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THE INTERNET, SEARCH FRICTIONS AND AGGREGATE UNEMPLOYMENT

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ABSTRACT

How has the internet affected search and hiring, and what are the implications for aggregate unemployment? Answering these questions empirically has proven difficult due to selection in internet use and difficulty in measuring the search activities of both sides of the labor market. This paper overcomes these challenges by combining plausibly exogenous variation in the availability of high-speed internet in Norway with large-scale survey and administrative data on hiring firms, job seekers, and vacancies. Our empirical analysis shows that the internet expansion led more firms to recruit online and caused 9% shorter vacancy durations and 13% fewer unsuccessful hiring attempts. While the expansion increased job-finding rates by 2.4% and starting wages by 6% among the unemployed, we find no evidence of changes in job-to-job mobility or wage growth for employees. To interpret these findings, we develop and calibrate an equilibrium search model with endogenous job creation and destruction where workers decide how much search effort to exert on and off the job. Through the lens of the calibrated model, we find that better search technology is the main driving force behind our quasi-experimental evidence. Our calculations indicate that the steady-state unemployment rate fell by as much as 14% due to the broadband internet expansion.

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1 Introduction

The internet has changed how workers and firms search for one another. The fraction of job applicants using the internet for job search increased from 25 percent in 2000 to 75 percent in 2011 in the US (Faberman & Kudlyak, 2016), and nearly 70 percent of job openings were posted online by 2015 (Carnevale *et al.*, 2014). While this shift has increased the flow of information about available jobs and workers, the questions of how it affects vacancy behavior and job search remain open – limiting our understanding of how the internet has shaped aggregate unemployment and labor market trends.[1] Key empirical challenges are measuring the search and recruitment activities of both sides of the market and addressing the potential for reverse causality and selection bias from internet use. For instance, firms' online recruitment can reflect high underlying productivity growth. Similarly, searching online may reflect that people have limited access to information about jobs from social networks or because they live in areas with few employment opportunities.

This paper makes two main contributions toward bridging these gaps. Our first contribution is empirical, as we provide the first quasi-experimental evidence on how the internet has jointly affected the search and recruitment process and whether it has improved the quality of new employment relationships. Our second contribution is quantitative, as we develop an equilibrium search-theoretic model that we calibrate to fit key moments and our quasi-experimental evidence. The combination of theory and data allows us to assess the potential mechanisms behind our causal evidence and quantify the implications of the internet for aggregate unemployment.

Our empirical contribution builds on a unique combination of large-scale survey and administrative data, covering detailed information on vacancy behavior, job search, employment relationships, and a national broadband policy in Norway. The policy's main goal was to ensure broadband access to all households and establishments at a reasonable price. However, because of limited funding, the access points were progressively rolled out in different municipalities at different times, generating exogenous variation in internet availability. We combine these unique features of the Norwegian setting to overcome the measurement challenges and selection in internet use and search methods.[2]

Our quasi-experimental evidence can be summarized with four broad conclusions. First, the internet expansion increased online vacancy postings and the share of households that browse ads online. Second, the internet significantly improved the recruitment process. We find that the average vacancy duration fell by nine percent and the prevalence of unsuccessful hiring attempts reduced by more than ten percent. Third, the unemployed job seekers' labor market prospects improved. The average re-employment rates went up by 2.4 percent, and job seekers' labor market earnings increased by six percent. The internet expansion also increased the likelihood of new employment spells lasting longer than a year and caused a 12 percent decline in the subsequent likelihood of repeated unemployment spells. Fourth, the internet expansion did not affect the labor market outcomes of the employed. We find no discernible effect on the job-to-job transition rate, nor do we detect a statistically significant impact on wages among workers who move between employers. We take several steps to verify the internal validity of our findings, all of which support our main

[1] Existing studies have explored associations between the use of internet as a method of job search and job seekers' re-employment outcomes (e.g., Kuhn & Skuterud, 2004, Kuhn & Mansour, 2014, Denzer *et al.*, 2018, Gürtzgen *et al.*, 2018) or wages (e.g., Kuhn & Mansour, 2014). A notable exception is Kroft & Pope (2014), who expand on the worker-level analysis by assessing the equilibrium effects of the advertisement website "Craigslist's" geographically dispersed expansion across local labor markets. However, there is no evidence of how the internet affected firms' behavior, including recruitment, the duration of new employment relationships, vacancy filling rates, nor the search behavior of people with a job and the quality of new job matches.

[2] The national broadband policy has been previously used by Bhuller *et al.* (2013), who study the effects of the internet on sex crime rates, and by Akerman *et al.* (2015), who study the skill-complementarity of the internet. See Report no. 38 to the Storting (1997-1998) and Report no. 49 to the Storting (2002-2003) for further program details.

conclusions.

Turning to our quantitative contribution, we develop and calibrate an equilibrium search-theoretic model in the spirit of Mortensen & Pissarides (1994). There are three main ingredients of our framework. First, people choose how hard to search for a new job while employed and unemployed. Second, employment relationships are endogenously created and destroyed when no longer profitable for the firm or when a worker is contacted by an employer of higher "match quality" – which is associated with higher wages and lower exogenous layoff risk. Third, as Martellini & Menzio (2020), we assume that match quality can be verified before starting an employment relationship and that match-specific productivity evolves stochastically over the lifecycle of a job. We calibrate the model using pre-expansion aggregate labor market flows and identify search cost parameters using survey data on the search intensity of employed and unemployed workers.

The calibrated model allows us to examine the mechanisms that are qualitatively and quantitatively consistent with our empirical evidence. We think of the internet expansion as a once-and-for-all change in the model parameters governing (i) "matching efficiency," i.e., the scale parameter in the constant-returns-to-scale matching technology, (ii) the cost of posting and maintaining a job vacancy, and (iii) the utility costs of the search effort of employed and unemployed. We hypothesize that the internet expansion might simultaneously change these model parameters. Theoretically, changes in these model parameters move key labor market statistics, such as the job vacancy filling rate and the job-finding rate, in opposite directions; hence, assessing the relative contribution of each of these forces makes for an interesting quantitative exercise. Our quantitative results, disciplined by the quasi-experimental evidence, strongly support the hypothesis that the search and matching technology has improved, while search costs for firms and workers have played a minor role. Our calculations indicate that the steady-state unemployment rate fell by as much as 14% due to the broadband internet expansion. Moreover, we show that the implied changes in the internet-related parameters can account for a substantial fraction of the observed inward shift of the Beveridge curve in Norway.

Our study advances existing research on internet use and unemployment in three important ways. In the first empirical study of online job search, Kuhn & Skuterud (2004) found that people who search for jobs online are unemployed longer than job seekers who use more traditional search strategies. We extend their study by using exogenous variation in internet availability and by examining outcomes that allow us to distinguish between the many mechanisms at play.[3] Secondly, we show that the internet improves wages, job duration and lowers the risk of unemployment. In a related paper, Kroft & Pope (2014) used variation in the use of Craigslist – a website that allows users to post job ads – across metropolitan areas in the US to examine equilibrium effects of online job search. The authors found no change in aggregate unemployment, but a significant decrease in housing vacancies, suggesting the online marketplace reduced search frictions. We contribute to their study by showing that broadband internet substantially reduced vacancy durations, and by quantifying the implications of our quasi-experimental findings for aggregate unemployment and the location of the Beveridge curve.[4]

[3] Our evidence is consistent with the more recent studies documenting a positive relationship between internet use and employment outcomes. Kuhn & Mansour (2014) use a more recent sample of job seekers and find that internet usage is associated with a 25 percent reduction in unemployment duration. Using similar empirical approaches, Stevenson (2009) finds that workers who look for jobs online have more job-to-job transitions than workers that use other strategies, and Atasoy (2013) finds a strong association between internet access and employment in the US. Denzer *et al.* (2018) and Gürtzgen *et al.* (2018) use variation in broadband internet availability across German municipalities to study how the internet as a means of job search affects job finding probabilities.

[4] Our study also relates to studies of vacancy posting and hiring decisions at the establishment-level. Davis *et al.* (2013) examine time-varying and cross-sectional variation in vacancy filling rates and argue that higher employment growth is explained by more intense recruiting. Kettemann *et al.* (2018) is the only other study that combines administrative data on vacancies, establishments, and

Our paper contributes to a growing line of research on the role of labor market frictions. Consistent with our findings, Belot *et al.* (2019) show that information provision about jobs broadens the scope of job openings young job seekers apply to and end up interviewing for.[5] Martellini & Menzio (2020) offer a historical perspective of the inverse relationship between vacancies and unemployment rates in the US in light of large improvements in search efficiency due to the diffusion of telephones, computers and the internet. They argue that a model where better matching makes job seekers more selective about the offers they are willing to accept can rationalize the evidence. Our evidence on rising tenure in new employment relationships and relatively small effects on re-employment supports their model. Similarly, the vacancy behavior we document is consistent with Hagedorn *et al.* (2013), who document theoretically and empirically how job creation decisions respond to unemployment benefit extensions and longer unemployment durations. Moreover, our paper speaks to the debate about the declining job-to-job mobility in the US (e.g., Molloy *et al.*, 2016). Consistent with empirical work documenting the role of worker screening mechanisms (e.g., Autor & Scarborough, 2008, Dustmann *et al.*, 2016, and Hoffman *et al.*, 2017), our evidence indicate that lower search frictions and better job matching may have contributed to this trend. This interpretation is also in line with recent theoretical work by Pries & Rogerson (2019), who show that improvements in employer screening (e.g., online employment tests) can explain the observed fall in job-to-job mobility in the US.

The paper proceeds as follows. Section 2 presents a theoretical framework. Section 3 describes the data sources and the policy variation underlying our empirical design, and Section 4 presents our main quasi-experimental findings. Section 5 describes the quantification strategy and the implications of our findings for aggregate unemployment. Section 6 concludes.

2 Model

To motivate and guide our empirical analysis, this section develops an equilibrium search-and-matching model in the spirit of Mortensen & Pissarides (1994). The central features of the model are off- and on-the-job search with variable search intensity and idiosyncratic match quality. A better match is associated with higher wages and lower exogenous layoff risk, which we assume can be verified before starting an employment relationship.

2.1 Setup

Environment. Time is discrete. The economy consists of workers and employers who are infinitely-lived, risk-neutral, and discount future values at the same rate β. The mass of workers is normalized to one, which also corresponds to the size of the labor force. Workers and employers are ex-ante identical. However, the quality of an employment relationship can differ ex-post due to match-specific productivity, denoted z. These match values are drawn from the cumulative distribution function $F(z)$. We let $\overline{F}(z) = 1 - F(z)$ denote the survival function. As in Martellini & Menzio (2020), we assume that match quality is an "inspec-

workers, and finds that high-paying firms fill their vacancies faster. Related research finds similar evidence using survey data or data from online platforms (e.g., Banfi & Villena-Roldan, 2019 and Marinescu & Wolthoff, 2020).

[5] Our evidence is consistent with the findings in Hjort & Poulsen (2019), who document large employment effects from expansions in the internet across the African continent. Relatedly, our study is also related to the literature on productivity-effects of digital technology adoption at the firm level (for a review, see Goldfarb & Tucker, 2019). Notably, Akerman *et al.* (2015) use the same expansion in broadband coverage, and estimate using 2SLS that broadband internet adoption widened the pay-gap of skilled relative to unskilled workers in Norway. Our paper also relates to studies of vacancy posting behavior using survey data (e.g., Holzer *et al.*, 1991, van Ours & Ridder, 1991, van Ours & Ridder, 1992, Burdett & Cunningham, 1998, Davis *et al.*, 2014, Faberman & Menzio, 2018), and micro-data from online job boards (e.g., Barron *et al.*, 1997, Modestino *et al.*, 2016, Hershbein & Kahn, 2018).

tion good," meaning that when a worker and an employer meet, they observe the value of the idiosyncratic match productivity and, given this information, decide whether to start an employment relationship. When unemployed, a worker enjoys flow utility b, which consists of home production, leisure, and unemployment insurance benefits. Employers post job vacancies at unit cost k and the mass of employers is determined by free-entry.

Searching for a job is costly. Specifically, an unemployed individual searching for a job with effort x_u incurs the utility cost $\nu_u(x_u) = (\phi_u/\varphi)x_u^{\varphi}$, with $\phi_u \geq 0$ and $\varphi > 1$. Similarly, an employed individual searching for a job with effort x_e incurs the utility cost $\nu_e(x_e) = (\phi_e/\varphi)x_e^{\varphi}$, with $\phi_e \geq 0$ and $\phi_e \lesseqgtr \phi_u$. As in Christensen *et al.* (2005), Hornstein *et al.* (2011), Lise (2013), and Faberman *et al.* (2022), the elasticity parameter φ does not vary by labor force status, whereas the shifter parameters ϕ_u and ϕ_e are allowed to vary in a way that we explain further below.

Search and matching frictions prevent instantaneous matching of available job seekers and vacancies. This gives rise to equilibrium unemployment. We assume that a constant-returns-to-scale meeting technology determines how often job seekers and employers meet. This process involves the total number of posted vacancies, v, and a measure of aggregate search effort, defined as the effort-weighted mass of job seekers, $s \equiv x_u u + \int x_e(z)e(z)dz$. We make explicit that the search effort of the employed and the mass of employed individuals vary by match quality, z, and specify a standard matching function, $M = Av^{\alpha}s^{1-\alpha}$, with matching elasticity $\alpha \in (0,1)$ and "matching efficiency" A. Due to constant returns, the labor market condition is summarized by the tightness ratio, $\theta \equiv v/s$. The probability that an unemployed individual meets a job vacancy is $p_u \equiv p(\theta)x_u$, where $p(\theta) = A\theta^{\alpha}$. Similarly, the probability that an employed individual meets a vacancy is $p_e \equiv p(\theta)x_e$, and the probability that a vacancy meets a job seeker is $q(\theta) = p(\theta)/\theta = A\theta^{\alpha-1}$.

The model incorporates three types of job separations. First, an employment relationship (or match) with productivity z is destroyed at a constant exogenous rate δ_z, which is decreasing in z. These separations are exogenous from both workers' and employers' perspective. Second, if the match is not exogenously destroyed, $1-\delta_z$, the match can be hit by an idiosyncratic productivity shock with probability ξ. The worker and employer then decides whether to continue the match with the new level of match quality z', or to enter unemployment if the new match quality is below the threshold $z' \leq z_R^u$. Otherwise, the match continues. Third, if a match survives the exogenous job destruction and idiosyncratic productivity shocks, an event occurring at rate $(1-\delta_z)(1-\xi)$, the worker gets contacted by an outside employer with probability $p_e(\theta, x_e)$. The workers decide to join the new employer when z'' exceeds the threshold $z_R^e(z)$ but continues in her current job when z'' is below.

Worker's Problem. Let $W(z)$ be the value of working in a job with match quality z. An employed individual solves the following dynamic problem:

$$W(z) = \max_{x_e \geq 0} \Bigg[w(z) - \nu_e(x_e) + \beta\delta_z U + \beta(1-\delta_z)\xi \int \max\left\{W(z'), U\right\} dF(z')$$

$$+\beta(1-\delta_z)(1-\xi)p_e(\theta, x_e) \int \max\left\{W(z'), W(z)\right\} dF(z') + \beta(1-\delta_z)(1-\xi)(1-p_e(\theta, x_e))W(z) \Bigg], \quad (1)$$

where $w(z)$ is the wage and $p_e(\theta, x_e) \equiv p(\theta)x_e$ is the probability that an employed individual meets a vacancy. The value of unemployment is denoted U and an unemployed individual solves the following dynamic problem:

$$U = \max_{x_u \geq 0} \left[b - \nu_u(x_u) + \beta p_u(\theta, x_u) \int \max\left\{ W(z'), U \right\} dF(z') + \beta(1 - p_u(\theta, x_u))U \right], \tag{2}$$

where $p_u(\theta, x_u) \equiv p(\theta)x_u$ is the probability that an unemployed individual meets a vacancy. Note that in (1)-(2), $p_e(\theta, x_e)$ and $p_u(\theta, x_u)$ depend on the market tightness ratio, θ, an equilibrium object taken as given by the individuals, and on the search effort levels, x_e and x_u, which are determined according to the following first-order conditions (FOCs), in which the marginal disutility of search effort equals the marginal gain from search:

$$\nu_e'(x_e) = \beta(1 - \delta_z)(1 - \xi)p(\theta) \int \max\left\{ W(z') - W(z), 0 \right\} dF(z'); \tag{3}$$

$$\nu_u'(x_u) = \beta p(\theta) \int \max\left\{ W(z') - U, 0 \right\} dF(z'). \tag{4}$$

Note that the FOC (3) implies that search effort, x_e, is decreasing in match quality, z. Since the net gain from joining a new employer, $W(z') - W(z)$, is decreasing in z, the higher an employed individual is in the quality ladder, the less intensively he or she searches. In contrast, the FOC (4) pins down one value of x_u, since the net gain from starting a new job from unemployment, $W(z') - U$, is the same across unemployed individuals.

Employer's Problem. The value of a filled job with match quality z is

$$\begin{aligned} J(z) = z - w(z) + \beta\delta_z V + \beta(1 - \delta_z)\xi \int \max\left\{ J(z'), V \right\} dF(z') \\ + \beta(1 - \delta_z)(1 - \xi) \left[p_e(\theta, x_e)F(z_R^e) + (1 - p_e(\theta, x_e)) \right] J(z) + \beta(1 - \delta_z)(1 - \xi)p_e(\theta, x_e)\overline{F}(z_R^e)V, \end{aligned} \tag{5}$$

where the last term on the right-hand side of (5) reflects the likelihood that a worker is contacted by a new employer and quits.

The value of a posted vacancy is

$$V = -k + \beta q(\theta) \int \max\left\{ J(z'), V \right\} dF(z') + \beta \left(1 - q(\theta) \right) V. \tag{6}$$

Free-Entry Equilibrium. As customary in the literature, we consider an equilibrium with free entry. At each point in time, $V = 0$, such that the value of a filled job (5) reduces to

$$\begin{aligned} J(z) = z - w(z) + \beta(1 - \delta_z) \Big[\xi \int \max\left\{ J(z'), 0 \right\} dF(z') + (1 - \xi)p_e(\theta, x_e)F(z_R^e)J(z) \\ + (1 - \xi)(1 - p_e(\theta, x_e))J(z) \Big]. \end{aligned} \tag{7}$$

Also, given $V = 0$, the value of a posted vacancy (6) gives the free-entry condition

$$k \geq \beta q(\theta) \int \max \{J(z'), 0\}\, dF(z'), \tag{8}$$

which holds with equality at the interior solution for $\theta > 0$.

We assume that wages are determined by Nash-bargaining. This assumption gives the optimal sharing rule $J(z) = (1-\eta)\,(W(z) - U)$, where $0 \leq \eta \leq 1$ is the worker's bargaining weight. The sharing rule pins down the wage and how the total surplus generated by the match is split between workers and employers.[6]

The value functions of the worker (1)-(2), the FOCs for optimal search effort (3)-(4), the value of a job (7), and the free-entry condition (8) can be conveniently rewritten in terms of total match surplus, $S(z) \equiv W(z) + J(z) - U$, which greatly simplifies the computation of the equilibrium. Moreover, the equilibrium of the model is block-recursive, meaning that we can solve for the productivity thresholds z_R^u and $z_R^e(z)$, search effort levels, x_u and $x_e(z)$, and the tightness ratio, θ, independently of the stocks of unemployment and of the distribution of employed workers over match quality. Once these equilibrium objects are determined, the unemployment rate and the cross-sectional distribution of employment over match quality are computed using steady-state equations that balance inflows and outflows of unemployment and inflows and outflows for each quality level, respectively. The model thus retains the computational tractability of the standard search-and-matching model of unemployment (see, e.g., Pissarides, 2000, Ch. 4).

2.2 Expected Impacts

This section shows that the expected impacts of the broadband expansion on labor market flows depend on the mechanisms through which the internet operates. We consider the theoretical effects of changing one parameter at the time, and provide further numerical comparative statics based on the baseline parameterization of the model in Section 5.

We begin by showing that a permanent and unexpected increase in matching efficiency, as captured by a higher value of A, unambiguously increases job-finding rates, vacancy-filling rates, and employment-to-employment transitions. However, once we let the internet affect the cost of posting job vacancies, k, and the utility costs of search effort for the unemployed and employed, ϕ_u and ϕ_e, we can no longer sign the expected impacts on any of these outcomes.

Transition Probabilities. In the model, the unemployment-to-employment (UE) rate, job-to-job (EE) rate, employment-to-unemployment (EU) rate, and the vacancy filling rate are calculated as follows:

$$\text{EU rate} = \delta_z + (1-\delta_z)\xi F(z_R^u); \tag{9}$$

$$\text{UE rate} = p(\theta) x_u \overline{F}(z_R^u); \tag{10}$$

$$\text{EE rate} = (1-\delta_z)(1-\xi) p(\theta) x_e(z) \overline{F}(z_R^e(z)); \tag{11}$$

$$\text{Vacancy filling rate} = q(\theta)\overline{F}(z_R^u). \tag{12}$$

These rates are functions of the reservation productivity thresholds z_R^u and $z_R^e(z)$, the tightness ratio, θ, and the optimal search intensities of the unemployed, x_u, and of the employed, $x_e(z)$. A few remarks are

[6] As is customary in the literature, we assume wages are renegotiated period by period. In addition, we follow Fujita & Ramey (2012) and Pissarides (2000, Ch. 4) in assuming that workers must resign before bargaining with the new employer.

in order. First, the term $F(z_R^u)$ in (9) reflects endogenous job separation. With probability $F(z_R^u)$, the new realization of match quality is below the threshold, which results in endogenous separation and transition into unemployment. Second, the term $\overline{F}(z_R^u)$ in (10) reflects "selection" in job acceptance decisions. With probability $\overline{F}(z_R^u)$, the realization of match quality is sufficiently high, match creation is viable, and unemployed workers who get contacted move to employment. Third, the EE rates implied by (11) vary by match quality, as $x_e(z)$ and $z_R^e(z)$ are decreasing and increasing in z, respectively. Higher match quality means lower search intensity, $x_e(z)$; hence, the probability $\overline{F}(z_R^e(z))$ that a worker quits and for a better paid job falls too.[7]

(i) Matching Efficiency. Starting with an unexpected increase in A, the model implies a direct, across-the-board increase in the probability that workers meet employers. Since the rate of return to search rises, both employers and workers search more intensively, implying higher vacancy rates and search effort. As a result, expected vacancy and job durations fall: vacancies are filled at a higher rate, and the average EE rate rises as the increased search effort by the employed causes the employed to transition to higher quality jobs. The mean EU rate can either rise or fall. On the one hand, the worker realizes that a higher tightness ratio makes it easier to find a new job, which lowers the cost of unemployment. On the other hand, unemployed workers become more selective in their initial job acceptance decisions. This match quality channel implies that they move from unemployment to jobs with lower exogenous job destruction rates and longer expected duration.

(ii) Unit Vacancy Cost. Next, we consider a reduction in k that induces firms to post more vacancies. This raises the tightness ratio and, thus, the rate at which job seekers meet vacancies – thereby initiating an equilibrium response from the unemployed. However, since competition for workers has increased, the vacancy filling rate goes down. Hence, the combination of the two mechanisms (i) and (ii) render the expected impact on the vacancy filling rate ambiguous.

(iii) Search Costs. Finally, we consider the effects of changing the cost of search. A priori, it is challenging to determine whether the utility costs would increase or decrease as a consequence of the internet — which depend on whether online search complements or replaces traditional search, and whether learning a new search technology is costly. Here we show that a *reduction* in the utility cost of searching while unemployed, ϕ_u, moves the expected impacts on EE and UE in opposite direction than an increase in matching efficiency.[8] The initial effect of lowering the search cost is to make unemployed job seekers more selective (i.e., z_R^u rises). Given k, A, and the free-entry condition, hiring firms meet workers at a higher rate, i.e., $q(\theta)$ goes up, implying that the tightness ratio θ falls, so that the probability that a worker meets a vacancy falls, too. These two opposing forces render the overall impact on the search effort ambiguous; therefore, the expected impact on UE rate is also ambiguous. This exercise motivates our empirical analysis in Section 4. We return to a quantitative analysis of the relative contribution of each of these forces in Section 5.

[7] The mean EE transition rate is calculated as $\overline{\text{EE rate}} = (1-\xi)p(\theta)\int(1-\delta_z)x_e(z)\overline{F}(z_R^e(z))dG(z)$, where $G(z)$ is the endogenous distribution of employment over match quality, whose shape naturally depends on model parameters, including those related to internet. Similarly, the mean EU transition rate is calculated as $\overline{\text{EU rate}} = \int \delta_z + (1-\delta_z)\xi F(z_R^u)dG(z)$.

[8] The expected impact of lowering the search cost when employed, ϕ_e, depends on whether we consider the impacts among the *initially* unemployed or employed. While lower search cost for employed unambiguously increases the search effort of the employed, the search effort of the unemployed falls because the unemployed become less selective (i.e., z_R^u falls) – raising the UE rate and lowering the starting wage out of unemployment. Intuitively, this happens because they anticipate that searching will become less costly once they get a job. Hence, they accept a match of lower quality to climb the quality ladder by searching more intensively on the job.

3 Data, Research Design and Setting

This section describes the data sources and the research design we will use in our empirical analysis.

3.1 Data Sources

Our empirical analysis combines several administrative data sources that can be linked by unique and anonymized identifiers for every resident individual, establishment, and firm, in addition to various sources of survey data. We briefly mention some of these and provide more detailed information about the data sources in Appendix A.1.

To measure establishments recruitment and vacancy behavior, we combine several administrative and survey data sources. First, newly collected vacancy data from the National Public Employment Agency (NAV) provides us with detailed data on the posting dates, job titles and duration of vacancies at the establishment level.[9] Second, we combine the vacancy data with survey data on firms' internet use and recruitment efforts using unique establishment identifiers.[10] Third, we augment the public employment agency's vacancy data with advertisement-level data from FINN.no, the only major online job board in Norway, which is similar to indeed.com in that hiring firms can post ads, and candidates can apply directly on the website or via the employers' own portals.[11]

To measure the employed and unemployed workers' search and mobility, we use linked employer-employee data and an administrative register of job seekers from Statistics Norway. We complement the worker-level information with the anonymized individual-level Survey on Media Use, allowing us to examine peoples' information technology use, online search behavior, and whether a person uses the internet for work purposes. We augment the job seeker data with measures of unemployed and employed workers' job search intensities from Statistics Norway's Labor Force Survey.

Finally, we combine the data on both sides of the market with information about the availability of broadband internet access points. We obtained a measure of the fraction of households covered by broadband internet in each municipality, i.e., the broadband availability rate, from the Norwegian Communications Authority (NKOM), a government agency that monitors the coverage of broadband internet across Norway. The agency requires suppliers of broadband access to file annual reports about the locations of their broadband infrastructure and availability rates. Using the coverage area of each access point and detailed information on the location of households, the agency computes the broadband availability rates at the municipal level at the beginning of each year.[12] This availability rate serves as our proxy for the availability of broadband internet across areas and over time in Norway. Throughout this paper, broadband coverage is

[9] The employment agency collects information about vacancies from several sources including online job boards and newspapers, as well as vacancies that are directly reported by employers to the agency in accordance with the Norwegian Labor Market Act §7.

[10] The Survey of Establishments' Recruitment Behavior (SERB) covers around 10 percent of establishments in each cross-section. The SERB provides an indicator for whether an establishment failed in an attempt to recruit during the last three months. Appendix Figure C1 plots the average fraction of establishments reporting having experienced recruitment problems in each year, and shows a highly pro-cyclical pattern where recruitment problems reach a peak at the beginning of the Great Recession. Recruitment problems are also highly correlated with labor market tightness or the vacancy-unemployment ratio. The dashed line illustrates that the more vacancies per job seeker, the more likely establishments are to report being unsuccessful in recruitment.

[11] We use Statistics Norway's Survey of Establishments' Vacancies (SEV) to compare survey-based information on vacancies to the data on vacancies from the employment agency and Finn.no. This website is the only major online board in Norway, was established in March 2000, and held a market share of around 95 percent (Anand & Hood, 2007). Appendix A.2 illustrates that the employment agency's vacancy data track both the survey data and online job board well. However, SEV is only available from 2010 and onward.

[12] The agency takes into account that multiple suppliers may provide coverage to households living in the same area, so that double-counting is avoided. Note that we distinguish between actual take-up (access or use) of broadband internet, which could be an endogenous choice of a household or a firm, and having the possibility of use (coverage or availability), which is determined by the existence of broadband infrastructure in a local area.

defined as having the possibility to connect to the internet with a download speed that exceeds 256 kbit/s. Earlier studies by Bhuller *et al.* (2013) and Akerman *et al.* (2015) use the same data source over a shorter period.

3.2 Research Design

Our research design uses quasi-experimental variation in the availability of broadband internet from the National Broadband Policy of 2003.[13] The policy had two main goals: First, it was meant to ensure that every household and private enterprise had access to broadband at a reasonable and uniform price. Second, it meant to stimulate adoption by the public sector. The Norwegian government invested heavily in infrastructure to reach these goals, largely channeled through the (state-owned) telecom company Telenor – the sole supplier of broadband access to end-users in the early 2000s. Local governments were also required to ensure access to broadband internet by 2005 to local public institutions, such as administrations, schools, and hospitals. To facilitate this requirement, local governments were eligible for funding from the government-provided Høykom program, subject to submitting a project plan to be evaluated by a program board with expert evaluations. Once approved, financial support was provided in the initial years of broadband access to cover relatively high initial costs.

While the expansion was primarily policy-driven, supply and demand factors played a role in the roll-out. On the supply side, the transmission of broadband signals through fiber-optic cables required installation of local access points. Since 2000, such access points were progressively rolled out, generating considerable spatial and temporal variation in broadband coverage. The staged expansion of access points was in part due to limited public funding. Another reason was geographical: Norway is a large and sparsely populated country, with long driving distances between populated areas often partitioned by mountains or fjord-broken shorelines.[14] Important supply factors determining the timing of roll-out and marginal costs of extending the broadband access points were topographical features and existing cable infrastructure (including roads, tunnels, and railway routes). In terms of demand factors, it is reasonable to expect observable characteristics such as income level, educational attainment, and the degree of urbanization in the municipality to affect the timing. Another factor is the size of the public service sector, where take-up and productivity-gains in public service was an explicit policy goal.[15]

We address the role of these factors by assessing how growth rates in broadband coverage vary with baseline municipality characteristics. We begin by verifying that (i) the population size and (ii) the degree of urbanization predict early increases in broadband coverage. However, we show that key labor market characteristics are unrelated to the broadband roll-out timing. This includes local labor market characteristics, such as unemployment rate, average income, and industry composition, and socio-economic factors, such as years of education, the fraction of student enrollment, population age, and immigrant share. We also find that other infrastructure features, including distance to the city center, travel time, and road networks, do not predict the roll-out patterns. These results are presented in Appendix Figure C3.

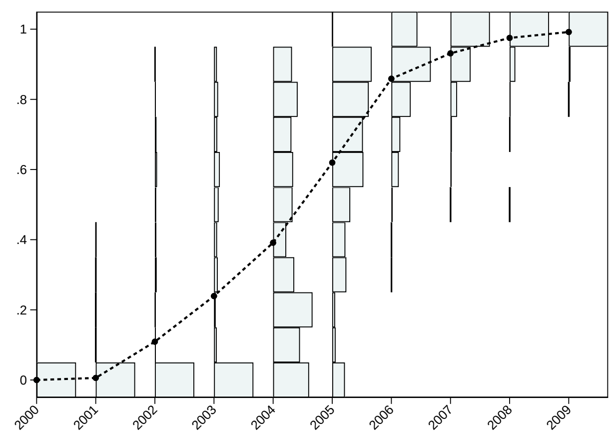
[13] These attempts started with the *Policy for Regional ICT Competence* introduced by the Norwegian parliament in 1998 (Report no. 38 to the Storting, 1997–1998), followed by the introduction of the *Program for High-Speed ICT (Høykom) Innovation in the Public Sector* in 1999 (Statskonsult, 2007; Bygstad & Lanestedt, 2009), and passing of the *National Broadband Policy* by the Norwegian parliament in 2003 (Report no. 49 to the Storting). The policy goals are outlined in Report no. 38 to the Storting (1997–1998), Section 4.5, and Report no. 49 to the Storting (2002–2003), page 7.

[14] The Norwegian territory covers about 149,400 square miles, an area about the size of California or Germany, with around 13 percent and 6 percent of those regions' populations (in 2008), respectively. The country is dominated by mountainous or high terrain, as well as a rugged coastline stretching about 1,650 miles, broken by numerous fjords and thousands of islands.

[15] See, e.g., Report no. 38 to the Storting (1997–1998), Report no. 49 to the Storting (2002–2003) and Bhuller *et al.* (2013).

Next, we illustrate the considerable variation in broadband coverage across municipalities and over time resulting from the progressive roll-out of broadband access points. Figure 1 summarizes the evolution of broadband availability rates between 2000 and 2009. For each year, we report the overall means and the distributions across municipalities. While virtually no municipalities had broadband access points available in 2000, the average availability rate increased to almost 40 percent by early 2004 and exceeded 80 percent by early 2006. The geographic variation in broadband coverage is illustrated by heat maps in Appendix Figure C2, documenting wide variation in availability rates across and within municipalities over time. Few municipalities experienced an abrupt change from zero to full coverage from one year to the next. The access points were progressively rolled out within and across municipalities, generating a continuous measure of broadband availability with considerable temporal and spatial variation. Figure 1 illustrates that by 2009 there was almost complete coverage across the country.

Figure 1: The Evolution of Broadband Internet Availability in Norway.



Notes: This figure shows the mean and distribution of broadband availability across 420 municipalities using data from the Norwegian Communications Authority (NKOM). For each year, the mean broadband availability rate across municipalities is displayed by black circles as a fraction along the vertical axis. Similarly, the distribution of broadband availability rates is displayed as a blue-shaded histogram in 11 equidistant bins.

3.2.1 Estimation Sample

Our main sample contains all establishments with at least one (part-time or full-time) employee over the period 2000 to 2014. Columns 1-2 in Appendix Table C1 report summary statistics for this sample, while columns 3-4 do the same for the sample restricted to the years 2002-2014 when vacancy data is available.[16] In columns 5-6, we focus on establishments in the employment agency's recruitment survey, which covers 102,771 establishments, sharing many similarities to the main sample. The most notable difference is that the survey covers larger establishments. By comparison, the survey of firms' information, communication and technology (ICT) use provides us with 22,422 firms, and columns 7-8 illustrate that firms in the ICT survey employ more workers and are older than the main sample of establishments. While the size of a firm is by construction larger than the size of an establishment, we apply survey weights when using this survey data in our empirical analysis to adjust for the differences in size between firms and their establishments.

Our main sample of workers includes 2.8 million individuals in the ages 25–55. Summary statistics

[16]There are 255,678 establishments and more than 1.8 million establishment-year observations in the main sample. The average establishment is 17.5 years old, and has 9.5 employees. The average employee has completed 12.5 years of education and earns an annual salary of about USD 51,700. The vacancy postings sample includes 240,793 establishments and more than 1.6 million establishment-year observations. The main difference in the two samples is that vacancies were only available from 2002 onward.

for working-age individuals is reported in Appendix Table C2. While the average age of workers is 40 and average years of education is 12.5 years, the average job seeker is three years younger and has lower educational attainment. We also see a few notable differences between the survey sample and the sample of workers, where survey respondents are more likely to be married, have older children and have completed high school than the overall working-age population.

3.2.2 Estimation Strategies

While randomizing the use of broadband internet is not feasible, our empirical analysis uses the broadband policy as a natural experiment that generates plausibly exogenous variation in broadband availability. To illustrate our empirical approach, we begin with the event study design

$$y_{jmt} = \sum_{k=-K}^{K} \gamma_k d_{mt}^k + \kappa_m + \tau_t + \varepsilon_{jmt}, \tag{13}$$

where y_{jmt} is an outcome measured for an establishment j located in municipality m in year t. Our main outcomes of interest for establishments include the average duration of vacancies posted, an indicator for whether a vacancy was posted at all, and for job seekers, the probability of finding a job and the associated starting wage, among others. For each municipality, we observe the broadband internet availability rate BI_{mt} at the start of every year, and consider the calendar year with the *largest* increase in broadband availability rate, i.e., $e_m = (t : \max_t \{BI_{mt} - BI_{mt-1}\})$ across all t. We refer to e_m as the event time, denote the relative time to event by k, and define relative time dummies $d_{mt}^k := \mathbf{1}(t - e_m = k)$ that equal one at each relative time k and are zero otherwise.[17] The coefficients on these relative time dummies are captured by parameters γ_k. Temporal changes that may influence labor market outcomes but are common across areas are absorbed by the year indicators τ_t. Municipality fixed effects κ_m control for permanent differences across municipalities exposed to early and late broadband internet expansions.

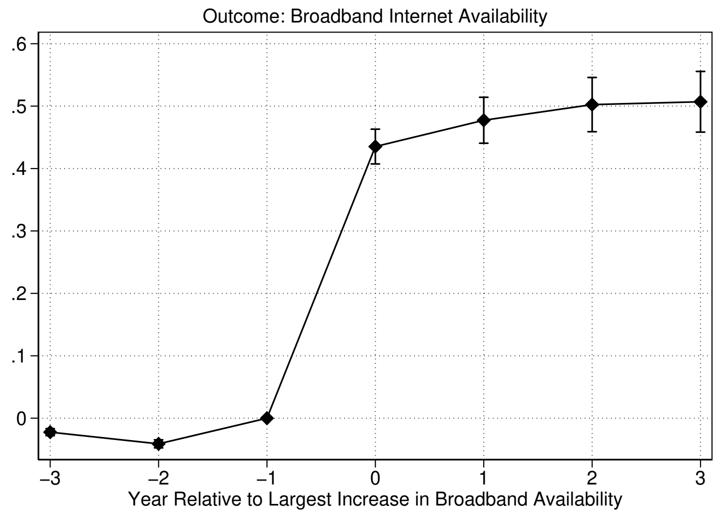
In a standard event study design (see, e.g., Sun & Abraham (2021)), the parameters γ_k from Equation (13) represent average treatment effects at different time periods relative to the event among those experiencing the event. Subject to a normalization (e.g., $\gamma_{-1} = 0$), the identifying assumptions are (i) parallel trends in baseline outcomes, (ii) no anticipatory behavior prior to the event, and (iii) homogeneity of treatment effects across units treated at different periods. Under these assumptions, we can examine the dynamic path of responses to the event and assess whether the outcomes display a significant trend prior to the event.

To visualize the variation in broadband availability, we estimate Equation (13) using the broadband availability rate BI_{mt} as the outcome, and plot the coefficient estimates on the relative time dummies in Figure 2. This plot shows an increase in the broadband availability rate at around 40 percentage points in the year with the largest increase (year 0). This indicates that a large portion of the increase in broadband availability – from zero to full coverage in our study period – actually takes place in years when municipalities receive major expansions. After the year of largest expansion, we observe slight increases in broadband coverage with the overall increase in broadband coverage stabilizing around 50 percentage points three years later as compared to the year prior to event.[18]

[17] As all municipalities experience an increase in broadband availability and reach full coverage at some point in our sample period, it is straightforward to calculate the 'largest increase' event time e_m for all municipalities.

[18] As an alternative, we also consider an 'initial expansion' event around the year of first broadband expansion of 20% or more in each municipality, i.e., $e_m^f = (t : \min_t \{BI_{mt} - BI_{mt-1} \geq 0.2\})$. Figure C7, panel (b), provides event study estimates around this

Figure 2: Event Study – Broadband Internet Availability.



Notes: For each municipality, time zero represents the year with the largest increase in broadband availability rate (i.e., the event year). The figure shows the coefficient estimates (black solid dots), along with the associated 90% confidence intervals, on relative event time dummies for a three-year window around the event year from Equation (13) on broadband availability rate as the outcome, including controls for municipality and calendar time fixed effects. The coefficient on the relative event time dummy for the year prior to the largest increase is normalized to zero (i.e., $\gamma_{-1} = 0$), so that the coefficients on the other relative event time dummies show responses relative to this year. Appendix Figure C7 implements the treatment effect heterogeneity-robust estimator by Sun & Abraham (2021).

We complement the graphical evidence using the event study design with the baseline specification from prior studies (see, e.g., Bhuller *et al.*, 2013 and Akerman *et al.*, 2015),

$$y_{jmt} \quad = \quad \gamma BI_{mt} + \kappa_m + \tau_t + \varepsilon_{jmt}, \tag{14}$$

where γ is the parameter of interest and gives the change in hiring outcomes from increasing the broadband availability rate from zero to one.[19] As in the event study, this specification includes a full set of municipality indicators κ_m and year indicators τ_t. This specification thereby uses *within* municipalities changes in broadband coverage over time, while removing all changes over time in the outcome and increases in broadband coverage that are *common* across municipalities. We assume that conditional on municipality and time fixed effects, the roll-out of broadband infrastructure is independent of potential labor market outcomes.[20] The expected value of the regression coefficient of γ in Equation (14) can thus be written as the expected value of a weighted sum of the average treatment effects for each municipality-year pair (see de Chaisemastin & D'Haultfoeuille (2020), Online Appendix Section 2).

We estimate Equation (14) for both establishments and job seekers. When studying outcomes of the job search process, we replace the outcome with y_{imt} (e.g., an employment indicator) for person i and control for the person's residence municipality κ_m.[21] In all regressions, we control for a set of time-varying municipal characteristics, including average travel time to municipal center (in hours), distance covered by municipal

first broadband expansion event, finding that broadband coverage increases by almost 70% from the year prior to the event to three years after. We provide additional evidence in Appendix C showing that our event study results are robust to these alternative event definitions.

[19]Compared to Equation (13), Equation (14) is a more parsimonious specification, which exploits changes in broadband availability across all years, and imposes linearity in availability.

[20]This means that broadband availability is exogenous and uncorrelated with unobserved factors ε_{jmt}, so there should be parallel trends in labor market outcomes across all municipalities for all periods in the absence of roll-out.

[21]For the establishment-level analysis, we follow Akerman *et al.* (2015) in measuring broadband availability rate at the start of the same year as when the outcome is measured. For the analysis of job seekers, we use the broadband availability rate in the year a job seeker enters unemployment as our variable of interest, and measure re-employment outcomes over the following two years.

road networks (in kilometers) and municipal spending on infrastructure. Since these factors may be correlated with demand and supply factors of broadband expansion (see Bhuller *et al.* (2013)), controlling for these factors reduces the residual variation and improves precision in our regression analyses. Similarly, we further include dummies for 4-digit past occupation categories to remove permanent variation in levels of outcomes between occupations.[22] Throughout the paper, all standard errors are robust to heteroskedasticity and clustered at the level of the commuting zone. By clustering at this higher level of aggregation, we account for spatial correlations across municipalities within the same commuting zone.[23]

3.3 Interpreting the Broadband Policy

To help interpret the policy change, we estimate the effects of the broadband expansions on broadband internet use and search behavior. Table 1 report our findings, documenting that the broadband expansion triggered a large increase in adoption rate among firms (panel A) and workers (panel B). A 10 percentage point increase in broadband availability increases the adoption rate by almost 3 percentage points (row 1).[24] The coefficient estimates are remarkably similar across both groups and are highly robust to adding controls for firm characteristics (panel A) or worker characteristics (panel B). In Appendix Table C3, we show that the survey-based estimates remain similar if we use population-weights from our main samples.

Turning to the use of online job boards, Table 1 reports our evidence from firms (panel A) and workers (panel B). The second row considers the use of Finn.no, the main job board in Norway and covers close to 100 percent of the market (see Figure A1). Our estimate shows that firms with full broadband coverage are 20 percentage points more likely to use the job board for posting job vacancies compared to firms with zero coverage. Relative to the baseline mean, the estimate corresponds to a 70 percentage increase.[25] Considering households' use of the internet to browse online advertisements from the media use survey in Panel B2, we find that broadband coverage led to a four-fold increase. In sum, these findings strongly suggest that broadband internet significantly affected search and recruitment behavior.

It is worth noting that the coefficient estimates in Table 1 could be interpreted as the first-stage coefficients in a 2SLS model where the outcome in Equation (14) is replaced by either use of broadband or use of online job boards and is instrumented using our measure of broadband availability rate. The second-stage would estimate the effect of predicted treatment from this first-stage on an outcome of interest. The results in Table 1 indicate a highly significant first-stage coefficient. However, as we doubt the IV exclusion restriction is likely to be satisfied in our context, we present the reduced-form relationships throughout our paper. Our estimates should, therefore, be interpreted as intention-to-treat effects of broadband internet availability on job matching.

[22] The inclusion of these controls is solely to improve precision of our baseline estimates and the validity of our design is not contingent upon this. Establishment-level results without time-varying controls and worker-level results without both time-varying controls and occupation fixed effects are quite similar to our baseline estimates, and are available upon request. Notably, our graphical evidence based on the event study specification does not include these control variables.

[23] For this purpose, we use 46 commuting zones in Norway defined by commuting statistics in Bhuller (2009). On average, a commuting zone comprises around nine municipalities and may cross administrative boundaries.

[24] These estimates show that both firms and households are more likely to use broadband internet (i.e., have a device with broadband installed) as a consequence of an increase in broadband availability in their municipality. By contrast, we do not find that any impact on the probability of using internet via an ISDN connection. This result is available upon request.

[25] The outcome in panel A, row 2, is at the municipality level and combines data from the ICT survey and FINN.no.

Table 1: Firms' and Workers' Internet Access and Online Activities.

	A. Firms in the ICT Use Survey		B. Working-age Individuals in the Media Use Survey	
	(1) Baseline	(2) Controls	(3) Baseline	(4) Controls
Dependent Variable:	1. Has Broadband Internet Access		1. Has Broadband Internet Access	
Broadband Availability	0.276***	0.278***	0.282***	0.282***
(Standard Error)	(0.029)	(0.028)	(0.027)	(0.026)
[p-value]	[0.000]	[0.000]	[0.000]	[0.000]
Base Dep. Mean	0.380	0.380	0.059	0.059
Obs. ($B \times T \,/\, N \times T$)	50,265	50,265	10,959	10,959
Dependent Variable:	2. Online Job Board Use Rate		2. Uses Internet for Browsing Ads	
Broadband Availability	0.198***	0.197***	0.091**	0.088**
(Standard Error)	(0.041)	(0.041)	(0.044)	(0.044)
[p-value]	[0.000]	[0.000]	[0.043]	[0.049]
Base Dep. Mean	0.284	0.284	0.022	0.022
Obs. ($B \times T \,/\, N \times T$)	50,265	50,265	8,612	8,612

Notes: This table displays estimation results of firms from the ICT Use Survey for various outcomes in year t on broadband internet availability rate in year t, with $t \in [2001,2014]$ (panel A) and working-age individuals from the Media Use Survey for various outcomes in year $t+1$ on broadband internet availability rate in year t, with $t \in [1999,2012]$ (panel B). Results in panel A are constructed using survey weights, while the results in panel B are based on a representative survey. Control variables for firms (panel A, column 2) include establishment age, size and establishment composition. Control variables for individuals (panel B, column 4) include age, gender, family background and education. The reported dependent mean is pre-assignment, i.e. when the broadband internet availability rate equals zero. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on commuting zone (CZ) levels. $^{**}p < 0.05$, $^{***}p < 0.01$.

3.4 The Norwegian Labor Market

Before turning to our main empirical analysis, we describe the Norwegian labor market and how it compares to the US. The labor market is characterized by a combination of institutional regulation and flexibility. Appendix Figure C4a shows that turnover rates in the private sector are comparable to those in many other countries. For example, the rates are about 20 percent lower than corresponding numbers in the US private sector (see Davis *et al.*, 2006). Wages and working hours are typically negotiated and set in accordance with collective bargaining agreements, while European labor laws regulate firms' hiring and firing practices, which includes mandatory dismissal time and stronger employment protection for older and tenured workers. People who lose their job are eligible for unemployment insurance (UI) benefits after a three-day waiting period, where UI benefits replace around 62 percent of workers' past earnings for a maximum of 104 weeks of benefits (see, e.g., Røed & Zhang, 2003). Appendix Figure C4b shows the unemployment and vacancy rate in Norway from 2002 to 2016, illustrating that Norway experienced a relatively mild increase in unemployment during the Great Recession, where unemployment peaked at 4.4 percent by the end of 2009, which is lower than the US and other European countries.

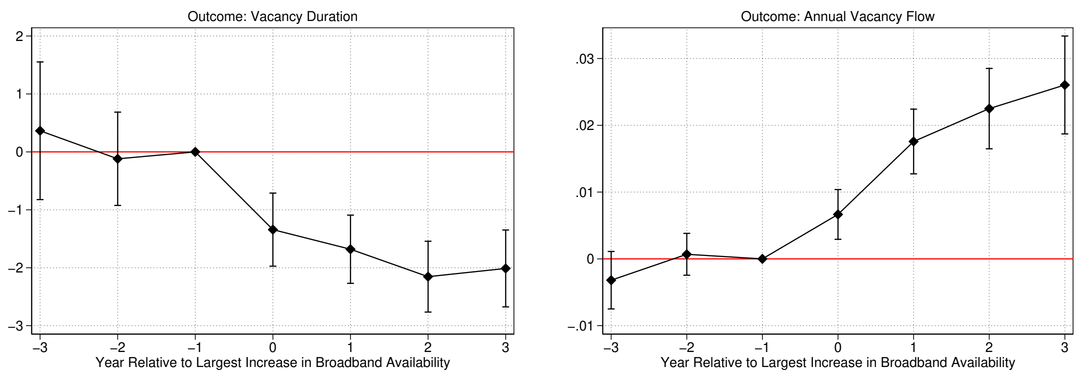
4 Quasi-Experimental Evidence

In this section, we present quasi-experimental evidence on how the internet expansion affected firms' recruitment process and unemployed and employed workers' job search process.

4.1 Recruitment Process

We begin with a graphical illustration of the event study estimates based on Equation (13) on the outcomes of the recruitment process. Panel (a) of Figure 3 shows the change in vacancy duration around the year of the largest increase in broadband availability (i.e., the event year). Vacancy duration is measured from the posting date to the date when the vacancy is either filled or removed. The average duration is 15.2 days.[26] The plot shows that the duration of vacancies falls by around one day. Note that this abrupt, immediate and persistent change is consistent with the theoretical predictions of improving the search technology and lowering the search costs for workers. In contrast, shorter vacancy duration is not consistent with the implications of a reduction in hiring costs, which would move vacancy filling rates in the opposite direction. Next, we present the evolution of vacancy posting in Figure 3 (b). The figure shows that the likelihood of posting increases immediately after the expansion, and the effect grows in size over time.

Figure 3: Event Study – Vacancy Duration and Vacancy Flow.



(a) Vacancy Duration

(b) Vacancy Flow

Notes: For each municipality, time zero represents the year with the largest increase in broadband availability rate (i.e., the event year). The figure plots the coefficient estimates (black solid dots) of relative time dummies $\hat{\gamma}_k$ in Equation (13), along with the associated 90% confidence intervals (vertical bars), on establishments' (a) vacancy duration, i.e., mean duration in days of posted vacancies, and (b) vacancy posting flow, i.e., an indicator for posting at least one vacancy, for a three-year window around the event year. The coefficient on the relative event time dummy for the year prior to the largest increase is normalized to zero ($\gamma_{-1} = 0$), so that the coefficients on the other relative event time dummies show responses relative to this year. In each plot, we control for municipality and calendar time fixed effects. Appendix Figure C8 implements the treatment effect heterogeneity-robust estimator by Sun & Abraham (2021).

Next, we turn to our baseline specification and report estimates of γ from Equation (14). The first column of Table 2 reports the estimate of broadband coverage on the duration of vacancies among establishments with at least one vacancy in a calendar year. Our estimate shows that vacancy duration falls by 1.4 days when expanding broadband coverage from zero to full, implying that a ten percentage point increase in coverage reduces the time it takes to fill a vacancy by 1 percent. Appendix Figure B2 shows that higher broadband internet coverage affects the overall distribution of vacancy duration and is not driven by outliers. Turning to job posting, column 2 in Table 2 reports a 3.2 percentage points increase when broadband coverage goes from zero to full. Compared to the dependent mean of 22.2 percent, a ten percentage point increase in coverage implies a 1.4 percent increase in the share of establishments posting at least one vacancy.

[26] By comparison, Burdett & Cunningham (1998) report a mean vacancy duration of 20 days using the 1982 Employment Opportunity Pilot Project.

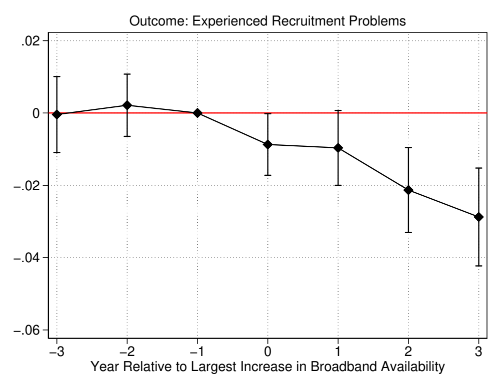
Table 2: Establishments' Vacancy Duration, Vacancy Flow and Recruitment Problems.

Dependent Variable:	Vacancy Duration	Vacancy Flow	Recruitment Problems
	(1)	(2)	(3)
Broadband Availability	-1.376***	0.032***	-0.027***
(Standard Error)	(0.469)	(0.008)	(0.009)
[p-value]	[0.005]	[0.000]	[0.003]
Dep. Mean	15.2	0.222	0.205
Obs. ($B \times T$)	358,266	1,611,573	222,481

Notes: Column 1 displays estimation results of mean duration in days of vacancies posted during year t on broadband internet availability rate in year t using data from the vacancy database. Column 2 displays estimation results of posting at least one vacancy (vacancy flow) during year t on broadband internet availability rate in year t using data from the vacancy database. Column 3 displays estimation results of establishments from the Annual Survey of Establishments' Recruitment Behavior reporting recruitment problems in year t ("Have you encountered problems in recruiting staff during the last three months?") on broadband internet availability rate in year t, with $t \in [2000,2014]$. The Recruitment Survey is conducted in the first quarter of year t, usually opening in February and closing in late March. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels. ***$p < 0.01$.

Next, we further gauge the matching channel by assessing the prevalence of failed recruitment attempts using the Survey of Establishments' Recruitment Activities. To this end, we matched each establishment's survey responses when asked, "Have you encountered problems in recruiting staff during the last three months?" to our main sample using establishment identifiers and the timing of survey responses.[27] On average, around 20 percent of establishments experienced recruitment problems. The graphical evidence using the event study design is presented in Figure 4, and column 3 in Table 2 reports the regression evidence. Our point estimate of -2.7 percentage points is highly significant and economically meaningful. A ten percentage point increase in broadband availability reduces the fraction of firms with recruitment problems by 2 percent. This finding strengthens the conclusion that broadband internet has improved the search and matching process.

Figure 4: Event Study – Experienced Recruitment Problems.



Notes: For each municipality, time zero represents the year with the largest increase in broadband availability rate (i.e., the event year). The figure plots the coefficient estimates (black solid dots) of relative time dummies $\hat{\gamma}_k$ in Equation (13), along with the associated 90% confidence intervals (vertical bars), on establishments' experienced recruitment problems for a three-year window around the event year. The coefficient on the relative event time dummy for the year prior to the largest increase is normalized to zero ($\gamma_{-1} = 0$), so that the coefficients on the other relative event time dummies show responses relative to this year. In each plot, we control for municipality and calendar time fixed effects.

4.2 Job Search Process

We now turn our attention to unemployed and employed workers' job search process.

[27] The broadband internet availability rate, our variable of interest, is measured three months before the recruitment survey date.

4.2.1 Unemployed Job Seekers

This section focuses on unemployed workers actively searching for a job. Our estimation sample is restricted to individuals registered as job seekers at the employment agency for at least one month in the year broadband availability is measured. We estimate equation (14) with the main outcome of interest being whether the job seeker becomes re-employed for at least one month after the unemployment spell. Column 1 in Table 3 reports the regression evidence, and the graphical evidence using the event study is presented in Appendix Figure C8, panel (d). We find that the internet expansion increased the probability of employment by 1.6 percentage points, corresponding to a 2.4 percent increase compared to a mean re-employment rate of 65.9 percent.[28] Decomposing the re-employment increase across new and previous employers in Appendix Table C4, columns 5-6, we find that the whole effect is concentrated among new employers (i.e., not recall hiring).[29] The latter finding is consistent with an increased flow of information about employment opportunities.

Next, we rely on survey-based measures to investigate how the internet expansion affected unemployed individuals' intensity of job search. Column 2 in Table 3 reports a positive coefficient of 1.635 week, amounting to a 10.7 percent increase in time spent on job search. However, the effect estimate is not statistically significant.

Table 3: Unemployed Job Seekers' Outcomes.

Dependent Variable:	Re-employment	Time Spent on Job Search (Weeks)	Wage in First Job (USD)	Subsequent Unemployment	Tenure in First Job (Months)
	(1)	(2)	(3)	(4)	(5)
Broadband Availability	0.016***	1.635	124***	-0.008**	0.397***
(Standard Error)	(0.006)	(1.543)	(34)	(0.004)	(0.088)
[p-value]	[0.006]	[0.295]	[0.001]	[0.047]	[0.000]
Dep. Mean	0.659	15.291	2,061	0.184	7.3
Obs. ($N \times T$)	1,339,779	21,171	1,339,779	1,339,779	1,191,827

Notes: The sample consists of individuals registered as unemployed job seekers with the public employment agency (NAV) for at least one month in year t. This table displays estimation results of availability of broadband internet in year t on the cumulative probability of re-employment over the next two years (Column 1), weeks spent on job search (Column 2), starting monthly wage in new job following unemployment measured in 2014-USD (Column 3), the subsequent probability of unemployment in year t or t+1 after being employed (Column 4), and tenure length in the first job measured in months (Column 5), respectively, on broadband internet availability rate in year t, with $t \in [2000,2012]$. In Column 1, employment is defined as at least one month of employment in year $t+1$ or $t+2$. In Column 2, the outcome is unconditional on search and is set to zero for those who report not searching for a job in the Labor Force Survey. The outcomes in Columns 3-5 are not conditional on finding a job in either year $t+1$ or t+2, and tenure and entry wage level are set to zero for non-job outcomes. In Column 3, monthly wage is deflated to 2014-NOK using the CPI and then converted to USD (1 USD = 8 NOK). In Column 5, we drop observations with tenure equal or greater than 48 months due to censoring. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time, municipality and 4-digit code for past occupation. Heteroskedastic robust standard errors are clustered on CZ levels. $^{**}p < 0.05$, $^{***}p < 0.01$.

We proceed by examining the effects of broadband coverage on starting wages in the first job after an unemployment spell. As wages are only observed among those who find a new job, an outcome that we know is positively affected itself, we report estimates on unconditional outcomes where we include observations where the value of outcomes is set to zero for non-employed individuals. Column 3 in Table 3 presents our regression-based evidence, and the graphical evidence using the event study is presented in Appendix Figure C8, panel (e). We find that compared to a counterfactual scenario of no broadband coverage, the internet policy raised labor earnings by six percent.

[28] Columns 1-4 in Appendix Table C4 show the re-employment effects measured across months 6-24 since the start of an unemployed spell, suggesting the strongest re-employment effects among job seekers with relatively long spells.

[29] Recalls account for 30 percent of hires ($0.188/0.659 \approx 0.3$) in our sample of unemployed workers. By comparison, Fujita & Moscarini (2017) find that 40 percent of all unemployed workers in the US return to their last employer.

To examine the impacts of broadband internet on subsequent employment outcomes, we follow earlier literature that proxies match quality with subsequent unemployment risk and job tenure (e.g., Card *et al.*, 2007, Schmieder *et al.*, 2016 and Nekoei & Weber, 2017). We measure subsequent unemployment risk using an indicator for whether a person re-enters unemployment after having an employment spell, and we measure job tenure as the number of months a person stays in the first job out of unemployment. Column 4 in Table 3 shows that the broadband expansion reduces the subsequent unemployment risk by 0.8 percentage points – equal to a four percent reduction relative to the 18.4 percentage point dependent mean. Moreover, Column 5 in Table 3 shows that the broadband expansion improves the stability of new jobs after unemployment, as job tenure increases by more than five percent.[30]

While the evidence above shows that the unemployed benefited in terms of their re-employment rates and the quality of new employment relationships, we find no evidence that the internet affected the job search process for individuals outside the labor force. In Appendix Table C5, we show that neither the time spent on job search (column 1) nor the transitions to employment (column 2) or job seeker (column 3) status change for these individuals.

4.2.2 Employed Workers

We now consider the population of employed individuals. Our estimation sample is restricted to individuals registered as being either full-time or part-time employed in the year when broadband availability is measured. Column 1 in Table 4 shows that the internet does not affect the likelihood of job-to-job transitions among incumbent workers. Consistently, we find no changes in the time spent on job search among the employed (column 2), nor any changes in their wages (column 3), future unemployment risk (column 4), or job tenure (column 5). In sum, our evidence points to the conclusion that the internet expansion did not affect the job search process for the employed. A possible explanation for the lack of improvements in the job search process of the employed is that they rely more heavily on social networks in their job search (see, e.g., Montgomery, 1991 and Eliason *et al.*, 2019). By contrast, the unemployed may face larger informational barriers and gain relatively more from the information from online job platforms than the employed.

[30] Appendix Figure C5 plots the impacts on the distribution of tenure in new employment relationships, showing that broadband availability primarily affects job spells that would have otherwise lasted less than twenty months.

Table 4: Employed Workers' Outcomes.

Dependent Variable:	Job-to-Job Transition	Time Spent on Job Search (Weeks)	Wage (USD)	Job-to-Unemployment	Tenure (Months)
	(1)	(2)	(3)	(4)	(5)
Broadband Availability	0.001	0.198	19.9	-0.003	0.704
(Standard Error)	(0.004)	(0.211)	(73.5)	(0.002)	(0.509)
[p-value]	[0.839]	[0.352]	[0.787]	[0.224]	[0.174]
Dep. Mean	0.141	1.932	4,347	0.082	86.3
Obs. ($N \times T$)	18,961,171	328,116	18,961,171	18,961,171	17,779,246

Notes: The sample consists of individuals registered as employed in year t. This table displays estimation results of availability of broadband internet in year t on the cumulative probability of a job-to-job transition (Column 1), i.e., being employed in year t to a new employment in year $t+1$ or $t+2$, weeks spent on job search (Column 2), wage in next job (Column 3), the transition from employment in year t to unemployment in year $t+1$ or $t+2$ (Column 4), and tenure in next job (Column 5), respectively, on broadband internet availability rate in year t. In Column 2, the outcome is unconditional on search and is set to zero for those who report not searching for a job in the Labor Force Survey. The wage in Column 3 is the first observed monthly wage in year $t+1$ or $t+2$ (set to zero if no employer in year $t+1$ or $t+2$, and is unconditional on making a job-to-job transition). Monthly wage is deflated to 2014-NOK using the CPI and then converted to USD (1 USD = 8 NOK). Tenure in Column 5 is measured from year $t+1$ or $t+2$ and onwards for job movers, while for job stayers this is measured from the start of their current employment relationship and is censored to 48 months for job movers, and not censored for job stayers. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels.

4.3 Robustness and Heterogeneity

We take several steps to verify the internal validity of our findings, besides testing for the presence of geographic spillovers and heterogeneous effects. All of these results are presented and described in detail in Appendix B. We now briefly summarize these results.

Robustness. Our research design rests on the assumption that there must be parallel trends in labor market outcomes across all municipalities for all periods in the absence of broadband internet roll-out. In Appendix B, Section B.1, we test the robustness of our findings to the concern of differential trends in two ways. First, we include region-specific trends as additional controls in our regression specifications (Table B1, Columns 6-8), and second, we perform placebo tests examining whether future broadband internet availability predicts current outcomes (Figure B1). We do not reject the assumption of parallel trends in either of these tests. Another concern relates to compositional changes across municipalities that experience broadband expansions. To address this concern, we perform a series of specification checks, including assessing entry and exit rates of establishments and changes in their industrial compositions (Table B2), providing impact estimates by a wide range of attributes of posted vacancies (Table B3, Figure B2), and controlling flexibly for industry fixed effects and occupation and industry fixed effects, respectively, in our analysis of vacancy durations (Table B4). We further check for the presence of vacancies that are filled without being withdrawn, i.e., 'phantom' vacancies, in Table B5, and address concerns related to whether our estimates reflect reallocation effects in multi-establishment firms in Table B6. All of these robustness analyses support our main conclusions.

Geographic Spillovers. To the extent internet lowered information frictions, job seekers may search more broadly, which could increase the probability of finding a job with a new employer located further away from a person's home residence. While the presence of such geographical spillovers can be informative about the mechanisms through which the internet affects labor market matching, if such effects are large enough then this may also cause concerns about our research design.[31] To assess the role of geographic spillovers, we further decompose the re-employment effect for the unemployed in Appendix Table B7, Columns 2-3, and find that this effect is concentrated within the same commuting zone (CZ). This finding indicates that our definition of CZs is sufficiently broad to ensure there are minimal spillovers beyond its borders, i.e., geographic spillovers are not a concern for our analysis. Reassuringly, in Appendix Table B7, Column 4, we also find that broadband internet only increases the geographic distance between employees and their workplace by 230 meters on average, which is concentrated at shorter commuting distances (Figure B3), and we do not find any evidence on residential mobility (Table B8).

Heterogeneity. Our evidence so far indicates that the benefits of internet are concentrated among the unemployed (Table 3), while we observe no changes in the job search processes for the employed (Table 4) or for individuals outside the labor force (Appendix Table C5). In Appendix B, Section B.3, we consider additional evidence on heterogeneous effects by a wide range of characteristics for the unemployed. In Appendix Table B10, we explore heterogeneity by age and gender. Noting a general lack of statistical precision, we see that the re-employment effects are larger among younger females, while the impacts on starting wages and job tenure are broadly similar across age groups. We also explore whether the internet-skill-complementarity hypothesis extends to the unemployed (see, e.g., Akerman *et al.*, 2015). Appendix Table B3 documents stronger reductions in vacancy duration and higher increases in vacancy posting towards low-skilled workers than among the high-skilled. However, the estimates are too imprecisely estimated to draw firm conclusions.[32] Similarly, in Appendix Table B9, we fail to detect statistically significant differences between college vs. non-college workers, nor do we find significant differences between workers in occupations with different levels of routine tasks.

4.4 Regional Analysis

Having established that the commuting zone encapsulates the matching effects of the internet, we conclude our quasi-experimental analysis with a regional approach allowing us to examine whether the internet has changed the distribution of wages. We implement this approach by aggregating Equation (14) to the CZ level and include year and region (i.e., CZ) fixed effects as well as regional averages of population-weighted municipal infrastructure characteristics. We weight each regression with the size of the regional labor force and the number of job seekers.

To examine the impacts on the wage distribution, we use log wages and calculate the mean and standard deviation of starting wages out of unemployment. Panel A of Table 5 document a significant effect of the broadband expansion on average log wages of 8.9 percent. However, we do not find any statistically significant impact on the standard deviation – where a 10 percent increase lies outside the 99 percent confidence interval, indicating that the null effect is relatively precise. Similar to our municipality-level evidence, we do not detect any significant effect on the average or standard deviation of the log wage distribution among the employed.

[31] Formally, this would lead to a violation of the stable unit treatment value assumption (SUTVA).

[32] Akerman *et al.* (2015) document that broadband favored high-skilled workers, while the relative wages of low-skilled workers in the manufacturing sector fell. One possible explanation for why our heterogeneity results for the unemployed do not corroborate their evidence on skill complementarity of broadband could be that skill-biased productivity effects are more prominent among incumbent workers. In contrast, skill-neutral matching effects dominate among the unemployed.

Table 5: Commuting Zone Analysis of the Impacts on Wage Distributions.

	A. Unemployed		B. Employed	
Dependent Variable:	Log Wage	St. Dev. Log Wage	Log Wage	St. Dev. Log Wage
	(1)	(2)	(3)	(4)
Broadband Availability	0.089**	0.023	-0.010	0.002
(Standard Error)	(0.040)	(0.027)	(0.019)	(0.011)
[p-value]	[0.031]	[0.395]	[0.604]	[0.845]
Obs. ($R \times T$)	598	598	598	598

Notes: This table displays estimation results of broadband internet availability rate on the log monthly wage and the standard deviation of log mean monthly wages on the CZ level for job seekers (Panel A) and employed workers (Panel B). The monthly wage is rebased to 2014-NOK using the CPI and then converted to USD (1 USD = 8 NOK), and set to zero for non-job outcomes. The log wage and standard deviation of the mean log wage are measures on the CZ level. All specifications controls for commuting zones and year fixed effects. Local labor markets are defined based on the classification of Norway into 46 commuting zones by Bhuller (2009) based on commuting statistics. Heteroskedastic robust standard errors are clustered on the CZ level. **p < 0.05.

Next, we examine the impacts on transition rates. We find that job-finding rates increase by four percentage points and that the subsequent unemployment risk fell by 2.5 percentage points – corresponding to a 6 percent and 14 percent increase. While these estimates are somewhat larger, they are not statistically distinguishable from the individual-level evidence. These results are reported in Appendix Table C6. Finally, we verify that our conclusion regarding vacancy behavior holds in Appendix Table C7, and Appendix Table C8 reproduces the remaining findings from Section 4.2 with our regional specification.

5 Quantification of the Mechanisms

In this section, we parameterize the equilibrium model and use it for two main purposes. The first is to quantify the role of underlying and unobserved mechanisms discussed n Section 2. We do this by calibrating the model on pre-expansion data moments and then using the calibrated model to infer the implied changes to model parameters that best fit our quasi-experimental evidence. The second purpose is to quantify the impacts of the internet expansion on the aggregate unemployment rate and the location of the Beveridge curve in Norway.

5.1 Parameterization

We calibrate the model at the weekly frequency to match data moments from the period prior to broadband internet expansion.

Exogenously Set Parameters. We begin by exogenously setting the values of a subset of parameters. Following standard practice in the literature, we set the weekly discount factor β to 0.9992 – consistent with an annual interest rate of 4 percent. We then use common values from the literature: The elasticity of the matching function with respect to vacancies α is set to 0.5 (Petrongolo & Pissarides, 2001) and the worker's bargaining weight η to 0.5, which implies symmetric Nash bargaining (Hall, 2005). We set the elasticity of the utility search cost with respect to search effort φ to 1.2 based on the estimates of Faberman *et al.* (2022). As in Shimer (2005), we normalize the tightness ratio to one and back out the implied unit cost of posting and maintaining a vacancy at $k = 47$.

Calibrated Parameters. Next, we calibrate the remaining parameters to reproduce a selected number of data moments from *before* the broadband internet expansion. While the mapping between these model parameters and sample moments is indirect, we discuss below the moments that intuitively provide identifying information. Table 6 summarizes how the model performs relative to the targeted moments.

We describe our calibration procedure as five distinct steps. First, the exogenous job destruction rate as function of match quality is specified as $\delta_z = \delta(\psi_0 + e^{-\psi_1 z})$, such that δ_z is approximately equal to $\delta(1+\psi_0)$ for low values of match quality and δ_z limits to $\delta\psi_0$ for very large values of match quality. This specification reproduces in a parsimonious way the pattern that in the data EU rates are decreasing in the wage. Second, the arrival rate of idiosyncratic productivity shocks, ξ, and the opportunity cost of employment, b, govern the rate at which employed workers are contacted by new employers and the attractiveness of unemployment relative to employment, respectively. Moreover, normalizing the tightness ratio to one, the probability that an unemployed worker meets a vacancy, p_u, equals Ax_u, so that for given search effort x_u, the level of matching efficiency, A, pins down the scale of p_u. Third, the values of these four parameters, (δ, ξ, b, A) are further disciplined by EU, UE, and EE rates and vacancy duration in the data. Fourth, the level parameters of the search costs for unemployed and employed workers, (ϕ_u, ϕ_e), are calibrated for the model to match the average search effort of 0.117 for the unemployed and 0.009 for the employed.[33] Finally, we assume that match quality is log-normal with parameters μ_z and σ_z and bounded support $z \in [\underline{z}, \overline{z}]$. We set $\underline{z} = 0$, normalize $\mu_z = 0$, and jointly calibrate the values of σ_z and $\overline{z}$ for the model to reproduce the standard deviation of (log) wages for workers at the first job after an unemployment spell and the standard deviation of the overall (log) wage distribution. This procedure gives $\sigma_z = 1.14$ and $\overline{z}$ =8.3.

Table 6: Targeted Moments.

Moment	Model	Data
UE Rate	0.0533	0.0763
EU Rate	0.0035	0.0033
EE Rate	0.0017	0.0016
Vacancy Duration	1.5935	1.8466
Search Effort: Unemployed	0.1382	0.1175
Search Effort: Employed	0.0093	0.0094
EU Rate: 1st Wage Quintile	0.0071	0.0077
EU Rate: 5th Wage Quintile	0.0021	0.0022
SD Starting Log Wages	0.5936	0.5798
SD Log Wages	0.4601	0.4807

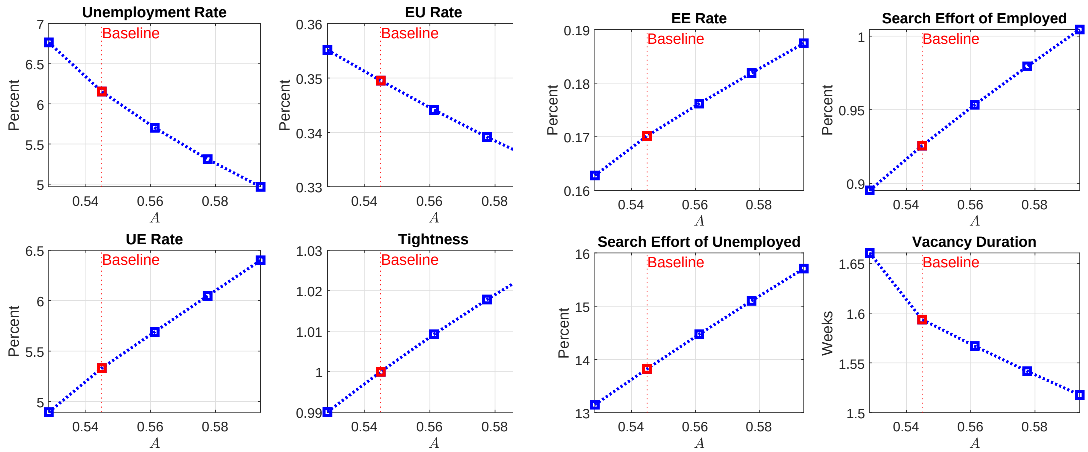
Notes: The monthly EU and UE rates are taken from Hobijn & Şahin (2009), who estimate the rates using data from 1995-2004 and divided by 4 to get weekly rates. EE rates are computed from the quarterly LFS from 2000 to 2004. The vacancy duration is computed from the vacancy data from 2002-2004. Search efforts for unemployed and employed are from the quarterly LFS from 2000 to 2004, divided by 104 weeks. EU rates at the first and fifth quintile use data from the quarterly LFS survey and are re-scaled to have the same mean as Hobijn & Şahin (2009). The average of the standard deviation of the starting log wage and log wage are based on individual-level observations of full-time workers (defined as contracted working hours per week greater than 30) from administrative data. See Appendix Table C9 for further details and for how the transition ratios vary after residualizing for age and, gender and education.

5.2 Inspecting the Mechanisms

To assess potential mechanisms, we begin inspecting how changes in matching efficiency, A, the vacancy cost, k, and the search cost parameters, (ϕ_u, ϕ_e) translate into changes in key labor market outcomes. We provide comparative statics by changing one parameter at a time, while keeping the other parameters at their baseline values. Importantly, the results here also serve as a heuristic discussion of the type of variation in the data that informs the calibrated parameter values.

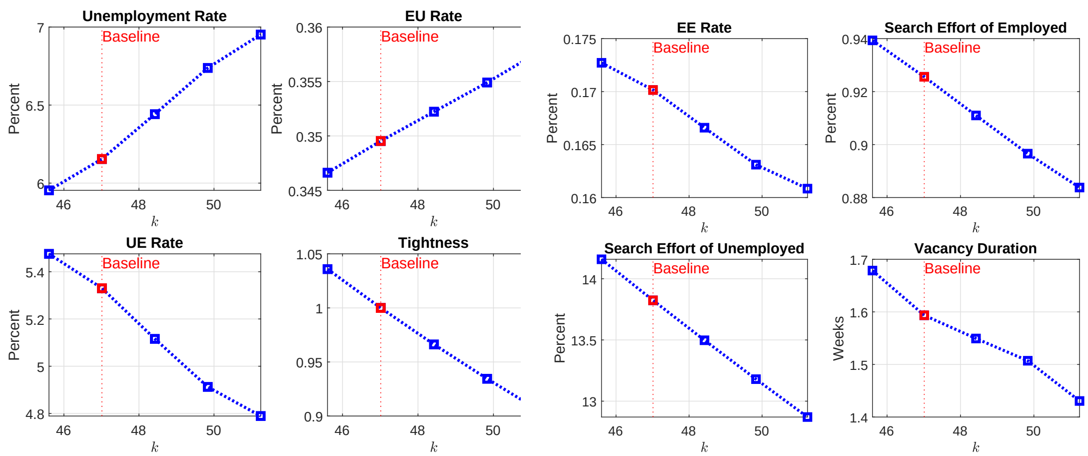
[33] Specifically, we use the average number of weeks spent searching for jobs among the unemployed and employed in the labor force survey. We divide by the maximum potential weeks of UI benefits to get the average search effort.

Figure 5: Changes in Matching Efficiency.



Notes: This figure plots comparative statics results for matching efficiency, A. We progressively increase the value of A, while keeping the other parameters at their baseline values. The vertical dotted line indicates the parameter's value in the model's baseline parametrization.

Figure 6: Changes in the Vacancy Cost.



Notes: This figure plots comparative statics results for the vacancy cost, k. We progressively increase the value of k, while keeping the other parameters at their baseline values. The vertical dotted line indicates the parameter's value in the model's baseline parametrization.

We examine how model moments vary with different values of matching efficiency in Figure 5. Increases in A are associated with rising tightness ratios, higher UE rates, and falling EU rates. The fall in the EU rate is the result of two opposing forces. On the one hand, a higher A makes workers more willing to enter unemployment, anticipating that a higher matching efficiency guarantees a higher probability of finding a job. This tends to raise the mean EU rate. On the other hand, higher matching efficiency implies that workers climb the quality ladder at a faster pace moving to jobs with lower exogenous job destruction rates, which lowers the mean EU rate. Absent the decreasing profile of exogenous job destruction rates, the EU rate would unambiguously rise with matching efficiency.

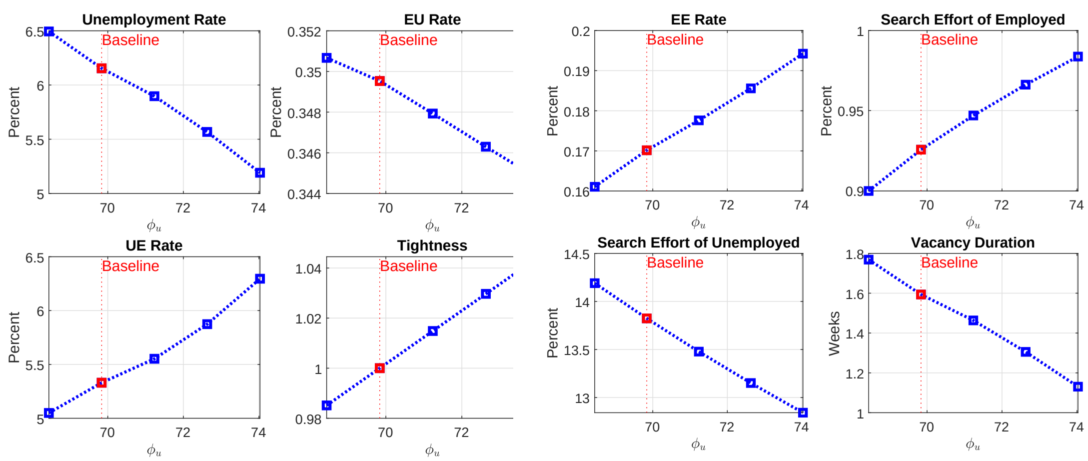
Note that search effort of the unemployed, x_u, monotonically rises with matching efficiency driven by the rise in the tightness ratio. Using the first-order condition for search effort (4) and the free-entry condition (8), we obtain search effort in closed form as

$$x_u = \left(\frac{\eta k}{1-\eta} \frac{\theta}{\phi_u} \right)^{\frac{1}{\varphi - 1}}. \tag{15}$$

As evident from (15), matching efficiency has no direct effect on x_u, but only an indirect effect through changes in the tightness ratio, θ.

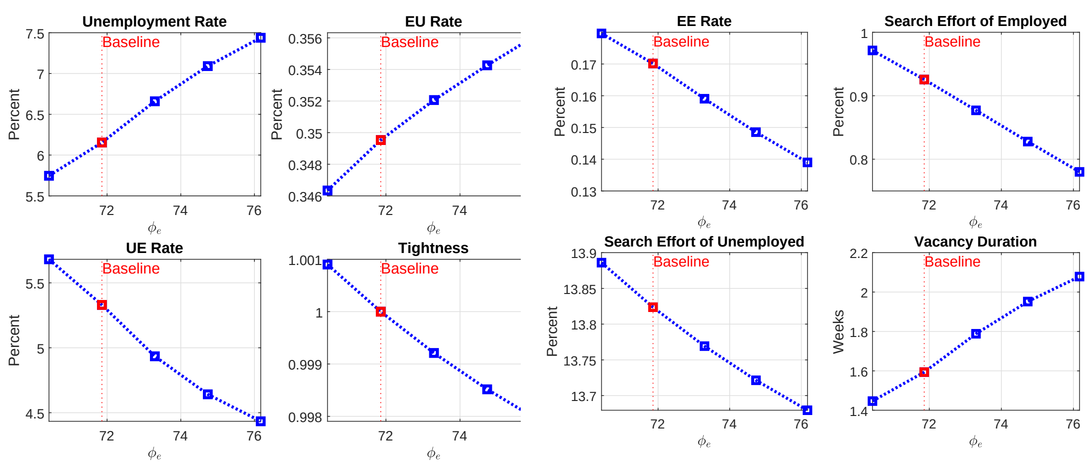
In contrast, the relationship between search effort of the employed, x_e, and matching efficiency is in principle non-monotonic. This non-monotonicity comes from two opposing forces. First, everything else equal, search effort of the employed is increasing in matching efficiency. Second, search effort is decreasing in match quality. As matching efficiency rises, employed workers climb the quality ladder faster, resulting in a larger share of workers at the top of the quality ladder. Higher matching efficiency thus reallocates workers from higher to lower search effort, so that mean search effort may decline.

Figure 7: Changes in the Search Cost of Unemployed.



Notes: This figure plots comparative statics results for the search cost of unemployed individuals, ϕ_u. We progressively increase the value of ϕ_u, while keeping the other parameters at their baseline values. The vertical dotted line indicates the parameter's value in the model's baseline parametrization.

Figure 8: Changes in the Search Cost of Employed.



Notes: This figure plots comparative statics results for the search cost of employed individuals, ϕ_e. We progressively increase the value of ϕ_e, while keeping the other parameters at their baseline values. The vertical dotted line indicates the parameter's value in the model's baseline parametrization.

Turning to vacancy costs, Figure 6 shows the impacts of that lowering k leads to higher tightness ratios, higher search effort and UE rates. In contrast, the EU rate falls because the probability that an employed worker meets a vacancy, $p(\theta)x_e$, rise, and because the EE rate increase – implying that a larger share of workers move up the match quality ladder, which is associated with both higher wages and lower EU rates.

A key observation is that lowering the vacancy cost raises vacancy duration, while an increase in matching efficiency lowers the duration – which is consistent with our evidence from Figure 3. If k falls, vacancies increase, which raises the tightness ratio. A higher tightness ratio, in turn, lowers the probability that a vacancy is filled so that everything else equal, vacancy duration increases. In the case of an increase in matching efficiency, instead, the probability of filling a vacancy rises, lowering vacancy duration. This difference in expected impacts highlights that the effect of broadband internet on vacancy duration is an important data moment that can allow us to disentangle changes in k versus changes in A.

Finally, Figures 7-8 show the comparative statics results of changing the search cost of unemployed, ϕ_u, and employed individuals, ϕ_e, respectively. Increases in ϕ_u are associated with lower search efforts of unemployed individuals. In contrast, the tightness ratios rise. Since searching for a job is costlier, unemployed individuals accept jobs of lower match quality, which in turn implies a higher expected return of posting, and so from the free-entry condition, more posted vacancies and higher tightness ratios. Overall, unemployment rates fall as a result of higher UE rates and lower EU rates.

Unemployment rates are increasing in the search cost of employed individuals, ϕ_e. The higher ϕ_e, the lower the search effort of the employed and EE rates. Lower EE rates imply that a larger share of employed individuals remains at matches with higher exogenous job destruction rates, which means higher EU rates. Tightness ratios are decreasing in ϕ_e. Higher search costs for employed individuals effectively reduce total match surplus, which implies fewer vacancies and lower tightness ratios.

5.3 Aggregate Implications

Our final inquiry is examining the changes in model parameters that are qualitatively and quantitatively consistent with our evidence. This exercise will allow us to both understand the mechanisms behind our causal evidence and to quantify the implications of the internet for aggregate unemployment. Specifically, we return to the discussion of matching efficiency, hiring and search costs from Section 2.2. In our model simulations, we target the estimated impacts of moving from zero to full broadband coverage on UE rates ($+6.1\%$), EU rates (-13.7%), EE rates ($+7.1\%$), vacancy duration (-9.5%), search effort of employed (-14.1%), and search effort of unemployed workers (-0.4%) — and weigh these quasi-experimental estimates by their respective t-statistics to account for the fact that some targets are more precisely estimated than others.[34] We then calculate the model-implied response to the percentage change in matching efficiency, hiring, and search costs, while keeping all other parameters at their baseline (pre-expansion) values.

In the first counterfactual exercise ($\mathcal{C}.1$), we let the value of matching efficiency change to fit the quasi-experimental evidence. We find that the model-implied change in matching efficiency that best rationalizes the evidence is a 4.3 percent increase. The second-to-last row shows the sum of squared deviations is 0.0077, corresponding to an average deviation of 8.7 percent, and columns (1)-(2) in Table 7 show that the model fits the sign of the targets except for the search effort moments. In short, this exercise shows that matching efficiency alone can explain a large fraction of the causal evidence.

[34] We rely on the quasi-experimental estimates from our regional analysis reported in Appendix C, which accounts for potential geographic spillovers occurring within regions. The impacts on UE rate, EU rate and search effort of unemployed are based on Table C6, columns (1), (4) and (2), respectively. The impacts on EE rate and search effort of employed are based on Table C8, columns 1 and 2, respectively. Finally, the impact on vacancy duration is based on Table C7, column 1.

Table 7: Changes in Aggregate Labor Market Outcomes.

	Quasi-experimental Analysis	Counterfactual Analysis $\mathcal{C}.1$	$\mathcal{C}.2$	$\mathcal{C}.3$
	(1)	(2)	(3)	(4)
Potential Mechanisms:		Parameter Change (%)		
ΔA		4.33	5.61	36.95
Δk			5.01	22.04
$\Delta \phi_u$				16.70
$\Delta \phi_e$				23.56
Labor Market Outcomes:	Estimated Response (%)	Implied Response (%)		
ΔUE Rate	+6.1	+10.51	+6.94	+10.88
ΔEU Rate	-13.7	-2.86	-2.86	-5.71
ΔEE Rate	+7.1	+5.88	+5.88	0.00
ΔVacancy Duration	-9.5	-3.42	-9.44	-9.50
ΔSearch Effort: Unemployed	-0.4	+6.73	+4.85	+7.67
ΔSearch Effort: Employed	-14.1	+4.30	+2.15	-12.90
ΔUnemployment Rate		-10.73	-7.48	-13.82
Sum of Squared Deviations:		0.0077	0.0056	0.0029
Bayesian Information Criteria:		-38.156	-38.300	-38.644

Notes: We infer changes in internet-related model parameters by minimizing the distance between the implied responses based on our model simulations and the estimated responses based on our quasi-experimental evidence. The distances between the implied and the estimated responses are moments used in the distance minimization where we weight each moment by the t-statistics corresponding to each quasi-experimental estimate to account for statistical uncertainty. In column (2), we allow the matching efficiency A to change, while using changes in UE rate, EU rate, EE rate and vacancy duration as moments. In column (3), we allow both the matching efficiency A and the vacancy cost k to change, while using the same set of moments. In column (4), we allow all parameters $\{A, k, \phi_u, \phi_e\}$ to change, and also include changes in search effort for unemployed and employed as additional moments. The Bayesian information criteria (BIC) is calculated using $\text{BIC} = n\ln(\hat{\sigma^2}) + k\ln(n)$ where $\hat{\sigma^2} = \frac{1}{n}\sum^{n}(x_i - \hat{x}_i)^2$, x_i is a data moment and $\hat{x}_i$ is the corresponding simulated moment. There are n moments and k is the number of parameters we allow to change.

In the second exercise ($\mathcal{C}.2$), we allow both matching efficiency and the vacancy cost to change. We obtain a 5.6 percent rise in matching efficiency and a 5 percent higher vacancy cost. Comparing columns (2) and (3) of Table 7 shows that the model does slightly better in reproducing the change in vacancy duration and job-finding rates. The model-implied change goes from 3.4 percent to 9.4 percent, very close to the quasi-experimental evidence of 9.5 percent shorter duration and 6.9 percent model-implied increase in job finding rate relative to 6.1 from the data. We calculate the Bayesian information criteria (BIC) associated with the two counterfactuals. This statistic balances the explained variation and the number of parameters, showing that allowing more parameters to change in exercise $\mathcal{C}.2$ improves the model's ability to fit the quasi-experimental evidence.[35]

In the third exercise ($\mathcal{C}.3$), we fit the causal evidence by simultaneously changing all four parameters. We find the implied disutility of search efforts among the employed and unemployed must have increased to rationalize our evidence. Column (4) shows that with the added flexibility, the model generates declining search efforts among the employed but increasing efforts among the unemployed.[36] Allowing the search cost parameters to adjust improves the model's ability to fit the EU transition rates. At the same time, it performs slightly worse in matching the EE transition rate while doing a better job in matching the impact

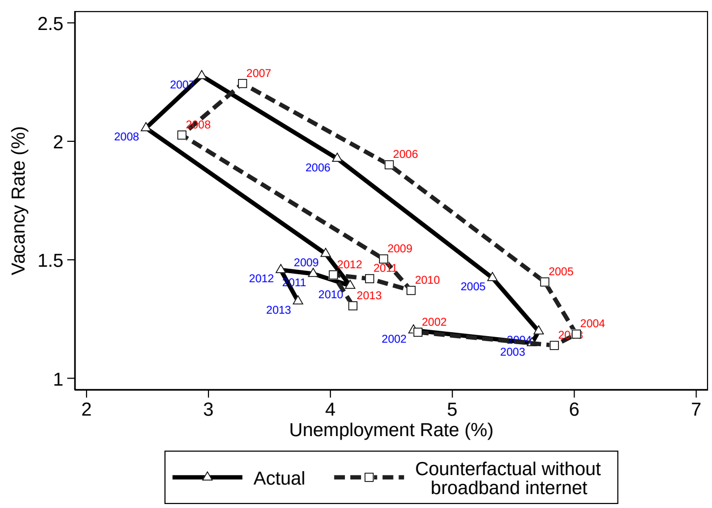
[35]The increase in the vacancy cost implied by the model might seem surprising; however, it is easily explained by the model's mechanics. In the model, a reduction in k raises vacancy postings, thereby increasing the tightness ratio, which in turn reduces the job-filling probability, leading to an increase in vacancy duration. Such an increase in vacancy duration would be at odds with the sizable fall in vacancy duration in the post-internet sample.

[36]However, as the evidence is imprecise, we perform two robustness checks, where we add one and two standard errors to the estimated impacts on search effort. With two standard errors, the implied change in search costs switches sign, while the change in transition rates and aggregate unemployment barely move. Here, matching efficiency increases by 16.55 percent, vacancy cost increases by 15.32 percent, and search cost of employed and unemployed falls by 8.19 and 5.16 percent, respectively.

on EU transition in columns (2) and (3). To account for the differential precision of the moments, we calculate the BIC and find that the improved flexibility improves the model's overall performance slightly.

Implications for Aggregate Unemployment and Vacancies. Our next exercise uses the model to examine whether the broadband internet expansion can account for the observed labor market trends in Norway and the US. Specifically, Appendix Figure C6 shows that monthly vacancy and unemployment rates have steadily moved closer to the origin from 2003 to 2014 – consistent with inward shift of the Beveridge curve.

Figure 9: The Actual and Counterfactual Beveridge Curve in Norway.



Notes: This figure plots the aggregate unemployment and vacancy rates in Norway from the period 2002 to 2013. The dashed line uses the implied change in unemployment and vacancies from counterfactual $\mathcal{C}.1$, and re-scales the actual numbers by the implied change in unemployment and vacancy rates.

We begin our assessment by first quantifying the relative importance of the various mechanisms and conclude that improved matching efficiency is unambiguously the main driving force behind the reduction in the unemployment rate.[37] These calculations are reported in Appendix Table C10. Motivated by these calculations, and to provide a conservative estimate, we focus our attention on the role of matching efficiency in explaining the trends. In the next step, we calculate a gradual improvement in search and matching technology over time. To do so, we use the aggregate broadband coverage rate – from no coverage in 2000 to near full coverage in 2013 – and calculate the model-implied change in unemployment and vacancy rates. Lastly, we use the actual aggregate unemployment and vacancy rates in Norway over the same period and scale them by the implied change in the aggregate quantities to obtain the counterfactual levels. The solid line in Figure 9 shows the actual rates, and the counterfactual, where we shut off the matching efficiency channel of the broadband expansion, is illustrated by the dashed line. This exercise illustrates that the internet appears to have gradually shifted the Beveridge curve inward in Norway. For example, aggregate

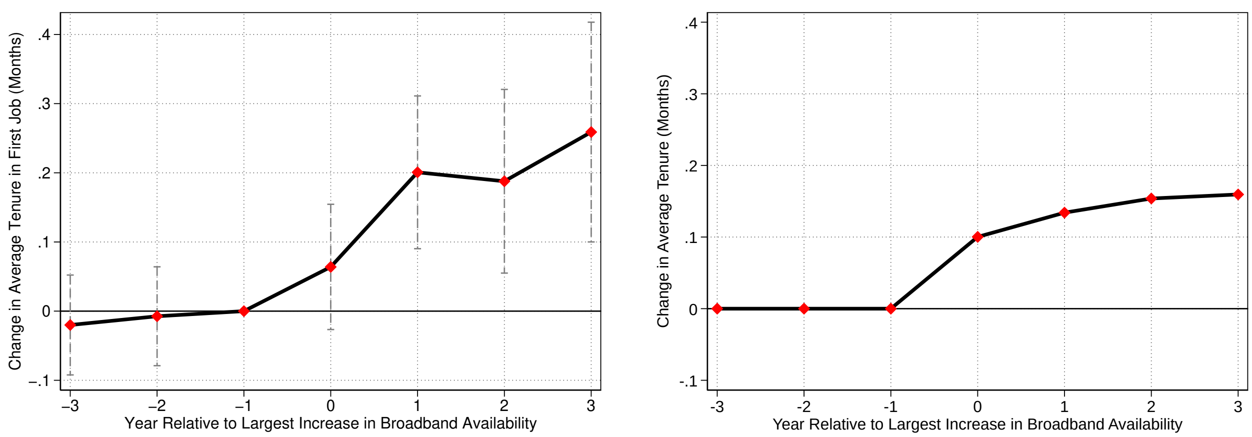
[37]Columns (1)-(2) of Panel A in Appendix Table C10 quantifies the relative contribution of each of our proposed mechanisms in explaining changes in unemployment flows and rates. Specifically, the first column reports the role of changing matching efficiency alone ($\mathcal{C}.1$) relative to the total change, i.e., letting all parameters change simultaneously ($\mathcal{C}.3$). The second row compares changing matching efficiency and vacancy costs. We interpret these ratios as the share of the total impact that is accounted for by matching efficiency and the combined change in the matching efficiency and the vacancy cost. In panel B, column (3) reports the difference in the statistics reported in columns (2) and (1), and columns (4)-(5) report the shares accounted for by changes in search costs relative to the change in matching efficiency alone and the combined change in matching efficiency and vacancy cost, respectively. In sum, matching efficiency accounts for 50 percent of the total change in the EU rate and 80 percent of the reduction in aggregate unemployment. The increase in the vacancy cost implied by the model contributes negatively to the unemployment rate change and has no impact on the EU rate. Finally, the search cost parameters changes account for only a small share of the unemployment rate change.

unemployment would have reached 4.7 percent instead of 4.1 in the aftermath of the 2008-2009 recession had it not been for the improved matching efficiency from the internet expansion.

Figure 10: The Impacts of Matching Efficiency on Job Duration.

(a) Quasi-Experimental Evidence

(b) Model Prediction: Increased Matching Efficiency



Notes: Panel (a) provides estimates on average duration in new employment spells for job seekers from our quasi-experimental evidence. As in Figure 3, time zero represents the year with the largest increase in broadband availability rate (i.e., the event year) in each municipality. The figure plots the coefficient estimates (black solid dots) of relative time dummies $\hat{\delta}_k$ in Equation (13), along with the associated 90% confidence intervals (vertical bars) on job seekers' average job duration in new employment spells for a three-year window around the event year. The coefficient on the relative event time dummy for the year prior to the largest increase is normalized to zero ($\delta_{-1} = 0$), so that the coefficients on the other relative event time dummies show responses relative to this year. In each plot, we control for municipality and calendar time fixed effects. Panel (b) plots the model-implied increase in aggregate job duration associated with improved matching efficiency (exercise $\mathcal{C}.1$) and expanding coverage from 70 percent to full coverage over the period 2006-2009, relative to the model-implied job duration of staying at 70 percent coverage.

Finally, our framework allows us to quantify the role of improved search technology for aggregate job mobility. Recent trends in the US indicate that job mobility rates have declined and have fueled a debate about underlying barriers to labor mobility. Our quasi-experimental evidence lends support to the view that the expansion of broadband coverage could be a factor that drives these trends. As shown in Figure 10, panel (a), we find that the average job duration of new employment spells for job seekers increases by around a week, when we consider changes in average job durations across the three-year window around the largest expansion in broadband availability in each municipality. We now use our calibrated model to simulate the average duration of an employment spell with the implied changes in matching efficiency associated with different broadband coverage levels to examine this mechanism. To emulate the event-study design from Section 3.2.2, we use 2006 as the average year with the highest expansion rate. Three years later, the average coverage rate in the economy reached 99 percent. The counterfactual we consider here is that the coverage rate would have stalled at 70 percent. Figure 10, panel (b) shows that the average duration increased by almost a week, reconciling our quasi-experimental evidence. This effect arises from a combination of better initial matches, which lowers the separation rates into unemployment and the rate at which employees climb the ladder. In contrast, if we use the implied parameter changes from $\mathcal{C}.3$, where search costs for the employed also rise, thereby lowering their search effort, the average job duration increases by another 50%. In sum, improved matching efficiency, i.e., $\mathcal{C}.1$, accounts for about two-thirds of the total model-implied increase in job duration, i.e., $\mathcal{C}.3$. These calculations illustrate that matching efficiency is a key candidate to explain declining job mobility and the inward shift in the Beveridge curve.

6 Conclusion

The internet has shifted search and recruitment activities from traditional platforms, such as newspapers and employment offices, to online platforms and digital communication. This fundamental shift may have had important implications for aggregate labor markets. However, assessing how the internet has affected the behavior of hiring firms and job seekers has proven difficult because of the observational challenges of selection in early internet adoption and measuring the search activities of both sides of the labor market. On top of these challenges, theoretical predictions depend on the relative importance of the channels through which the internet might operate, such as improvements in matching technology and lower search and recruitment costs.

The goal of this paper was to help fill this gap using a combination of quasi-experimental data and theory. Two features of Norwegian labor markets make it an ideal setting to examine how the internet has affected job matching and aggregate unemployment. The first was a national broadband policy in Norway generating quasi-experimental variation in broadband internet infrastructure and high-speed internet availability to firms and workers. The second key feature was the availability of large-scale survey and administrative data on hiring firms, job seekers, and vacancies.

Our empirical and quantitative analysis offered several novel findings. We found that the internet led more firms to recruit online. It further caused a nine percent decline in the duration of posted vacancies and 13 percent fewer unsuccessful hiring attempts. Next, we showed that the expansion increased job-finding rates by 2.4 percent and starting wages by six percent among the unemployed. However, we found no evidence of changes in job-to-job mobility or wage growth for the employed. Our quantitative exercise allowed us to interpret the strength of the potential mechanisms and quantify the implications for aggregate unemployment. We specified a model with endogenous job creation and destruction where workers decide how much search effort to exert on and off the job. We calibrated the model to key labor market moments before the internet expansion. Through the lens of the calibrated model, we found that search technology is the primary mechanism behind the quasi-experimental evidence. Our calculations indicated that the broadband internet expansion may have caused a 14 percent decline in the steady-state unemployment rate.

Our paper sheds light on two recent macroeconomic trends. First, the falling rates of worker mobility in the US have fueled a concern about the causes and consequences of declining labor market mobility. Our results suggest that online job search and recruitment may have improved match quality by providing more information about potential jobs and better tools to screen potential candidates. In turn, this improvement may have reduced the need to switch employers in search for a better match – consistent with a more optimistic view of recent trends in job mobility. Second, our evidence helps explain the inward shift in the Beveridge curve observed in Norway and in other countries from the 1990s to the early 2000s (see, e.g., Bova *et al.*, 2018). Our evidence suggests that without the near-universal internet adoption rates, the unemployment rate after the Great Recession would have reached even higher levels.

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A Appendix: Details on the Data Sources

A.1 Overview of Data Sources

Matched Employer-Empoyee Register. Workers' earnings and employment histories, and transitions between jobs and occupations come from the Norwegian Matched Employer-Employee Register maintained by Statistics Norway. This data set covers all employment contracts from 1995 to 2014 except contracts for work below four hours per week or NOK 10,000 annually. Every worker-level contract is reported by the employer to the authorities at the end of the year, and includes information on the dates of alterations to the contract, and the corresponding wage, industry and occupational codes, geographic location and tenure at the establishment. From this source, we construct time series of monthly earnings for each worker, and the transitions between establishments and occupations.

Job-Seeker/Unemployment Register. Information on participation in the unemployment insurance (UI) program comes from the job-seeker register, which has complete records for all individuals who entered or exited this program between 1992 and 2014. This information is maintained by Statistics Norway and builds on administrative records kept by the National Public Employment Agency (NAV). The data includes every job-seeker, both the fully unemployed and those who have a part-time job but are looking for full-time work, as well as participants in active labor market programs. To assist workers in job search, caseworkers in the employment agency keep a record of details about workers' occupational experience, and the occupations job seekers want to work in.

Register of Job Vacancies. The public employment agency maintains a database of job vacancies used for statistical purposes and by caseworkers to match unemployed workers to potential employers. Individual vacancies are either manually collected from job boards and help-wanted ads, or are reported directly by employers.[38] These vacancies are then classified by the number of positions the establishment is trying to fill, the workplace location (e.g., zip code) and the corresponding four-digit occupational code. Occupational codes are based on the International Standard Classification of Occupations (ISCO). The vacancy data is available from 2002 and onward.

Administrative Population Registers. To capture complete information on workers' geographic location, education, annual earnings, and household income, social security data is merged with longitudinal administrative registers provided by Statistics Norway and covering every Norwegian resident from 1967 to 2014. These administrative data sources contain individual demographic information (including sex, age, zip codes, and years of education) and, since 1993, all sources of annual income, including earnings, self employment income, capital income, and cash transfers. From the early 2000s, we have geographic coordinates of the residential location for almost all workers and the workplace location for a large fraction of establishments. A strength of the administrative data is that outcomes such as income and wages are measured with

[38]The Norwegian Labor Market Act (*Loven om arbeidsmarkedstjenester §7-1*) requires employers to report vacant positions to the public employment agency. The public employment agency employs data collectors that manually record vacancies from various alternative sources. As a result, the quality of the vacancy register naturally depends on the degree to which establishments comply with the reporting requirements and the accuracy of manual recording performed by data collectors. A natural question is then to what extent are data recorded in the vacancy register representative of all job openings. To assess the representativeness of our data we collected additional data on job openings from Statistics Norway that is based on representative surveys of establishments from 2010 to 2016. Our comparisons reveal that data on vacancies from the public employment agency tracks the time variation in aggregate job openings from the survey data on vacancies remarkably well (see Appendix Figure A1).

relatively little measurement error, as individual employment histories and most income components are third-party reported (e.g., employers, financial intermediaries). Since the administrative data are a matter of public record there is no attrition due to non-response or non-consent by individuals or establishments. The coverage and the reliability of the population data are rated as exceptional by international quality assessments (see, e.g., Atkinson *et al.* 1995).

Survey of Firms' ICT Use. Since 1999, Statistics Norway has surveyed firms' ICT use using repeated cross-sections. About 4,000 firms are drawn from stratified random samples by firm size and industry from the population of firms. Crucial to our analysis, the surveys include information on the use of dial-up or broadband internet by firms. The surveys also collect information about online activities, including whether a firm has a marketing website and other measures of firms' digital presence and online search behavior. We received extracts from these data sets for years 1999 to 2014, which contain responses from around 3,600 firms each year. Statistics Norway mandates the collection of this information for the purpose of preparing official statistics on firms' ICT use and can threaten to impose coercive fines in case of non-response. As a result, the average response rate is nearly 95 percent.

Survey of Establishments' Vacancies (SER). Since 2010, Statistics Norway has conducted quarterly surveys of establishments' vacancy posting behavior. These surveys are used primarily for statistical reporting purposes, and are designed as repeated cross-sections, with a sample of around 8,000 representative establishments drawn from the population of registered establishments. The definition of a vacant position in this survey is that it can start within 30 days, recruitment must be from outside the firm, and full-time, part-time, permanent, temporary, and short-term job openings are included. The survey arguably provides the most reliable data on the aggregate level of vacancies, and includes the number of vacant positions and establishment identifiers. Since this survey starts only in 2010, which is after the period of broadband expansions in Norway, we only use data from this survey for comparisons and to perform a quality assessment of the public employment agency's register of job vacancies (discussed above and in Section A.2).

Survey of Establishments' Recruitment Behavior (SERB). Since 1994, the public employment agency has conducted annual surveys of establishments' recruitment efforts. These surveys are used for various policy analyses and in forecasts of labor market trends across local labor markets and industries, and are designed as repeated cross-sections, with a sample of around 20,000 representative establishments drawn from the population of registered establishments. The data includes establishment-level information on expected changes in labor demand, planned vacancy posting and questions about the recruitment challenges an establishment is facing. For our analysis, we received extracts of the surveys for the years 1996 to 2014 with responses from around 14,000 establishments in each year – where an average response rate of 70 percent. The data includes establishment and firm identifiers allowing us to link the survey information to the various other establishment-level data sources mentioned above.

Survey of Media Use. Since 1991, Statistics Norway has surveyed individuals' media use annually. These surveys are designed as repeated cross-sections, with representative survey samples of around 2,000-3,000 individuals drawn from the population aged 7-79. Each individual is interviewed about a wide array of topics related to media use behavior, including questions on whether the individual had access to dial-up or broadband internet, used the internet for work-related purposes, and a number of other measures of online search activities. We received anonymized extracts from these survey data sets from Statistics Norway for years 2000 to 2013, with an average response rate of 65 percent over these years. Even though these data sets are anonymized, identifiers for municipality of residence and time of survey were retained, which allows us to use this information in our research design.

Labor Force Survey. Since 1972, Statistics Norway has published quarterly labor force surveys. These surveys are primarily cross-sectional (with a rotational panel design with interviews across as many as eight consecutive quarters) covering around 20,000 individual respondents in each quarter drawn from the working-age population of individuals aged 15-74. Each individual is interviewed about a wide array of topics related to labor market, including questions on time spent on job search for unemployed and employed individuals, which allowed us to construct measures of search intensity. We received extracts from these surveys from Statistics Norway from 1996 to 2016, which we were allowed to link to our worker-level analytical samples.

A.2 Quality of Vacancy Data

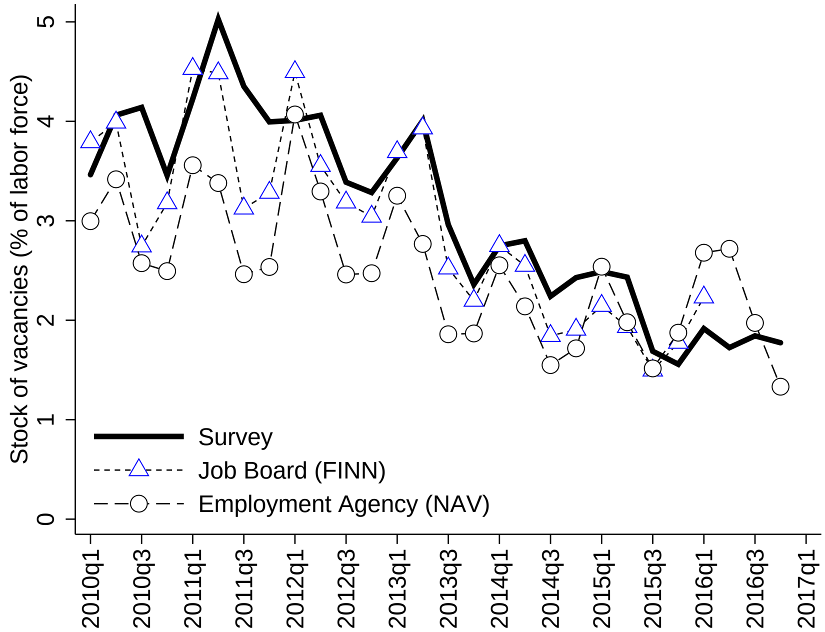
The Register of Job Vacancies is a data set covering 2002 to 2018 based on employer-filled reports of vacant positions sent to the public employment agency. The quality of this vacancy register would naturally depend on the degree to which firms comply with the reporting requirements. To assess the quality and representatives of the public employment agency's vacancy data, we first (i) aggregate vacancies using ad-level data to occupation, municipality, and month in which job vacancy was created, (ii) create vacancy stocks based on the duration of each vacancy, and next, (iii) compare these vacancy stocks to two alternative sources of vacancy data.

First, we use a representative survey performed by Statistics Norway, which includes vacancies for 8,000 establishments, i.e., almost 5 percent of all establishments (see details in Section A.1). Next, we also collected vacancy data from the largest Norwegian online job-board (Finn.no), which has had an online market share at around 95 percent (Anand & Hood, 2007). Unfortunately, the online job board data does not include establishment identifiers for all online vacancy postings, limiting the scope for a direct use of this data set in our main analysis.

Figure A1 displays the aggregate trends of quarterly vacancy stocks, starting in 2010, the first year the survey data are available. The stock of vacancies is divided by the labor force, comprising every worker aged between 25 to 66 who is either employed or unemployed but actively looking for work. The time pattern shows a clear seasonality in the vacancy postings: the survey shows a distinct peak in the second quarter, while the two other sources have peaks that vary between the first two quarters of the year. Importantly, the graph shows that the three sources track each other well over time, and that the relative differences between the sources are quite stable over time.[39]

[39] The aggregate numbers from NAV and Finn are approximately 20 percent below the survey at their respective peaks.

Figure A1: Trends in Vacancy Stocks Across Three Sources of Data on Vacancies.



Notes: This figure shows the aggregate trend of vacancy rates using three data sources on vacant jobs. The total number of vacancies is divided by the labor force.

B Appendix: Robustness and Heterogeneity Analysis

This section summarizes our robustness analysis, which provides various specification checks related to differential trends, compositional changes and reallocation effects, and further assesses spillovers across local labor markets and heterogeneous effects.

B.1 Specification Checks

Differential Trends. Our quasi-experimental analysis maintains the assumption of parallel trends in outcomes across areas over time in the absence of the broadband expansion. We assess the validity of this assumption by including trends that vary by commuting zones. Using pre-broadband expansion data for each outcome (available back to 1997 for most of our variables), we obtain a slope estimate for each CZ. This procedure will account for variation in broadband availability that coincides with pre-existing differential trends in the outcome.[40] Next, we include additional controls that interact the baseline year (2000) outcome with time dummies, allowing for differential time trends across CZs depending on the levels of the outcome in the baseline year. The time dummies allow these trends to take any non-linear functional form. Columns 6-8 in Table B1 report the estimates based on these specifications. The estimates are quantitatively similar to our baseline estimates and our qualitative conclusion remain the same across the alternative specifications.

Similarly, we assume that broadband expansions are unrelated to other drivers of labor market matching. We further examine the validity of this assumption including additional time-varying observable characteristics measured prior to the broadband expansion. In column 3 of panel A in Table B1, we add controls for establishment age (51 dummies) and size (6 dummies), and further add controls for average level of education and average annual wage of workers in column 4. In panel B, we similarly control for worker's gender and age in column 2, add marital status and number of children (by age group) in column 3, and further add flexible controls for level of education (18 dummies) in column 4. In all specifications, we already control for average travel time to municipal center (in hours), distance covered by municipal road networks (in kilometers), and municipal spending on infrastructure (deemed important for the roll-out of broadband internet in Bhuller *et al.* (2013)). Reassuringly, our main estimates for both establishments and job seekers remain stable across columns 1-4. Finally, controlling for lagged coverage rate in Column 5 does not alter our findings.

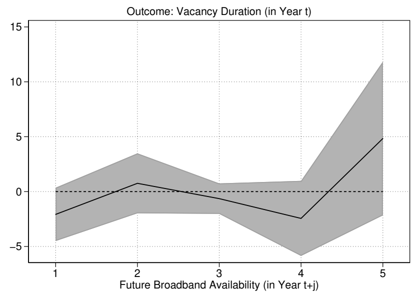
[40] Specifically, we obtain a slope estimate $\hat{v}_{r(m)}$ for each commuting zone. We then include fitted pre-expansion time trends in our specification as follows $y_{jmt} = \delta BI_{mt} + \kappa_m + \tau_t + \lambda_1 \hat{v}_{r(m)} t + \lambda_2 \hat{v}_{r(m)} t^2 + \varepsilon_{jmt}$

Table B1: Specification Checks.

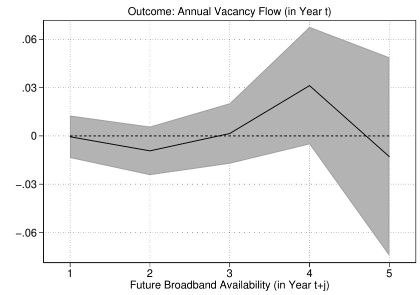
	Baseline	Additional Time-Varying Controls				CZ-Specific Time Trends		
						Linear	Quadratic	Baseline Interacted FEs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Establishments' Recruitment								
Vacancy Duration	-1.376***	-1.233**	-1.153**	-1.121**	-1.393***	-1.063**	-1.017**	-1.017*
	(0.468)	(0.496)	(0.477)	(0.492)	(0.378)	(0.499)	(0.474)	(0.507)
Annual Vacancy Flow	0.032***	0.033***	0.032***	0.031***	0.022***	0.030***	0.029***	0.027***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Recruitment Problems	-0.027***	-0.031***	-0.032***	-0.032***	-0.026***	-0.031***	-0.032***	-0.031***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Municipality and Year FEs	√	√	√	√	√	√	√	√
Industry FEs		√	√	√	√	√	√	√
Establishment Age and Size			√	√		√	√	√
Establishment Composition				√		√	√	√
Lagged Coverage Rate					√			
B. Job Seekers's Re-Employment Outcomes								
Re-employment	0.016***	0.015***	0.014***	0.012**	0.014**	0.008*	0.007*	0.007*
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)
Wage in First Job (unconditional)	124***	120***	119***	101***	123***	96***	94***	93***
	(34)	(32)	(31)	(31)	(33)	(27)	(27)	(27)
Tenure in First Job (unconditional)	0.397***	0.381***	0.379***	0.343***	0.312***	0.336***	0.301***	0.231**
	(0.088)	(0.084)	(0.083)	(0.083)	(0.088)	(0.083)	(0.082)	(0.092)
Municipality and Year FEs	√	√	√	√	√	√	√	√
Occupation FEs	√	√	√	√	√	√	√	√
Worker Age and Gender		√	√	√		√	√	√
Family Background			√	√		√	√	√
Dummies for Education Levels				√		√	√	√
Lagged Coverage Rate					√			

Notes: See notes provided in Tables 2-3 relating to the definitions of each outcome variable and samples. In panel A, column 2, 3-digit industry dummies (264 categories) are included. In panel A, column 3, establishment age and size include dummies for establishment age (51 dummies) and size (6 dummies), and in column 4, establishment composition includes average level of education of workers in the establishment and average annual wage deflated to 2014-USD. In panel B, column 1 includes dummies for 4-digit past occupation (pre-determined), column 2 includes a vector of controls for age and gender, column 3 further includes indicators for marital status and number of children (by age group), and in column 4, controls for education (18 dummies) are added. Columns 5 further includes controls for the lagged broadband coverage rate. Columns 6 and 7 include linear and quadratic CZ-specific time trends, respectively, in the outcome variable constructing using pre-rollout data and the classification of 46 commuting zones (CZ) in Bhuller (2009). Column 8 further adds controls time dummies interacted with baseline year (2000) value of the outcome variable. Heteroskedastic robust standard errors are clustered on CZ levels. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

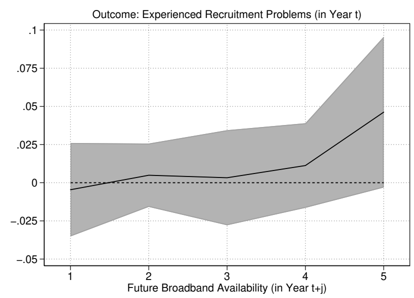
Figure B1: Placebo Tests.



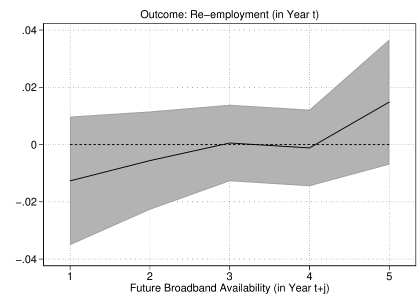
(a) Establishments: Vacancy Duration



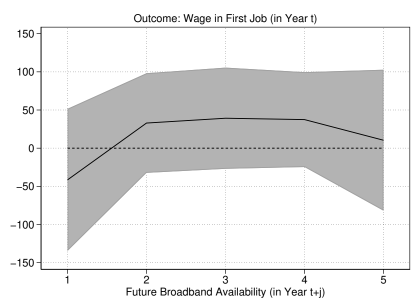
(b) Establishments: Vacancy Flow



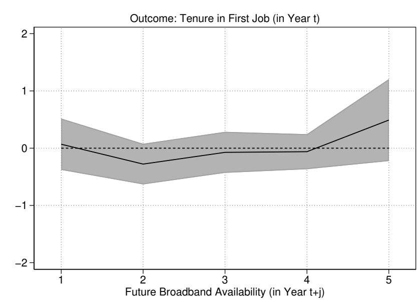
(c) Establishments: Recruitment Problems



(d) Job Seekers: Re-employment



(e) Job Seekers: Wage in First Job



(f) Job Seekers: Tenure in First Job

Notes: The figures shows the estimated effect and associated 90% confidence intervals of future broadband availability in years 1-5 after each outcome is measured. The specification includes municipality and time fixed effects, controls for past broadband availability, as well as controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure) and all additional controls listed in Table B1, column 4. Heteroskedastic robust standard errors are clustered on CZ levels.

Another way to assess the validity of our research design is to perform placebo tests that examine whether future broadband internet availability affects current outcomes. While the event study suggested that expansions are not predicted by past labor market outcomes, we test this formally by regressing the outcome in year t on a set of variables capturing broadband availability in years $t+1$ to $t+5$ (i.e., the lead values of BI_{mt}), where the coefficient estimate on each lead variable represents a placebo test. Since the broadband availability rate is cumulative, we control for the broadband availability measured at the start of year t (i.e., BI_{mt}) in these regressions. Not controlling for broadband availability at the start of year t would raise the concern that we are incorporating variation that precedes the outcome in the placebo test. We report the results from this placebo test for the key establishment-level and worker-level outcomes in our analysis in Figure B1. Reassuringly, we find no effect of future availability on recruitment and outcomes of job seekers.

Composition Effects. An additional concern with our analysis could be that our estimates are driven by a change in the composition of establishments. We address this concern by verifying that internet does not affect the exit and entry of establishments in Table B2.

Table B2: Composition of Establishments at the Municipality-Year Level.

Dependent Variable:	A. Number of Establishments	B. Entry/Exit:		C. Industry Affiliation:	
		Entry Rate	Exit Rate	ICT Intensive	Non-ICT
	(1)	(2)	(3)	(4)	(5)
Broadband Availability	2	0.004	0.003	-0.001	0.001
(Standard Error)	(2)	(0.003)	(0.004)	(0.004)	(0.004)
[p-value]	[0.379]	[0.214]	[0.399]	[0.846]	[0.846]
Dep. Mean	335	0.113	0.169	0.284	0.716
Obs. ($M \times T$)	6,240	6,240	6,240	6,240	6,240

Notes: This table displays estimation results from regressions at the municipality-year level of the number of establishments (panel A) in year t, the fraction of establishments that enter and exit (panel B) in year t, respectively, and the fraction of establishments in year t that are ICT-intensive or non-ICT-intensive (panel C) measured on the municipality level on broadband internet availability rate in year t, with $t \in [2000,2014]$. In column 1, we include the total numbers of establishments existing in year t-1 as a control variable. In columns 2 and 3, the entry and exit rates are expressed as fraction of establishments in year t-1 and the regressions are weighted by the number of establishments in the municipality in year t-1. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels.

A related concern with the results on vacancy duration is that part of the response may reflect a change in the type of occupations that firms target in their ads. To address this concern, we include three-digit industry-fixed effects (264 categories) and occupation fixed effects (403 categories) as additional controls to ensure that we compare vacancies posted within the same industry and occupation. Our main findings do not materially change under these specifications and are reported in the second and third columns in Table B4.

Using the task descriptions of the vacancy postings, we further assess this concern by showing that our results hold across several sample splits, including occupational skill requirements (college/non-college), routine task intensity (RTI), and categories of manual/non-manual occupations. The results from these exercises are provided in Table B3, and support the conclusion that improved matching efficiency explains the shorter vacancy durations.

Table B3: Vacancy Duration and Vacancy Flow By Characteristics of the Posted Vacancy.

Panel:	A. College Occupation		B. Non-College Occupation	
Dependent Variable:	Vacancy Duration (1)	Vacancy Flow (2)	Vacancy Duration (3)	Vacancy Flow (4)
Broadband Availability	-1.254***	0.010**	-1.568**	0.027***
(Standard Error)	(0.309)	(0.004)	(0.688)	(0.005)
[*p*-value]	[0.000]	[0.020]	[0.027]	[0.000]
Dep. Mean	15.5	0.137	14.9	0.140
Obs. ($B \times T$)	220,841	1,611,573	225,486	1,611,573
Panel:	C. RTI Occupation		D. Non-RTI Occupation	
Dependent Variable:	Vacancy Duration (1)	Vacancy Flow (2)	Vacancy Duration (3)	Vacancy Flow (4)
Broadband Availability	-1.059*	0.017***	-1.581***	0.015***
(Standard Error)	(0.615)	(0.006)	(0.450)	(0.004)
[*p*-value]	[0.092]	[0.006]	[0.001]	[0.000]
Dep. Mean	14.9	0.150	15.8	0.125
Obs. ($B \times T$)	240,950	1,611,573	200,688	1,611,573
Panel:	G. Manual Occupation		H. Non-Manual Occupation	
Dependent Variable:	Vacancy Duration (1)	Vacancy Flow (2)	Vacancy Duration (3)	Vacancy Flow (4)
Broadband Availability	-2.309**	0.012***	-1.396***	0.026***
(Standard Error)	(0.921)	(0.002)	(0.413)	(0.008)
[*p*-value]	[0.016]	[0.000]	[0.002]	[0.001]
Dep. Mean	14.8	0.040	15.3	0.204
Obs. ($B \times T$)	63,663	1,611,573	329,139	1,611,573

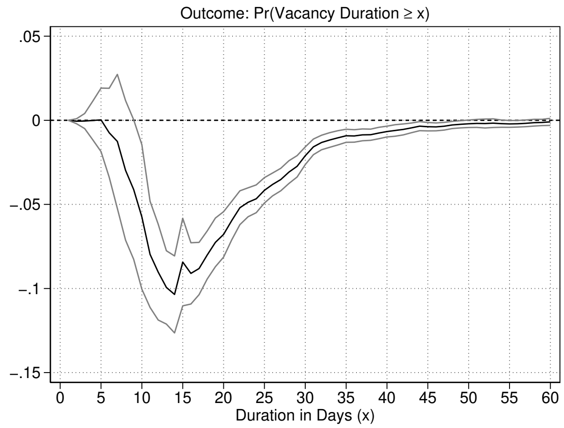
Notes: Panel A-H display estimation results of mean duration in days of a vacancy posted during year t (column 1 and 3) and posting at least one vacancy during year t (column 2 and 4) on broadband internet availability rate in year t. Both variables are from the vacancy register, and duration is conditional on an establishment having posted a vacancy. In panels A-B, the skill requirement of a posted vacancy (college or non-college) is defined as whether the average incidence of workers with a certain educational level in that (four-digit) occupation exceeds the average incidence of workers with a certain educational level for all occupations, based on a cross-section of all employed workers between ages 25-55 in 2003. In panels C-D, RTI-Intensive is defined as a (four-digit) occupation where the RTI score of the occupation is greater than the median, and vice versa for non-RTI-Intensive. In panels G-H, manual occupations are defined as the occupations (i) Elementary Occupations, (ii) Extraction and building trades workers, (iii) Founders, welders, sheet-metal workers, (iv) Blacksmiths, gunsmiths, locksmiths and related trades workers, (v) Machinery mechanics and fitters, and (vi) Other craft and related trades workers. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table B4: Vacancy Duration Estimates With Industry Fixed Effects and Occupation Fixed Effects.

Dependent Variable:	Vacancy Duration		
Panel:	A. Baseline Specification	B. Industry Fixed Effects	C. Industry and Occupation Fixed Effects
Broadband Availability	-1.376***	-1.233**	-1.296***
(Standard Error)	(0.468)	(0.496)	(0.477)
[*p*-value]	[0.005]	[0.017]	[0.009]
Dep. Mean	15.2	15.2	15.2
Obs. ($B \times T$)	358,266	358,266	357,948

Notes: Panel A-C display estimation results of conditional mean duration in days of vacancy postings posted during year t on broadband internet availability rate in year t using data from the vacancy database. Panel B includes industry (three-digit) fixed effects, while panel C includes both industry (three-digit) and occupation (four-digit) fixed effects for the posted vacancy. If an establishment posts more than one vacancy, the occupation of the vacancy with most positions is used. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels. **$p < 0.05$, ***$p < 0.01$.

Figure B2: The Distribution of Vacancy Duration.



Notes: The figure shows the estimated effect and associated 90% confidence intervals of broadband availability on the probability that a vacancy is active and unfilled for at least x days (measured on the horizontal axis). The specification includes municipality and calendar year fixed effects, as well as controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure). Heteroskedastic robust standard errors are clustered on CZ levels.

Yet another concern is that the internet may affect the rate of 'phantom' vacancies, i.e., vacancies that have been filled, yet the ads are not withdrawn from an online job board (see, e.g., Albrecht *et al.* (2017)). We consider this not an important concern in our setting, as the Norwegian employment agency requires employers to report both the dates of posting and removal or filling, which limits the extent of erroneous recording of vacancy durations. Indeed, Figure B2 shows that broadband internet availability impacts the overall distribution of vacancy duration and is not driven by outliers. To further address this concern, we consider in panel A of Table B5 vacancies with durations above 90 days, finding no changes in posting rates of such vacancies. Notably, less than 0.4% vacancies in our sample have a duration above 90 days. Further, conditioning our sample to vacancies with durations shorter than 90 days in panel B, we find very similar estimates as in our baseline, which support the conclusion that the presence of 'phantom' vacancies is not a concern for our analysis.

Table B5: Vacancy Duration and Vacancy Flow – Presence of 'Phantom' Vacancies.

Dependent Variable:	A. Vacancy Flow	B. Vacancy Duration
	Vacancy Duration > 90 Days (1)	Sample: Duration ≤ 90 Days (2)
Broadband Availability	0.000	-1.652***
(Standard Error)	(0.000)	(0.269)
[p-value]	[0.228]	[0.000]
Dep. Mean	0.001	14.5
Obs. ($F \times T$)	1,611,573	356,711

Notes: Panel A displays estimation results of posting at least one vacancy (vacancy flow) during year t with duration above 90 days on broadband internet availability rate in year t using data from the vacancy database. Panel B displays estimation results of conditional mean duration in days during year t on broadband internet availability rate in year t using data from the vacancy database, dropping vacancies with durations above 90 days. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels. ***$p < 0.01$.

Reallocation Effects. One may worry that the effects are driven by multi-establishment firms that reallocate activity to establishments in high-coverage areas at the expense of low-coverage areas. Such internal labor market reallocation has been shown to be important in other contexts (e.g., Giroud & Mueller, 2019). We assess this concern by aggregating both sides of Equation (14) to the firm level, and redoing the empirical analysis for the vacancy outcomes. Reassuringly, Table B6 shows the main findings are quantitatively similar and qualitatively the same.

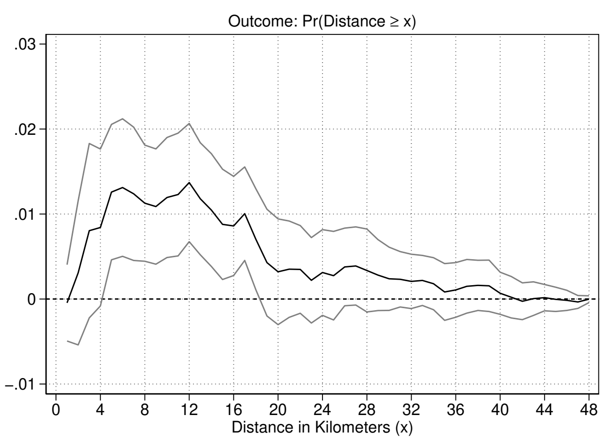
Table B6: Firms' Vacancy Duration, Vacancy Flow and Recruitment Problems.

Dependent Variable:	Vacancy Duration (1)	Vacancy Flow (2)	Recruitment Problems (3)
Broadband Availability	-0.928**	0.022***	-0.030***
(Standard Error)	(0.418)	(0.007)	(0.011)
[p-value]	[0.031]	[0.003]	[0.007]
Dep. Mean	15.3	0.191	0.267
Obs. ($F \times T$)	210,812	1,101,147	129,503

Notes: Column 1 displays estimation results of conditional mean duration in days of vacancy postings posted during year t on broadband internet availability rate in year t using data from the vacancy database. The outcome variable is aggregated to firm level by defining the firms' conditional vacancy duration as the weighted mean of the vacancy durations across establishments within the firm (weighted with the number of vacancies posted). Column B displays estimation results of posting at least one vacancy during year t on broadband internet availability rate in year t using data from the vacancy database. The outcome variable is aggregated to firm level by defining the firm as posting a vacancy if at least one establishment within the firm posts a vacancy. Column C displays estimation results of establishments from the Annual Survey of Establishments' Recruitment Behavior reporting recruitment problems in year t ("Have you encountered problems in recruiting staff during the last three months?") on broadband internet availability rate in year t, with $t \in [2000,2014]$. The Recruitment Survey is conducted in the first quarter of year t, usually opening in February and closing in late March. The outcome variable is aggregated to firm level by defining the firm as having recruitment problems if at least one establishment within the firm reports having recruitment problems. For all panels, the municipality identifier of the largest establishment in the firm (defined by means of number of FTE in year t-1) is defined as the municipality of the firm (and thus a CZ is implied), and the broadband coverage rate is defined as the weighted mean across establishments (weights being the number of FTE in year t-1). For the municipality-level control variables, the simple mean across establishments is used. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels. **p < 0.05, ***p < 0.01.

B.2 Geographic Spillovers

Figure B3: The Distribution of Geographical Distance Between Worker and Establishment.



Notes: The figure shows the estimated effect and associated 90% confidence intervals of broadband availability on the probability that the distance between the employer and the previously unemployed worker is at least x kilometers (measured on the horizontal axis). The specification includes occupation, municipality and calendar year fixed effects, as well as controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure). Heteroskedastic robust standard errors are clustered on CZ levels.

Table B7: Job Seekers' Re-Employment By Commuting Zone of the New Employer.

Dependent Variable:	Re-employment	Re-employment in the Same Commuting Zone	Re-employment in a Different Commuting Zone	Distance to Workplace (Conditional)
	(1)	(2)	(3)	(4)
Broadband Availability	0.016***	0.019***	-0.002	0.230**
(Standard Error)	(0.006)	(0.005)	(0.003)	(0.107)
[p-value]	[0.006]	[0.001]	[0.456]	[0.037]
Dep. Mean	0.659	0.533	0.125	8.5
Obs. ($N \times T$)	1,339,779	1,339,779	1,339,779	695,807

Notes: The sample consists of individuals registered as job seekers with the public employment agency (NAV) for at least one month in year t. This table displays estimation results of availability of broadband internet in year t on the cumulative probability of re-employment (Column 1), employment with establishments in the same commuting zone (CZ) as the worker (Column 2), employment with establishments in the a different CZ as the worker (Column 3) in year t+1 or t+2, with $t \in$ [2000,2012]. Employment is defined as at least one month of employment the following two years after the installation of broadband internet access points. In Column (4), the distance is conditional on being re-employed, which happens for 66% of job-seekers within a two-year period ($N \times T$ = 882,569), and restricted to observations where we could match both workers' residential address and establishments' address at location of operation to exact geographic coordinates and construct reliable distance measures. We could do this for almost 80% of job seekers who were re-employed ($N \times T$ = 695,807). Since matching of establishments' addresses to geographic coordinates was done based on fuzzy matching on text strings, we tried to minimize measurement errors in geographic distance by excluding matches with a distance above 30 miles (approx. 50 kilometers). All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time, municipality and 4-digit code for past occupation. Heteroskedastic robust standard errors are clustered on CZ levels. **$p < 0.05$, ***$p < 0.01$.

Table B8: Workers' Residential Mobility.

Dependent Variable:	Probability of Relocating to a Different Commuting Zone		
Panel:	All Workers	Employed	Unemployed
	(1)	(2)	(3)
Broadband Availability	-0.001	-0.002	0.004
(Standard Error)	(0.001)	(0.002)	(0.004)
[p-value]	[0.347]	[0.227]	[0.244]
Dep. Mean	0.041	0.040	0.056
Obs. ($N \times T$)	24,248,439	18,961,171	1,339,779

Notes: This table displays estimation results of relocating to a different commuting zone (CZ) among employed workers who transfer to a new job (Column 2), and relocating among the sample of unemployed workers who find work (Column 3) on broadband internet availability rate in year t, with $t \in$ [2000,2012]. Employment is defined as at least one month of employment and unemployment is defined as at least one month of unemployment (either full-time or part-time), both measured in year t. CZs are defined based on the classification of Norway into 46 regions by Bhuller (2009) based on commuting patterns. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels.

B.3 Heterogeneity

Table B9: Job Seekers' Outcomes By Education and Occupation.

Panel:	A. College Education			B. Non-College Education		
Dependent Variable:	Re-Employment (1)	Wage (2)	Tenure (3)	Re-Employment (4)	Wage (5)	Tenure (6)
Broadband Availability	0.019***	154***	0.219	0.017**	126***	0.404***
(Standard Error)	(0.007)	(48)	(0.136)	(0.006)	(34)	(0.100)
[p-value]	[0.007]	[0.003]	[0.113]	[0.010]	[0.001]	[0.004]
Dep. Mean	0.725	2,572	8.1	0.640	1,915	7.0
Obs. ($N \times T$)	297,759	297,759	265,174	1,042,020	1,042,020	926,653
Panel:	C. RTI Occupation			D. Non-RTI Occupation		
Dependent Variable:	Re-Employment (1)	Wage (2)	Tenure (3)	Re-Employment (4)	Wage (5)	Tenure (6)
Broadband Availability	0.016**	123***	0.496***	0.017***	127***	0.263***
(Standard Error)	(0.008)	(43)	(0.148)	(0.004)	(34)	(0.086)
[p-value]	[0.045]	[0.006]	[0.002]	[0.000]	[0.001]	[0.004]
Dep. Mean	0.666	2,032	7.3	0.651	2,103	7.2
Obs. ($N \times T$)	720,389	720,389	635,988	602,962	602,962	541,106

Notes: The sample consists of individuals registered as job seekers with the public employment agency (NAV) for at least one month in year t. Panels A-D display estimation results of re-employment (column 1 and 4), starting monthly wage level measured in 2014-USD (column 2 and 5) and tenure length in the first establishment measured in months (column 3 and 6) on broadband internet availability rate in year t, with $t \in$ [2000,2012]. Monthly wage is deflated to 2014-NOK using the CPI and then converted to USD (1 USD = 8 NOK). We drop observations with tenure equal or greater than 48 months due to censoring. Tenure and wages are not conditional on finding a job in either year $t+1$ or year $t+2$, and is set to zero for non-job outcomes. The individuals' education level is defined in year t-1. College education (panel A) is defined according to the first digit in the Norwegian Standard Classification of Education (NUS) as either having bachelor (6), master (7), or doctoral (8) degree, and vice versa for non-college education (panel B). We use information on past occupation to classify job seekers by their routine task intensity (RTI) score. A four-digit occupation is classified as Routine Task Intensive (panel E) if the RTI score of the occupation is greater than the median, and vice versa for non-RTI (panel F). All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time, municipality and 4-digit code for past occupation. Heteroskedastic robust standard errors are clustered on CZ levels. **p < 0.05, ***p < 0.01.

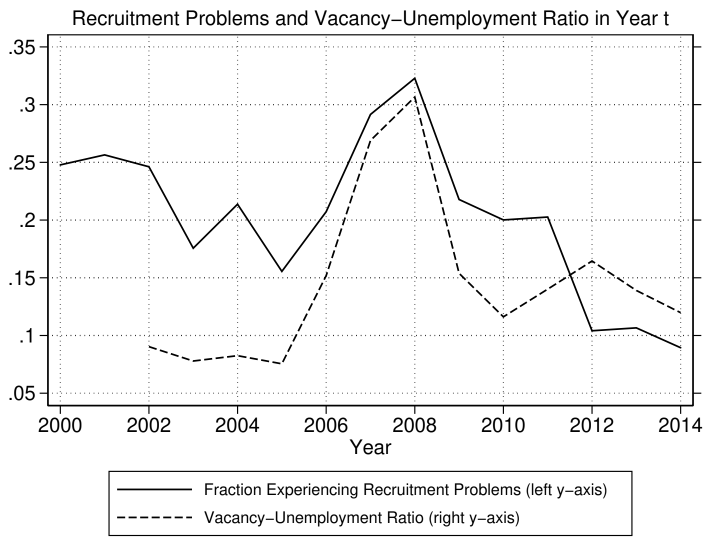
Table B10: Job Seekers' Outcomes By Age and Gender.

	All		Males			Females	
		25-35	35-45	45-55	25-35	35-45	45-55
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Broadband Internet Use							
Has Broadband Internet Access	0.282***	0.144**	0.451***	0.204***	0.316***	0.213***	0.261***
	(0.027)	(0.071)	(0.048)	(0.064)	(0.067)	(0.057)	(0.087)
Number of Observations ($N \times T$)	10,939	1,810	2,087	1,712	1,784	2,142	1,636
B. Job Seekers' Re-Employment Outcomes							
Re-employment	0.024***	0.006	0.005	0.016*	0.039***	0.031**	0.027
	(0.008)	(0.006)	(0.006)	(0.009)	(0.012)	(0.013)	(0.022)
Wage in First Job (unconditional)	201***	189***	275***	272***	111***	152**	192
	(53)	(40)	(70)	(73)	(33)	(59)	(123)
Tenure in First Job (unconditional)	0.531***	0.411**	0.427***	0.682***	0.583**	0.333**	0.244
	(0.116)	(0.163)	(0.154)	(0.208)	(0.230)	(0.159)	(0.256)
Number of Observations ($N \times T$)	1,339,779	309,387	237,276	164,763	329,159	244,488	141,931

Notes: Panel A displays estimation results from the Media Use Survey on the probability of broadband internet access in year *t+1* on broadband internet availability rate in year t, with $t \in [2001{,}2014]$. Panel B displays estimation results for previously unemployed workers on probability of re-employment within the next two years, tenure length in the first establishment measured in months and starting monthly wage level measured in 2014-USD on broadband internet availability rate in year t, with $t \in [2000{,}2012]$. The sample in panel B consists of individuals registered as job seekers with the public employment agency (NAV) for at least one month in year t. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for municipality and year. Heteroskedastic robust standard errors are clustered on CZ levels. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

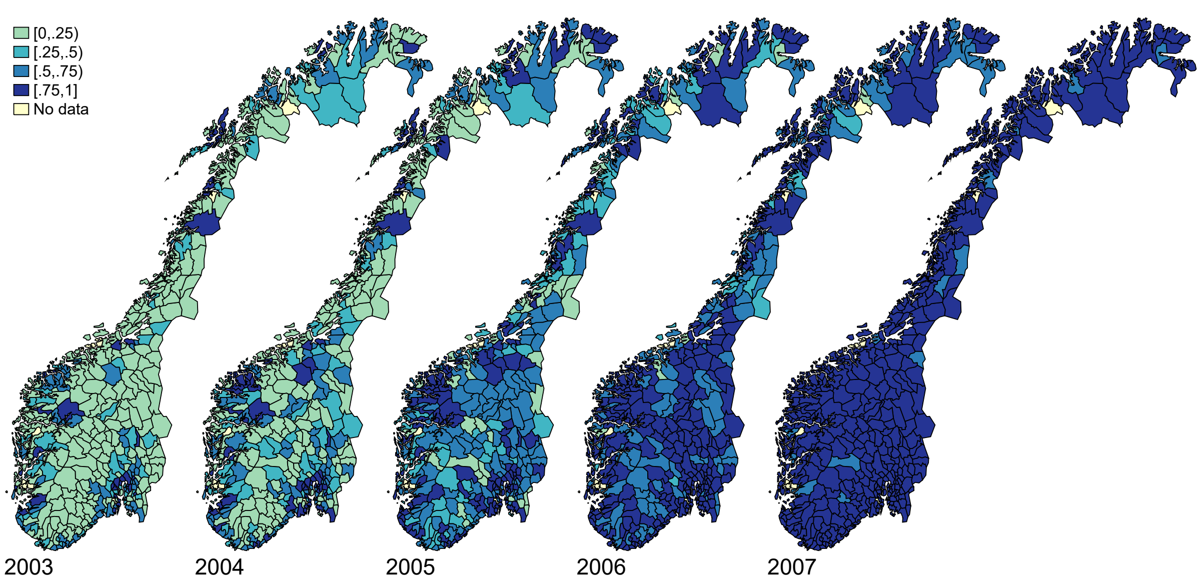
C Appendix: Additional Figures and Tables

Figure C1: Indicator for Recruitment Problems in the Recruitment Survey.



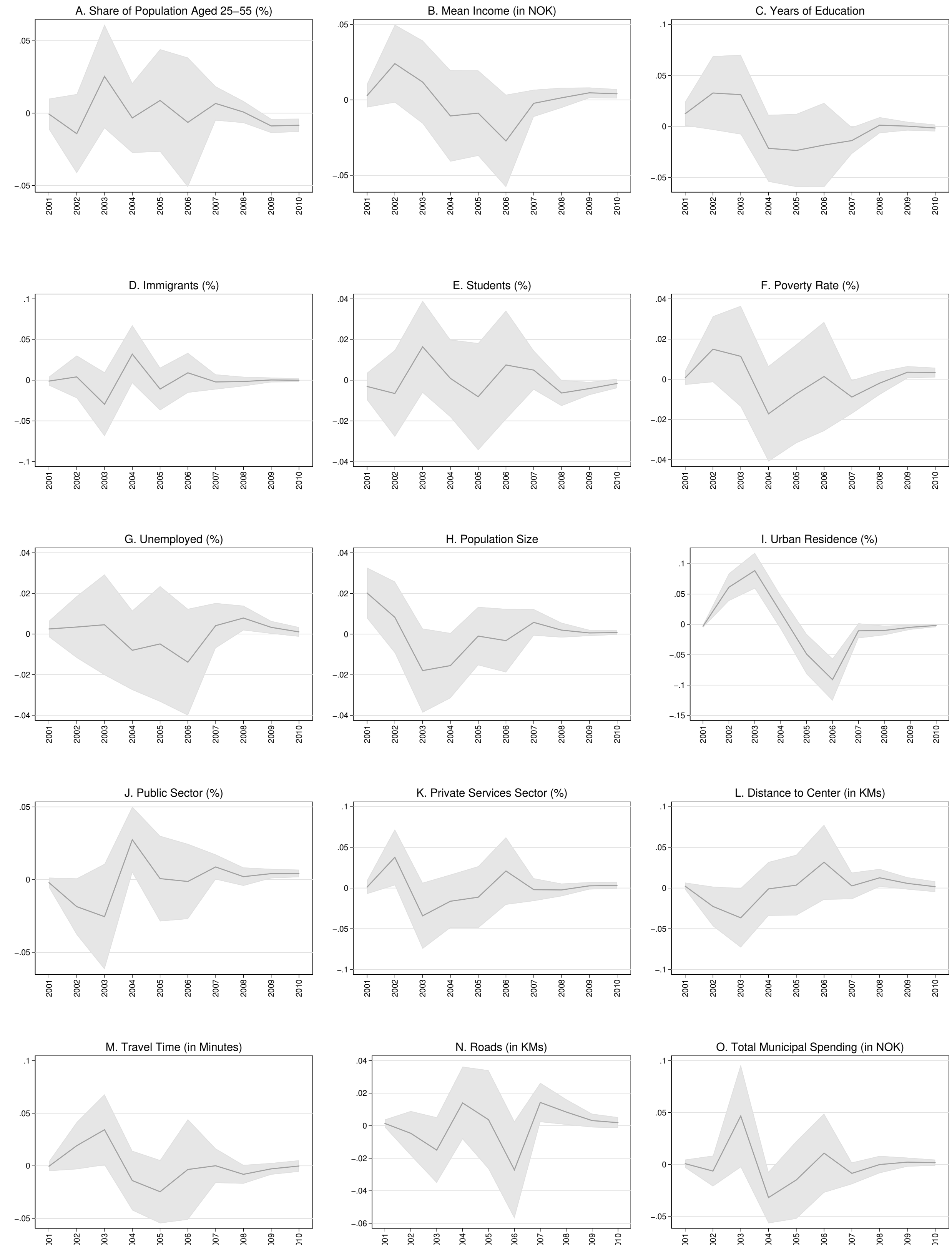
Notes: The figure shows for each year the fraction of establishments experiencing recruitment problems along the vertical axis to the left, and the aggregate vacancy-unemployment ratio along the vertical axis to the right. The fraction of establishments reporting a recruitment problem is from the Annual Survey of Establishments' Recruitment Behavior performed by the National Public Employment Agency (NAV), and the vacancy-unemployment ratio is from the administrative data of job seekers and vacancies maintained by the same agency (see Appendix A.1).

Figure C2: The Geographical Dispersion of Broadband Internet Availability Rates across Norway.



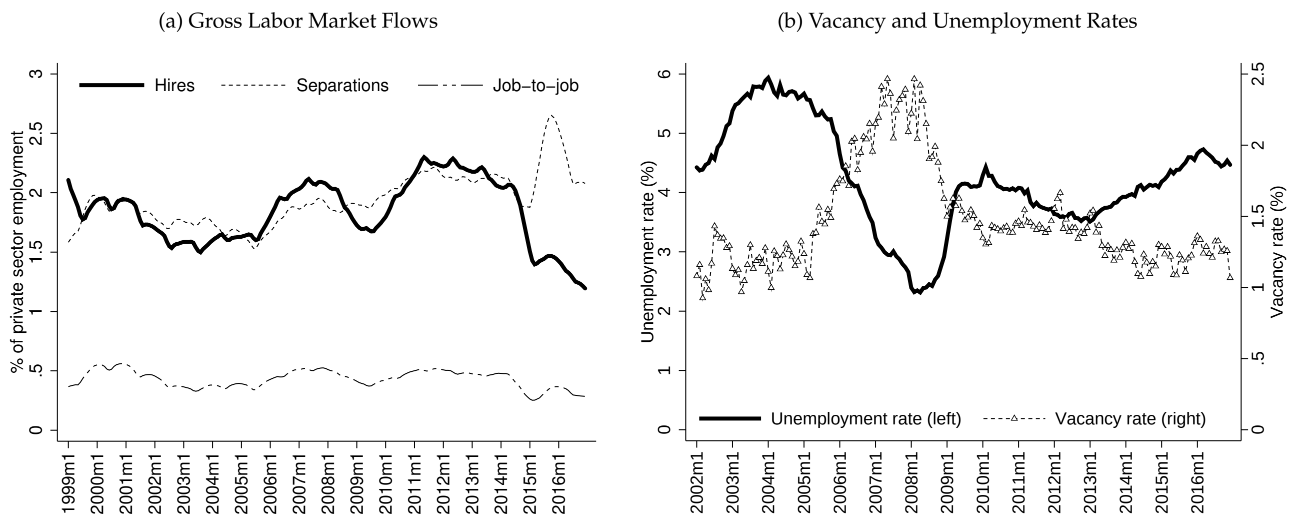
Notes: The figures show the geographical distribution of broadband internet availability rates across Norway in each year from 2003-2007 based on data from the Norwegian Communications Authority (NKOM). For each municipality and year, broadband internet availability rate is plotted, with different colors indicating different levels of coverage.

Figure C3: The Expansion of Broadband Internet by Baseline Municipality Characteristics.



Notes: Figures display the change in broadband internet availability rate, Δz_{mt}, regressed on baseline municipality characteristics. In order to construct these plots, we regress changes in availability rates on municipality-specific baseline characteristics interacted with time dummies, while controlling for the overall time effects. The figures plot the interaction terms for each variable, along with the associated 95 percent confidence intervals.

Figure C4: Stocks and Flows in Norwegian Labor Market.

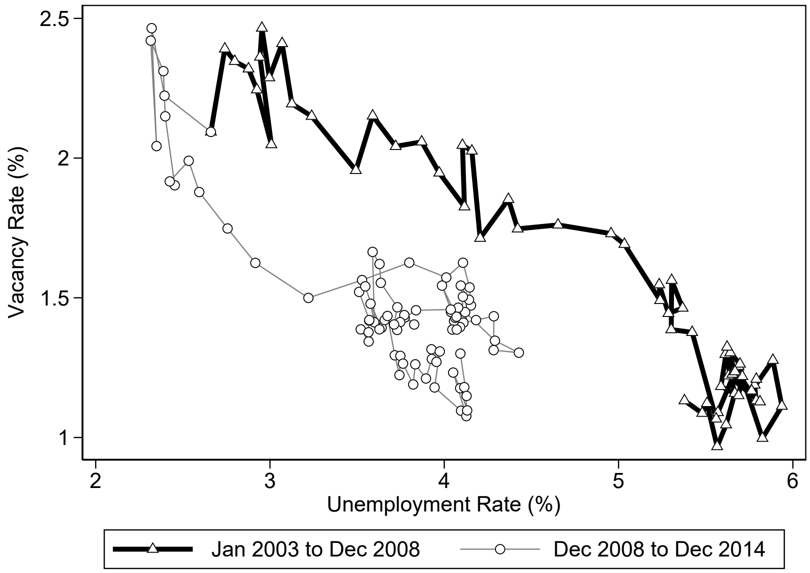


Notes: Figure C4a shows hires and separations in the private sector in Norway for workers aged 25-66. The time series are seasonally adjusted, and smoothed using a three month moving average. Figure C4b shows the monthly unemployment rate among workers aged 25-66, and includes workers who are partially employed and participating in active labor market programs. The vacancy rate is based on vacancy data provided by the National Public Employment Agency (NAV), and is divided by the labor force aged 25-66.

Figure C5: The Distribution of Tenure in First Job.

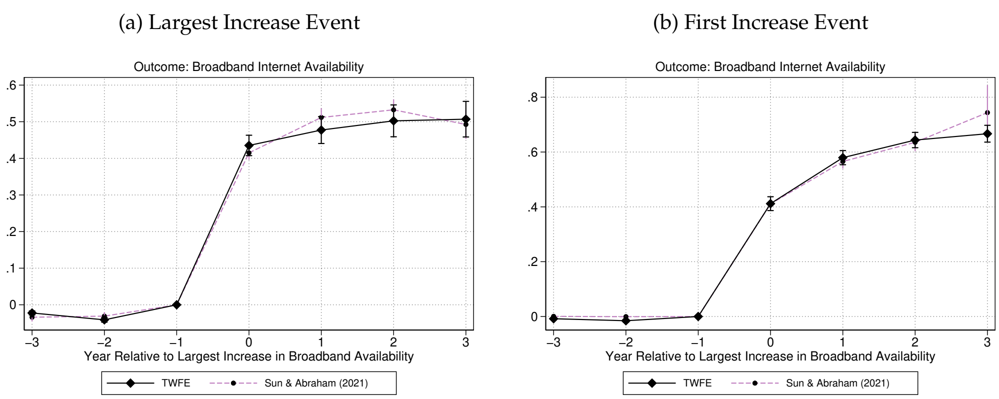
Notes: The figure shows the estimated effect and associated 90% confidence intervals of broadband availability on the probability of having more than x months of tenure (measured on the horizontal axis), unconditional on finding a job. The specification includes municipality and time fixed effects, as well as controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure). Heteroskedastic robust standard errors are clustered on CZ levels.

Figure C6: The Beveridge Curve in Norway.



Notes: This figure plots the relationship between vacancy rates and unemployment rates in Norway using monthly data, divided by the labor force aged 25 to 67.

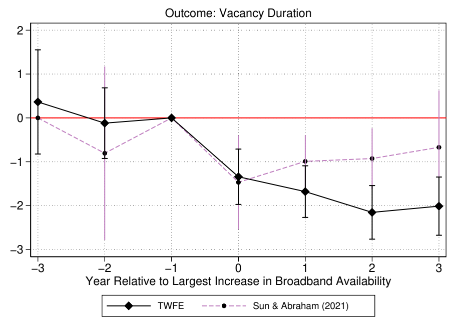
Figure C7: Event Study – Broadband Internet Availability.



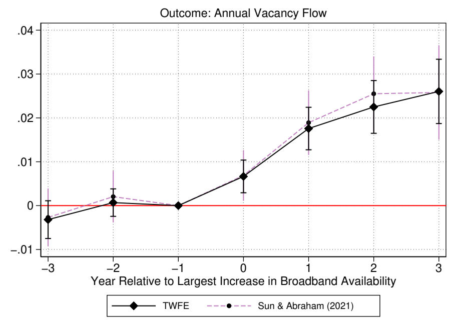
Notes: For each municipality, time zero (i.e., the event year) represents the year with the largest increase in broadband availability rate in panel (a) and the year with the first increase in broadband availability rate of 20% or more in panel (b). The figure plots the coefficient estimates (black solid dots) of relative time dummies $\hat{\delta}_k$ in Equation (13) with the broadband availability rate (BI_{mt}) as the outcome, along with the associated 90% confidence intervals (vertical bars), for a three-year window around the event year. The coefficient on the relative event time dummy for the year prior to the largest increase is normalized to zero ($\delta_{-1} = 0$), so that the coefficients on the other relative event time dummies show responses relative to this year. The black solid lines show estimates based on the standard two-way fixed effects (TWFE) estimation of Equation (13), while the purple dashed lines show the corresponding estimates based on an approach suggested by Sun & Abraham (2021) that uses the last treated cohort as the control group, which is valid under heterogeneous treatment effects. In each plot, we control for municipality and calendar time fixed effects.

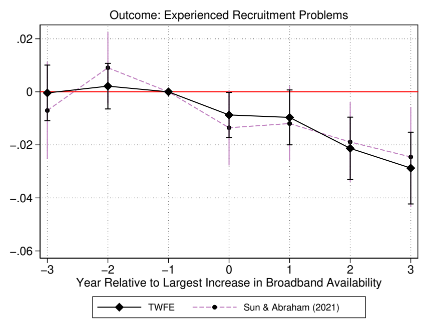
Figure C8: Event Study Around the Year of Largest Increase in Broadband Availability.

(a) Establishments: Vacancy Duration

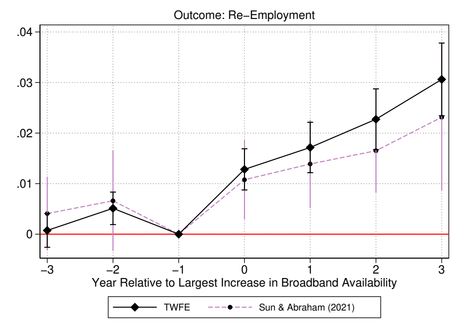


(b) Establishments: Vacancy Flow

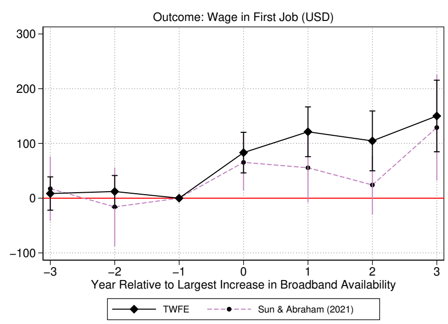




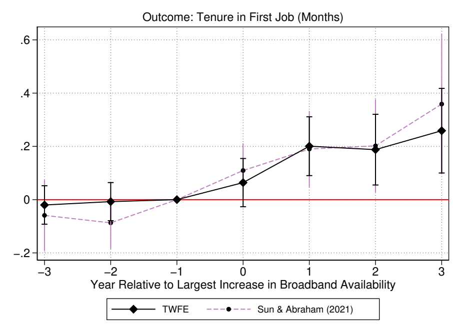
(c) Establishments: Recruitment Problems



(d) Job Seekers: Re-Employment



(e) Job Seekers: Wage in First Job

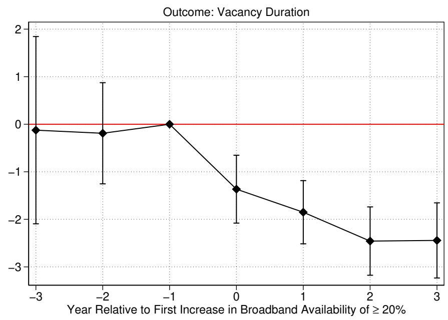


(f) Job Seekers: Tenure in First Job

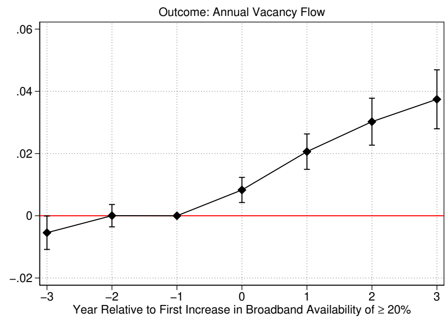
Notes: For each municipality, time zero represents the year with the largest increase in broadband availability rate (i.e., the event year). The figure plots the coefficient estimates (black solid dots) of relative time dummies $\hat{\delta}_k$ in Equation (13), along with the associated 90% confidence intervals (vertical bars), on various establishment and job seeker outcomes for a three-year window around the event year. The coefficient on the relative event time dummy for the year prior to the largest increase is normalized to zero ($\delta_{-1} = 0$), so that the coefficients on the other relative event time dummies show responses relative to this year. The black solid lines show estimates based on the standard two-way fixed effects (TWFE) estimation of Equation (13), while the purple dashed lines show the corresponding estimates based on an approach suggested by Sun & Abraham (2021) that uses the last treated cohort as the control group, which is valid under heterogeneous treatment effects. In each plot, we control for municipality and calendar time fixed effects.

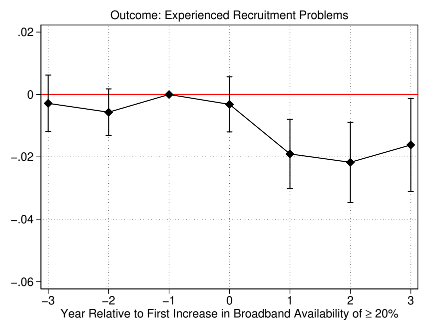
Figure C9: Event Study Around the Year of First Increase in Broadband Availability.

(a) Establishments: Vacancy Duration

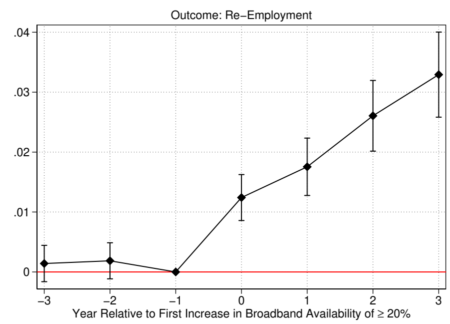


(b) Establishments: Vacancy Flow

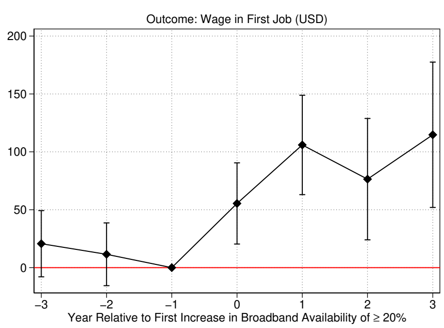




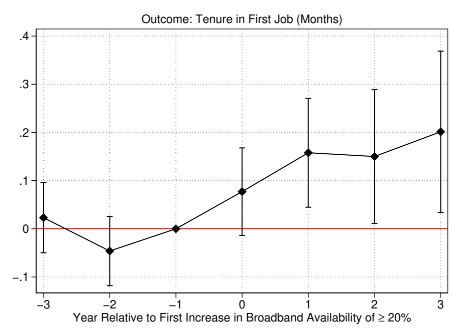
(c) Establishments: Recruitment Problems



(d) Job Seekers: Re-Employment



(e) Job Seekers: Wage in First Job



(f) Job Seekers: Tenure in First Job

Notes: For each municipality, time zero represents the year with the first increase in broadband availability rate of 20% or more (i.e., the event year). The figure plots the coefficient estimates (black solid dots) of relative time dummies δ_k in Equation (13), along with the associated 90% confidence intervals (vertical bars), on various establishment and job seeker outcomes for a three-year window around the event year. The coefficient on the relative event time dummy for the year prior to the largest increase is normalized to zero ($\delta_{-1} = 0$), so that the coefficients on the other relative event time dummies show responses relative to this year. In each plot, we control for municipality and calendar time fixed effects.

Table C1: Summary Statistics – Establishments.

Establishment Characteristics:	Administrative Data: Main Sample (1) Mean	(2) Std. Dev.	Administrative Data: Vacancy Posting Sample (3) Mean	(4) Std. Dev.	Survey Data: Recruitment Survey Sample (5) Mean	(6) Std. Dev.	Survey Data: ICT Use Survey Sample (7) Mean	(8) Std. Dev.
Age	17.5	[13.5]	17.7	[13.7]	20.8	[14.0]	21.5	[13.7]
Size	9.5	[47.3]	9.5	[47.5]	24.1	[109.6]	32.3	[59.6]
< 1	21.8	-	21.9	-	6.1	-	1.7	-
1-3	29.0	-	28.9	-	23.2	-	9.1	-
3-5	14.5	-	14.5	-	16.4	-	10.3	-
5-10	15.5	-	15.5	-	19.9	-	19.4	-
10-50	16.6	-	16.7	-	25.0	-	42.6	-
> 50	2.7	-	2.6	-	9.5	-	16.9	-
Average Years of Education	12.5	[2.6]	12.5	[2.7]	12.5	[2.1]	12.1	[1.9]
Average Annual Wage (2014-USD)	51,689	[60,452]	53,076	[75,249]	52,215	[39,468]	57,629	[35,996]
No. of Obs. ($B \times T$)	1,821,902		1,611,573		222,481		50,265	
No. of Establishments (B)	255,678		240,793		102,771		22,422	
Time Period	2000-2014		2002-2014		2000-2014		2001-2014	

Notes: The table displays means and standard deviations of the establishment characteristics in the samples of establishments used in the analysis. The samples are restricted to establishments with at least one worker. Note that the ICT Use Survey Sample (columns 7-8) consists of firms, while all other samples (columns 1-6) are defined at the establishment level. For consistency, in columns 7-8, if a firm in the ICT Use Survey consists of more than one establishment, establishment characteristics are averaged across all establishments within the firm. Establishment age is top coded to 51 years, while establishment size measures the number of workers employed in the establishment. The distribution of establishments across size categories shows percentage of establishments in each category. Average level of education is measured in years across all workers in the establishment, while the average annual wage (annualized using annual wage paid and annual total number of hours) is deflated to 2014-NOK using the CPI and then converted to USD (1 USD = 8 NOK). All control variables are measured in year t-1.

Table C2: Summary Statistics – Working-age Individuals and Job Seekers.

	Administrative Data				Media Use Survey	
	Working-age Individuals		Job Seekers		Working-age Individuals	
	(1)	(2)	(3)	(4)	(5)	(6)
Worker Characteristics:	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	40.0	[8.72]	37.3	[8.43]	39.6	[8.44]
Female	0.49	[0.50]	0.50	[0.50]	0.50	[0.50]
Married	0.60	[0.49]	0.50	[0.50]	0.75	[0.43]
Fraction with Young Children	0.56	[0.50]	0.57	[0.50]	0.37	[0.48]
Number of Young Children	1.04	[1.12]	1.05	[1.14]	-	-
Fraction with Old Children	0.28	[0.45]	0.19	[0.39]	0.26	[0.43]
Number of Old Children	0.50	[0.92]	0.33	[0.78]	-	-
Years of Education	12.5	[4.22]	11.1	[4.75]	-	-
< 11 years	0.25	-	0.38	-	0.14	-
11-13 years	0.41	-	0.40	-	0.66	-
14-16 years	0.20	-	0.15	-	0.03	-
> 16 years	0.14	-	0.08	-	0.16	-
Number of Obs. ($N \times T$)	24,248,439		1,339,779		10,959	
Number of Individuals (N)	2,758,357		736,467		-	
Time Period	2000-2012		2000-2012		2000-2013	

Notes: The table displays means and standard deviations of worker characteristics for the population of working-age individuals and job seekers. The samples are restricted to individuals aged 25-55. The sample of job seekers in columns 3-4 is further restricted to individuals who were registered as job seekers with the National Public Employment Agency (NAV), being either full-time or part-time unemployed for at least one month. In the administrative data, all control variables are measured in year *t*-1. In the survey data, all control variables are measured in year *t* (and not year *t*-1). Young children are those younger than 18 years, older children are aged 18 and over.

Table C3: Firms' and Workers' Internet Access and Online Activities – Using Analytical Weights.

	A. Firms in the ICT Use Survey		B. Working-age Individuals in the Media Use Survey	
	(1) Unweighted	(2) Analytical Weights	(3) Unweighted	(4) Analytical Weights
Dependent Variable:	1. Has Broadband Internet Access		1. Has Broadband Internet Access	
Broadband Availability	0.301***	0.301***	0.282***	0.267***
(Standard Error)	(0.024)	(0.024)	(0.027)	(0.027)
Base Dep. Mean	0.380	0.380	0.059	0.059
Dependent Variable:	2. Online Job Board Use Rate		2. Uses Internet for Browsing Ads	
Broadband Availability	0.171***	0.170***	0.091**	0.091**
(Standard Error)	(0.038)	(0.038)	(0.044)	(0.043)
Base Dep. Mean	0.284	0.284	0.022	0.022
Obs. ($B \times T$ / $N \times T$)	50,265	50,265	10,959	10,119

Notes: This table displays estimation results of firms from the ICT Use Survey of various outcomes in year *t* on broadband internet availability rate in year *t*, with $t \in [2001,2014]$ (panel A) and households from the annual Media Use Survey on various outcomes in year *t+1* on broadband internet availability rate in year *t*, with $t \in [1999,2012]$ (panel B). The reported dependent mean is pre-assignment, i.e., measured in the year when the broadband internet availability rate equals zero. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels. $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C4: Job Seekers' Re-Employment Outcomes.

Dependent Variable:	A. Re-Employed Within				B. Re-Employed With	
	6 Months	12 Months	18 Months	24 Months	New Employer	Previous Employer (Recall)
	(1)	(2)	(3)	(4)	(5)	(6)
Broadband Availability	0.003	0.009*	0.015***	0.016***	0.016*	0.001
(Standard Error)	(0.004)	(0.005)	(0.005)	(0.006)	(0.009)	(0.006)
[p-value]	[0.489]	[0.099]	[0.009]	[0.006]	[0.090]	[0.879]
Dep. Mean	0.477	0.553	0.622	0.659	0.471	0.188
Obs. ($N \times T$)	1,339,779	1,339,779	1,339,779	1,339,779	1,339,779	1,339,779

Notes: The sample consists of individuals registered as job seekers with the public employment agency (NAV) for at least one month in year t. Panel A displays estimation results of availability of broadband internet in year t on the cumulative probability of re-employment within 6 months (Column 1), within 12 months (Column 2), within 18 months (Column 3) and within 24 months (Column 4). Panel B reports the re-employment rate with a new employer within 24 months after the spell starts (Column 5) and the re-employment with a previous employer (Column 6). All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time, municipality and 4-digit code for past occupation. Heteroskedastic robust standard errors are clustered on CZ levels. *p < 0.10, ***p < 0.01.

Table C5: Outcomes for Individuals Outside the Labor Force.

Dependent Variable:	A. Time Spent on Job Search (Weeks)	B. Labor Market Flows	
		Outside LF to Employment	Outside LF to Job Seeker Status
	(1)	(2)	(3)
Broadband Availability	0.153	-0.005	-0.005
(Standard Error)	(0.095)	(0.006)	(0.007)
[p-value]	[0.114]	[0.345]	[0.424]
Dep. Mean	0.258	0.311	0.120
Obs. ($N \times T$)	68,415	6,232,398	6,232,398

Notes: Panel A displays the estimation results of availability of broadband internet in year t on weeks spent on job search, with $t \in [2000,2012]$. This panel uses data from the Labor Force Surveys, where we focus on individuals outside the labor force. Panel B displays the estimation results of availability of broadband internet in year t on the cumulative probability of moving from outside the labor force to employment in year t+1 and t+2 (column 2) and the cumulative probability of moving from outside the labor force to job seeker status in year t+1 and t+2 (column 3), with $t \in [2000,2012]$. This panel uses administrative register data. Employment is defined as at least one month of employment, unemployment is defined as at least one month of unemployment (either full-time or part-time), and non-employment is defined by the sum of number of months employed and unemployed (either full-time or part-time) within a year being 6 months or less. All specifications include controls for municipal infrastructure (municipal road networks (in kilometers) per capita, average travel time to municipal center (in hours) and public spending on infrastructure), and fixed effects for time and municipality. Heteroskedastic robust standard errors are clustered on CZ levels.

Table C6: Commuting Zone Analysis: Job Seekers' Outcomes.

Dependent Variable:	Reemployment	Time Spent on Job Search (Weeks)	Wage in First Job (USD)	Subsequent Unemploy-ment	Tenure in First Job (Months)
	(1)	(2)	(3)	(4)	(5)
Broadband Availability	0.040**	-0.058	342***	-0.025**	0.893***
(Standard Error)	(0.018)	(1.725)	(103)	(0.010)	(0.284)
[p-value]	[0.029]	[0.973]	[0.002]	[0.019]	[0.003]
Dep. Mean	0.655	15.3	2,051	0.183	7.2
Obs. ($R \times T$)	598	678	598	598	598

Notes: This table displays estimation results of availability of broadband internet on the cumulative probability of re-employment over the next two years (Column 1), weeks spent on job search in year t (Column 2), starting monthly wage in new job following unemployment measured in 2014-USD (Column 3), the subsequent probability of unemployment in year t or t+1 after being employed (Column 4), and tenure length in the first job measured in months (Column 5), respectively. All specifications include controls commuting zones and year fixed effects. Estimates in Column (3) are weighted by the number of job seekers in the CZ that participate in the LFS. The other columns are weighted by the number of job seekers in the CZ. Heteroskedastic robust standard errors are clustered on the CZ level. **p < 0.05, ***p < 0.01.

Table C7: Commuting Zone Analysis: Establishments' Vacancy Duration, Vacancy Flow and Recruitment Problems

Dependent Variable:	Vacancy Duration	Vacancy Flow	Recruitment Problems
	(1)	(2)	(3)
Broadband Availability	-1.436**	0.082***	-0.041**
(Standard Error)	(0.568)	(0.021)	(0.018)
[p-value]	[0.015]	[0.000]	[0.026]
Dep. Mean	15.2	0.222	0.205
Obs. ($R \times T$)	598	598	687

Notes: This table displays estimation results of availability of broadband internet on the conditional mean duration of posted vacancies in days (Column 1), the fraction of establishments posting at least one vacancy (Column 2) and fraction of establishments reporting recruitment problems (Column 3). The regressions are weighted by the number of establishments in the CZ. All specifications include controls commuting zones and year fixed effects. Heteroskedastic robust standard errors are clustered on CZ levels. **$p < 0.05$, ***$p < 0.01$.

Table C8: Commuting Zone Analysis: Employed Workers' Outcomes.

Dependent Variable:	Job-to-Job Transition	Time Spent on Job Search (Weeks)	Wage (USD)	Job-to-Unemployment	Tenure (Months)
	(1)	(2)	(3)	(4)	(5)
Broadband Availability	0.010	-0.267	143.0	-0.012*	0.298
(Standard Error)	(0.009)	(0.320)	(217.6)	(0.007)	(1.766)
[p-value]	[0.233]	[0.408]	[0.514]	[0.072]	[0.867]
Dep. Mean	0.141	1.9	4,347	0.082	87.5
Obs. ($R \times T$)	598	690	598	598	598

Notes: This table displays estimation results of availability of broadband internet on the cumulative probability of a job-to-job transition (Column 1), i.e., having an employment in year t to a new employment in year $t+1$ or $t+2$, weeks spent on job search (Column 2), wage in next job (Column 3), the transition from employment in year t to unemployment in year $t+1$ or $t+2$ (Column 4), and tenure in next job (Column 5), respectively. All specifications include controls commuting zones and year fixed effects. Column (2) is weighted by the number of employed workers in the CZ that participate in the LFS. The other columns are weighted by the number of employed workers in the CZ. Estimates in all columns are weighted by the number of employed in the CZ. Heteroskedastic robust standard errors are clustered on the CZ level. *$p < 0.10$.

Table C9: Calibration Moments.

	Raw Data	Residualized Data: Age	Gender	Age and Gender	Age and Education	Gender and Education	Age, Gender and Education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Transition Rates, All Workers			
A. Weekly Average U-E Rate	0.07625						
B. Weekly Average E-U Rate	0.00335						
1st Wage Quintile	0.0077	0.0074	0.0078	0.0069	0.0071	0.0074	0.0069
5th Wage Quintile	0.0022	0.0026	0.0026	0.0027	0.0022	0.0025	0.0027
C. Weekly Average E-E Rate	0.0016						
1st Wage Quintile	0.0028	0.0026	0.0028	0.0026	0.0027	0.0028	0.0027
5th Wage Quintile	0.0014	0.0015	0.0016	0.0016	0.0016	0.0015	0.0016
				Other Moments			
D Vacancy Duration (Weeks)	1.8466						
E. Search Effort: Unemployed	0.1175						
F. Search Effort: Employed	0.0094						
G. SD Starting Log Wages	0.5798	0.6204	0.6670	0.5980	0.5923	0.6108	0.5724
H. SD Log Wages	0.4807	0.4820	0.6063	0.4656	0.4317	0.4331	0.4245

Notes: This table details the moments used for calibration of the model in Section 5. The weekly U-E and E-U rates (Panels A-B) are taken from Hobijn & Şahin (2009), who estimate the monthly rates using data from 1995–2004, and are here divided by 4 to get weekly rates. E-U rates across quintiles (Panel B) use data from the quarterly LFS survey from 2000–2004, then divided by 12 to get weekly rates, and finally re-scaled to have the same mean as the weekly rate from Hobijn & Şahin (2009) (by multiplying the rates with the factor $0.00335/(0.0070/12)) \approx 5.74$). E-E rates (Panel C) are computed from the quarterly LFS from 2000–2004, and converted into weekly rates by dividing by 12. Column (2)–(7) in Panels B-C show the weekly E-U and E-E rates by wage quintiles, where the distribution is based on the residual from a regression of wage on indicator variables and a constant term. The vacancy duration (Panel D) is computed from the vacancy data from 2002–2004. Search effort for unemployed and employed (Panels E-F) are weeks of search from the quarterly LFS from 2000–2004, divided by 104 weeks. The standard deviation of the starting log wage and log wage in Column (1) of Panels G-H are based on individual-level observations of full-time workers (defined as contracted working hours per week greater than 30) from administrative data covering the years 2000–2004, with wage levels windsorized at 1st and 99th percentile. Column (2)–(7) in Panels G-H show the standard deviations of the residualized wage, where the individual wage is equal to the average wage across either incumbent workers (Panel H) or starting workers (Panel G) plus the residual from a regression of wage level (windsorized at 1st and 99th percentile) on indicator variables, an indicator for starting worker, and a constant term.

Table C10: Implications for Aggregate Unemployment.

	A. Share of Total Change (%)		B. Contribution of Δk, $\Delta\phi_u$ and $\Delta\phi_e$ (%)		
	$\frac{\mathcal{C}.1}{\mathcal{C}.3}$	$\frac{\mathcal{C}.2}{\mathcal{C}.3}$	(2) − (1)	100 − (1)	100 − (2)
	(1)	(2)	(3)	(4)	(5)
ΔUE Rate	96.6	63.8	-32.8	36.2	3.4
ΔEU Rate	50.0	50.0	0.0	50.0	50.0
ΔUnemployment Rate	77.6	54.1	-23.5	45.9	22.4

Notes: We calculate the share of the % of the total model-implied change in Table 7 column 4 that can be attributed to matching efficiency only (column 1) and matching efficiency and vacancy cost (column 2). The final three columns further decompose the marginal contribution of vacancy cost and search cost parameters in explaining the change in unemployment flows and stocks.