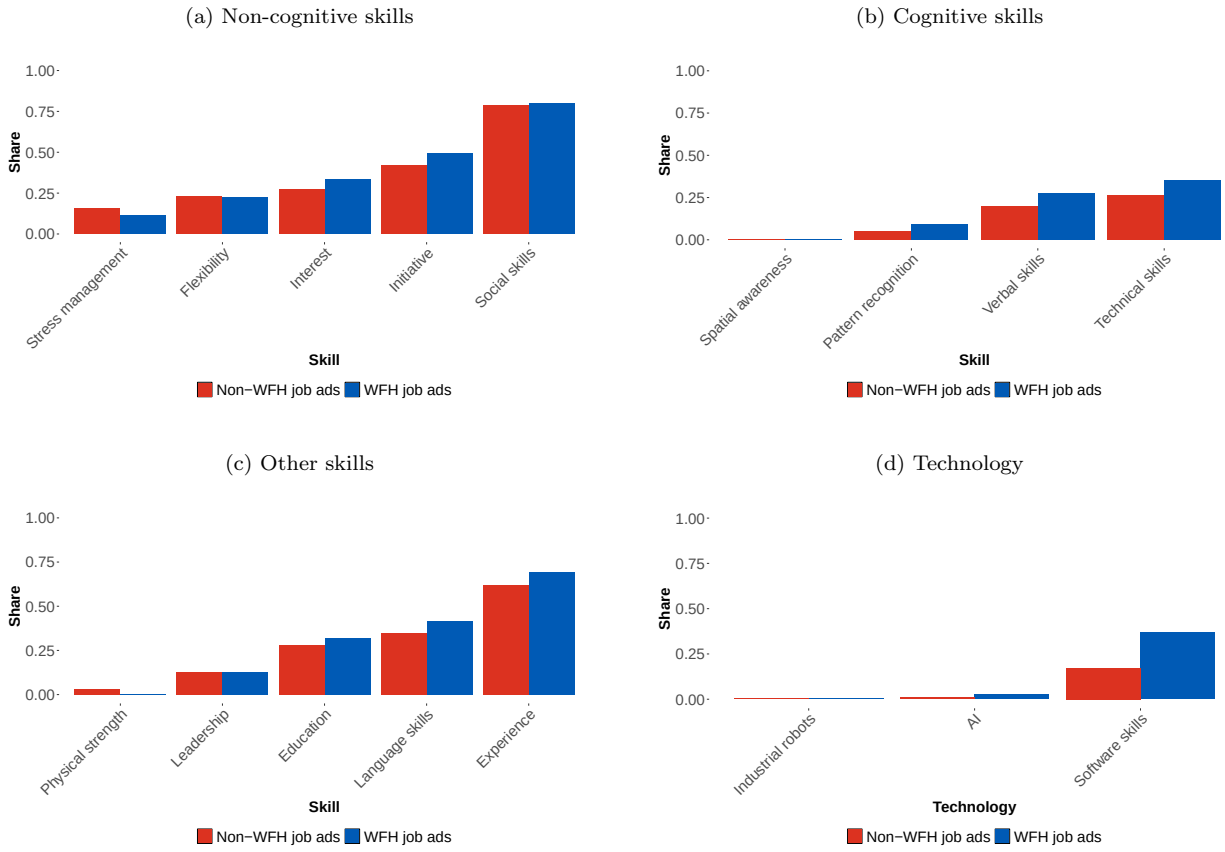
Some non-WFH words also appear relatively often among the words unique to WFH postings, especially terms related to technology (for example, "digitala," "tekniska," and "data") and social or non-cognitive skills (for example, "support" and "teamet"). To examine these potential confounders more directly, I use separate text-based measures of skills and technologies extracted from the vacancy descriptions.[6] Figure 4 compares the raw frequencies of these skills and technologies across WFH and non-WFH vacancies.[7] The shares are generally low for both groups: no skill or technology is mentioned

6. The skills and technology variables are extracted using a method similar to the WFH-classification procedure.

7. The corresponding differences in means and t-tests are reported in Table B.4. Year-specific differences are shown in Figure B.14.

in all WFH or all non-WFH vacancies, and all but two categories (social skills and experience) appear in fewer than 50% of ads. Moreover, the differences between WFH and non-WFH vacancies are small in nearly all cases and economically modest. Taken together, this evidence suggests that the classification primarily captures WFH signaling rather than broader differences in vacancy content. Nevertheless, I include the skills and technology controls in the main regressions to account for any remaining correlation.

Figure 4: Share of job ads asking for specific skills/technology by WFH offering



Notes: These panels show the share of WFH vacancies (blue) and non-WFH vacancies (red) that mention each listed skill or technology using vacancy data from 2018–2022. Panels (a)–(c) cover skill groups and panel (d) covers technology. In each panel, categories are ordered by the share of WFH vacancies that mention them. Most skills and technologies appear in a minority of both WFH and non-WFH vacancies, and the differences between the two groups are small in most cases. Table B.4 reports the corresponding formal tests, and Figure B.14 shows the differences by year.

In addition to the main text-based WFH measure, I construct an alternative classification based on whether the vacancy headline explicitly mentions WFH. For this measure, I use a simple dictionary approach and classify a posting as WFH if its headline contains at least one WFH-related keyword.[8] This procedure identifies 3,128 vacancies. I use this alternative measure to study the salience of WFH signaling, since the headline is among the few pieces of information visible to job seekers on the search page before they click into the full ad. This definition of WFH captures a different margin from fully remote vacancies, as the two measures are only moderately correlated (Pearson's $\rho = 0.43$, p-value

8. The eleven keywords, in Swedish and English, are: "distansarbete", "hemarbete", "jobba hemifrån", "fjärrarbete", "arbeta på distans", "telependling", "hemmajobb", "arbeta hemifrån", "work from home", "remote work", and "telecommute".

< 0.001).

3.2 Views and applications data

To study how WFH signaling shapes firms' access to labor at the pre-hiring stage, I match the vacancy data to measures of job seekers' search behavior on *Platsbanken*.[9] These data are central to the paper because they allow me to observe how job seekers respond to vacancy postings before hiring occurs, and therefore to study whether vacancies signaling WFH attract more attention and more application activity from a broader set of job seekers.

The search data are generated from a tracking cookie on the Swedish Public Employment Service's job portal that records interactions between devices and vacancy postings. I define an "individual" in these data as a device identified by an anonymized device ID. This definition implicitly assumes that the same person does not search from multiple devices and that multiple individuals do not systematically share a single device. While this introduces measurement error, the data nevertheless provide a detailed record of search behavior at scale.

I observe two search margins: *views* and *applications*. The views data span January 2019 to September 2022, while the applications data span May 2020 to September 2022.[10] Each observation corresponds to a single interaction and contains the vacancy identifier, the anonymized device ID, and the exact time of the action.

A *view* is recorded when a device clicks on a vacancy and opens the full job-ad page. I interpret this margin as a measure of vacancy *attention*. This is a useful outcome because it captures an early stage of search, before the job seeker initiates an application. At the search-results stage, job seekers observe only limited information, including the vacancy title, employer name, and location. In general, the full WFH signal studied in this paper is not visible until the job seeker opens the vacancy text. However, some WFH-signaling vacancies may still attract disproportionate attention at the view stage because job seekers can search for WFH-related terms, and because a subset of vacancies explicitly mentions WFH in the headline. This makes the views margin informative about how WFH signaling affects early search behavior, even when the main WFH measure is based on the full vacancy text.

An *application* is recorded when a device clicks the "apply" button on the vacancy page.[11] I interpret this as the *initiation* of an application, rather than a verified completed application, since I do not observe the full downstream submission process or the exact number of unique job seekers who ultimately apply. Even so, this margin is substantially closer to active search effort than a view and provides a useful measure of recruitment interest.

Together, the two margins capture distinct stages of job search. Views measure initial attention to a vacancy, while applications measure a more active step toward matching. The two are strongly

9. These search data are first used in Hensvik, Le Barbanchon, and Rathelot (2021).

10. I also observe earlier views data for March 2018–December 2018, but I exclude these observations from the main analysis because early bugs in the tracking software may introduce non-classical measurement error. For transparency, I also report robustness checks that include them.

11. Screenshots of the job-portal pages at the view and application margins are shown in Figures B.4 and B.3, respectively.

positively correlated across vacancies (Pearson's $\rho = 0.63$, $p < 0.001$), but they do not perfectly overlap. I therefore use both outcomes in the analysis. Views allow me to study how WFH signaling affects early attention, while applications capture a more substantive form of search activity and firms' effective access to potential applicants.[12]

3.3 Swedish registry and geographic data

I next link the vacancy, view, and application data to Swedish matched employer-employee registry data. These registry data are important for the analysis because they allow me to enrich the vacancy and search data with firm characteristics, worker demographics for a subset of job seekers, and detailed geographic information. Together, these links make it possible to study not only whether WFH-signaling vacancies attract more search activity, but also whether they expand firms' access to workers across space and across worker types.

First, the vacancy data can be linked to firm-level registry information using firm identifiers reported in the job ads. This match provides information on firm characteristics including industry, size (measured by the number of employees), legal status, and employee wages.[13] These variables are used both to describe the firms posting vacancies and as controls in the main empirical specifications.

Second, I can link a subset of job seekers, specifically, unemployed job seekers registered with the Swedish Public Employment Service, to registry-based demographic information. Registered unemployed workers, who account for a large share of unemployment in Sweden, must log in to the agency's online platform and document their job-search activity to remain eligible for benefits. For job seekers in this group, I can match views and applications to the device used to log in to the platform, provided that job search occurs on the same device. This match allows me to connect search behavior to individual registry characteristics, including age, gender, education, and immigration background.

Third, I observe geographic information at the DeSO (neighborhood) level for both workplaces and the subset of unemployed job seekers matched to the registries.[14] DeSOs are designed to contain roughly similar resident populations, although they vary substantially in land area and in the number of jobs located within them. In particular, DeSOs tend to cover much larger geographic areas in rural parts of the country. In the 2018 classification, there are 5,984 DeSOs, each assigned to one of three area types: category A (rural areas, 18.0%), category B (population-concentrated areas outside major municipal centers, 9.7%), and category C (central areas within municipalities, 72.3%). Throughout the paper, I refer to workplaces located in category A as *rural* workplaces and category C as *urban* workplaces.

The DeSO geography is mapped to workplaces, unemployed job seekers residences, and vacancies.

12. The distribution of applications and views for WFH and in-person job ads is found in Figures B.7 and B.8, respectively.

13. Legal status captures the firm's registered organizational form at the Swedish Tax Agency and includes categories such as limited liability companies, non-profit organizations, and "natural individuals" (individual ownerships). In total, there are 24 legal-status categories. The distribution of firms with job ads and without job ads in my data by legal status is found in Figure B.6.

14. DeSO is a neighborhood-level statistical geography defined by Statistics Sweden. The DeSO system was introduced in 2018, applied retroactively, and updated periodically. I use the original 2018 DeSO definitions throughout the paper.

For workplaces and unemployed job seekers linked to the registry data, the DeSO is observed directly through the anonymized registry identifier. For vacancies, I assign workplace DeSOs by overlaying the posted workplace coordinates with DeSO polygon boundaries and assigning each vacancy to the DeSO in which its coordinates fall. These geographic links are central for the later analysis because they allow me to study how WFH signaling affects the spatial reach of applicant pools and whether the effects are stronger for firms located outside dense urban labor markets.

3.4 Revealed commuting preferences

To study whether signaling WFH relaxes geographic frictions in hiring, I require a measure of applicants' usual commuting market. A natural benchmark would be the distance between job seekers' residences and workplace locations. However, residential locations are only observed for a subset of applicants in my data, so that approach would substantially reduce the usable sample. More importantly, residential location is not the key behavioral margin for the question I study. Commuting preferences differ across individuals, and residential locations themselves are shaped by equilibrium forces in housing and labor markets. The more relevant margin is therefore whether WFH leads job seekers to apply outside their usual in-person commuting range.

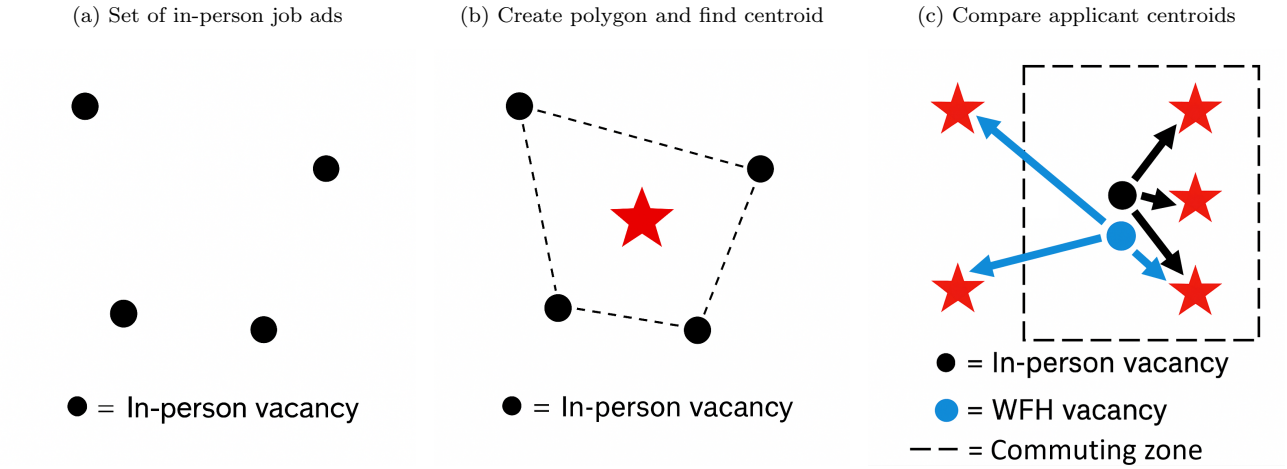
To capture this margin, I construct a novel measure of *revealed commuting preferences* using job seekers' application behavior. The idea is to recover each job seeker's preferred workplace location under standard in-person work arrangements from the set of in-person jobs to which they apply. Relative to survey-based measures of commuting preferences, this approach is based on revealed search behavior. Relative to realized commuting-distance measures, it is less directly shaped by equilibrium sorting in housing and hiring. Because the measure is built from applications rather than residential addresses, it can also be implemented for the full set of applicants observed in the application data.

Figure 5 illustrates the construction. For each job seeker, I take the coordinates of all vacancies classified as in person which that job seeker applies to. This gives me an approximation of the geographic boundary of where this individual would apply if they had to commute. I then construct the polygon composed by connecting these coordinates and compute its centroid. I interpret this centroid as the job seeker's preferred workplace location under in-person work. Panels (a) and (b) of Figure 5 illustrate this intuition.

To reduce noise in this measure, I restrict the sample to job seekers who apply to at least two in-person vacancies. This restriction introduces some selection, since it excludes job seekers who apply only to WFH vacancies and who may therefore have the strongest preferences for remote work. If those job seekers are also the most willing to deviate from their usual commuting market, then this restriction will tend to attenuate the estimated WFH effects. In that sense, the resulting estimates should be interpreted as conservative.

Using the applicant-specific commuting-preference locations, I then calculate the straight-line distance between each job seeker's preferred commuting location and the workplace coordinates of every vacancy to which that individual applies, including both in-person and WFH vacancies. This distance

Figure 5: Construction of the revealed commuting-preference measure



Notes: This figure illustrates the construction of the revealed commuting-preference measure. Panel (a) shows the spatial distribution of the in-person vacancies for one job seeker. Panel (b) shows the polygon spanned by those vacancies and its centroid, which is interpreted as the job seeker's preferred workplace location under in-person work. Panel (c) shows how the distance between this centroid and the location of each applied-to vacancy is used to measure deviations from the job seeker's usual commuting market. These applicant-level deviations are then aggregated to the vacancy level.

measures how far a job seeker is willing to deviate from their usual in-person commuting market in order to apply to a given job. Panel (c) of Figure 5 illustrates this final step.

I then aggregate these applicant-level deviations to the vacancy level. My main outcome is the average deviation from revealed commuting preferences among applicants to a vacancy. I also construct two alternative measures: the maximum deviation among applicants to the vacancy, and the average deviation among applicants in the top quartile of the within-vacancy deviation distribution. Together, these measures capture both the average geographic expansion of the applicant pool and the extent to which WFH attracts especially distant applicants.

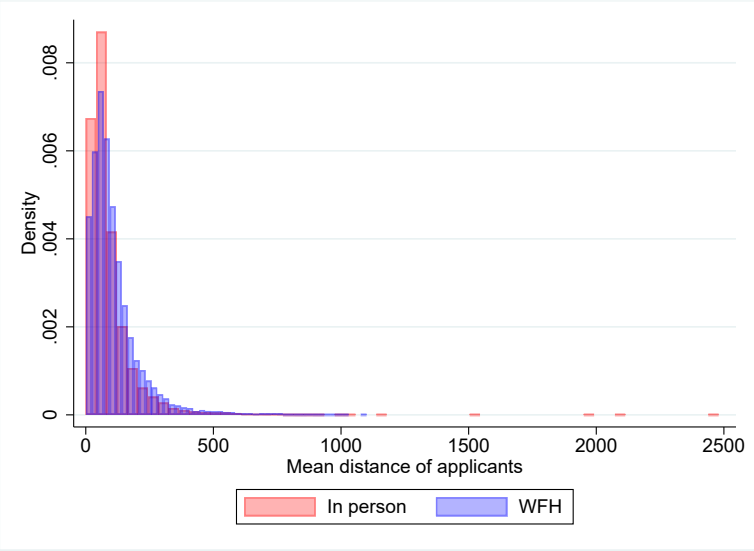
The vacancy-level distributions of the mean deviation measure for in person and WFH job ads are shown in Figure 6.[15] The distribution for WFH vacancies is shifted to the right relative to the distribution for in-person vacancies, indicating that applicants to WFH-signaling jobs tend to come from outside their usual commuting market. This pattern is consistent with the idea that signaling WFH relaxes geographic constraints in job search and expands firms' effective labor-market reach. Section 6 examines this relationship more formally in the regression analysis.

3.5 Applicant quality

In addition to applicant geography, the paper studies whether signaling WFH changes the quality composition of firms' applicant pools. Measuring applicant quality directly is difficult, since applications data rarely contain a canonical measure of worker quality at the time of search. To address this, I construct a proxy for applicant quality based on search patterns and the empirical regularity that

15. The distributions for the maximum distance and top quartile distance are similar to the mean distance (see Figure B.15).

Figure 6: Distributions of mean deviations from revealed commuting preferences by WFH offering



Notes: This figure plots the distributions of the mean distances between applicants' revealed commuting-preference locations and the locations of the vacancies to which they apply. The distribution for in-person vacancies is shown in red and the distribution for WFH vacancies is shown in blue.

higher-quality workers tend to sort disproportionately toward higher-quality firms (e.g. Abowd, Kramarz, and Margolis 1999, Card et al. 2018, and Braunschweig, Dauth, and Roth 2024). The idea is that applicants who systematically target higher-quality firms are, on average, likely to be higher-quality workers themselves.

The construction proceeds in two steps. First, I estimate firm quality using firm pay premia, defined as the firm fixed effects from an AKM wage model estimated on all workers employed at these firms during 2016–2019.[16] I interpret these firm pay premia as a measure of firm quality.

Second, for each application (job-seeker–vacancy pair), I assign the AKM pay premium of the firm posting the vacancy and then compute a leave-one-out measure of applicant quality at the job-seeker level. Specifically, for applicant i applying to vacancy v, I define applicant quality as the mean firm pay premium among all other firms to which applicant i applies, excluding the firm associated with vacancy v:

$$\text{LOO_job_seeker_quality}_{i,v} \equiv \frac{1}{|F_i \setminus \{f_v\}|} \sum_{f \in F_i \setminus \{f_v\}} \phi_f \tag{1}$$

where F_i is the set of firms to which applicant i applies, f_v is the firm posting vacancy v, and ϕ_f is firm f's AKM pay premium. The leave-one-out construction avoids mechanically inflating the quality measure using the firm associated with the focal application itself.

The intuition is straightforward: applicants who systematically target firms with higher pay premia are, on average, likely to be stronger applicants. Under the assumption that, conditional on observed job characteristics, higher-quality job seekers disproportionately apply to higher-quality firms, this

16. The estimates are restricted to the maximum connected set of firms and workers. I estimate a standard AKM model with worker fixed effects, firm fixed effects, and year fixed effects. Under the standard AKM assumptions, worker mobility across firms identifies the firm pay premia. I estimate the AKM model prior to the main analysis period in order to avoid mechanical correlations with the search outcomes studied in the paper.

leave-one-out application pattern provides a plausible proxy for applicant quality. The measure should therefore be interpreted as a revealed-preference-based indicator of applicant quality rather than a direct measure of productive ability.

A potential concern is that application patterns may reflect not only worker quality, but also preferences over job attributes, including WFH itself. In the empirical analysis, I address this by conditioning on the rich set of job characteristics observed in vacancy text and registry data. Under the additional assumption that job seekers do not systematically possess private information about vacancies beyond what is observed in the ad, remaining differences in the leave-one-out measure primarily reflect differences in the types of firms applicants target. To the extent that self-assessment errors affect application behavior, they matter for the WFH estimates only if such errors are systematically correlated with preferences for WFH.

As a validation exercise, I compare this search-based quality measure to AKM worker fixed effects for the subset of unemployed job seekers that can be linked to the registry data. I find a positive relationship between worker AKM effects and the quality of the firms to which these job seekers apply, both on average and at the top of their application distribution (Figure B.16). This pattern is consistent with the interpretation that stronger workers disproportionately target higher-quality firms, in line with the broader literature on worker-firm sorting.

Once the applicant-level quality measure is constructed, I aggregate it to the vacancy level. My main measure is the mean applicant quality for each vacancy. I also construct two alternative measures: the mean quality among applicants in the top quartile of the within-vacancy quality distribution, and the maximum applicant quality. Together, these measures allow me to study whether signaling WFH changes not only the average quality of the applicant pool, but also the upper tail of applicants available to the firm. These measures are useful because firms typically hire only a small number of workers from the applicant pool, so both the average quality and the upper tail of the quality distribution may be relevant for recruitment outcomes.

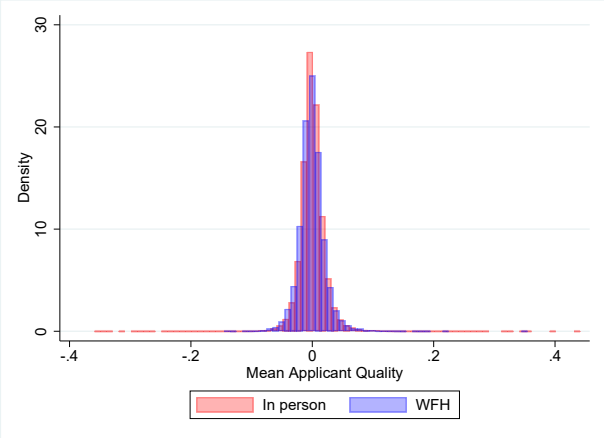
Figure 7 presents the raw distributions of the mean and maximum applicant-quality measures by vacancy WFH status. The distributions overlap substantially, suggesting that any differences in applicant quality are not driven by mechanically different support across WFH and in-person vacancies. At the same time, the upper tail appears somewhat more favorable for WFH vacancies, especially when focusing on top applicants. Section 7.2 examines these relationships more formally in the regression analysis.

3.6 Occupation-level WFH potential

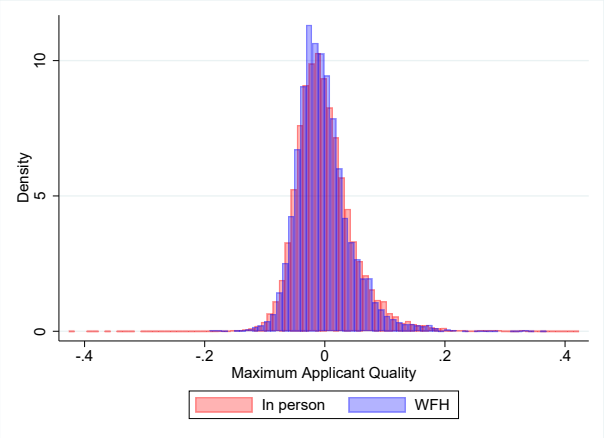
As an external benchmark for heterogeneity in the feasibility of WFH across jobs, I construct an occupation-level measure of WFH potential using the 2021 Swedish Labour Force Survey (LFS; Eurostat 2021). Specifically, I calculate, for each 3-digit occupation, the share of employed respondents who report working from home either "mainly" or "sometimes" in their main job. I then map these occupation-level WFH shares to the vacancy data and classify occupations into quartiles of WFH

Figure 7: Distributions of applicant quality by whether the job ad offers WFH

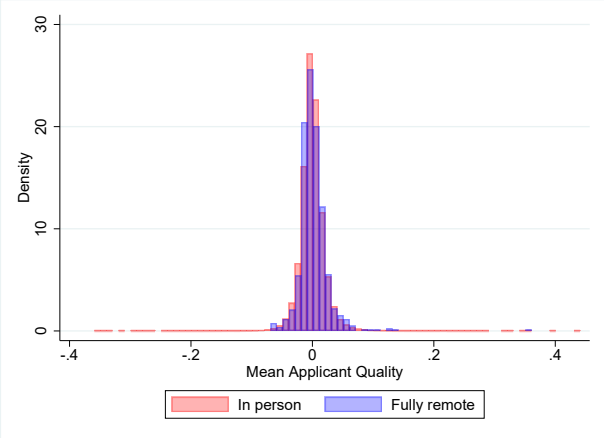
(a) Mean quality (All WFH)



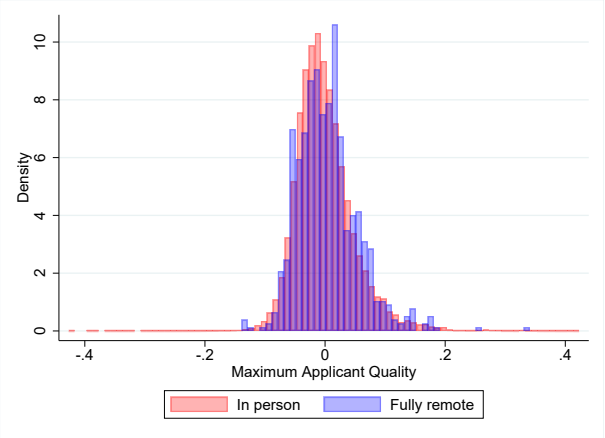
(b) Max quality (All WFH)



(c) Mean quality (Fully remote)



(d) Max quality (Fully remote)



Notes: This figure plots the distributions of the mean and top applicant-quality measures by vacancy WFH status, comparing in-person vacancies with all WFH vacancies (Panels (a) and (b)) and with fully remote vacancies only (Panels (c) and (d)). Applicant quality is defined as the leave-one-out mean firm pay premium among the other firms to which an applicant applies, residualized with respect to occupation fixed effects. Panels (a) and (c) plot the mean applicant quality measure, while Panels (b) and (d) plot the maximum applicant-quality measure. The distributions for in-person vacancies are shown in red and those for WFH vacancies are shown in blue. The corresponding distribution for the top-quartile mean is reported in Figure B.17.

potential.

This measure is not used as the main definition of WFH in the paper. Rather, it serves as an external occupation-based benchmark that I use to study heterogeneity and to compare the text-based vacancy measure to a more traditional occupation-level proxy for remote-work feasibility. Occupations in the highest quartile are those with the greatest survey-based prevalence of WFH, while occupations in the lowest quartile have the least.

The occupation-level benchmark aligns reasonably well with the vacancy-based WFH classification. In 2021, the within-occupation share of job ads classified as WFH is positively correlated with the LFS-based occupation-level WFH measure (Pearson's $\rho = 0.67$, $p < 0.001$), suggesting that the survey-based classification captures broadly similar underlying differences in WFH potential across occupations.

For some robustness analyses, I also use a simpler binary classification of "high WFH potential" based on broad white-collar occupation groups. Additional details on the construction of both measures are reported in Appendix Section B.5.

4 Labor Market Tightness

Before turning to the main results, I document a descriptive relationship between local labor market tightness and firms' propensity to offer WFH. If signaling WFH relaxes geographic hiring frictions by expanding firms' effective labor markets, then WFH should be particularly valuable when local applicant pools are relatively thin. Under this interpretation, tighter labor markets should be associated with a higher share of vacancies that explicitly offer WFH.

To study this relationship, I construct a market-level measure of labor market tightness as the ratio of available jobs to available job seekers. I exploit the job-search data to measure both sides of the market. On the worker side, I use the number of unique applicants, defined as the number of unique device IDs that applied to at least one vacancy in a given local labor market and quarter, as my measure of active job seekers.[17] This measure captures both unemployed workers and employed workers who are actively searching. On the firm side, I use the number of unique vacancies first posted in that local labor market and quarter. I then define labor market tightness as the number of unique vacancies divided by the number of unique applicants in each quarter.

Local labor markets in this section are defined at the commuting-zone-by-3-digit-occupation level. I use the broader 3-digit occupation definition because it better captures the set of workers over which firms are likely to compete. Vacancies in related occupations often draw from overlapping applicant pools even when they do not share the same narrow occupation code. I also measure tightness at the quarterly level. This aggregation smooths high-frequency noise and is more likely to capture changes in hiring conditions that are salient to firms' vacancy-posting decisions.

Figure 8 plots the average share of WFH vacancies against average labor market tightness for each local labor market over May 2020 to September 2022. The raw relationship is positive: labor markets with higher vacancy-to-applicant ratios also tend to have higher shares of vacancies that signal WFH. This pattern is consistent with the idea that firms are more likely to use WFH when local hiring conditions are more difficult. It is also consistent with descriptive evidence from the United States reported by Autor, Dube, and McGrew (2024).

To assess whether this relationship also appears within markets over time, I estimate a simple fixed-effects specification relating changes in WFH vacancy shares to lagged labor market tightness:

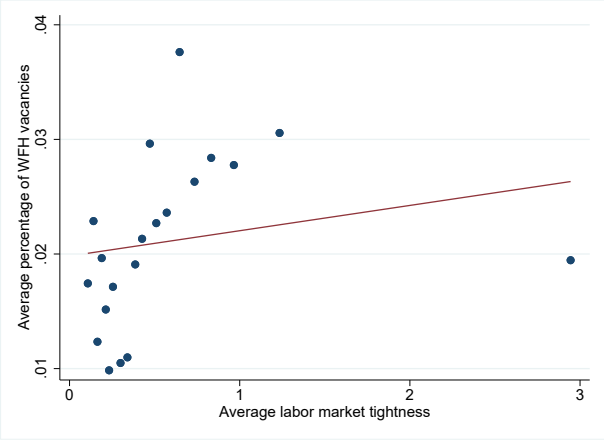
$$\Delta WFH_Share_{z,o,t} = \beta_0 + \beta_1 Tightness_{z,o,t-1} + \theta_{z,o} + \theta_z + \theta_o + \theta_t + \epsilon_{z,o,t}. \quad (2)$$

Here, z indexes commuting zones, o indexes 3-digit occupations, and t indexes quarters. $\Delta WFH_Share_{z,o,t}$ denotes the change in the share of vacancies in local labor market (z, o) that explicitly signal WFH

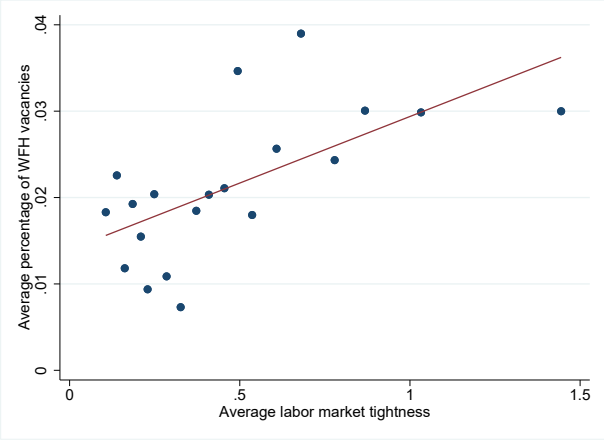
17. I use unique applicants rather than unique viewers in order to focus on workers displaying more active search behavior. Initiating an application is a stronger signal of job search than merely viewing a vacancy.

Figure 8: Correlations between labor market tightness and the share of WFH vacancies

(a) All observations



(b) Truncated (Tightness < 2)



Notes: These figures show binned scatterplots of average local labor market tightness against the average share of vacancies offering WFH. Local labor markets are defined as commuting-zone-by-3-digit-occupation cells. The sample includes all labor markets in each month from May 2020 to September 2022 with at least one applicant. Panel (a) uses the full sample. Panel (b) excludes outliers by restricting the sample to observations with labor market tightness below 2, removing 717 observations. $N = 16{,}724$ in Panel (a) and $N = 16{,}007$ in Panel (b). Full scatterplots are reported in Figure C.1.

between $t-1$ and t. $Tightness_{z,o,t-1}$ is lagged labor market tightness in the same market. I use lagged tightness to reduce the mechanical contemporaneous relationship between WFH posting behavior and the measured vacancy-to-applicant ratio. I report estimates from this specification, along with a baseline specification and a specification with commuting-zone, occupation, and time fixed effects, as descriptive evidence.

Table 1 reports the regression results. In the baseline specification, lagged labor market tightness is positively associated with subsequent growth in the share of WFH vacancies. The association remains positive and statistically significant when adding commuting-zone, occupation, and time fixed effects. In the specification with local-labor-market fixed effects, the coefficient remains positive but becomes statistically imprecise. Across specifications, the point estimates imply economically meaningful differences in WFH growth between relatively slack and relatively tight labor markets, although the within-market estimates should be interpreted cautiously.

Overall, this section documents a positive descriptive relationship between labor market tightness and WFH offering. One interpretation is that firms facing tighter hiring conditions have stronger incentives to use WFH as a recruitment margin, in part because WFH can relax geographic constraints and broaden access to potential applicants. This evidence is only suggestive, but it helps motivate the main analysis of how signaling WFH affects applicant geography and labor market access.

5 Methodology

To study how signaling WFH is associated with hiring outcomes, I estimate vacancy-level regressions of each outcome on an indicator for whether the job ad explicitly signals that it offers WFH. The

Table 1: Association between lagged labor market tightness and changes in WFH vacancy shares

	(1) Baseline	(2) CZ, occ., and time FEs	(3) LLM FEs
Labor market tightness	0.014***	0.018**	0.010
	(0.005)	(0.009)	(0.011)
Commuting zone F.E.	N	Y	Y
Time F.E.	N	Y	Y
Occupation F.E.	N	Y	Y
Local labor market F.E.	N	N	Y
Sample mean (change in share)	0.004	0.004	0.004
N	34,790	34,033	33,240

Notes: This table reports descriptive regressions of changes in the share of WFH vacancies on lagged labor market tightness. Labor market tightness is defined as unique job ads divided by unique applicants. Unique job ads consist of all vacancies first posted in that quarter in that local labor market. Unique applicants are all unique device IDs that applied to at least one vacancy in that local labor market in that quarter. Column (1) reports the baseline specification. Column (2) adds fixed effects for 3-digit occupation, commuting zone, and time. Column (3) adds local labor market fixed effects. The sample includes all quarters from May 2020 to September 2022. Local labor markets with at least one quarter with labor market tightness greater than or equal to 2 are excluded from the estimation sample (20 local labor markets). Standard errors are clustered at the local labor market level. These estimates are intended as descriptive evidence and should not be interpreted causally.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

empirical design compares WFH vacancies to observationally similar non-WFH vacancies within the same local labor market, while absorbing time-varying shocks at the commuting-zone and occupation levels. Occupations are defined at the 4-digit level, which is the most granular occupation classification available in the data, and local labor markets are defined as commuting-zone-by-occupation cells. The main specification includes local labor market fixed effects, commuting-zone-by-time fixed effects, and occupation-by-time fixed effects. Together, these fixed effects absorb permanent differences across local labor markets as well as time-varying shocks specific to geographic areas and occupations that could otherwise confound the relationship between WFH signaling and hiring outcomes.

To improve comparability across vacancies, I also control for a rich set of vacancy- and firm-level covariates. The vacancy-level controls include employment type (ordinary work, summer job, on-call employment, and work abroad), salary type (fixed, variable, or hybrid), working-hours category (part-time or full-time), job-duration category, posted vacancy duration, vacancy-description length, and indicators for whether specific skills or technologies are mentioned in the job-ad text.[18] The firm-level controls include firm size, industry, and legal status. Firm size is measured as the number of employees linked to the firm in a given year, industry is defined at the 5-digit level using the Swedish SNI classification, and legal status captures the firm's registered organizational form. The main specification is:

18. The skills and technology measures are discussed in Section 3.1; see, for example, Figure 4.

$$\text{Outcome}_{i,f,z,o,t} = \beta_0 + \beta_1 \mathbf{1}[\text{WFH} = 1]_i + \boldsymbol{\gamma}\mathbf{X}_i + \boldsymbol{\alpha}\mathbf{Z}_f + \theta_{z,o} + \theta_{z,t} + \theta_{o,t} + \epsilon_{i,f,z,o,t} \tag{3}$$

Here, i indexes vacancies, f firms, z commuting zones, o occupations, and t month-years. $\mathbf{X}_i$ denotes the vector of vacancy-level covariates, and $\mathbf{Z}_f$ denotes the vector of firm-level covariates. $\mathbf{1}[\text{WFH} = 1]_i$ is an indicator for whether vacancy i explicitly signals WFH. The fixed effects $\theta_{z,o}$, $\theta_{z,t}$, and $\theta_{o,t}$ absorb local labor market differences, commuting-zone-specific time shocks, and occupation-specific time shocks, respectively. The coefficient of interest is β_1, which captures the conditional difference in the outcome between WFH and non-WFH vacancies.

As an additional robustness check, I estimate a specification that replaces the firm-level covariates with firm fixed effects, θ_f. This specification identifies β_1 from comparisons between WFH and non-WFH vacancies posted by the same firm within the same occupation and commuting zone. Because this considerably narrows the identifying variation, I do not use the firm-fixed-effects specification as the main specification. Nevertheless, it is informative about the extent to which the main results may be driven by unobserved differences across firms. In practice, the firm-fixed-effects estimates are generally similar to the baseline results, suggesting that across-firm differences are unlikely to be the sole driver of the main findings.

I also estimate specifications with firm-by-time fixed effects as a further robustness check. These specifications absorb time-varying firm-level shocks, but they also restrict the identifying variation substantially and may absorb part of the economically relevant within-firm variation in WFH policies. Even under this demanding specification, the results remain broadly consistent with the main analysis.

6 Geographic Distribution of Job Seekers

A central question in this paper is whether signaling WFH relaxes geographic frictions in hiring by expanding firms' effective labor markets. The key prediction is that, if WFH reduces the importance of commuting, then vacancies signaling WFH should attract applications from workers who lie outside the firm's usual in-person commuting market. By contrast, if WFH operates only as a general job amenity valued by workers within the same local labor market, then WFH-signaling vacancies may attract more applicants without materially changing the geography of the applicant pool.

The analysis in this section tests this question using the revealed commuting-preference measure developed in Section 3.4. Because that measure captures deviations from workers' usual in-person application geography, it provides a direct way to study whether WFH changes the spatial reach of firms' applicant pools rather than simply shifting applications across nearby employers.

6.1 Results

To estimate the effect of WFH signaling on firms' geographic access to applicants, I use the fixed-effects specification in equation 5 and apply it to the three distance measures defined in Section 3.4. My main outcome is the log of the mean deviation from revealed commuting preferences among applicants to a vacancy. I also report results using two alternative measures: the maximum deviation among applicants to the vacancy and the mean deviation among applicants in the top quartile of the within-vacancy distance distribution.

Because the distribution of the mean deviation measure has a long right tail (Figure 6), I restrict the main sample to job seekers whose maximum deviation in their in-person applications is at most 20 km. This reduces the influence of extreme outliers in the revealed commuting-preference construction. I show below, however, that the results are robust to using alternative thresholds, including no restriction at all.

Table 2: WFH and geographic dispersion of applicants (using log mean distance)

	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects	(4) Unemployed residence location
WFH offering	0.209***	0.367***	0.417***	0.103***
	(0.028)	(0.019)	(0.019)	(0.021)
Vacancy Controls	N	Y	Y	Y
Firm Controls	N	Y	N	Y
Local Labor Market F.E.	N	Y	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y	Y
Occupation × month-year F.E.	N	Y	Y	Y
Firm F.E.	N	N	Y	N
Sample mean (km)	39.8	39.8	39.8	62.5
N	1,326,144	927,677	1,241,048	354,795

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) regression. Column (2) corresponds to the main specification outlined in equation 5. Column (3) corresponds to the firm fixed effects regression. Column (4) reports results using an alternative measure for geographic dispersion for unemployed job seekers, where the distance between the applicant and the job is determined using the distance from the centroid of the neighborhood where the applicant lives to the coordinate of the job ad, using the main specification outlined in equation 5. 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 fewer 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 C.1). In column (4), individuals not in the unemployed sample and job ads with no unemployed applicants are additionally excluded. Sample means are presented as the mean average distance of job seeker "workplace location preference" and job ad location of the sample (in kilometers). In column (4), the sample mean is based on the unemployed residence-location measure. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns (1)–(3) of Table 2 report the main results. Consistent with the raw distributions, I find a

positive and statistically significant effect of WFH signaling on applicant distance. In the main specification, vacancies signaling WFH attract applicants whose revealed commuting-preference locations are 36.7% farther from the job location than applicants to otherwise similar in-person vacancies (Column (2)). Relative to the sample mean of 39.8 km, this implies an increase of approximately 14.6 km in the average deviation from applicants' usual in-person commuting market.

This effect is economically meaningful. It indicates that WFH-signaling vacancies draw applicants from substantially farther outside their normal commuting range, consistent with WFH relaxing spatial frictions in job search. Since the distance measure is based on straight-line distance rather than realized travel routes, these estimates should also be interpreted as conservative with respect to the actual travel burden avoided by remote or hybrid work arrangements.

The results are robust to alternative restrictions on the support of the distance measure. When I re-estimate the main specification using looser thresholds, ranging from a 40 km cutoff to no distance restriction, the percentage coefficients become somewhat smaller, but they remain economically large and statistically significant throughout (Table C.1). Moreover, when translated into level differences using the relevant sample means, the implied effects remain very stable, corresponding to roughly 14.4 to 14.9 km. This suggests that the main result is not driven by the skewness of the underlying distance distribution.[19]

I find similar patterns using alternative measures of geographic expansion. Table C.2 reports results using the maximum applicant deviation within each vacancy, and Table C.3 reports results using the mean deviation among applicants in the top quartile of the within-vacancy distance distribution. In the main specification of Table C.2, the most distant applicant to a WFH-signaling vacancy is 30.9% farther away than the most distant applicant to a comparable in-person vacancy, corresponding to 44.9 km relative to a sample mean of 145.3 km. Likewise, in the main specification of Table C.3, the upper-quartile applicants to WFH vacancies are 34.0% farther away on average, corresponding to 27.1 km relative to a sample mean of 79.8 km. Together, these results indicate that the effect of WFH signaling is not confined to the mean of the applicant pool, but also appears in the upper tail of the distance distribution.

As an additional validation exercise, I use an alternative geography measure based on applicant residence locations rather than revealed commuting preferences. In Column (4) of Table 2, the outcome is the distance between the applicant's residential neighborhood and the workplace location. Because exact residential addresses are unavailable, I proxy for applicant residence using the centroid of the applicant's neighborhood polygon and then calculate the straight-line distance between that centroid and the vacancy coordinates. This measure can only be constructed for unemployed applicants, who are the only job seekers that can be linked to residence-location data. Even in this restricted sample, I find that WFH-signaling vacancies attract unemployed applicants who live 10.3% farther from the prospective workplace, on average. Relative to the sample mean of 62.5 km, this corresponds to an

19. The results are also consistent when using alternative sample constructions, an alternative measure of WFH, and alternative specifications controlling for Firm AKM F.E.s or using firm-by-time fixed effects (Table C.5).

increase of about 6.4 km. The corresponding estimates are positive and statistically significant across all neighborhood types (Table C.4).

Taken together, these results provide strong evidence that signaling WFH changes the geography of the applicant pool in a way that is consistent with reduced spatial frictions. WFH-signaling vacancies do not merely attract more applicants from within the same local labor market. Instead, they attract applicants who are willing to apply outside their usual in-person commuting market and who, in the unemployed subsample, also live farther from the workplace. This pattern is exactly what one would expect if WFH expands firms' effective labor-market reach by relaxing the importance of commuting distance.

One important dimension of heterogeneity is the intensity of the WFH arrangement. The main WFH measure combines hybrid and fully remote vacancies, but these two forms of remote work may differ in the extent to which they relax geographic constraints. I therefore re-estimate the geography specifications using only fully remote vacancies, dropping hybrid vacancies from the treatment group. The corresponding results are reported in Table 3. This comparison is useful because fully remote jobs eliminate commuting requirements more completely and therefore provide a natural test of whether stronger remote-work arrangements generate stronger geographic responses. I find that the effects for fully remote vacancies are very similar in magnitude to the main results. Applicants to fully remote vacancies deviate 35.5% farther from their revealed commuting preferences, corresponding to an increase of about 14.1 km relative to the sample mean. This suggests that the main geography result is not driven solely by hybrid vacancies and that fully remote work likewise expands the geographic reach of the applicant pool. At the same time, there is no evidence that the geographic effect for fully remote vacancies is larger than the average effect estimated for the broader WFH category.

I also examine an alternative WFH measure based on whether the vacancy explicitly mentions WFH in the job title. In contrast to the fully remote results, I find no statistically discernible effect of this headline-based measure on applicant geography (Column (2)). This contrast suggests that geographic expansion is more closely related to the underlying remote-work arrangement than to whether WFH is explicitly highlighted in the title of the ad. One possible interpretation is that title-based WFH signaling affects how job seekers perceive the vacancy without necessarily changing the set of workers willing to apply from outside their usual commuting markets. Because the share of vacancies explicitly mentioning WFH in the headline is relatively small, these results should be interpreted cautiously. Still, they suggest that not all forms of WFH signaling operate through the same geographic channel.

A second important source of heterogeneity is workplace location. The paper's broader framework suggests that the geographic effects of WFH should be strongest for workplaces in thinner and more spatially isolated labor markets. This would be especially likely if those firms offer more specialized jobs since the mass of workers, particularly skilled workers, tend to concentrate around cities (European Labour Authority 2024) I therefore repeat the analysis for rural workplaces only. The results support this prediction. In Table C.6, I find that the main-specification effect for rural vacancies is 55.9%, substantially larger than the corresponding estimate in the full sample. This pattern is consistent with

Table 3: Effect of WFH signaling on geographic dispersion - more salient WFH signals

	(1) Fully remote job ads	(2) Job ads with WFH in headline
WFH offering	0.355***	−0.050
	(0.061)	(0.102)
Sample mean (km)	39.8	39.8
N	900,216	927,677
Vacancy Controls	Y	Y
Firm Controls	Y	Y
Local Labor Market F.E.	Y	Y
Commuting Zone × month-year F.E.	Y	Y
Occupation × month-year F.E.	Y	Y

Notes: This table presents the results of the main regression estimates (equation 5) for the logged mean distance of applicants' "workplace location preference" and the location of the job ad on WFH offering for alternate treatment definitions using more salient WFH signals. Column (1) restricts treatment to fully remote vacancies only, dropping hybrid vacancies. Column (2) uses the alternative headline-based WFH measure that classifies a vacancy as WFH if it explicitly mentions WFH in the job title. 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 fewer 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. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

WFH being particularly valuable for geographically isolated firms, for which even modest relaxations in commuting constraints can meaningfully expand the set of reachable applicants.

Overall, the evidence in this section supports the paper's central mechanism: signaling WFH expands firms' effective labor markets by drawing applications from workers outside their usual commuting markets. The effects are economically large in the full sample, robust across alternative geography measures, and especially pronounced for more isolated workplaces. In that sense, WFH appears to reduce geographic mismatch not simply by making vacancies more attractive in general, but by relaxing the spatial boundaries that ordinarily limit who applies to whom.

7 Changes to the Applicant Pool

The previous section shows that signaling WFH expands a firm's effective labor market by attracting applicants from outside their usual commuting markets. I next examine whether this broader geographic reach translates into larger or systematically different applicant pools. This is a central consideration for firms. If WFH-signaling vacancies draw in more applicants, stronger applicants at the top of the distribution, or a different mix of job seekers, then WFH can affect recruitment even

before any hiring takes place.

I study three related outcomes. First, I examine whether WFH signaling increases applicant quantity by raising attention to vacancies and the number of initiated applications. Second, I study whether WFH changes the quality composition of the applicant pool. Third, I examine whether it changes the demographic composition of who searches for and applies to vacancies. Together, these results show how WFH affects firms' access to labor through the size and composition of the pre-hiring search pool.

7.1 Applicant quantity

A first-order implication of the paper's mechanism is that WFH-signaling vacancies should attract more job seekers. This can occur through at least two channels. First, by relaxing commuting constraints, WFH expands the set of workers for whom a vacancy is geographically feasible. Second, independent of geography, WFH may raise the value of the vacancy because many workers view it as a desirable non-wage amenity. Under either channel, WFH-signaling vacancies should receive more attention and more applications than otherwise similar in-person vacancies.

To study this margin, I estimate the main fixed-effects specification in equation 5 using two outcomes. The first is the log number of initiated applications a vacancy receives, which I interpret as the more active recruitment margin. The second is the log number of views, which I interpret as a measure of early attention. These two outcomes capture different stages of job search where views reflect initial interest in a vacancy, while applications reflect a more substantive step toward matching.

7.1.1 Main results

Table 4 reports the main estimates. Panel A shows results for applications and Panel B shows results for views. Column (1) uses the baseline vacancy-level WFH measure that combines hybrid and fully remote vacancies.

The results indicate that WFH-signaling vacancies attract both more attention and more applications. In the main specification, WFH vacancies receive 3.9% more initiated applications than otherwise similar in-person vacancies. Relative to the sample mean of 28.78 applications, this corresponds to roughly 1.1 additional applications per vacancy. The effect is larger at the attention stage. WFH vacancies receive 9.9% more views, which corresponds to about 21.7 additional views relative to a sample mean of 217.54. These results suggest that WFH signaling matters already at the first stage of search, increasing the number of job seekers who engage with the vacancy, and that part of this additional attention converts into application activity.

The results remain similar in more demanding specifications. When I replace firm characteristics with firm fixed effects, so that identification comes from within-firm comparisons, the estimates remain positive and economically meaningful, with effects of 2.8% for applications and 6.9% for views.[20] This

20. The results are also consistent when using alternative sample constructions, an alternative measure of WFH, and alternative specifications controlling for Firm AKM F.E.s or using firm-by-time fixed effects (Table C.11) and when including views from 2018 for attention analysis (Table C.12).

Table 4: Effect of WFH signaling on applications and attention

	(1) All WFH job ads	(2) Fully remote job ads	(3) Job ads with WFH in headline	(4) Probability of an application
Panel A: Applications				
WFH offering	0.039**	0.240***	0.482***	0.011***
	(0.017)	(0.084)	(0.108)	(0.002)
Sample mean (# of applications)	28.78	29.20	28.78	
Sample mean (share with ≥ 1 application)				0.881
N	1,060,687	1,028,283	1,060,687	1,187,663
Panel B: Attention				
WFH offering	0.099***	0.445***	0.748***	—
	(0.021)	(0.103)	(0.156)	
Sample mean (# of views)	217.54	219.50	217.54	
N	1,793,449	1,751,107	1,793,449	
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

Notes: This table reports estimates of how signaling WFH affects vacancy-level applications and attention using the main specification in equation 5. Panel A uses the log number of initiated applications as the dependent variable in Columns (1)–(3), and an indicator for whether the vacancy receives at least one application in Column (4). Panel B uses the log number of views as the dependent variable. Column (1) defines treatment using the baseline vacancy-level WFH measure that combines hybrid and fully remote vacancies. Column (2) restricts treatment to fully remote vacancies only, dropping hybrid vacancies. Column (3) uses an alternative headline-based measure that classifies a vacancy as WFH if it explicitly mentions WFH in the job title. For Panel A, the sample includes vacancies posted between May 2020 and September 2022. For Panel B, the sample includes vacancies posted between January 2019 and September 2022. In both panels, I exclude individuals with only one total view, vacancies with one or fewer total views, and vacancies with no text description. In Panel A, vacancies with zero applications are excluded in Columns (1)–(3), while Column (4) uses the full vacancy sample to estimate the extensive-margin effect on the probability of receiving at least one application. All specifications include vacancy controls, firm controls, local labor market fixed effects, commuting-zone-by-month-year fixed effects, and occupation-by-month-year fixed effects. The full tables with the baseline and firm-fixed-effects analysis is found in Table C.7, Table C.8, Table C.9, and Table C.10, for Columns (1), (2), (3), and (4), respectively. Standard errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

suggests that the main findings are not driven solely by persistent differences across firms that choose to advertise WFH.

In addition to the intensive margin, WFH signaling also affects the extensive margin of applications. Column (4) of Panel A estimates a linear probability model where the dependent variable is an indicator for whether the vacancy receives at least one application. I find that WFH-signaling vacancies are 1.1 percentage points more likely to receive at least one application than comparable in-person vacancies. This result indicates that WFH not only increases the number of applications among vacancies that already attract applicants, but also raises the probability that a vacancy receives any application at all.

The effects are substantially larger when the WFH signal is stronger or more salient. Column (2) restricts the treatment group to fully remote vacancies, dropping hybrid vacancies. These ads receive 24.0% more applications and 44.5% more views than otherwise similar in-person vacancies, corresponding to roughly 7 additional applications and 98 additional views relative to the relevant

sample means. Column (3) instead defines treatment using the alternative headline-based WFH measure. Vacancies that explicitly mention WFH in the title receive 48.2% more applications and 74.8% more views, equivalent to roughly 14 additional applications and 163 additional views.

These patterns suggest that both the intensity and the salience of WFH signaling matter for recruitment outcomes, but likely through different channels. As shown in the geography section, fully remote vacancies expand applicant geography to a similar extent as the broader WFH measure, consistent with a relaxation of commuting constraints. By contrast, vacancies that explicitly mention WFH in the headline generate very large increases in attention and applications, but do not attract applicants from farther outside their usual commuting markets. This suggests that headline-based WFH signals primarily affect the visibility or perceived attractiveness of the vacancy at the search stage, whereas fully remote arrangements also operate through geographic market expansion. More broadly, the results imply that firms benefit both from making WFH highly visible and from offering arrangements that more substantially relax commuting constraints, although these two margins appear to affect recruitment through different mechanisms.

Occupational heterogeneity further supports this interpretation. The average positive recruitment effect of WFH masks substantial variation across occupations (Figure C.2). The effects on applications and views are strongest in occupations where WFH is feasible but not already taken for granted. In occupations with very high WFH prevalence, signaling WFH is less informative and therefore has smaller effects. By contrast, in occupations where WFH is largely infeasible, signaling WFH may be viewed as unusual or less credible. The largest positive effects instead appear in the middle of the occupational WFH-potential distribution, where the signal is both feasible and informative.

Finally, I examine whether the quantity effects differ for rural workplaces (Table C.13). In contrast to the geography results, I find little evidence that WFH-signaling or fully-remote-signaling rural vacancies receive meaningfully more views or applications than comparable in-person rural vacancies. This suggests that, for rural firms, the main benefit of WFH may operate less through the total size of the applicant pool and more through its composition. In particular, the earlier geography results imply that WFH helps rural firms draw applicants from farther away, even if it does not substantially increase the overall number of applicants.

7.1.2 Decomposing the quantity effect

The previous sections show that signaling WFH increases total applications and draws applicants from outside their usual commuting markets. I next examine whether these two results are directly connected. In particular, I ask whether the increase in applications to WFH-signaling vacancies is driven primarily by additional applications from geographically distant job seekers, or whether WFH also changes application behavior among workers who are already close to the job's usual in-person labor market.

This decomposition is useful because the overall application effect can reflect two distinct channels. First, WFH may relax spatial frictions by making the vacancy attractive to workers who would oth-

erwise be too far away to apply. Second, WFH may affect the value of the vacancy even for workers who are already nearby, either because remote work is a valued amenity or because it changes the perceived desirability of the job in other ways. Distinguishing between these channels helps clarify whether the application effect operates mainly through market expansion or through reallocation within the pre-existing local labor market.

To study this, I split applications into "far" and "close" groups based on the revealed commuting-preference measure developed in Section 3.4. I define an application as *far* if the distance between the applicant's revealed in-person commuting location and the workplace lies in the top quartile of the distance distribution within the local labor market. I define an application as *close* if that distance lies below the median of the local distribution. To maintain comparability with the geography results, I apply the same 20 km sample restriction used in Section 6.1, although the conclusions are similar without this restriction (Table C.14).

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

	Log applications		Number of applications	
	Far applications	Close applications	Far applications	Close applications
WFH offering	0.078***	−0.188***	0.256***	−1.840***
	(0.015)	(0.015)	(0.081)	(0.173)
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)	5.94	10.74	5.04	10.06
N	680,962	795,231	942,784	942,784

Notes: This table reports how signaling WFH changes the number of applications from geographically "far" and "close" job seekers relative to similar in-person vacancies. "Far" applications are those for which the distance between the applicant's revealed in-person commuting location and the job location lies in the top quartile of the distance distribution within the local labor market (commuting zone by four-digit occupation). "Close" applications are those for which this distance lies below the median of the local distribution. Columns (1) and (2) report log application outcomes for far and close applications, respectively. Columns (3) and (4) report the corresponding level outcomes, including vacancies with zero applications in the relevant category. Job seekers with a minimum distance between their preferred location and closest job ad greater than 20 km are excluded so that the sample matches the main geography analysis. Table C.14 reports the same decomposition without this distance-threshold restriction. All specifications include vacancy controls, firm controls, local labor market fixed effects, commuting-zone-by-month-year fixed effects, and occupation-by-month-year fixed effects. Standard errors are clustered at the local labor market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 reports the results. I focus on the log specifications in Columns (1) and (2), which show a clear geographic reallocation of the applicant pool. Relative to comparable in-person vacancies, WFH-signaling vacancies receive 7.8% more *far* applications but 18.8% fewer *close* applications. Thus, the application response to WFH is not uniform across space: WFH-signaling vacancies draw in relatively more distant applicants while losing some nearby ones. The level specifications in Columns (3) and (4), which include vacancies with zero applications in the relevant category, point to the same qualitative pattern.

These results indicate that the increase in applications to WFH-signaling vacancies is not uniform across space. Rather, WFH shifts the geographic composition of applications away from workers

located near the vacancy's usual in-person commuting market and toward workers located farther away. This pattern complements the earlier geography results by showing that the expansion of firms' effective labor markets is not simply a matter of distant workers entering on top of an unchanged local pool. Instead, the applicant pool is reallocated across space.

There are at least two plausible interpretations of the decline in close applications. The first interpretation is a competition channel which suggests nearby job seekers may anticipate that WFH-signaling vacancies attract a broader and more competitive applicant pool. This may lead some of them to substitute toward less competitive in-person vacancies. A second possibility is that WFH is a weaker amenity, or even a relative disamenity, for workers who are already located close to the workplace. When commuting costs are low, these workers may value in-person interaction more highly or may prefer workplaces where remote work is less prevalent. Under this interpretation, some nearby workers may be less inclined to apply to WFH-signaling vacancies precisely because the remote component is less valuable to them. This table alone does not allow me to cleanly distinguish between these mechanisms. However, the applicant-quality results in the next subsection provide additional evidence that helps clarify whether the decline in close applications is more consistent with increased competition or with WFH being a weaker amenity for nearby workers.

7.2 Applicant quality

The previous section shows that signaling WFH expands firms' access to job seekers and increases the size of the applicant pool. However, quantity alone does not determine whether firms benefit from offering WFH. From a recruitment perspective, what matters is not only how many applicants a vacancy attracts, but also the quality of the candidates from whom the firm can choose. In this section, I therefore examine how signaling WFH changes the quality composition of the applicant pool.

7.2.1 Main results

To study this margin, I estimate the main specification in equation 5 using the applicant-quality measures defined in Section 3.5. Panel A of Table 6 reports results for the mean quality of applicants to a vacancy, while Panel B reports results for the quality of the top applicant.[21]

The results in Panel A indicate that WFH-signaling vacancies attract applicants who are slightly lower quality on average. In the main specification, the mean applicant-quality measure is 0.031 standard deviations lower for WFH vacancies than for otherwise similar in-person vacancies (Column (1)). The corresponding estimate for fully remote vacancies is close to zero and statistically insignificant (Column (2)), while vacancies that explicitly mention WFH in the headline exhibit a substantially larger decline in mean applicant quality of 0.191 standard deviations (Column (3)). Taken together, these estimates suggest that clearer or more salient WFH signals broaden the applicant pool in a way

21. The results in this table are also consistent when using alternative sample constructions, an alternative measure of WFH, and alternative specifications controlling for Firm AKM F.E.s or using firm-by-time fixed effects for both the full sample (Table C.17) and the set of fully remote job ads (Table C.18).

that draws in more applicants from the lower part of the quality distribution, even if the average effect for the overall WFH category remains modest.

Table 6: Effect of WFH signaling on applicant quality

	(1) All WFH job ads	(2) Fully remote job ads	(3) Job ads with WFH in headline
Panel A: Mean quality			
WFH offering	−0.031***	0.009	−0.191***
	(0.008)	(0.043)	(0.067)
Sample mean (standardized mean quality)	0.00	0.00	0.00
Original standard deviation	0.027	0.027	0.027
N	492,262	476,181	492,262
Panel B: Maximum applicant quality			
WFH offering	−0.009	0.115***	0.216**
	(0.007)	(0.043)	(0.097)
Sample mean (standardized maximum quality)	0.00	0.00	0.00
Original standard deviation	0.060	0.060	0.060
N	492,262	476,181	492,262
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

Notes: This table reports estimates of how signaling WFH affects vacancy-level applicant quality using the main specification in equation 5. Panel A uses the standardized mean quality of applicants to a vacancy as the dependent variable, and Panel B uses the standardized quality of the top applicant. Column (1) defines treatment using the baseline vacancy-level WFH measure that combines hybrid and fully remote vacancies. Column (2) restricts treatment to fully remote vacancies only, dropping hybrid vacancies. Column (3) uses the alternative headline-based WFH measure that classifies a vacancy as WFH if it explicitly mentions WFH in the job title. Individuals with only one total view, vacancies with one or fewer total views, and vacancies with no text description are excluded from all samples. Applicant-quality measures are standardized to have mean zero and standard deviation one. All specifications include vacancy controls, firm controls, local labor market fixed effects, commuting-zone-by-month-year fixed effects, and occupation-by-month-year fixed effects. Standard errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Although mean applicant quality is informative, firms typically hire only one or a small number of workers per vacancy (Figure C.3), so the upper tail of the applicant distribution may be more relevant for recruiting outcomes than the mean alone. Panel B therefore turns to the quality of the top applicant. Here the pattern differs sharply from the results for the mean. For the full set of WFH vacancies, I find no statistically significant difference in the quality of the top applicant relative to comparable in-person vacancies (Column (1)). However, for vacancies with stronger or more salient WFH signals, the top of the applicant distribution improves. Fully remote vacancies attract a top applicant whose quality is 0.115 standard deviations higher (Column (2)), while vacancies that mention WFH in the headline attract a top applicant whose quality is 0.216 standard deviations higher (Column (3)). These effects

are economically meaningful and suggest that salient WFH offers improve firms' access to top-end talent even when average applicant quality does not increase. These results are qualitatively similar, although less precisely estimated, when I instead examine the mean quality of applicants in the top quartile of the within-vacancy quality distribution, particularly for fully remote vacancies (Table C.15).

Taken together, the results show that offering WFH does not simply increase applicant quantity at the cost of applicant quality. Instead, WFH reshapes the quality distribution of the applicant pool. Average quality declines slightly in some specifications, but stronger and more salient WFH signals improve the upper tail of applicants available to the firm. This suggests that WFH can provide firms with access to better matches, especially when the remote-work offer is communicated clearly.

I next examine whether these quality effects differ for workplaces in thinner labor markets. Table C.16 reports the corresponding estimates for rural workplaces. The results are less precisely estimated because the rural sample is much smaller, but they still provide useful evidence on how WFH affects applicant quality in more spatially isolated labor markets. For the full set of WFH vacancies, I find a small and statistically insignificant decline in mean applicant quality, together with a small and statistically insignificant increase in the quality of the top applicant. Thus, for rural workplaces, the broad WFH measure does not appear to generate meaningful changes in applicant quality on average.

The pattern is more pronounced for fully remote vacancies. For these jobs, the estimated effect on mean applicant quality is large and positive, though imprecisely estimated, while the effect on the quality of the top applicant is both large and statistically significant. This suggests that fully remote work may be especially valuable for isolated firms seeking access to stronger candidates beyond their local labor market. These results should still be interpreted cautiously given the limited rural sample, but they are consistent with the broader geography results in the paper. In thinner labor markets, hybrid WFH arrangements may leave commuting constraints sufficiently binding that applicant quality changes little, whereas fully remote arrangements relax those constraints more completely and therefore appear better able to connect rural firms to high-quality applicants outside their immediate labor market.

7.2.2 Decomposing the quality effect

The previous subsection showed that WFH-signaling vacancies receive more applications from distant job seekers but fewer applications from nearby job seekers. I now examine whether the quality composition of these two groups also changes. This helps clarify whether the decline in close applications is more consistent with nearby workers avoiding WFH-signaling vacancies, rather than simply being displaced one-for-one by additional distant applicants.

To do this, I re-estimate the quality regressions separately for *far* and *close* applicants using the same distance definitions as in Section 7.1.2. The applicant-quality measure is constructed in the same way as before, except that the leave-one-out means are calculated within the relevant subgroup of applicants (far or close) for each vacancy. Table 7 reports the results using the same 20 km restriction as in the main geography analysis. The conclusions are similar without this restriction (Table C.19).

Table 7: Quality of "close" and "far" applicants

	Mean quality		Top quality	
	Far applications	Close applications	Far applications	Close applications
WFH offering	−0.026**	0.003	0.048***	−0.067***
	(0.010)	(0.011)	(0.010)	(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 (standardized mean quality)	0.00	0.00	0.00	0.00
Original standard deviation	0.029	0.041	0.043	0.064
N	417,414	366,824	367,114	366,824

Note: This table presents the analysis looking at the differential change in applicant quality between WFH job ads and similar in-person job ads for applicants that apply "far" from their preferred in-person location (Columns (1) and (3)) and for applicants that apply "close" to their preferred in-person location (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 results for the mean quality of applicants. Columns (3) and (4) present the results for the quality of the top applicant (maximum quality). Job seekers with a minimum distance between their preferred location and closest job ad > 20km are dropped from the sample. The quality of applicants is standardized to have mean = 0 and standard deviation = 1. The results for the same analysis without applying the distance threshold restriction is found in Table C.19. The results for top quality applicants for both "close" and "far" applicants are qualitatively similar to the results for the mean quality of the top quartile of applicants (Table C.20). Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results show a clear asymmetry between nearby and distant applicants. For *close* applicants, I find essentially no effect on mean applicant quality (Column (2)). However, the quality of the top close applicant is 0.067 standard deviations lower for WFH-signaling vacancies than for otherwise similar in-person vacancies (Column (4)). By contrast, among *far* applicants, the quality of the top applicant is 0.048 standard deviations higher for WFH-signaling vacancies (Column (3)), even though mean far-applicant quality is 0.026 standard deviations lower on average (Column (1)). Thus, WFH appears to reduce quality at the very top of the nearby applicant pool while improving quality at the top of the distant applicant pool. These patterns are also consistent with the corresponding top-quartile-quality results reported in Table C.20.

This decomposition helps reconcile the earlier quality results. In the aggregate, WFH-signaling vacancies show little change in top applicant quality for the full sample of WFH jobs, but that average masks offsetting movements across space: a decline in the quality of the best nearby applicants and an increase in the quality of the best distant applicants. At the same time, the negative coefficient on mean far-applicant quality indicates that the additional distant applicants are not uniformly higher quality; rather, WFH broadens access to distant workers throughout the quality distribution.

Taken together, these findings suggest that the improvement in top-end talent associated with WFH is driven primarily by distant applicants rather than nearby ones. This pattern is consistent with the idea that relaxing spatial frictions allows firms to reach stronger candidates who would otherwise not apply. At the same time, the decline in the quality of the top close applicants is suggestive of a relative disamenity effect for some nearby workers. When commuting costs are low, working remotely may be less attractive, particularly for workers who value in-person interaction or a more populated workplace. The evidence therefore points to both mechanisms being relevant, but with the gains in top-end applicant quality coming mainly through the expansion of the firm's geographic reach.

7.3 Demographic composition of applicants

The previous subsection shows that signaling WFH changes the quality distribution of applicants. I next examine whether it also changes the demographic composition of the applicant pool. This is a natural margin to study because prior work shows substantial heterogeneity in preferences for WFH across worker groups (Aksoy et al. (2022)). If different groups value WFH differently, then vacancies signaling WFH should attract a different mix of applicants than otherwise similar in-person vacancies.

To study this margin, I use the same fixed-effects specification as in equation 5, but replace the outcome with the share of unemployed viewers or applicants belonging to a given demographic group. I consider five characteristics: the share female, the share highly educated (at least a bachelor's degree), the share young (below age 45), the share immigrant, and the share residing in rural neighborhoods (category A DeSOs). Because demographic information is only available for unemployed job seekers linked to the registry data, this analysis is necessarily restricted to that subset. The unemployed sample is therefore not representative of the full applicant pool (Table B.5), but it remains informative about how WFH signaling changes composition at the search stage.

Table 8 reports the results.[22] Panel A shows the composition of unemployed applicants, while Panel B shows the composition of unemployed viewers. Because the outcomes are shares, the coefficients should be interpreted as changes in the demographic composition of the pool associated with a vacancy, rather than changes in the absolute number of applicants from each group.

The application results in Panel A indicate that WFH-signaling vacancies attract a systematically different mix of unemployed applicants. Relative to comparable in-person vacancies, WFH vacancies receive applicant pools with higher shares of females (1.8 percentage points), higher shares of highly educated (0.9 percentage points), and higher shares of young (1.2 percentage points). These patterns are consistent with the broader literature showing stronger preferences for WFH among women, younger workers, and more educated workers. They also complement the earlier results on applicant quality by showing that WFH changes not only the upper tail of applicants, but also the observable composition of the pool.

For immigrants, the estimated application effect is negative but imprecise. I therefore do not place

22. These results are also robust to including the shares of the other demographic characteristics as controls, indicating that the results are consistent with the effects being independent of each other (Table C.21).

Table 8: Compositional changes of unemployed applications and attention (in shares)

	(1) Female	(2) High Education ($\geq$ bachelor's)	(3) Young (< 45)	(4) Immigrant	(5) Rural
Panel A: Applications					
WFH offering	0.018***	0.009*	0.012**	−0.005	0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
Sample mean (share)	0.461	0.263	0.601	0.489	0.098
N	397,719	398,588	398,588	398,588	398,588
Panel B: Attention					
WFH offering	0.012***	0.008***	0.008***	−0.007***	0.007***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)
Sample mean (share)	0.526	0.279	0.554	0.411	0.112
N	401,639	401,674	401,674	401,674	401,674
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

Notes: This table reports estimates of how signaling WFH is associated with the demographic composition of unemployed viewers and applicants to a vacancy. Panel A uses the share of unemployed applicants with the listed characteristic as the dependent variable, and Panel B uses the corresponding share among unemployed viewers. Each column reports coefficients from the main specification in equation 5, where the key regressor is an indicator for whether the vacancy signals WFH. The demographic characteristics considered are: female (Column (1)), highly educated—defined as having at least a bachelor's degree—(Column (2)), young—defined as below age 45—(Column (3)), immigrant (Column (4)), and rural resident—defined as residing in a category A DeSO—(Column (5)). Because demographic information is only available for unemployed job seekers linked to the registry data, the analysis is restricted to that subset and should be interpreted as evidence on compositional changes within the unemployed search sample rather than the full applicant pool. In Panel A, the sample includes all vacancies posted between May 2020 and September 2022 with at least one unemployed applicant. In Panel B, the sample includes all vacancies posted between January 2019 and September 2022 with at least one unemployed viewer. Individuals with only one total view, vacancies with one or fewer total views, and vacancies with no text description are excluded. All specifications include vacancy controls, firm controls, local labor market fixed effects, commuting-zone-by-month-year fixed effects, and occupation-by-month-year fixed effects. Standard errors are clustered at the local labor market level.
$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

much weight on the application coefficient alone. At the attention stage, however, Panel B shows a statistically significant reduction in the immigrant share of viewers. One possible interpretation is that WFH-signaling vacancies are relatively less attractive to some immigrant job seekers, perhaps because in-person work provides greater opportunities for workplace integration, language acquisition, or local network formation. Given the imprecision in applications, however, this interpretation should be treated as suggestive rather than definitive.

The results for rural job seekers are also informative. Panel B shows that WFH-signaling vacancies attract a larger share of attention from job seekers in rural neighborhoods, but Panel A shows no corresponding increase in the rural share of applicants. This pattern is consistent with rural job seekers expressing greater initial interest in WFH opportunities, but not converting that interest into disproportionately higher application shares. More importantly, it is also consistent with the paper's broader geography results. WFH expands the spatial reach of applicant pools, but this need not imply

a higher rural share of applicants. The additional distant applicants attracted by WFH may come disproportionately from other non-local urban or suburban labor markets rather than from rural areas specifically.

Taken together, these results indicate that signaling WFH changes applicant composition along several observable dimensions, and that these compositional shifts begin at the attention stage. WFH-signaling vacancies attract relatively more women, younger job seekers, and highly educated job seekers, while the evidence for immigrants is weaker and the evidence for rural applicants differs between attention and applications. The broader implication is that WFH changes firms' access to labor not only by increasing the size of applicant pools and relaxing geographic frictions, but also by changing who is represented within those pools. This is important both substantively and methodologically: substantively, because WFH may affect the composition of potential hires; methodologically, because downstream WFH effects on hiring and wages may partly reflect selection in who chooses to search and apply.

8 Hiring Outcomes

The previous sections show that signaling WFH changes the applicant pool along several dimensions. WFH-signaling vacancies attract more applications, receive applications from job seekers outside their usual commuting markets, and, for stronger WFH signals, draw stronger applicants at the top of the applicant-quality distribution. I next examine whether these changes in the applicant pool translate into differences in realized hires. Even if WFH changes who applies, firms benefit only to the extent that these changes affect whom they ultimately hire.

8.1 Main results

To study this margin, I estimate the main specification in equation 5 using characteristics of realized hires as the dependent variables. I focus on two outcomes. First, I examine the geography of hires by measuring the distance between the hired worker's residence and the workplace. Second, I examine the quality of hires using pre-period AKM worker fixed effects from the matched employer–employee registry data.

The results are reported in Table 9. I find that WFH-signaling vacancies hire workers from farther away. In the main specification, new hires associated with WFH job ads live about 6% farther from the workplace than new hires connected to otherwise similar in-person vacancies. Relative to the sample mean, this corresponds to an increase of about 6.5 km. This pattern is consistent with the earlier evidence on applicant geography, including the residence-based applicant-distance results, and suggests that the geographic expansion of the applicant pool induced by WFH carries through, at least in part, to realized matches.

To assess this mechanism more directly, I also estimate a specification that interacts the WFH indicator with the average applicant distance to the vacancy. The interaction coefficient is positive, at

Table 9: Effect of WFH signaling on hiring outcomes

	(1) Distance of hires	(2) Distance of hires	(3) Quality of hires
Offering WFH	0.060***	0.043**	0.000
	(0.019)	(0.021)	(0.004)
WFH × distance of applicants	—	0.008**	—
		(0.004)	
Sample mean (km)	108.62	108.62	—
Sample mean (standardized quality)	—	—	0.00
N	558,087	513,180	951,285
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

Notes: This table reports estimates of how signaling WFH affects hiring outcomes using the main regression specification in equation 5. Columns (1) and (2) use the log distance between the hired worker's residence and the workplace as the dependent variable. Column (2) additionally includes an interaction between the WFH indicator and the average applicant distance to the vacancy. Column (3) uses the standardized AKM worker fixed effect of the hired worker as the dependent variable. All specifications include vacancy controls, firm controls, local labor market fixed effects, commuting-zone-by-month-year fixed effects, and occupation-by-month-year fixed effects. Standard errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

0.8%, indicating that the hiring-distance effect of WFH is stronger for vacancies that attract geographically broader applicant pools. I interpret this as evidence of partial pass-through from the expansion of applicant geography to the geography of realized hires. Because applicant distance is itself affected by WFH, this interaction should not be interpreted as a formal mediation estimate. Nevertheless, the positive interaction provides evidence consistent with the paper's central mechanism that WFH expands firms' effective labor markets, and some of that expansion is reflected in who gets hired.

By contrast, I find no discernible effect of WFH signaling on the AKM quality of hired workers. This null result suggests that, although WFH changes the quality composition of the applicant pool, especially at the top of the applicant distribution for stronger WFH signals, these differences do not translate into clear differences in the average quality of the workers ultimately hired. One interpretation is that firms use the broader applicant pool created by WFH primarily to hire from a wider geographic set of workers rather than to raise the average quality of realized hires. However, because the hiring sample is likely noisier than the applicant sample, the absence of a statistically discernible effect on the quality of hires should be interpreted as evidence of no clear average quality effect at the hiring

stage, rather than as strong evidence that no such effect exists.

Taken together, the hiring results suggest that the main downstream effect of signaling WFH operates through geography rather than through average hire quality. WFH-signaling vacancies hire workers from farther away, and this effect is stronger when the vacancy attracts a geographically broader applicant pool. At the same time, there is little evidence that WFH changes the AKM quality of the workers ultimately hired. This pattern is consistent with the broader findings of the paper where I find that signaling WFH relaxes geographic frictions in hiring by expanding firms' effective labor markets and widening the spatial reach of realized matches, even if it does not measurably raise the average quality of hires.

9 Conclusion

A perennial challenge for firms, job seekers, and policy makers is finding good matches in the labor market, but geographic frictions can limit the extent to which firms attract and hire workers. This paper studies whether signaling WFH in job ads relaxes geographic frictions in hiring by expanding firms' effective labor markets. Using Swedish vacancy data linked to employer–employee registry data and detailed information on job-search behavior, I show that it does. WFH-signaling vacancies attract applicants from outside firms' usual commuting markets, reshape the size and composition of applicant pools, and lead to hires from farther away.

The clearest evidence comes from the geography margin. Relative to applicants to similar in-person vacancies, applicants to WFH-signaling vacancies apply to jobs that are 36.7% farther from their revealed commuting preferences and also apply from farther from home. These patterns are consistent across alternative geography measures and indicate that signaling WFH relaxes geographic constraints in job search by expanding firms' effective labor markets.

I also find that WFH changes the quantity and composition of the applicant pool. WFH-signaling vacancies receive more attention and more applications than comparable in-person vacancies, and these gains are driven primarily by applicants coming from farther outside the firm's usual commuting market. At the same time, mean applicant quality declines slightly in some specifications, but stronger WFH signals improve the upper tail of the applicant-quality distribution. Decomposing the quality results by applicant geography shows that these gains at the top are driven mainly by more distant applicants, while the decline in nearby applications is consistent with a geographic reallocation of the applicant pool rather than a uniform increase in applications from all workers.

The hiring results suggest that these applicant-pool changes carry through, at least in part, to realized matches. WFH-signaling vacancies hire workers from farther away, and this effect is stronger for vacancies that attract geographically broader applicant pools. By contrast, I find no clear effect on the average AKM quality of hired workers. Taken together, these results suggest that the main downstream effect of signaling WFH operates through geography rather than through average hire quality.

The geographic benefits of WFH are especially pronounced for firms in thinner and more isolated labor markets. In particular, rural workplaces experience larger geography effects, consistent with WFH being especially valuable where local labor markets are thin. The evidence on applicant quality in these markets is less precise, but the most favorable results appear for fully remote vacancies, which seem particularly effective at connecting isolated firms to strong applicants outside their immediate labor market.

Overall, the findings suggest that WFH may be an important tool for alleviating geographic frictions in hiring. By reducing the importance of commuting distance, signaling WFH expands firms' effective labor markets and allows them to attract applicants from outside their usual commuting range, with especially strong effects in thinner and more isolated labor markets. In this sense, WFH can help connect firms to workers who would otherwise be unlikely to apply or be hired, and may therefore be an important margin through which some firms respond to spatial mismatch. At the same time, the evidence suggests that the main effect operates through geography and the composition of applicant pools, rather than through clear improvements in the average quality of realized hires.

These findings also have potential policy relevance, but they should be interpreted with caution. This paper shows that WFH can broaden firms' access to labor at the recruitment stage, but it does not estimate the full welfare consequences of encouraging more remote work. In particular, the analysis does not measure productivity effects, coordination costs, monitoring costs, or other organizational and monetary costs that may accompany WFH adoption. As a result, the findings do not imply that expanding WFH is always efficient, nor that it should be viewed as a direct substitute for relocation policies or other labor-market interventions. Rather, they suggest that WFH may be one useful margin for reducing spatial frictions when such frictions are important.

More broadly, the scope for WFH remains uneven across occupations and industries, meaning that the benefits documented in the paper are unlikely to generalize uniformly across the labor market. To the extent that WFH opportunities remain concentrated among higher-skill or higher-income jobs, broader adoption could also have distributional consequences for workers and firms in occupations where remote work is not feasible. Understanding these broader equilibrium, distributional, and productivity effects is an important direction for future research.

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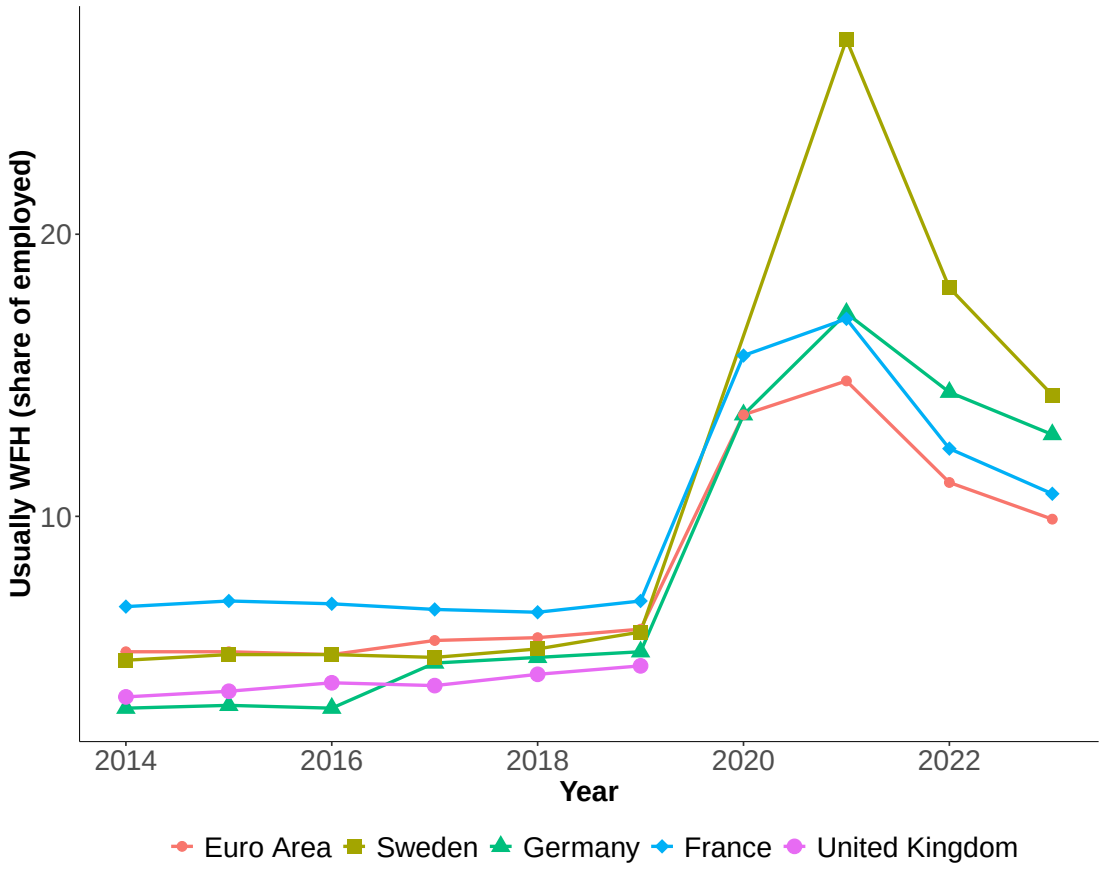
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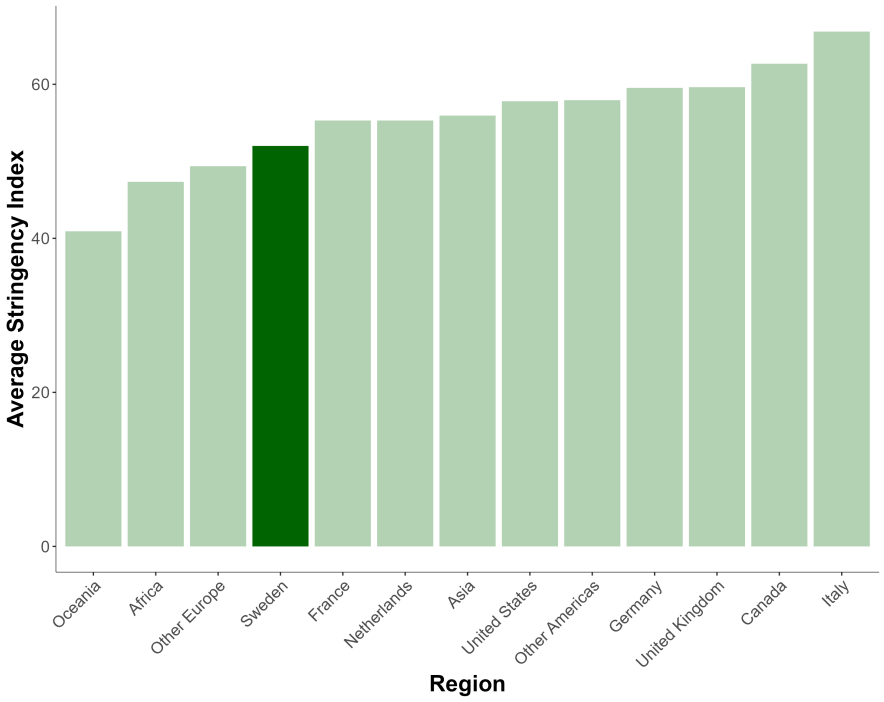
A Institutional Setting Appendix

Figure A.1: 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: Eurostat 2014-2023

Figure A.2: COVID-19 Stringency Index



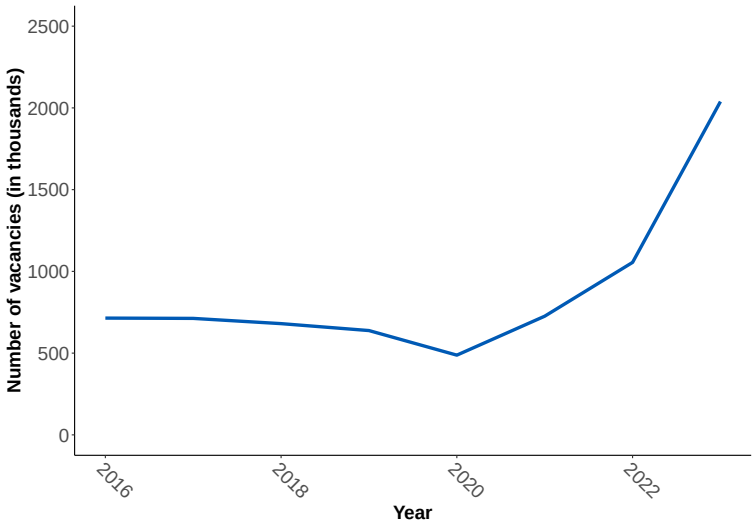
Notes: The COVID-19 Stringency Index is an index created by the Oxford Coronavirus Government Response Tracker (OxCGRT) project to measure the extent of government responses to COVID-19. The nine metrics used to calculate the Stringency Index are: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls. A higher number indicates stricter COVID-19 policies. We look at the stringency index over the period which runs from January 1, 2020 through September 30, 2021. Sweden is colored in dark green for easy identification.
Source: Hale et al. 2021; processed by Our World in Data

B Data Appendix

B.1 Job ad characteristics

Job board (Platsbanken) descriptives

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



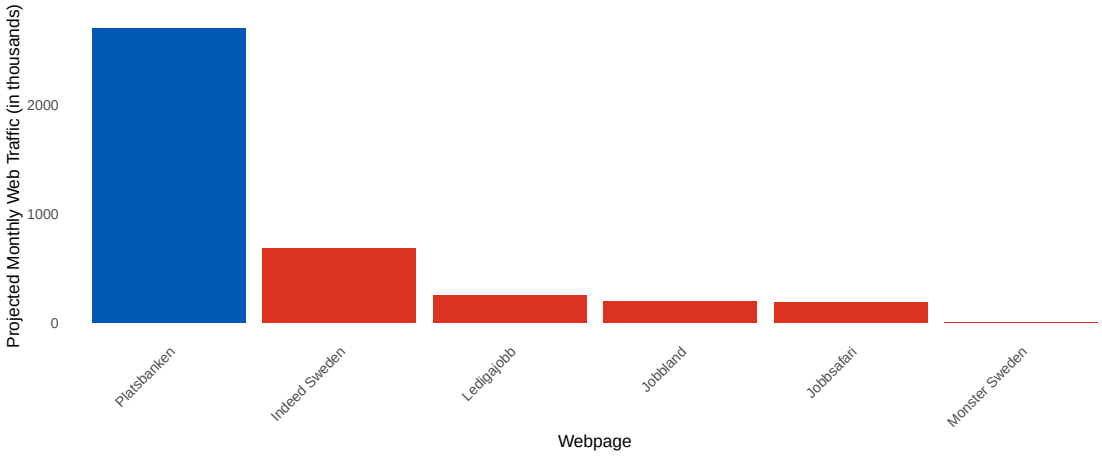
Notes: This figure plots the total number of vacancies per year (in thousands of vacancies) in the *Platsbanken* data after removing vacancies that are located outside Sweden.

Table B.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%**

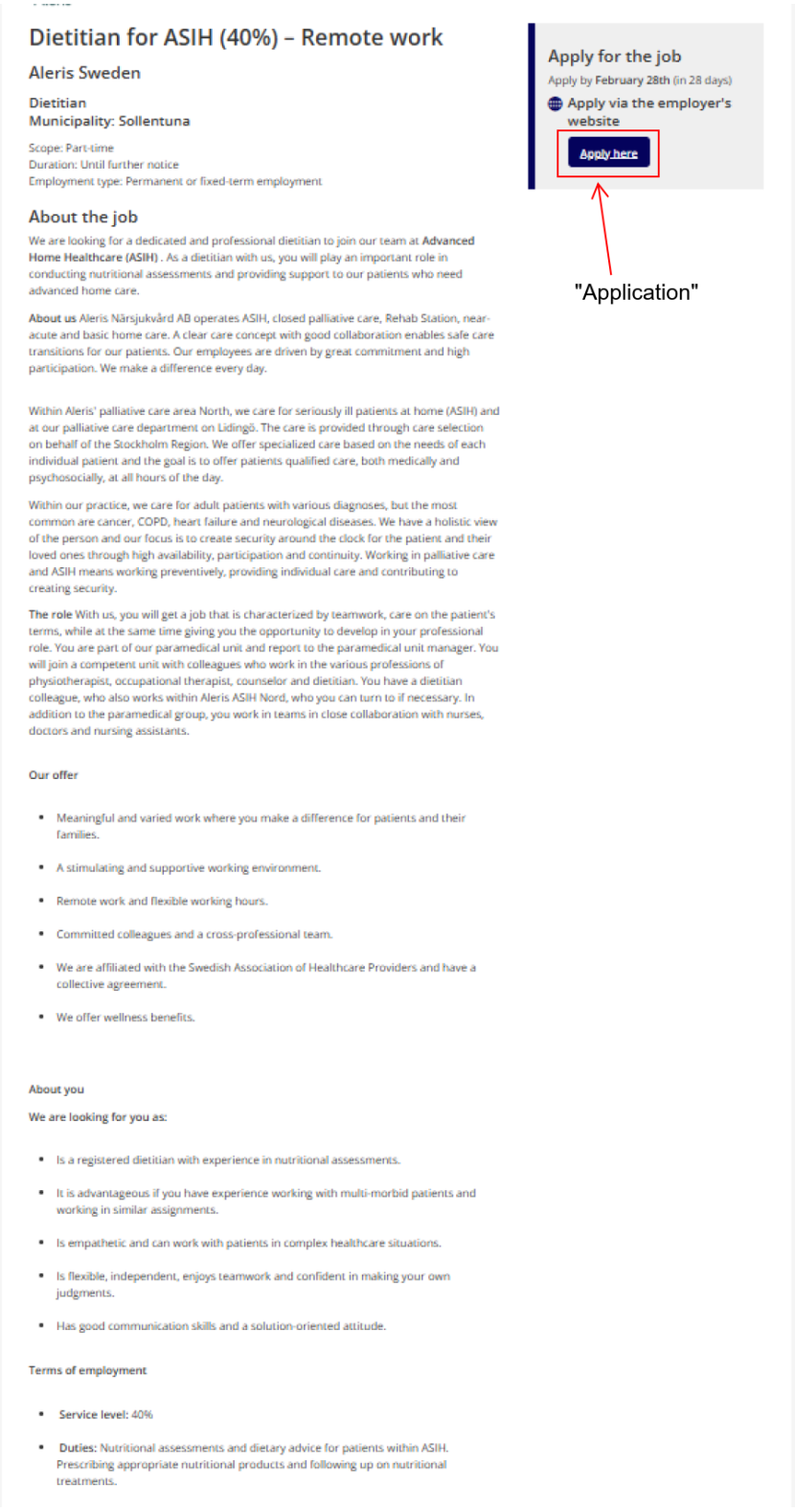
Notes: This table presents the breakdown of the vacancy data by years. The column "WFH vacancies" presents the number of vacancies that are categorized as WFH in that year and the column "Total vacancies" presents the total number of vacancies in my sample after the initial cleaning. The last column, "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.

Figure B.2: Projected Webpage Traffic for Swedish Job Boards



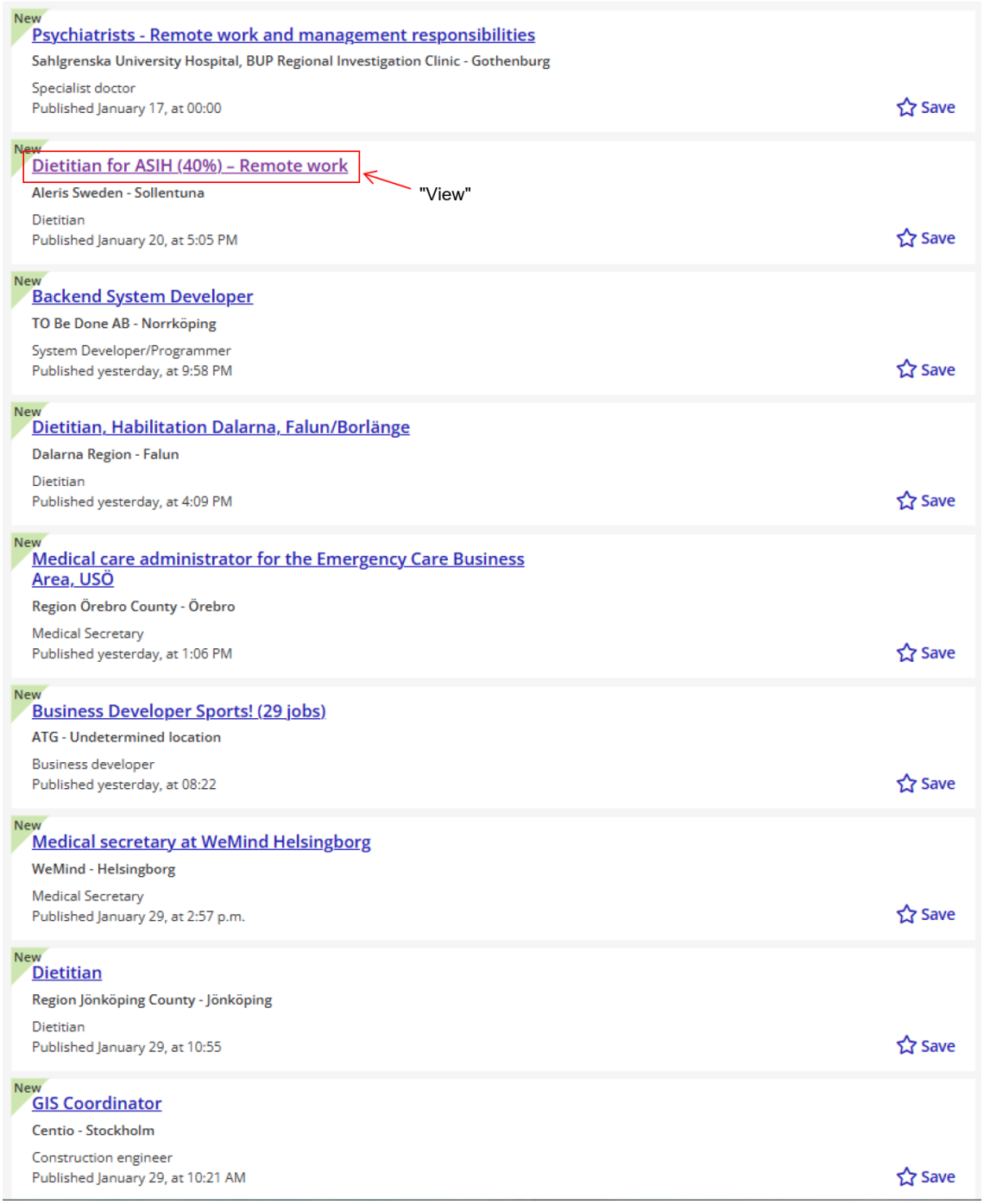
Notes: This figure plots the projected number of monthly clicks a webpage is projected to receive for several major online job boards in Sweden. Webpage clicks are reported in thousands of clicks. The traffic projections are projections for August 2025. Data comes from Ahref.com which was accessed August 28, 2025.

Figure B.3: *Platsbankan* example job ad



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 B.4), 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]

Figure B.4: *Platsbankan* example search page

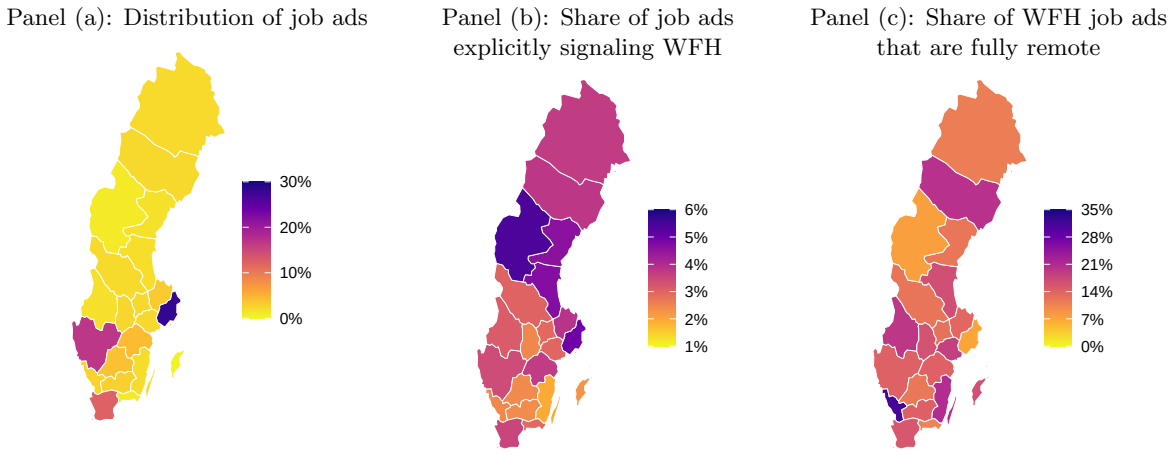


Notes: This figure shows a snapshot of the job ads board, *Platsbanken*, at the "view" stage. Job seekers would enter search terms on the main page, and would they would be given snapshots of job ads that look like this. A "view" is counted for each time an individual clicks on one of the ads from this page to take them to the more detailed description (Figure B.3). 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]

Covereage of job ads

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 B.6, 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).

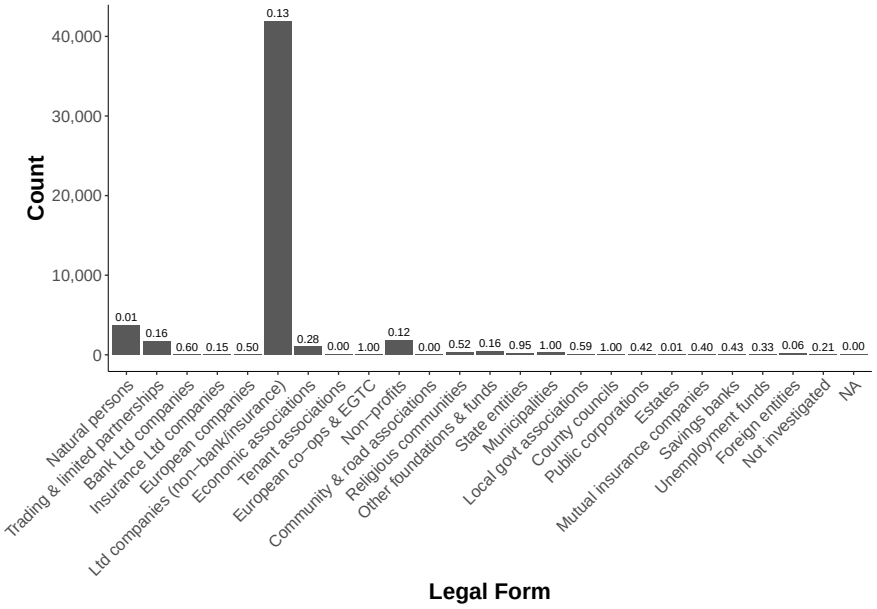
Figure B.5: Geographic distribution of job ads and work-from-home signals (county level)



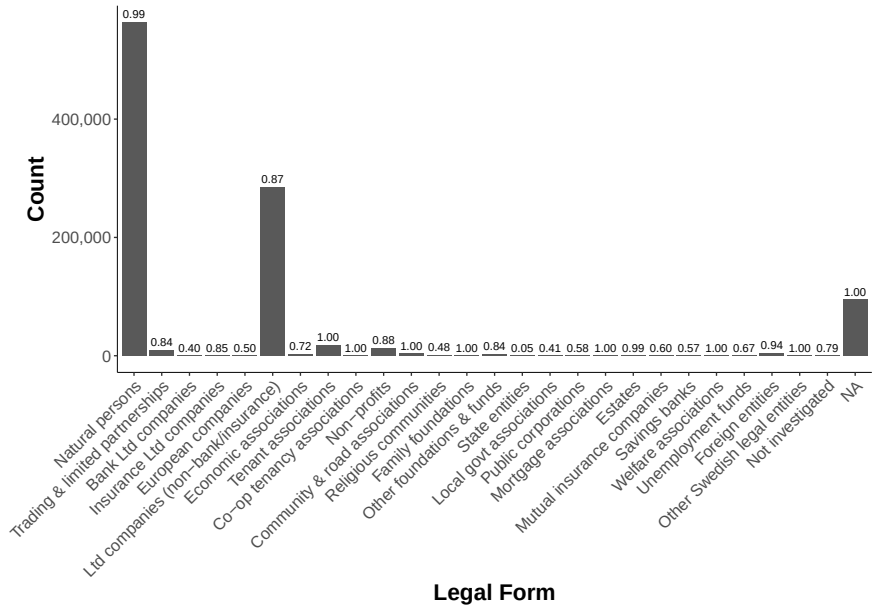
Notes: This figure shows county-level maps for Sweden over 2019–2022. Panel (a) shows the distribution of job ads across counties. Panel (b) shows the share of job ads in each county that explicitly signal work from home (WFH). Panel (c) shows the share of those WFH job ads in each county that are fully remote. In all panels, lighter-colored counties indicate lower values and darker-colored counties indicate higher values.

Figure B.6: Distribution of Swedish firms by legal type

(a) Linked to at least one vacancy



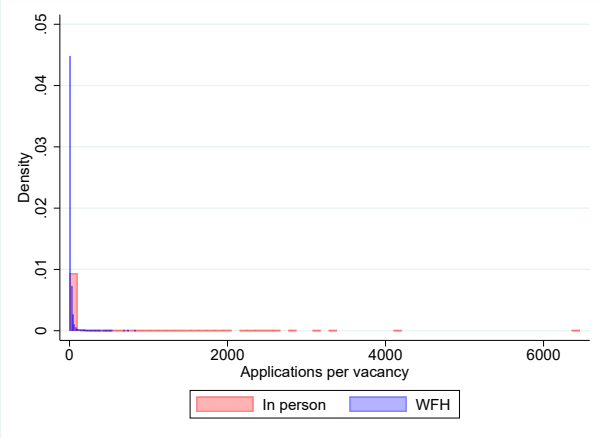
(b) Linked to no vacancies



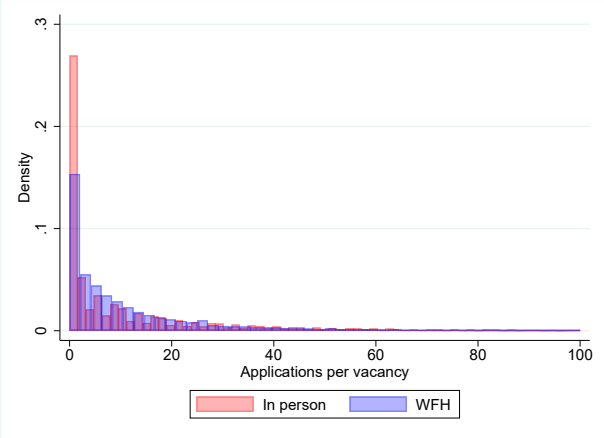
Notes: These figures present the distribution of firms by legal status based on the classification from the Swedish Tax Authority. Panel (a) presents the distributions for firms that are registered in Sweden and are connected to at least one vacancy from 2018–2022. Panel (b) presents the distributions 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 B.7: Distributions of applications per job ad by whether the job ad offers WFH

(a) Full distribution



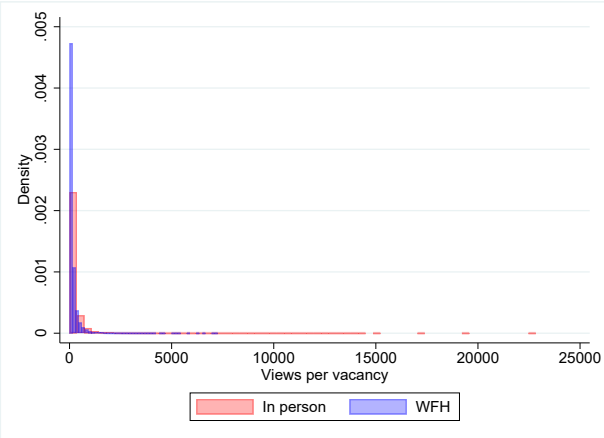
(b) Truncated ($\leq$ 100 applications)



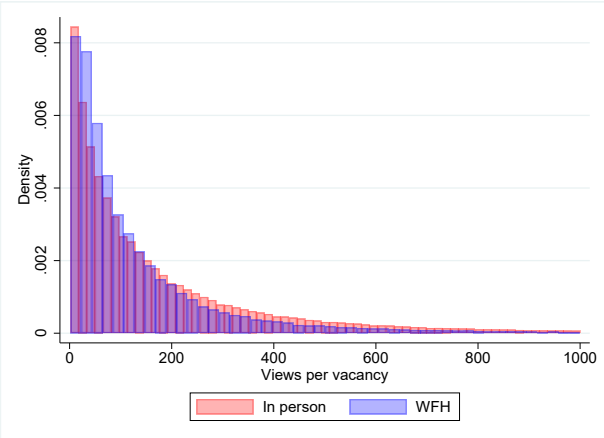
Notes: These figures plot the distributions of the number of applications the job ads receive by WFH offering. Panel (a) plots the distribution of the whole distribution. Panel (b) plots the distribution of the distribution truncated at job ads that received no more than 100 applications. Only vacancies 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 B.8: 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.

B.2 WFH classification validation

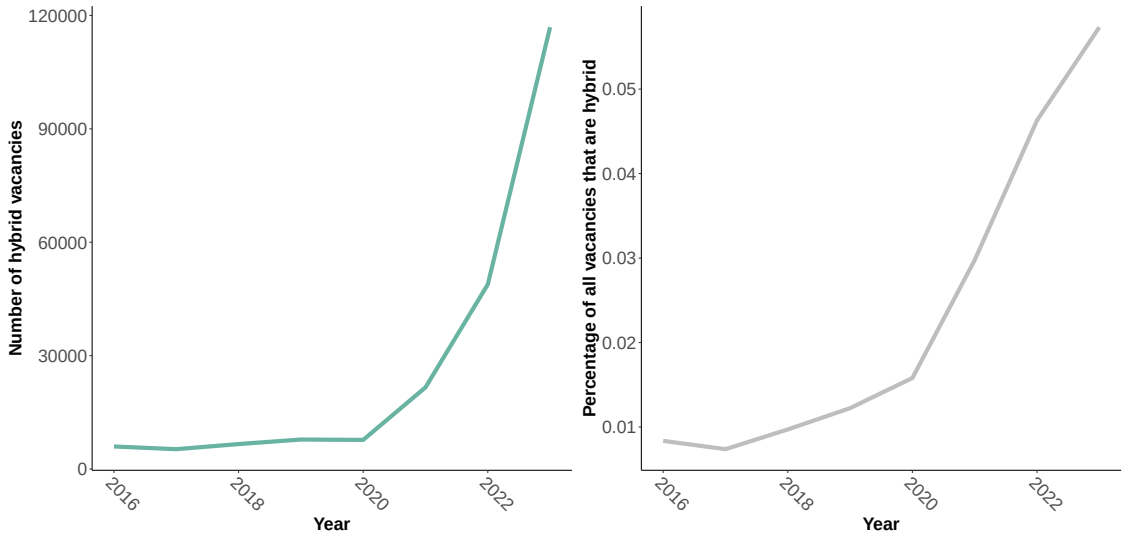
Table B.2: Most common WFH occupations

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:

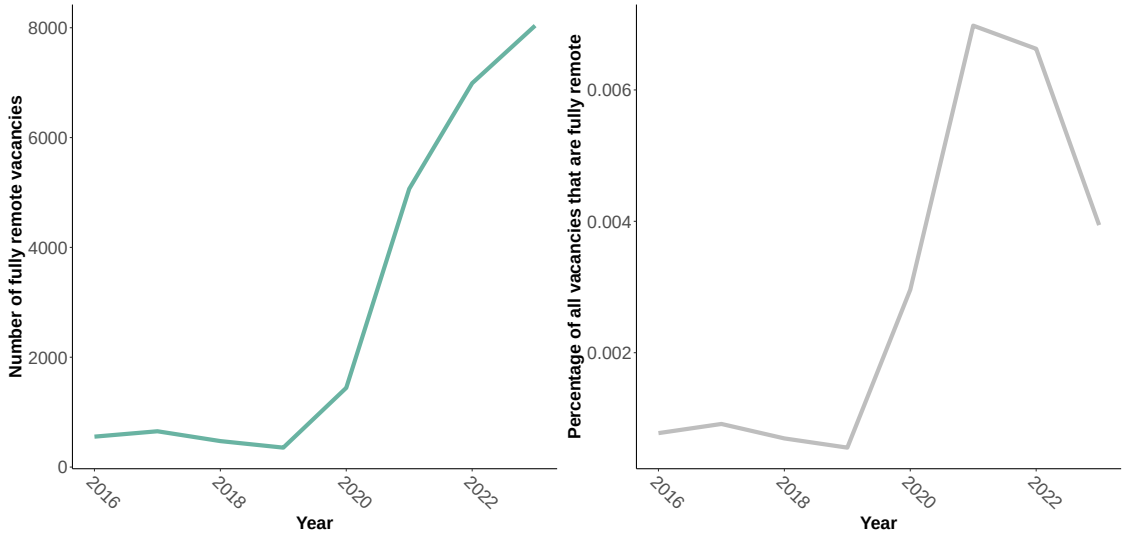
- 2017: Air traffic controller had highest percentage, but there was only 1 WFH vacancy (4 total vacancies)

Figure B.9: Hybrid Vacancy Trends



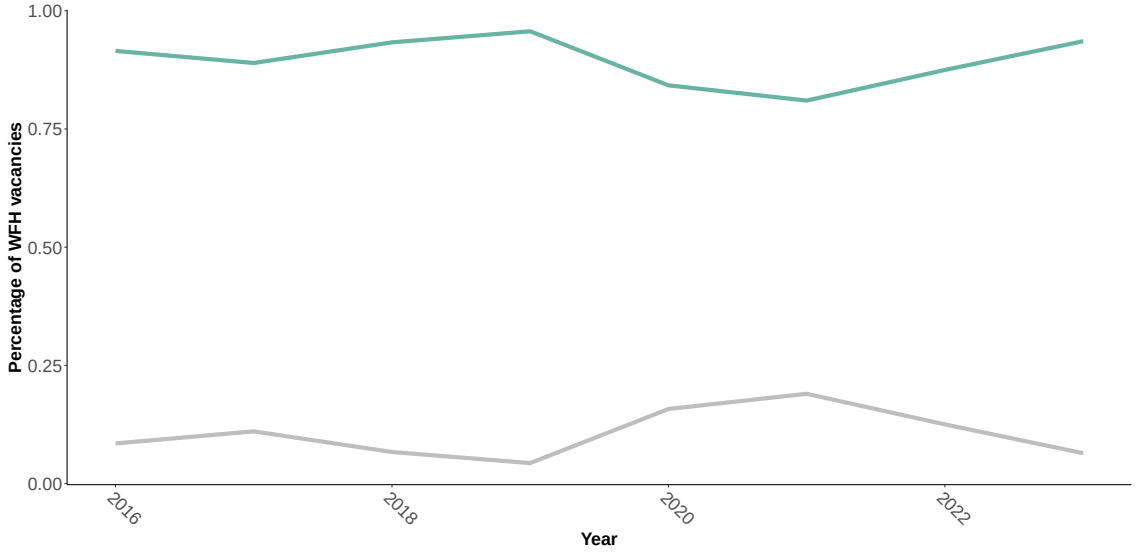
Notes: This figure plots the change in Swedish job ads that explicitly offer "hybrid" jobs from 2016-2023. The left graph plots the change in levels in hybrid job ads while the right graph plots the share of all job ads in that year that state they offer hybrid WFH. The share is out of all *Platsbanken* 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 2.

Figure B.10: Fully Remote Vacancy Trends



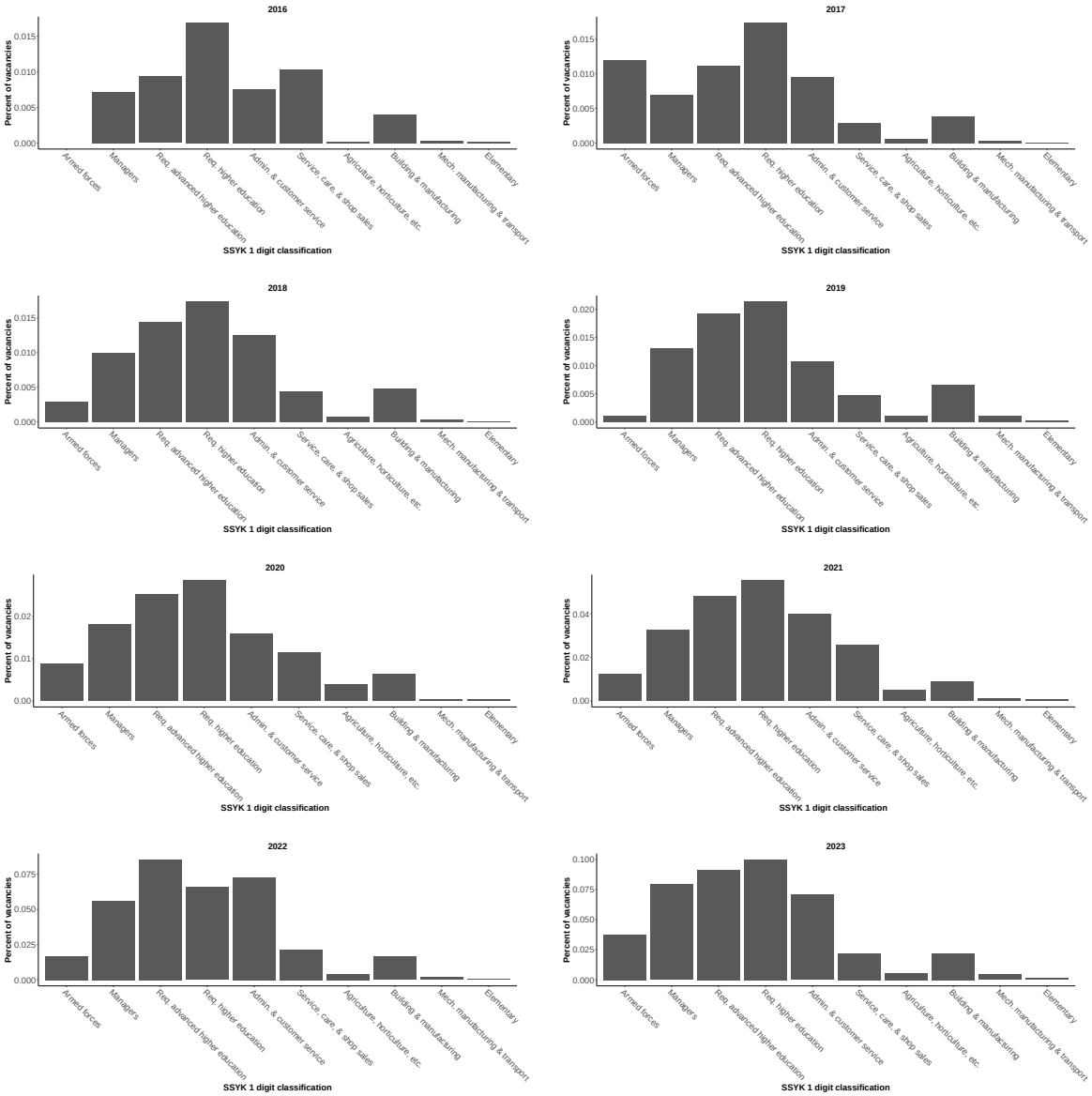
Notes: This figure plots the change in Swedish job ads that explicitly offer "fully remote" jobs from 2016-2023. The left graph plots the change in levels in fully remote job ads while the right graph plots the share of all job ads in that year that state they offer fully remote work. The share is out 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 2.

Figure B.11: 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 B.12: 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.

Validation through text analysis

The first part of the text analysis to validate the WFH classification is to look at the similarities between words in the WFH job ads compared to the in-person job ads and see where they diverge. To do this, I use the text of all the vacancies in this time period (2018-2022) and break the text into tokens. After removing the common "stop words" for Swedish, I separate the job ads by WFH classification and aggregate the counts for each word in each category. I then subset the tokens to the 200 most frequent words for each groups, to look at only the most relevant words. To get the "unique" common words for WFH job ads, I filter out the words from the "WFH" list that also appear in the "non-WFH" list of the top 200 words. Twenty-four words remain after filtering and those words are illustrated in Figure 3 with the size indicating the relative frequency. The name and frequencies of words in the WFH, non-WFH, and filtered WFH lists for the total sample and by year can be found in Table B.3. I do the same process by year and find similar unique words. The word clouds for the unique WFH words by year are found in Figure B.13. Together, this all points to the WFH classification correctly capturing job ads that signal WFH.

Using an extraction method similar to the WFH classification, I also extract the skills and the technology discussed in the job ads and compare them between WFH and non-WFH job ads. 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, Table B.4). 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. The raw shares are presented in Figure 4 and the differences are illustrated in Figure B.14. This suggests that skills and technology in the ads should not be major confounders of the WFH signal, but I include them as controls in my main analysis to remove even the small remaining correlations.

Table B.3: Frequencies of most common words in job ads by WFH type

WFH		**Non-WFH**		**Filtered**	
Word	Frequency	Word	Frequency	Word	Frequency
kommer	261052	kommer	5024378	distans	36705
arbeta	210532	samt	4802972	digitala	34872
samt	189402	erfarenhet	4005165	digital	24647
erfarenhet	187224	vill	3972282	business	24613
vill	182514	arbeta	3951017	support	24266
hos	143432	hos	3402966	working	23606
arbetar	127830	arbetar	3310231	arbetstider	22800
arbete	117743	arbete	2942931	kontoret	20865
kunder	111488	ska	2822970	teknisk	20862
team	107456	god	2750789	varandra	20627
finns	98950	ser	2627739	development	20598
tillsammans	98165	medarbetare	2381367	teknik	19766
ser	98154	arbetsuppgifter	2315633	tekniska	19685
erbjuder	97485	tillsammans	2285952	teamet	19517
god	96755	erbjuder	2143285	part	19411
ska	93303	finns	2124963	helt	19354
olika	91036	olika	2091956	us	19148
medarbetare	90957	kunder	2031459	snabbt	19070
del	89723	goda	1895908	data	18874
svenska	89649	andra	1819101	brinner	18829
genom	89285	del	1796635	per	18601
jobba	85883	person	1752776	bolag	18250
rollen	84889	arbetet	1728431	ekonomi	17999
goda	84340	svenska	1710046	befintliga	17969
arbetsuppgifter	84144	mer	1702551	motsvarande	17726
mer	79393	genom	1680530		
andra	78390	nya	1659935		
utveckling	78350	team	1632505		
nya	75913	bra	1564309		
arbetet	71917	meriterande	1561635		
meriterande	70547	stor	1542842		
ta	70395	uppdrag	1493903		

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WFH		**Non-WFH**		**Filtered**
via	69630	ta	1485780	
stor	68714	utveckling	1454580	
utbildning	64426	utbildning	1413273	
person	63624	jobba	1403155	
skapa	63368	via	1369140	
uppdrag	63046	krav	1328494	
roll	61733	skapa	1325717	
kollegor	61348	kollegor	1306297	
work	59690	rollen	1286877	
utveckla	59407	enligt	1283948	
hela	58842	hela	1273477	
bra	57919	kunna	1198070	
kunna	55492	utveckla	1186891	
sker	54617	idag	1183239	
idag	54457	ansvar	1154409	
kunskaper	54135	viktigt	1133362	
ansvar	52827	behov	1129895	
stort	51603	service	1129876	
krav	50066	personlig	1123666	
information	49106	utvecklas	1118557	
utvecklas	48337	kunskaper	1118309	
sverige	48274	sker	1111850	
stockholm	47799	stort	1101374	
tal	47248	tar	1082194	
kompetens	46410	tidigare	1072917	
skrift	46188	kompetens	1043623	
engelska	46092	tal	1042462	
behov	46058	roll	1007515	
tidigare	45389	verksamhet	996340	
enligt	45185	kommun	995243	
tar	44473	sverige	951839	
fokus	42389	skrift	938047	
jobbar	41338	information	922728	
verksamhet	41291	personliga	910557	
viktigt	40992	kvalifikationer	908418	

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WFH		Non-WFH		Filtered
projekt	38568	vikt	900599	
kunskap	38244	fokus	892427	
samarbete	38181	annat	843776	
trivs	37793	elever	836942	
kontor	36984	intresse	834027	
distans	36705	verksamheten	824464	
arbetsplats	36280	sveriges	820676	
jobbet	36212	barn	820334	
ger	35756	emot	818382	
annat	35717	kunskap	806737	
flera	35181	ge	801804	
intresse	35177	samarbete	793560	
digitala	34872	personal	791210	
minst	34798	bland	788708	
service	34730	alltid	786570	
fram	34721	redan	782703	
heltid	34194	trivs	782307	
kund	34150	rekrytering	776951	
komma	33919	jobb	768686	
tror	33791	kontakt	757073	
stora	33661	ansvarar	756622	
kontakt	33204	stockholm	753235	
personliga	33133	engagemang	752560	
bland	32865	komma	748353	
https	32490	ca	731068	
start	32144	kund	720270	
ab	32133	flera	718767	
alltid	31775	minst	718243	
verksamheten	31649	trygg	713514	
redan	31153	engelska	705678	
sveriges	30940	jobbar	703440	
vidare	30937	egenskaper	703216	
system	30731	jobbet	689643	
vikt	30524	positiv	684846	
experience	30431	se	684458	

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WFH		**Non-WFH**		**Filtered**
produkter	29947	arbetsplats	683657	
jobb	29469	flexibel	681803	
personlig	29340	skicka	676289	
bidra	29287	dag	672407	
egen	29100	heltid	672388	
egna	29062	ger	672270	
driva	28999	tror	660841	
emot	28851	https	642718	
ge	28585	in	635552	
in	28507	stora	634137	
samtidigt	28490	urval	625837	
plats	28326	bidra	622753	
rekrytering	27748	samtidigt	621034	
urval	27338	work	606359	
viktig	27061	tycker	601184	
lyckas	26781	viktig	599156	
ansvarar	26469	fram	596774	
sista	25717	erbjuda	594586	
kvalifikationer	25651	sista	591153	
arbetat	25304	kvalitet	590128	
egenskaper	25166	ab	589496	
organisation	25047	personer	585138	
bidrar	24929	vidare	584329	
bygga	24825	skapar	576778	
digital	24647	gillar	572305	
business	24613	egna	559315	
eget	24596	undanber	550188	
relevant	24546	egen	549879	
skapar	24505	kollektivavtal	544731	
flexibel	24332	ligger	541931	
erbjuda	24306	intervjuer	538759	
support	24266	kunden	537263	
skicka	24257	bidrar	536635	
se	24049	uppdraget	530200	
gillar	23932	start	522829	

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WFH		Non-WFH		Filtered
tycker	23861	varmt	510475	
intervjuer	23687	lyckas	496639	
working	23606	social	494675	
trygg	23596	ledande	491371	
kvalitet	23542	an	490632	
positiv	22976	trivas	488744	
ca	22953	profil	485434	
hantera	22950	lik de	479095	
kring	22807	cv	473923	
arbetstider	22800	aktivt	473697	
kunden	22709	cirka	471095	
personer	22542	region	470678	
erfarenheter	22335	uppgifter	466041	
fler	22305	noggrann	465044	
cv	22272	patienter	462969	
barn	22210	projekt	462682	
engagemang	22089	varierande	454727	
delar	21997	arbetat	450395	
kommun	21878	leda	449430	
konsult	21763	intresserad	447151	
ledande	21731	gott	446266	
driven	21547	skillnad	443832	
kontoret	20865	produkter	441710	
teknisk	20862	arbetsgivare	441576	
trivas	20712	eget	440250	
varandra	20627	driva	438626	
development	20598	samarbeta	436697	
aktivt	20404	skola	434676	
an	20322	konsult	433596	
erbjuds	20314	utmaningar	431940	
uppdraget	20187	organisation	427858	
tid	20090	resultat	424309	
resultat	19982	delar	421937	
teknik	19766	runt	416482	
dag	19761	kring	415947	

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WFH		**Non-WFH**		**Filtered**
utmaningar	19738	relationer	415552	
ligger	19709	system	413891	
tekniska	19685	engagerad	410408	
teamet	19517	hantera	410176	
part	19411	plats	409578	
uppgifter	19405	fler	404712	
helt	19354	personligt	399536	
intresserad	19297	bakgrund	399038	
us	19148	relevant	391411	
personligt	19087	skolan	390945	
snabbt	19070	ytterligare	380799	
data	18874	bygga	379212	
brinner	18829	experience	374372	
per	18601	driven	374030	
skillnad	18546	legitimerad	373484	
lik de	18544	dagliga	372082	
samarbeta	18448	tid	371920	
region	18439	hitta	371222	
varierande	18252	erfarenheter	366764	
bolag	18250	ny	366551	
hitta	18050	kontor	360505	
varmt	18005	ansvara	354441	
ekonomi	17999	erbjuds	353839	
befintliga	17969	ansvarstagande	352565	
motsvarande	17726	tre	352129	
patienter	17709	planera	349342	
relationer	17657	hemsida	346721	
ny	17591	utvecklar	343064	

Using an extraction method similar to the WFH classification, I also extract the skills and the technology discussed in the job ads.

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

Figure B.13: 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 3, 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.

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.

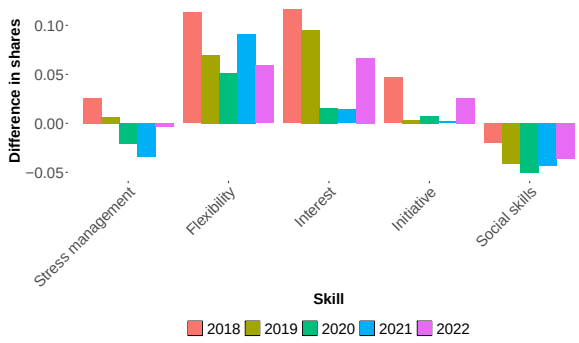
Table B.4: Shares of job ads mentioning skills or technology by WFH offering

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

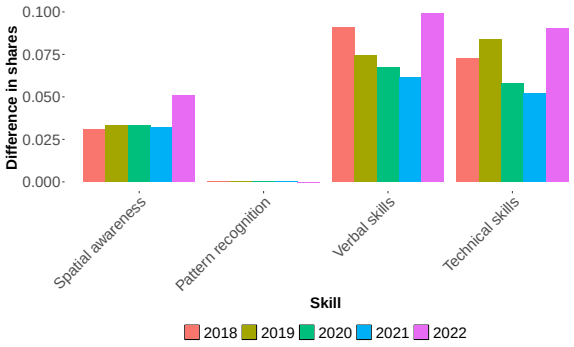
Note: This table formalizes the pattern seen in Figure 4. It presents the shares of job ads that contain different skills/technology by WFH job ads (Column 2) and non-WFH job ads (Column 3) and the differences between them (Column 4). Column 5 presents the p-values generated from t-tests testing the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

Figure B.14: Differences in the share of WFH and non-WFH job ads per skills/technology by year

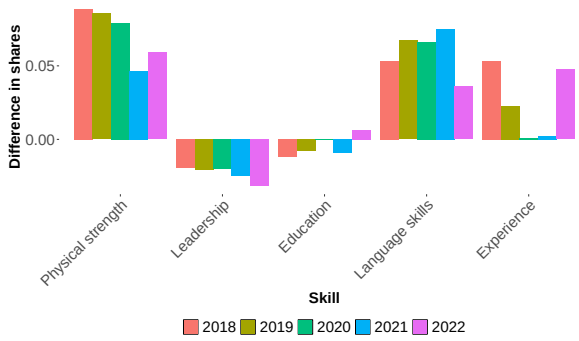
(a) Cognitive skills



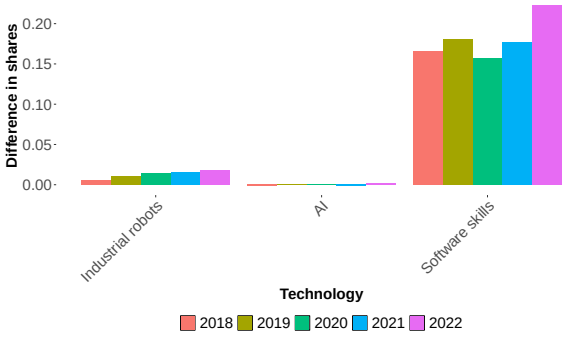
(b) Non-cognitive skills



(c) Other skills



(d) Technology

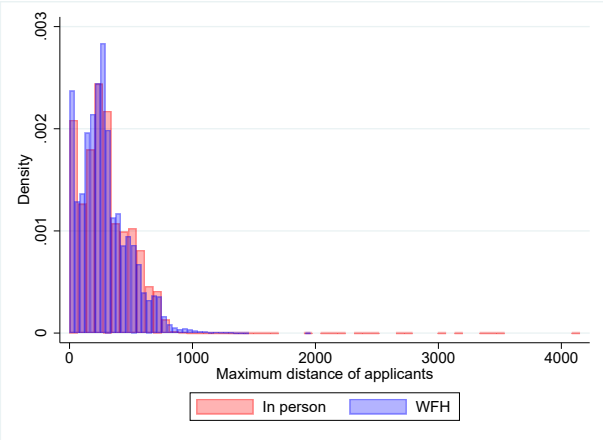


Notes: These figures present the difference between WFH and non-WFH vacancies in the shares of the specific skill (panels (a) to (c)) or technology (panel (d)) that the ad asks for. The differences are plotted separately by year from 2018-2022. For all four panels, the skills/technologies are presented in the same order as in Figure 4 (sorted by overall share of WFH job ads that mention them).

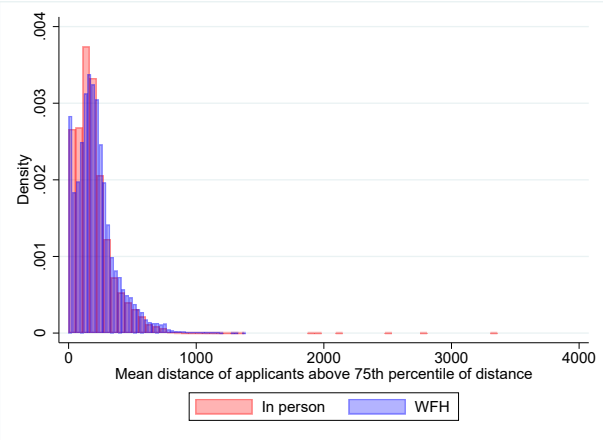
B.3 Applicant commuting preference measure - additional figures

Figure B.15: Distributions of distances of applicants by whether the job ad offers WFH

(a) Maximum distance



(b) Mean distance of top quartile

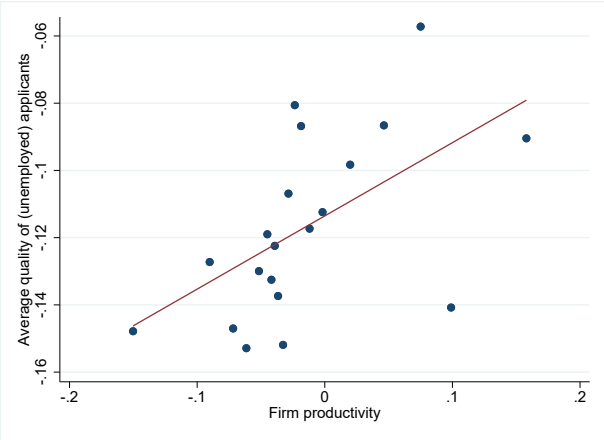


Notes: These figures plot the distributions of the distances of applicants' "workplace location preferences" from the job ads. Panel (a) plots the distributions of the maximum applicant distance. Panel (b) plots the distribution of the mean distance away for applicants in the 75^{th} percentile of distance 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.

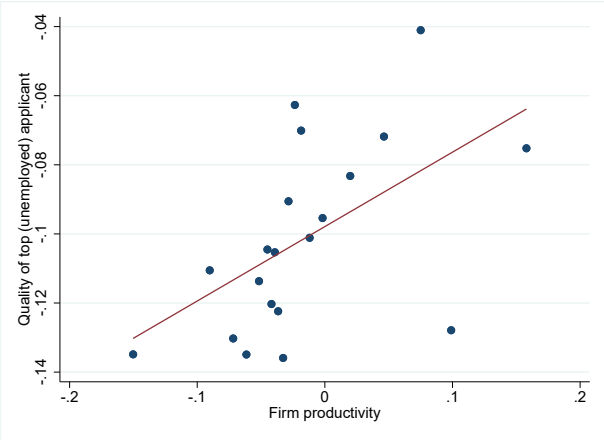
B.4 Applicant quality measure - additional figures

Figure B.16: Correlation between quality of unemployed applicants and firm quality

(a) Average applicant

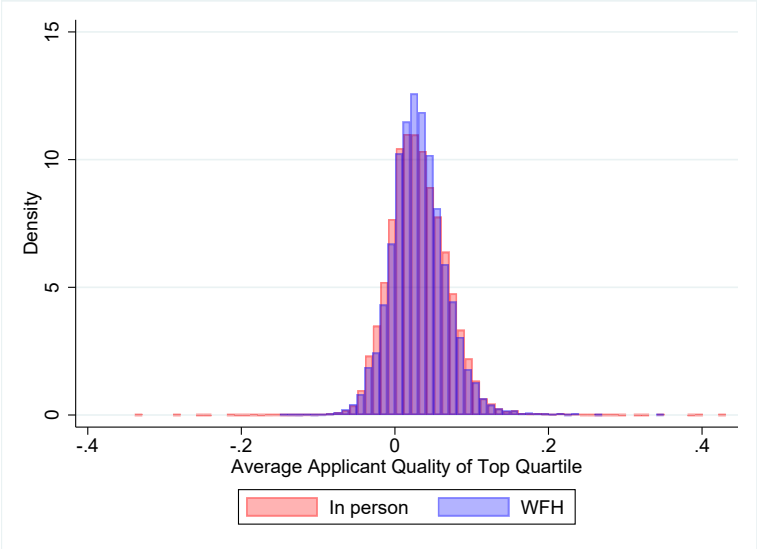


(b) Top applicant



Notes: These figures plot the relationships between the applicant quality (mean (Panel (a)) and top (Panel (b))) of unemployed applicants that apply to job ads and the firm quality. "Quality" for these figures is defined as the workers and firm fixed effects from an AKM model. The data consists only of unemployed applicants that held positions at at least two different firms from the period 2016-2019 in my wage data (needed to estimate the fixed effects) and only the set of firms where workers moved to/from the firm in that same data and posted job ads from May 2020-September 2022.

Figure B.17: 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 7.

B.5 Occupation-level WFH potential - additional information

This appendix describes the construction of the occupation-level WFH-potential measures used in the heterogeneity and robustness analyses.

I construct the main occupation-level benchmark using data from the 2021 Swedish Labour Force Survey (LFS; Eurostat 2021). The goal is to measure the general prevalence of WFH by occupation using an external survey source, rather than the vacancy text itself. This provides an occupation-based proxy for the underlying feasibility of WFH that can be compared with the job-ad-based classification used in the main analysis.

The LFS reports occupation using ISCO-08 codes, whereas the Swedish vacancy data use SSYK 2012 occupation codes. I therefore first map the ISCO-08 occupations in the LFS to 3-digit SSYK 2012 occupations. Because the correspondence between ISCO-08 and SSYK 2012 is not one-to-one, some ISCO-08 occupations map to multiple SSYK codes and vice versa. To avoid imposing arbitrary assignment rules, I allow an ISCO-08 occupation to contribute to all linked SSYK occupations. As a result, some individuals are counted in more than one SSYK occupation.[23]

After harmonizing the occupation codes, I compute for each 3-digit occupation the share of employed respondents who report working from home at least sometimes in their main job. In the LFS, employed respondents are asked how often they work from home and can report that they work from home "mainly," "sometimes," "never," or that the question is "not applicable." I define "at least some" WFH as the sum of the "mainly" and "sometimes" categories, divided by the total number of employed respondents in that occupation with a valid response.[24]

I then rank occupations by this survey-based WFH share and divide them into quartiles. The quartile thresholds are: below 15.6% for Quartile 1 (lowest WFH potential), below 45.0% for Quartile 2, below 75.1% for Quartile 3, and at least 75.1% for Quartile 4 (highest WFH potential). These quartile indicators are then matched to the job-ad and search data using the 3-digit SSYK occupation code reported in the vacancy.

As a validation exercise, I compare the LFS-based occupation-level WFH shares with the within-occupation share of vacancies in 2021 that are classified as WFH using the text-based vacancy measure. The correlation between the two measures is positive and substantial (Pearson's $\rho = 0.67$, $p < 0.001$), indicating that the survey-based measure provides a reasonable external ranking of occupations by WFH potential.

For some robustness analyses, I also construct a simpler binary indicator for "high WFH potential" based on broad occupation groups. Specifically, I classify as high WFH potential the four 1-digit SSYK occupation groups with the highest shares of WFH vacancies in the job-ad data: managers (SSYK 1), occupations requiring advanced higher education (SSYK 2), occupations requiring higher education

23. Because the purpose of this exercise is to rank occupations by their likelihood of offering WFH, I prefer this many-to-many assignment to making strong assumptions about how ambiguous occupation codes should be uniquely allocated. This procedure introduces some measurement error into the occupation-level WFH shares, but such error is likely to attenuate differences across occupations rather than create spurious ones.

24. I exclude respondents who are not employed. The LFS also contains a small number of "not stated" responses, which I treat as missing when constructing the occupation-level shares.

(SSYK 3), and administration and customer service occupations (SSYK 4). Together, these four broad groups account for roughly 64% of all job ads and about 89% of WFH job ads. This simpler binary measure is also positively correlated with the LFS-based classification when comparing these broad occupation groups with occupations in Quartiles 3 and 4 of the LFS measure (Pearson's $\rho = 0.67$, $p < 0.001$).

Overall, these occupation-level measures are used only as auxiliary benchmarks. The main WFH variable in the paper remains the vacancy-level text-based measure, which captures whether the job ad explicitly signals WFH to job seekers.

B.6 Unemployed sample characteristics

Table B.5: 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 rural individuals	0.095	0.099	0.150
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

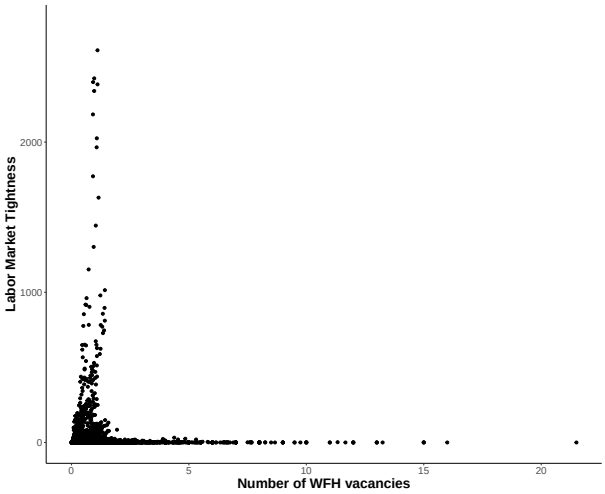
Note: This table presents the summary statistics for several demographic characteristics for the sample of unemployed applicants and unemployed viewers of job ads as well as the full population from the registry data. Specifically, I look at the share of female individuals, share of immigrants, the share of individuals living in rural 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.

C Additional Results and Descriptives

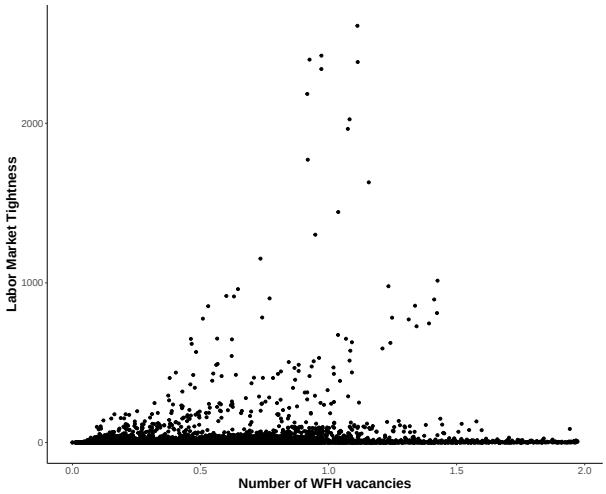
C.1 Additional material for "Labor Market Tightness"

Figure C.1: 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 8. 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).

C.2 Additional material for "Geographic Distribution of Job Seekers"

Table C.1: 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 5) 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 2, 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 fewer 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 C.2: WFH and geographic dispersion of applicants (maximum distance of applicants)

	All job ads		
	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects
WFH offering	-0.073^{*}	0.309^{***}	0.352^{***}
	(0.042)	(0.021)	(0.020)
Occupation and Time F.E.s	N	N	N
Vacancy Controls	N	Y	Y
Firm Controls	N	Y	N
Local Labor Market F.E.	N	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y
Occupation × month-year F.E.	N	Y	Y
Firm F.E.	N	N	Y
Sample mean (km)	145.3	145.3	145.3
N	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 main specification outlined in equation 5. Column (3) corresponds to the firm fixed effects regression. 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 fewer 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 C.3: WFH and geographic dispersion of applicants (mean distance of top quartile)

	All job ads		
	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects
WFH offering	0.118***	0.340***	0.380***
	(0.034)	(0.020)	(0.020)
Occupation and Time F.E.s	N	N	N
Vacancy Controls	N	Y	Y
Firm Controls	N	Y	N
Local Labor Market F.E.	N	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y
Occupation × month-year F.E.	N	Y	Y
Firm F.E.	N	N	Y
Sample mean (km)	79.8	79.8	79.8
N	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 main specification outlined in equation 5. Column (3) corresponds to the firm fixed effects regression. 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 fewer 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 C.4: Geographic dispersion using unemployed residence location

	(1) Mean distance (All)	(2) Mean distance ("A" DeSOs)	(3) Mean distance ("B" DeSOs)	(4) Mean distance ("C" DeSOs)	(5) Max distance (All)
WFH offering	0.103***	0.134***	0.210***	0.087***	0.109***
	(0.021)	(0.042)	(0.048)	(0.023)	(0.023)
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 (km)	62.5	77.0	68.1	59.6	100.4
N	354,795	70,432	52,339	333,742	354,795

Note: This table presents the results of the regression estimates using an alternative measure for geographic dispersion for unemployed job seekers. In these results, the distance between the applicant and the job are determined using the distance from the centroid of the neighborhood where the applicant lives to the coordinate of the job ad. I run all of these results using the main specification outlined in equation 5, and all of the outcomes are estimated in logs. Column (1) presents the results for the mean distance between the residence location and job location for all the job ads with unemployed applicants. The next three columns present those results broken down by neighborhood type, with estimates for "A" (rural), "B" (non-city population centers), and "C" (urban) DeSOs found in Columns (2), (3), and (4), respectively. Column (5) presents the results for the distance of the maximum applicant for the full sample. The data consists of all months from May 2020 to September 2022. Individuals not in my unemployed sample, individuals that have only one total view, vacancies that receive only one or fewer total views, vacancies with no applications, vacancies with no text written (text length = 0), and job ads with no unemployed applicants are dropped from all samples. 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 C.5: Robustness results for mean commuting preference deviation

	(1) Unemployed	(2) High WFH occupations	(3) Without big cities	(4) Alternate WFH classification	(5) Control for firm productivity	(6) Firm x Time FEs
WFH offering	0.436***	0.389***	0.412***	0.232***	0.391***	0.407***
	(0.024)	(0.021)	(0.025)	(0.018)	(0.030)	(0.020)
Vacancy Controls	Y	Y	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	N
AKM Firm F.E. Control	N	N	N	N	Y	N
Firm × month-year F.E.	N	N	N	N	N	Y
Sample mean	28.4	44.6	43.3	40.5	39.2	39.7
N	370,425	538,214	637,024	927,677	459,086	1,161,765

Note: This table presents the results for a series of robustness analysis for the mean commuting preference deviation results using alternative samples, treatment variable, or specifications. Columns (1)-(3) all use the same main specification as found in equation 5, but for different samples. Column (1) presents the results for just the unemployed sample (the sample that can be matched to the registry data). Column (2) presents the results for only the occupation categories that have high WFH signaling. These are the 1-digit occupations of "requires higher education" (ssyk 3), "requires advanced higher education" (ssyk 2), "managers" (ssyk 1), and "administration and customer service" (ssyk 4). Column (3) presents the results removing all the job ads located in the three largest municipalities in Sweden (Stockholm, Gothenburg, and Malmo). Column (4) presents the results also using this main specification, but the treatment variable is the alternate classification of WFH from the generative AI model. Column (5) presents the results for this same specification, but including controls for firm productivity (the firm fixed effects estimated from the AKM model). Column (6) presents the results for the specification that includes firm-by-time fixed effects (and drops the firm-level controls). The data consists of all months May 2020 to September 2022. Sample restrictions for these analyses correspond to the sample restrictions for the main analyses. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: WFH and geographic dispersion of applicants (using log mean distance) - rural firms

	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects
WFH offering	0.513***	0.559***	0.463***
	(0.052)	(0.153)	(0.134)
Vacancy Controls	N	Y	Y
Firm Controls	N	Y	N
Local Labor Market F.E.	N	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y
Occupation × month-year F.E.	N	Y	Y
Firm F.E.	N	N	Y
Sample mean (km)	65.46	65.46	65.46
N	49,760	26,364	37,844

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 rural areas. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the main specification outlined in equation 5. Column (3) corresponds to the firm fixed effects regression. 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 fewer 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. 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.3 Additional material for "Applicant quantity"

Table C.7: Effect of WFH signaling on applications and attention

	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects
Panel A: Applications			
WFH offering	−0.344***	0.039**	0.028***
	(0.044)	(0.017)	(0.010)
Sample mean (# of applications)	28.78	28.78	28.78
N	1,531,314	1,060,687	1,428,685
Panel B: Attention			
WFH offering	−0.231***	0.099***	0.069***
	(0.067)	(0.021)	(0.013)
Sample mean (# of views)	217.54	217.54	217.54
N	2,377,730	1,793,449	2,236,208
Firm Controls	N	Y	N
Vacancy Controls	N	Y	Y
Local Labor Market F.E.	N	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y
Occupation × month-year F.E.	N	Y	Y
Firm F.E.	N	N	Y

Note: This table presents the results of the main regression estimates for log job ad applications (Panel A) and log job ad attention (views, Panel B) on WFH offering. Column (1) corresponds to the baseline (uncontrolled) regressions. Column (2) corresponds to the main specification outlined in equation 5. Column (3) corresponds to the firm fixed effects regressions. For Panel A, the data consists of all months from May 2020 to September 2022. For Panel B, the data consists of all months from January 2019 to September 2022. For both panels, individuals that have only one total view, vacancies that receive only one or fewer total views, and vacancies with no text written (text length = 0) are dropped. For Panel A, vacancies with no applications are also dropped. 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 C.8: Applications and attention for fully remote job ads

	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects
Panel A: Applications			
WFH offering	0.011	0.240***	0.332***
	(0.058)	(0.084)	(0.055)
Sample mean (# of applications)	29.2	29.2	29.2
N	1,480,275	1,028,283	1,379,066
Panel B: Attention			
WFH offering	−0.011	0.445***	0.417***
	(0.063)	(0.103)	(0.078)
Sample mean (# of views)	219.5	219.5	219.5
N	2,314,163	1,751,107	2,174,301
Vacancy Controls	N	Y	Y
Firm Controls	N	Y	N
Local Labor Market F.E.	N	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y
Occupation × month-year F.E.	N	Y	Y
Firm F.E.	N	N	Y

Notes: This table presents the main regression estimates for fully remote job ads. Panel A reports estimates for log job ad applications, and Panel B reports estimates for log job ad attention (log views). Column (1) corresponds to the baseline (uncontrolled) regression, Column (2) corresponds to the main specification outlined in equation 5, and Column (3) corresponds to the firm fixed effects regression. In both panels, I present estimates for the entire sample of job ads. In Panel A, the data consist of job ads in all months from May 2020 to September 2022. In Panel B, the data consist of job ads in all months from January 2019 to September 2022. Individuals that have only one total view, vacancies that receive only one or fewer total views, vacancies with no text written (text length = 0), and job ads classified as "hybrid WFH" are dropped from all samples. Sample means report the average number of applications in Panel A and the average number of views in Panel B. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: Applications and attention for job ads with WFH in the title

	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects
Panel A: Applications			
WFH in title	0.254***	0.482***	0.452***
	(0.087)	(0.108)	(0.110)
Sample mean (# of applications)	28.78	28.78	28.78
N	1,531,314	1,060,687	1,428,685
Panel B: Attention			
WFH in title	0.082	0.748***	0.663***
	(0.101)	(0.156)	(0.106)
Sample mean (# of views)	217.54	217.54	217.54
N	2,377,730	1,793,449	2,236,208
Vacancy Controls	N	Y	Y
Firm Controls	N	Y	N
Local Labor Market F.E.	N	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y
Occupation × month-year F.E.	N	Y	Y
Firm F.E.	N	N	Y

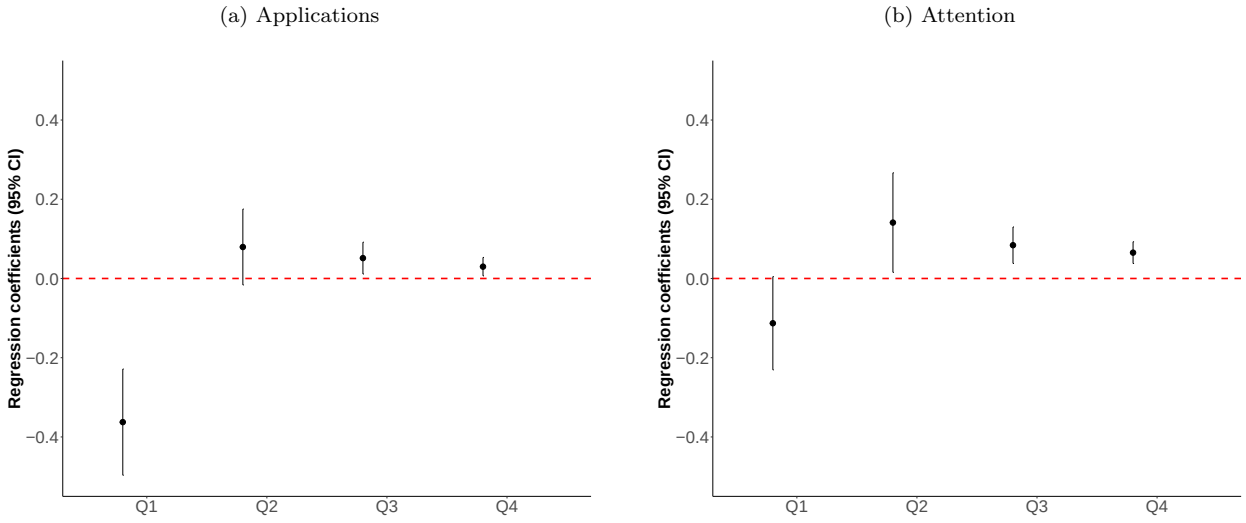
Notes: This table presents the main regression estimates using whether the job ad explicitly mentions WFH in the job title as the treatment. Panel A reports estimates for log job ad applications, and Panel B reports estimates for log job ad attention using the log number of views. Column (1) corresponds to the baseline (uncontrolled) regression, Column (2) corresponds to the main specification outlined in equation 5, and Column (3) corresponds to the firm fixed effects regression. In Panel A, the data consist of all months from May 2020 to September 2022. In Panel B, the data consist of all months from January 2019 to September 2022. In Panel A, individuals that have only one total view, vacancies that receive only one or fewer total views, vacancies with no applications, and vacancies with no text written (text length = 0) are dropped from all samples. In Panel B, individuals that have only one total view, vacancies that receive only one or fewer total views, and vacancies with no text written (text length = 0) are dropped from all samples. Sample means report the average number of applications in Panel A and the average number of views in Panel B. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.10: WFH on probability a job ad receives an application

	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects
WFH offering	0.036***	0.011***	0.005**
	(0.008)	(0.002)	(0.002)
Vacancy Controls	N	Y	Y
Firm Controls	N	Y	N
Local Labor Market F.E.	N	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y
Occupation × month-year F.E.	N	Y	Y
Firm F.E.	N	N	Y
Sample mean (share with ≥ 1 application)	0.881	0.881	0.881
N	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 main specification outlined in equation 5. Column (3) corresponds to the firm fixed effects regression. 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 fewer 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.2: Applications and attention by occupation 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.

Table C.11: Robustness results for quantity of applications and attention

	(1) Unemployed	(2) High WFH occupations	(3) Without big cities	(4) Alternate WFH classification	(5) Control for firm productivity	(6) Firm x Time FEs
Panel A: Application quantity						
WFH offering	0.013	0.036***	0.016	0.048***	0.036***	0.020**
	(0.021)	(0.012)	(0.017)	(0.017)	(0.013)	(0.009)
Sample mean	61.0	20.4	24.6	28.8	32.4	28.5
N	398,588	693,283	732,396	1,060,687	521,562	1,343,730
Panel B: Attention quantity						
WFH offering	0.073***	0.074***	0.087***	0.122***	0.061***	0.051***
	(0.025)	(0.013)	(0.018)	(0.024)	(0.012)	(0.009)
Sample mean	409.8	188.8	233.4	217.5	265.3	214.2
N	401,819	1,201,841	1,193,870	1,793,449	908,615	2,124,200
Vacancy Controls	Y	Y	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	N
AKM Firm F.E. Control	N	N	N	N	Y	N
Firm × month-year F.E.	N	N	N	N	N	Y

Notes: This table presents the results for a series of robustness analyses for application quantity in Panel A and attention quantity in Panel B using alternative samples, treatment variables, or specifications. Columns (1)–(3) all use the same main specification as found in equation 5, but for different samples. Column (1) presents the results for just the unemployed sample (the sample that can be matched to the registry data). Column (2) presents the results for only the occupation categories that have high WFH signaling. These are the 1-digit occupations of "requires higher education" (ssyk 3), "requires advanced higher education" (ssyk 2), "managers" (ssyk 1), and "administration and customer service" (ssyk 4). Column (3) presents the results removing all the job ads located in the three largest municipalities in Sweden (Stockholm, Gothenburg, and Malmo). Column (4) presents the results also using this main specification, but the treatment variable is the alternate classification of WFH from the generative AI model. Column (5) presents the results for this same specification, but including controls for firm productivity (the firm fixed effects estimated from the AKM model). Column (6) presents the results for the specification that includes firm-by-time fixed effects (and drops the firm-level controls). The data consist of all months from May 2020 to September 2022. Sample restrictions for these analyses correspond to the sample restrictions for the main analyses. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.12: WFH on attention (including 2018 views)

	(1) Baseline relationship	(2) Main analysis	(3) Firm fixed effects
WFH offering	−0.201***	0.099***	0.075***
	(0.063)	(0.021)	(0.014)
Vacancy Controls	N	Y	Y
Firm Controls	N	Y	N
Local Labor Market F.E.	N	Y	Y
Commuting Zone × month-year F.E.	N	Y	Y
Occupation × month-year F.E.	N	Y	Y
Firm F.E.	N	N	Y
Sample mean (# of views)	204.88	204.88	204.88
N	2,915,961	1,793,449	2,752,417

Note: This table is related to Panel B of Table 4. 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 main specification outlined in equation 5. Column (3) corresponds to the firm fixed effects regression. 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 fewer 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 C.13: Applications and attention for rural workplaces

	(1) All WFH job ads	(2) Fully remote job ads
Panel A: Applications		
WFH offering	0.021	0.042
	(0.073)	(0.316)
Sample mean (# of applications)	22.21	22.21
N	31,836	31,403
Panel B: Attention		
WFH offering	0.060	0.197
	(0.058)	(0.254)
Sample mean (# of views)	233.67	233.67
N	31,988	31,555
Vacancy Controls	Y	Y
Firm Controls	Y	Y
Local Labor Market F.E.	Y	Y
Commuting Zone × month-year F.E.	Y	Y
Occupation × month-year F.E.	Y	Y

Notes: This table presents the main regression estimates for rural workplaces. Panel A reports estimates for log job ad applications, and Panel B reports estimates for log job ad attention using the log number of views. Column (1) reports the main specification for all WFH job ads. Column (2) restricts treatment to fully remote vacancies only, dropping hybrid vacancies. In Panel A, the data consist of all months from May 2020 to September 2022. In Panel B, the data consist of all months from January 2019 to September 2022. In both panels, individuals that have only one total view, vacancies that receive only one or fewer total views, vacancies with no text written (text length = 0), and vacancies from firms in urban areas are dropped from all samples. In Panel A, vacancies with no applications are also dropped from all samples. Sample means report the average number of applications in Panel A and the average number of views in Panel B. Standard errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.14: Effect of WFH on quantity "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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4 Additional material for "Applicant quality"

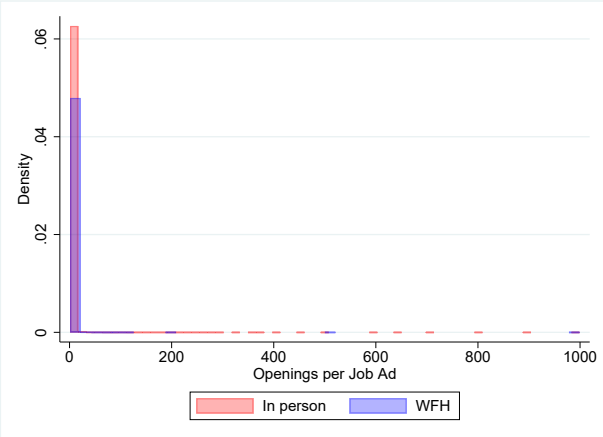
Table C.15: Average quality of the top quartile of applicants by WFH offering

	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 × 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

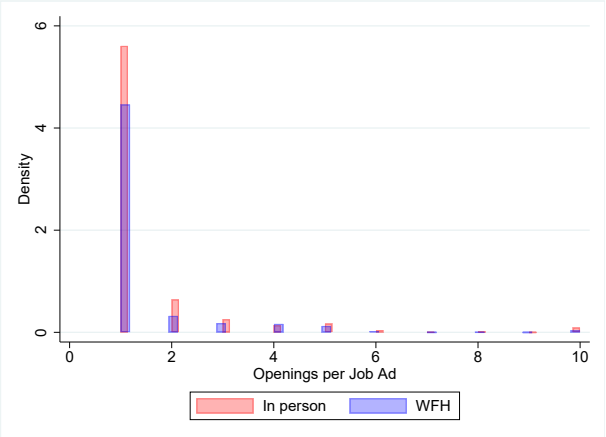
Note:This table presents the regression estimates for the main analysis (based on equation 5) for the average quality of the top quartile of applicants on whether the job ad offers WFH. The table presents the estimates for three versions of WFH, Column (1) uses all the job ads classified as WFH, Column (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 fewer 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.3: Distribution of the number of reported openings per job ad

(a) Full sample



(b) Truncated (≤ 10)



Notes: These figures plot the distribution of the number of open positions (openings) that the firm reports is available for the job ad by WFH type. Panel (a) plots the distribution for the full sample of job ads, and Panel (b) plots the truncated distribution for all job ads with 10 or fewer openings. $N = 2,377,730$ for Panel (a) and $N = 2,351,141$ for Panel (b); 26,589 job ads are dropped from the sample in Panel (b). The data for both of these panels consists of job ads from January 2019-September 2022. For both panels, the distributions for in-person vacancies are plotted in red and the distributions of WFH vacancies are plotted in blue.

Table C.16: Quality of applicants by WFH offering - rural firms

	(1) All WFH job ads	(2) Fully remote job ads	(3) Job ads with WFH in headline
Panel A: Standardized mean quality			
WFH offering	−0.097	0.418	−0.056
	(0.071)	(0.971)	(1.020)
Sample mean (standardized mean quality)	−0.10	−0.10	−0.10
N	11,855	11,605	11,855
Panel B: Standardized maximum quality			
WFH offering	0.037	0.548**	0.014
	(0.072)	(0.273)	(0.279)
Sample mean (standardized maximum quality)	−0.09	−0.09	−0.09
N	11,855	11,605	11,855
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

Note: This table presents the regression estimates for the main analysis (based on equation 5) for average quality of applicants (Panel A) and for the top quality applicant (Panel B) on whether the job ad offers WFH subset to firms in rural areas. The table presents 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 fewer 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 C.17: Robustness results for mean and top quality of applicants

	(1) Unemployed	(2) High WFH occupations	(3) Without big cities	(4) Alternate WFH classification	(5) Control for firm productivity	(6) Firm x Time FEs
Panel A: Mean quality of applicants						
WFH offering	−0.034***	−0.033***	−0.041***	−0.020**	−0.035***	−0.039***
	(0.011)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Sample mean	0.01	−0.03	−0.07	0.00	0.00	0.00
N	189,065	354,902	361,434	492,262	492,262	484,854
Panel B: Top quality of applicants						
WFH offering	−0.011	−0.005	−0.026***	−0.008	−0.010	−0.011
	(0.014)	(0.007)	(0.009)	(0.008)	(0.007)	(0.008)
Sample mean	0.47	−0.18	−0.02	0.00	0.00	0.00
N	189,065	354,902	361,434	492,262	492,262	484,854
Vacancy Controls	Y	Y	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	N
AKM Firm F.E. Control	N	N	N	N	Y	N
Firm × month-year F.E.	N	N	N	N	N	Y

Notes: This table presents the results for a series of robustness analyses for mean quality of applicants in Panel A and top quality of applicants in Panel B using alternative samples, treatment variables, or specifications. Columns (1)–(3) all use the same main specification as found in equation 5, but for different samples. Column (1) presents the results for just the unemployed sample (the sample that can be matched to the registry data). Column (2) presents the results for only the occupation categories that have high WFH signaling. These are the 1-digit occupations of "requires higher education" (ssyk 3), "requires advanced higher education" (ssyk 2), "managers" (ssyk 1), and "administration and customer service" (ssyk 4). Column (3) presents the results removing all the job ads located in the three largest municipalities in Sweden (Stockholm, Gothenburg, and Malmo). Column (4) presents the results also using this main specification, but the treatment variable is the alternate classification of WFH from the generative AI model. Column (5) presents the results for this same specification, but including controls for firm productivity (the firm fixed effects estimated from the AKM model). Column (6) presents the results for the specification that includes firm-by-time fixed effects (and drops the firm-level controls). The data consist of all months from May 2020 to September 2022. Sample restrictions for these analyses correspond to the sample restrictions for the main analyses. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.18: Robustness results for mean and top quality of applicants – fully remote

	(1) Unemployed	(2) High WFH occupations	(3) Without big cities	(4) Alternate WFH classification	(5) Control for firm productivity	(6) Firm x Time FEs
Panel A: Mean quality of applicants						
WFH offering	−0.067	0.003	−0.029	0.007	0.006	−0.006
	(0.046)	(0.044)	(0.041)	(0.013)	(0.043)	(0.047)
Sample mean	0.01	−0.03	−0.07	0.00	0.00	0.00
N	184,749	339,398	351,257	476,181	476,181	468,749
Panel B: Top quality of applicants						
WFH offering	0.111	0.115***	0.110*	0.002	0.114***	0.090*
	(0.070)	(0.007)	(0.063)	(0.014)	(0.043)	(0.049)
Sample mean	0.47	−0.18	−0.01	0.01	0.01	0.01
N	184,749	339,398	351,257	476,181	476,181	468,749
Vacancy Controls	Y	Y	Y	Y	Y	Y
Local Labor Market F.E.	Y	Y	Y	Y	Y	Y
Commuting Zone × month-year F.E.	Y	Y	Y	Y	Y	Y
Occupation × month-year F.E.	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	N
AKM Firm F.E. Control	N	N	N	N	Y	N
Firm × month-year F.E.	N	N	N	N	N	Y

Notes: This table presents the results for a series of robustness analyses for mean quality of applicants in Panel A and top quality of applicants in Panel B for fully remote job ads using alternative samples, treatment variables, or specifications. Columns (1)–(3) all use the same main specification as found in equation 5, but for different samples. Column (1) presents the results for just the unemployed sample (the sample that can be matched to the registry data). Column (2) presents the results for only the occupation categories that have high WFH signaling. These are the 1-digit occupations of "requires higher education" (ssyk 3), "requires advanced higher education" (ssyk 2), "managers" (ssyk 1), and "administration and customer service" (ssyk 4). Column (3) presents the results removing all the job ads located in the three largest municipalities in Sweden (Stockholm, Gothenburg, and Malmo). Column (4) presents the results also using this main specification, but the treatment variable is the alternate classification of WFH from the generative AI model. Column (5) presents the results for this same specification, but including controls for firm productivity (the firm fixed effects estimated from the AKM model). Column (6) presents the results for the specification that includes firm-by-time fixed effects (and drops the firm-level controls). The data consist of all months from May 2020 to September 2022. Sample restrictions for these analyses correspond to the sample restrictions for the main analyses. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.19: Quality of "close" and "far" applicants (no distance restrictions)

	Mean quality		Top quality	
	Far applications	Close applications	Far applications	Close applications
WFH offering	−0.029***	−0.003	0.023***	−0.071***
	(0.0)	(0.009)	(0.008)	(0.008)
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 (standardized mean quality)	0.00	0.00	0.00	0.00
N	417,414	433,674	417,414	433,674

Note: This table is analogous to Table 7 except there is no distance restriction imposed. This table presents the analysis looking at the differential change in applicant quality between WFH job ads and similar in-person job ads for applicants that apply "far" from their preferred in-person location (Columns (1) and (3)) and for applicants that apply "close" to their preferred in-person location (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 results for the mean quality of applicants. Columns (3) and (4) present the results for the quality of the top applicant (maximum quality). 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 C.20: Mean of top quartile quality of "close" and "far" applicants

	≤ 20km restriction		No distance restriction	
	Far applications	Close applications	Far applications	Close applications
WFH offering	0.015	−0.039***	0.003	−0.043***
	(0.010)	(0.011)	(0.008)	(0.008)
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 (standardized mean quality)	0.00	0.00	0.00	0.00
N	367,114	366,824	417,414	433,674

Note: This table presents the analysis looking at the differential change in the mean quality of the top quartile of applicants between WFH job ads and similar in-person job ads for applicants that apply "far" from their preferred in-person location (Columns (1) and (3)) and for applicants that apply "close" to their preferred in-person location (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 results including the distance restriction (related to the results in Table 7). Job seekers with a minimum distance between their preferred location and closest job ad > 20km are dropped from the sample in these columns. Columns (3) and (4) present the results with no distance restrictions (related to the results in Table C.19). The quality of applicants is standardized to have mean = 0 and standard deviation = 1. Standard Errors are clustered at the local labor market level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.5 Additional material for "Demographic composition of applicants"

Table C.21: Compositional changes of unemployed (controlling for other demographic shares)

	(1) Female	(2) High Education ($\geq$ bachelor's)	(3) Young (<45)	(4) Immigrant	(5) Rural
Panel A: Applications					
WFH offering	0.017***	0.010**	0.013**	−0.007	0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
Sample mean	0.461	0.263	0.601	0.489	0.098
N	397,719	397,719	397,719	397,719	397,719
Panel B: Attention					
WFH offering	0.010***	0.009***	0.011***	−0.006**	0.006***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)
Sample mean	0.526	0.279	0.554	0.411	0.185
N	401,639	401,639	401,639	401,639	401,639
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
Other Demographics Controls	Y	Y	Y	Y	Y

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 applicants (Panel A) and unemployed viewers (Panel B) 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 5. The characteristics are measured as the shares of the unemployed job seekers that apply to/view 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 (applicants under the age of 45, Column (3)), share of job seekers that are immigrants (Column (4)), and share of job seekers living in rural neighborhoods (Column (5)). In Panel A, 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. In Panel B, 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 fewer 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$