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Do digital information technologies help unemployed job seekers find a job? Evidence from the broadband internet expansion in Germany[a]

Nicole Gürtzgen[1)], André Diegmann (né Nolte)[2)], Laura Pohlan[2)] and Gerard J. van den Berg[3)]

[1)] IAB, University of Regensburg, ZEW
[2)] ZEW, IAB
[3)] University of Bristol, IFAU Uppsala, IZA, ZEW, CEPR and CESifo[b]

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Abstract

This paper studies effects of the introduction of a new digital mass medium on reemployment of unemployed job seekers. We combine data on high-speed (broadband) internet availability at the local level with German individual register data. We address endogeneity by exploiting technological peculiarities that affected the roll-out of high-speed internet. The results show that high-speed internet improves reemployment rates after the first months in unemployment. This is confirmed by complementary analyses with individual survey data suggesting that internet access increases online job search and the number of job interviews after a few months in unemployment.

Keywords: Unemployment, online job search, information frictions, matching technology, search channels.
JEL Classification: J64, K42, H40, L96, C26.

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[b] Corresponding author: Nicole Gürtzgen, Institute for Employment Research, Regensburger Str. 100, D-90478 Nuremberg, E-Mail: nicole.guertzgen@iab.de.

1 Introduction

The emergence of the internet as a mass medium has led to a dramatic decline in the cost of acquiring and disseminating information. During the last two decades, this has brought about a significant reduction in all kinds of information frictions, such as in the areas of elections as well as insurance, goods, housing and labor markets. Against this background, there has been a surge of empirical studies dealing with the internet's impact on outcomes such as product market performance (Brynjolfsson and Smith, 2000, Brown and Goolsbee, 2002), voting behavior (Falck et al., 2014) and crime (Bhuller et al., 2013) amongst others. In the context of labor markets, one of the major features that are likely to be affected by the internet is the way how workers and employers search for each other and eventually form a match (Autor, 2001).

The goal of this study is to identify the effect of the emergence of the internet on job search outcomes in the German labor market. Germany provides an interesting case, as - even though access to the internet has been improving considerably over the recent decade - there is still substantial regional variation in households' access to high-speed internet. Closing the last remaining gaps in internet coverage especially in Germany's rural areas is therefore currently considered a major policy goal. Against this background, our study shall help to improve our understanding of whether and to what extent the spread of the internet may have facilitated job search among unemployed job seekers. To investigate the impact of the emergence of high-speed internet on job search outcomes, we explore the effect of the introduction of the digital subscriber line (DSL) technology on reemployment probabilities of unemployed job seekers. To do so, we will exploit variation in DSL availability at the regional level in Germany in order to quantify the net effect of an increase in regional internet availability on the fraction of unemployed individuals who experience a transition into employment.

In exploring the impact of the internet expansion on search outcomes, our study contributes to the (still small) literature that concentrates on different job search channels - especially searching via the internet - and their impact on labor market outcomes. Kuhn and Skuterud (2004) were the first to exploit individual variation in internet *usage* and to evaluate the impact of online job search on unemployment durations for the years 1998-2000 based on the Current Population Survey (CPS). Their results suggest that after controlling for observables, unemployed workers searching online do not become reemployed more quickly than their non-online job-seeking counterparts. This leads the authors to conclude that either internet job search does not reduce unemployment durations or that workers who look for jobs online are negatively selected on unobservables. Based on the same data set, Fountain (2005) performs logistic regressions with a job finding indicator as the dependent variable. Her results provide evidence of a small internet advantage compared to non-online job search in 1998. Moreover, she finds that internet searching advantages had disappeared by 2000. Kuhn and Mansour (2014) replicate the analysis by Kuhn and Skuterud (2004) combining information from the CPS with the National Longitudinal Survey of Youth (NLSY). Comparing the relationship between internet usage and unemployment durations in 1998/2000 and 2008/2009, the authors find that while internet usage was ineffective one decade ago, it was associated with a reduction in the duration of unemployment of about 25% in 2008/2009. Using the German Socio-Economic Panel (GSOEP), Thomsen and Wittich (2010) explore the effectiveness of various job search channels for the job finding probability among unemployed job seekers in Germany. The authors find that internet usage does not raise the reemployment probabilities for this group of job seekers.

By presenting new evidence on the internet's impact on search outcomes for Germany, our study makes several contributions to this literature: First, other than the studies cited above, our empirical approach explicitly accounts for the endogeneity of job search channels. Finding exogenous variation in the availability and use of the internet is a key challenge, as individuals - as well as employers - are likely to self-select into different search channels. Moreover, when looking at regional variation in internet availability, regions with high-speed internet access are likely to differ from those with low-speed internet access along many dimensions. While much of the literature is not able to deal with these issues, our analysis exploits exogenous variation in the availability of high-speed internet access at the German municipality level. The source of this variation, as put forward by Falck et al. (2014), stems from technological restrictions in the roll-out of the first generation of DSL in the early 2000s in Germany. We concentrate on DSL availability as this is the dominant broadband technology in Germany. More specifically, the variation was caused by technological peculiarities of the traditional public switched telephone network (PSTN), through which the early generations of DSL had been implemented. As described by Falck et al. (2014), almost one-third of West German municipalities could not readily employ the new technology as early DSL availability relied on the copper wires between the household and the main distribution frame (MDF) of the regional PSTN. The crucial issue causing exogenous variation in DSL availability is that, while the length of the copper wires connecting households and MDFs - whose distribution was determined in the 1960s - did not matter for telephone services, it strongly affected the DSL connection. In particular, there exists a critical value of 4,200 meters, with municipalities further than this threshold from the MDF having no access to DSL. The only way to provide internet access was to replace copper wires with fiber wires, which took time and was costly. This exogenous variation in internet availability during the early DSL years allows us to use each municipality's distance to the next MDF as an instrument for DSL availability. This enables us to identify an intention to treatment effect (ITT) of an expansion in internet availability on the reemployment prospects of unemployed individuals for less agglomerated municipalities in West Germany.

A second feature that distinguishes our study from previous work is that our analysis relies on administrative data sources. In particular, we use German register data, the universe of the Integrated Employment Biographies (IEB) of the Federal Employment Agency. The data provide an ideal basis for estimating the internet's impact on individual unemployment durations for several reasons: First, the data permit us to precisely measure the duration of different labor market states and transitions between them, most notably transitions between unemployment and employment. Second, due to their administrative nature, the IEB are less prone to panel attrition than comparable information from survey data. This is especially relevant as panel attrition has been recognized to give rise to biased estimates of the rates at which unemployed individuals become employed (Van den Berg et al., 1994). An additional advantage over survey data is the considerably larger number of observations. The latter allows us to construct an inflow sample into unemployment, thereby avoiding the typical length bias that may arise in stock samples of unemployment durations.

Based on this empirical strategy, we document the following key results. Overall, we find that the OLS estimates of the DSL expansion on the reemployment prospects of unemployed individuals in Western German municipalities are downward biased. After accounting for potential endogeneity, our estimates point to modest positive effects for the pooled sample. Breaking down the analysis by socio-economic characteristics suggests that the internet's positive effect is particularly pronounced for males after about a quarter in unemployment. In terms of magnitude, assigning an individual from an "unlucky" municipality (i.e., one that could not readily be supplied with high-speed internet) to a "lucky" counterpart increases the reemployment probability for males by about 2-3% points.

Our results are robust according to a variety of sensitivity checks. In particular, by accounting for demand-side factors we show that the main findings are not driven by labor demand channels which may arise from, e.g., firms increasing online sales in response to the internet expansion. This is consistent with the idea that internet access constraints prior to the internet expansion were more binding for individuals than for employers.[1]

[1] Our study is related to the literature on the aggregate effects of the broadband internet expansion on regional labor market performance. Looking at city-level unemployment rates, Kroft and Pope (2014) exploit geographic and temporal variation in the availability of online search induced by the expansion of the U.S. website Craigslist. They do not find effects on local city-level unemployment rates. In a similar vein, Czernich (2014) points to absence of internet availability on regional unemployment rates in Germany. The author exploits regional variation in broadband internet availability and addresses the endogeneity of internet availability using a similar identification approach as in our study. However, her study is confined to unemployment stocks in the years 2002 and 2006 and does not take into account inflows and outflows into unemployment. Finally, a large body of empirical research analyzes the link between broadband internet and employment as well as economic growth. Examples include the study by Crandall et al. (2007), who exploit regional variation at the U.S.-state level and find a positive association between broadband deployment and private-sector non-farm employment. This evidence is confirmed by Whitacre et al. (2014) and Kolko (2012) for the U.S., who also document a positive association between the

To substantiate our findings we seek to provide more direct evidence on the relationship between an expansion in internet availability and job seekers' search behavior. Specifically, we investigate job search strategies at the individual level, using survey data from the Panel Study on Labour Markets and Social Security (PASS). In particular, we address first-stage effects by looking at whether the availability of internet at home increases the incidence of online job search, i.e. the *use* of the internet as a job search channel. To gain further insights into potential crowding out effects, we also look at whether the availability of internet at home changes the use of alternative job search channels. The results show that home internet access increases online job search activities and that especially male and skilled job seekers with a previous white-collar occupation are more likely to search online for a job. At the same time, we find some evidence for a reduction in the use of non-online search channels for skilled and white-collar workers. These findings suggest that the expansion in internet availability led to better reemployment prospects especially for male job seekers by increasing their overall search intensity, whereas the results for skilled white-collar workers suggest modest crowding out effects.

The remainder of the paper is structured as follows. The next section provides descriptive evidence for the diffusion of broadband internet at the individual and employer level and its importance for job search and recruiting behavior. Section 3 presents some theoretical considerations of how online job search may be expected to affect reemployment probabilities. While Section 4 deals with the sources of empirical identification, Section 5 lays out the overall empirical strategy. The data sources and the sample selection are described in Section 6. Section 7 shows descriptive statistics. Section 8 presents the empirical results, while Section 9 provides further empirical evidence on potential mechanisms underlying individuals' job search behavior. The final Section 10 concludes.

2 Broadband Internet, Online Job Search and Recruiting

Broadband internet diffusion. The diffusion of high-speed internet in Germany started during the years 2000/01 and was based entirely on digital subscriber line technologies (DSL). The fraction of non-DSL broadband technologies such as hybrid fiber coax (HFC) cable or satellite was relatively low at 8% (Bundesnetzagentur, 2012). Prior to the introduction of broadband internet, internet access was only feasible via low-speed technologies such as modems or integrated services digital network (ISDN). DSL provides an access speed that is at least 6-times faster than the old technologies and therefore leads to a considerable reduction in waiting times for loading webpages and downloading files. At the individual level, the fraction using the internet increased within five years from about 37% at the beginning of the new century to 55% in 2005.

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expansion of broadband infrastructure and employment growth. Using municipality data from Germany, Fabritz (2013) finds a moderate positive association between broadband availability and employment.

Online job search and recruiting tools. Turning to the role of the internet for online job search and recruiting, the most important tools include (1) online job boards, which provide websites including searchable databases for job advertisements; (2) job postings on the companies' websites which may (but do not necessarily) solicit online applications as well as (3) networks such as LinkedIn or Xing permitting online search on behalf of employers or headhunters targeting suitable candidates via their online CVs. Online job boards in Germany are typically divided into private job boards such as Monster and StepStone and public job boards, such as that from the Federal Employment Agency. As of 2005, there existed more than 1,000 online job boards in Germany (Crosswaters, 2005). In terms of market shares, the Federal Employment Agency's job board was the most important one, with about 325,000 jobs posted in February 2005, followed by JobScout24 and Monster with about 20,000 jobs. Regarding page views, it was also most frequently used by job seekers, with about 201 million views per month in 2005 compared to 41 million clicks at Monster and 9.2 million clicks at JobScout24 (Grund, 2006).

Other than market shares, the efficiency of the (job board) technology is rather difficult to measure. In December 2003, the Federal Employment Agency implemented a new online job board with the main purpose of aggregating 25 different single systems (*BA-Einzel-Börsen*) into one single portal, the "*Jobbörse*" (Bieber et al., 2005). By incorporating profile matching, this new system was explicitly designed to increase the efficiency of the match between job seekers and employers.[2]

Still, there exists evidence that the new technology was characterized by a couple of inefficiencies at the start of the DSL period. There is some evidence that customers used to stick to the traditional Federal Employment Agency's search engine and did not quickly adapt to the newly established *Jobbörse*, which may reflect initial limitations of its user-friendliness.[3] As described by Bieber et al. (2005), this may have been due to fact that the new job board was too complex for a broad customer segment. This was likely to be particularly relevant for simple jobs and tasks, such as cleaning staff or other low-wage occupations. Overall, these considerations point to a quite limited usability of the *Jobbörse* at the start of the DSL period.

Online search among employers. While the use of online recruiting tools among employers was already widespread in the mid 2000s in Germany, its importance has continued to increase during the last decade.[4] Based upon representative data, recent evidence from

[2]Related to that, Belot et al. (2016) provide experimental evidence on the effects of online advice to job seekers by suggesting relevant occupations. Their results point to a larger number of job interviews, which may provide some evidence in favor of an improvement in the technology to match job seekers and employers.

[3]For example, the first year was characterized by frequent system crashes, long waiting times and confusing search results. There is also evidence that already entered search criteria got deleted after pushing the "back" button.

[4]At the employer level, evidence based on firm-level survey data indicates that about 94% of all firms

the IAB Job Vacancy Survey (Brenzel et al., 2016) supports the importance of online recruiting tools for German employers. In 2015, over 50% of all completed hires were preceded by job postings on the companies' websites and 41% by advertisements on online job boards. Looking at the success rates, however, reveals that among completed hires only 22% (30%) of the vacancies posted on companies' websites (job boards) were successfully filled through these specific recruitment channels. The remaining fraction was eventually filled through other mechanisms such as social networks, newspaper advertisements and private and public employment agencies.

The study by Brenzel et al. (2016) also suggests that online recruiting channels and their success rates appear to play a larger role for high-skilled than medium- and low-skilled jobs. These figures provide some first evidence on an important selection issue, namely the type of jobs being posted online. This is of particular relevance, as the jobs individuals search for online might systematically differ from those job seekers search for via alternative search channels. This, in turn, might be correlated with the length of the unemployment period. The question which jobs are posted online is not only relevant for selection issues, but also important when assessing the internet's effectiveness in helping unemployed job seekers find a job. Clearly, the intensity with which employers use the internet for recruiting purposes is an important prerequisite for the internet's ability in improving job finding prospects. Unfortunately, empirical evidence on the incidence of online recruiting for different types of occupations during the early 2000s is lacking. For this reason, we complement the evidence with further descriptions from the IAB Job Vacancy Survey.[5] Panel (A) of Figure A.1 in Appendix A shows the overall fraction of jobs being posted online among all successful hirings. Panel (B) and (C) show the respective shares broken down by selected occupational categories. The graphs are shown for the years 2005 to 2008, which in most studies are considered to be the DSL period in Germany. Three noteworthy facts emerge from these graphs: First, the fraction of jobs posted online increased by about 15% points from 2005 to 2008 (Figure A.1 Panel

already had access to the internet in 2002. In 2007 the fraction increased to 98%, of whom 93% had high-speed internet access, with 86% having access via DSL or dedicated lines (ZEW ICT-Survey, 2007). Overall, the diffusion of high-speed internet in Germany in the early years of the 2000s suggests that any restriction in internet access was likely to be more binding for individual job seekers than for employers. According to a survey among 1,000 large German employers, the fraction of vacancies that were advertised on the surveyed companies' websites (via job boards) rose from 85% (52%) in 2005 to 90% (70%) in 2014, respectively. Moreover, among the surveyed companies the fraction of hires that resulted from online recruiting has increased from 50% in 2005 to over 70% in 2014 (Keim et al., 2005, Weitzel et al., 2015).

[5]The IAB Job Vacancy Survey is based on a repeated annual cross-section of German establishments, whose sampling frame encompasses all German establishments that employ at least one employee paying social security contributions. The data are available from 1989 onwards, with the most recent waves covering about 15,000 establishments. Apart from information on various establishment attributes, such as size, industry and regional affiliation, the surveyed establishments are asked to report information on their most recent (randomly determined) hiring process. This information includes individual characteristics of the hired employee and characteristics of the specific position to be filled. The data also contain information on employers' adopted search channels relating to the most recent hiring, such as social networks, newspaper ads, private and public employment agencies and most notably the use of companies' websites and online job boards.

(A)). Second, in terms of levels, the fraction of jobs being posted online is larger for more skilled white-collar occupations (Figure A.1 Panel (B)) than less skilled or blue-collar occupations (Figure A.1 Panel (C)).[6] Third, the graphs also illustrate that the first group of occupations experienced an increasing trend in online recruiting during this time period, whereas the relevance of online recruiting for the latter group rather remained constant.

Online search among job seekers. There is also some evidence on the incidence of online job search at the individual level in Germany. According to a survey among individual job seekers, the share of individuals preferring online over print applications rose from 48 to 88% between 2003 and 2014 (Weitzel et al., 2015). Using information from the German Socio-Economic Panel (GSOEP), Grund (2006) focuses on unemployed job seekers who were searching online in 2003. Consistent with the international evidence (e.g. Kuhn and Skuterud, 2004), his results suggest that the incidence was higher among younger and better qualified (unemployed) individuals. This pattern is confirmed by Thomsen and Wittich (2010) based on the same data set, who document an increase in the share of unemployed job seekers searching online from 37% in 2003 to 53% in 2007. Exploiting also the GSOEP, Mang (2012) focuses on job changers. His results suggest that the fraction of job changers who found a new job via the internet was in the year 2007 six times as high as in 2000. To date there is few evidence as to what extent an expansion in internet availability has translated into an increase in online job search and has given rise to potential crowding out effects of other job search channels. Against this background, we will complement the empirical evidence by own empirical analyses based on the PASS survey data in Section 9.

3 Theoretical Considerations

In job search theories, informational frictions (or search frictions) reflect the fact that it takes time and/or effort to find a suitable partner in the labor market (Mortensen, 1986). The process with which workers and firms with vacancies meet is often described by a meeting function m which is a function of the measure of unemployed workers u in the market and the measure of vacancies v. At a given point in time with given u and v, the rate at which meetings occur in the market is then $m(u, v)$. Accordingly, a randomly chosen unemployed individual faces a meeting rate equal to $m(u, v)/u$. The function m can be parameterized as $m(u, v) = \alpha u^{\beta} v^{\gamma}$, with $\alpha, \beta, \gamma > 0$ and with the special case of $\beta + \gamma = 1$ leading to a constant returns to scale function. If the flow of meetings increases for given u and v then this reflects that the meeting technology has improved. Hence, the parameter α is said to represent the meeting technology. In our context, the advent of the internet can be represented by an increase of α. Practical examples are that job boards

[6] Skilled white-collar occupations include managers, technicians, professionals and clerical support workers, whereas less skilled or blue-collar occupations include service and craft workers, plant and machine operators as wells as agricultural jobs.

facilitate the search for keywords and that they provide more information than comparable newspaper print advertisements. Furthermore, because job offers can be published on the internet without major time delays, they are also more up-to-date than comparable print offers.

If employers accept unemployed applicants upon meeting them then the meeting rate $m(u,v)/u$ (i.e., $\alpha u^{\beta-1}v^{\gamma}$) for an unemployed individual is equal to his or her job offer arrival rate which may be denoted by λ. In reality, unemployed job seekers have some leeway in influencing this quantity, by setting their job search effort level. This level is chosen with an eye on search costs. As a result, the parameter α may also depend on the unit search costs. The internet, if it reduces the flow of search costs, leads to an increase in search effort, and hence to an increase of α.[7] There is indeed evidence for this. Job boards allow for dissemination at a considerably lower cost than print advertisements. Also, application costs when applying on the internet may be much lower than the costs involved in sending a letter. The same type of argument applies to employers seeking applicants (see e.g. Autor, 2001 for evidence).

In standard job search models, unemployed individuals do not accept every vacancy they encounter. The reemployment rate can be expressed as $\lambda(1 - F(\phi))$ where F is the distribution of wage offers and ϕ is the reservation wage of the unemployed. An increase of the job offer arrival rate (e.g. due to the introduction of a high-speed internet) creates an incentive to be more selective regarding the quality of the offers: the reservation wage ϕ increases, and offers will be turned down more frequently. However, as shown in Van den Berg (1994), the direct positive effect on the reemployment rate dominates this indirect effect for virtually all possible functional forms of F, so that we may expect the effect of the introduction of high-speed internet on reemployment is still positive. The same type of argument applies to employers selecting appropriate applicants.

A number of equilibrium effects may arise in response to the introduction of fast internet. First, the market size may increase, meaning that, effectively, u and v increase as arguments of the meeting function $m(u,v)$. This may lead to congestion and crowding out, which would attenuate the total effect. The extent to which this is relevant depends on the returns to scale of the meeting function. Generally, this function has been found to display increasing returns to scale or constant returns to scale (see e.g. Eckstein and Van den Berg, 2007, for an overview). Thus, if high-speed internet is widely adopted by unemployed workers as well as firms, then such equilibrium effects do not lead to a reduction of individual reemployment rates. Equilibrium models of markets with informational frictions and heterogeneous agents often display multiple equilibria. It is possible that the adoption of a new information technology in the meeting process causes a shift to

[7] In search models, parameters of the search cost function as a function of search effort and multiplicative parameters in the job offer arrival rate are typically not separately identified from each other; see Van den Berg and Van der Klaauw (2006).

a different equilibrium. Along the lines of Van den Berg (2006), the introduction of the internet may interact with the range of profitable production technologies across firms, in the sense that in the new equilibrium the least efficient production technologies become obsolete. Such equilibrium shifts are of a larger order of magnitude than marginal comparative statics effects. The new equilibrium displays larger firm sizes among the more efficient firms. To the extent that larger firms are easier to locate, this may further reduce search frictions and increase reemployment rates.

We finish the brief overview of theoretical considerations by mentioning two additional issues that are of importance for our paper. First, it is useful to distinguish between different types of search channels or methods. Much of the literature compares formal and informal search channels, but the results are likely to carry over to online versus other search methods. Van den Berg and Van der Klaauw (2006) build a model with two channels and derive relatively mild conditions under which an increase in the rate at which one of the channels generates offers (or a decrease in its cost of usage) increases the optimal usage of that channel and subsequently raises the reemployment rate.

The distinction between channels is potentially important for the timing of the effect on reemployment rates. As argued in the literature (see e.g. Van den Berg and Van der Klaauw, 2018), informal search channels are most important in the early stages of the unemployment spell. Effort along informal channels is cheap. However, the number of friends and relatives is finite, and most friends can only be meaningfully asked a limited number of times whether they know about possible vacancies. Thus, at some point the informal search channel dries up. Newly unemployed workers may therefore first exhaust their informal channel before turning to formal channels. Formal channels remain available because of the arrival of new vacancies over time. Indeed, because of the stock-flow sampling phenomenon, the quality of newly arriving vacancies may exceed the quality of vacancies available online at the moment of entry into unemployment. In sum, the effect of high-speed internet may be increasing with the elapsed duration of unemployment, at least until more drastic disadvantages of long-term unemployment such as stigmatization kick in.

An alternative explanation for a smaller effect at the onset of the unemployment spell concerns the existence of recall options to return to the previous employer. Such options usually disappear after some months in unemployment. Exercising a recall option does not require search effort, and hence fast internet is unlikely to affect this type of reemployment early on in the spell. We investigate the importance of this explanation in the empirical analysis.

The second remaining theoretical issue is that the above deliberations have ignored that high-speed internet also reduces search costs for employed workers engaged in on-the-job search. The latter may lead to ambiguity of the sign of the overall effect on the reemployment rate. Let e denote the measure of employed job seekers and k denote the relative search efficiency of employed workers vis-à-vis unemployed workers. The job offer arrival rate in unemployment λ can now be expressed as $m(u+k\cdot e, v)/(u+k\cdot e)$. Employed job seekers potentially make more effective use of fast internet than their unemployed counterparts. The introduction of fast internet then boosts k and hence lead to crowding out of unemployed job seekers.[8]

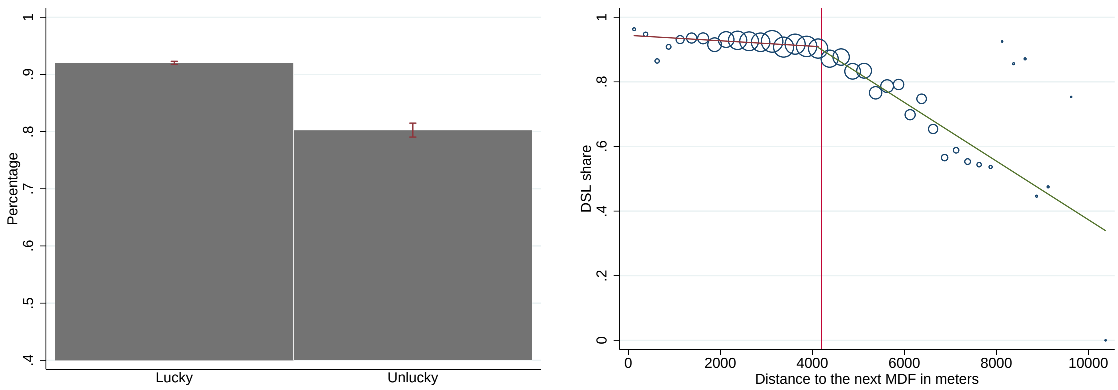
4 Identification

Identifying the effects of internet availability on labor market outcomes suffers from several endogeneity issues. Regions (in our case: municipalities) with high-speed internet access are different compared to regions with lower speed. By simply comparing e.g. unemployed job seekers' reemployment propensities across municipalities with two different high-speed internet levels, one would not be able to estimate the true causal effect. As a result, a simple regression of DSL availability on labor market outcomes at the municipality level would potentially be biased. The same is true when controlling for (municipality) observables, since the expansion of broadband internet might still be correlated with time-variant unobservables (see below).

To overcome potential endogeneity biases, we will make use of regional peculiarities of the West German traditional public switched telephone network (PSTN), which determined the capacity to provide DSL in certain municipalities. As described in Falck et al. (2014) and Steinmetz and Elias (1979), early DSL availability required copper wires between households and the main distribution frames (MDFs). The distribution of MDFs was originally determined in the 1960s with the overall purpose to provide telephone services in West Germany. While municipalities with a high population density have at least one MDF, less agglomerated areas typically share one MDF. The reason is that hosting a MDF required the acquisition of lots and buildings. As the distance to the next MDF did not affect the quality of telephone services, the choice of MDF locations in less agglomerated areas was determined by the availability of such facilities. The crucial issue causing exogenous variation in DSL availability is that, while the length of the copper wires connecting households and the MDFs did not matter for telephone services, it strongly affected the DSL connection. In particular, there exists a critical value of 4,200 meters,

[8] In the literature, such externalities are referred to as "congestion" externalities. At the same time, an increase in search intensity makes it easier for firms to find a match, which gives rise to a second type of externality, the "thick market" externality. Shimer and Smith (2001) argue that for more productive agents the "thick market" externality typically dominates the "congestion" externality, i.e. when stopping search they fail to internalize the inability of other firms to match with them. Thus, ex-ante heterogeneity renders the market solution of search and matching inefficient and implies that productive agents do not search enough, whereas the less productive ones search too much. To the extent that employed job seekers are more productive and potentially make more effective use of the internet than their unemployed counterparts, the internet embodies a subsidy for the more productive job seekers, leading to an efficiency gain. In Section 9.3, we directly address this issue and do not find evidence of such an effect.

with municipalities situated beyond this distance from the MDF had no access to DSL. The only way to provide internet availability was to replace copper wires by fiber wires, which took time and was costly. These technical peculiarities provide a quasi-experimental setting for less agglomerated municipalities without an own MDF, for whom the distance to each municipality's regional centroid to the MDF can be used as an instrument for DSL availability. We exploit this quasi-experimental set-up for West German municipalities that are connected to a MDF located in another municipality and where no closer MDF is available.[9] Because of the quasi-experimental setting spelled out above, we label municipalities with a distance below the threshold of 4,200 meters as *lucky* ones and municipalities with a distance above the threshold as *unlucky* ones.[10] To illustrate DSL availability rates at the household level for both groups, Figure 1 Panel (A) plots the mean fraction of households having access to DSL from 2007 to 2008. Municipalities with relatively short distances to the next MDF (below 4,200 meters) exhibit a fraction of about 92% of households for whom DSL is available. The low confidence intervals at the top of the bars indicate only little variation across municipalities. Once the distance surpasses



(A) Broadband by treatment *(B) Broadband by distance*

Notes: The figures plot the fraction of households with broadband internet (DSL) availability for lucky and unlucky West German municipalities between 2007 and 2008. The left Panel (A) reports averages by treatment status (lucky and unlucky municipalities). 95% confidence intervals are reported at the top of each bar in Panel (A). Panel (B) plots the DSL shares against the distance to the next main distribution frame. The size of the circles in Panel (B) corresponds to the number of municipalities within 250 meter bins. The figures are based on the German municipalities used in the empirical analysis.

Figure 1: Share of households with DSL availability

4,200 meters, the share drops considerably to about 82% with a higher variation across municipalities as reflected by the higher confidence intervals.

Panel (B) plots the DSL shares against the distances to the next MDF for 250 meter bins. The size of the circles corresponds to the number of municipalities. Lucky municipalities below the threshold exhibit a constant DSL share, whereas the DSL share

[9] Our analysis concentrates on West German municipalities because East Germany modernized the distribution frames after German unification.

[10] Roughly one third of the municipalities used in our analysis are unlucky municipalities.

decreases monotonically with higher distances among the unlucky municipalities. There are, however, some municipalities that exhibit a large distance to the next MDF, while simultaneously having relatively high DSL shares.[11] Note that this might violate the exogeneity assumption. To address potential endogeneity concerns for these municipalities, we will later perform robustness checks by excluding these outliers. Moreover, we will also narrow the bandwidth around the threshold, which creates a set of municipalities that are likely to be more comparable in terms of their observables.

5 Empirical Model

In our empirical analysis, we first compare changes in outcomes across municipalities i with different changes in DSL availabilities. Δ_t measures changes from a defined pre-DSL period to the DSL period, indexed by t. Thus, we regress the change in the outcome variable on the change of the share of households who technically have home internet access in municipality i and time period t, ΔDSL_{it}, and a vector of differences in covariates ΔX_{it}:

$$\Delta y_{itm} = \beta_{0m} + \beta_{1m} \cdot \Delta DSL_{it} + \Delta X_{it}' \cdot \beta_{2m} + (MDF_{im} \times \delta_{tm}) + \epsilon_{itm} \tag{1}$$

Given that DSL availability is zero in the pre-DSL period, equation (1) regresses the change in the outcome variable on the actual level of households with DSL availability, DSL_{it}. ΔX_{it} is a vector of characteristics at the municipality level (see Table 1) and ϵ_{itm} is an idiosyncratic error term. Moreover, we introduce MDF-fixed effects (MDF_{im}), thus comparing two municipalities that are connected to the same MDF but differ in their distance to the MDF.[12] In terms of the outcome variable, we concentrate on monthly reemployment probabilities by calculating the share of unemployed individuals experiencing a transition into employment in municipality i in month m.[13] As we estimate this equation separately by month m after the inflow into unemployment, the coefficients and the changes in the outcome variable are indexed by m as well.

The empirical model in equation (1) might be subject to endogeneity issues. Individuals in municipality i might acquire broadband internet in order to search for a job. Moreover, individuals' unobserved productivity attributes, such as the level of motivation and propensity to work, might be correlated with the willingness to pay for broadband internet, such that compositional changes at the regional level might also be correlated with the expansion in high-speed internet. To account for time-varying unobserved effects that are correlated with both, labor market performance and DSL availability at the municipality level, we follow an instrumental variable (IV) approach. As spelled out above, we

[11] Likely reasons for the observed outliers are, for instance, special investment programs for 100 municipalities in Bavaria in 2006 (Wissenschaftliche Dienste des Deutschen Bundestages, 2007).

[12] We interact the MDF-fixed effects with time-fixed effects δ_{tm}, thus, allowing for heterogeneous trends within smaller (MDF) regional units.

[13] See Section 6 for a precise definition of this variable.

use as an instrument the distance from each municipality's center (population-weighted) to the next MDF. The first-stage can thus be written as:

$$\Delta DSL_{it} = \gamma_0 + \gamma_1 \cdot PSTN_i + \Delta X'_{it} \cdot \gamma_2 + (MDF_i \times \delta_t) + \psi_{it} \tag{2}$$

In the first stage, $PSTN_i$ is a dummy variable that takes on the value of *1* for unlucky (treated) municipalities.[14] This IV strategy identifies a local average treatment effect for the compliant municipalities. The first stage does not contain a subscript for month m because the DSL variable only varies with t for each municipality.

6 Data and Sample Selection

Data. The data used in this study stem from different data sources. We measure high-speed internet availability by the share of households at the municipality level for whom digital subscriber line technologies (DSL) are potentially available. The original data stem from the broadband atlas (*Breitbandatlas Deutschland*) published by the Federal Ministry of Economics and Technology (2009). The telecommunication operators self-report covered households with a minimum data transfer rate of 384 kb/s. Hence, for these covered households a high-speed internet connection is technically available. The self-reported data is available for the universe of German municipalities from 2005 onwards. In this study, we use the territorial boundaries of the municipalities from the year 2008. In the literature, the DSL period is typically defined as covering the years from 2005 to 2008, whereas the pre-DSL period refers to the years 1996 to 1999 (Falck et al., 2014).

Even though we measure broadband availability at the household level, it might be conceivable that DSL effects capture some potential demand-side dynamics. Higher broadband internet availability might, e.g., alter the dynamics of firm entries and exits. If labor demand is affected by an increase in high-speed internet availability, unemployed individuals might experience different unemployment durations without necessarily searching online for a job. In our empirical analysis we therefore include demand-side controls in order to isolate the effect of online job search from potential demand-side effects. Using data provided by the *Mannheim Enterprise Panel* (MUP), we retrieve information on the number of firm exits and entries at the municipality level.[15] We further include variables provided by the *Establishment History Panel* of the Federal Employment Agency. These include the total number of establishments and establishment size.

The main outcome variable in this study is a measure of unemployment duration. To measure unemployment durations and reemployment probabilities, we will use German

[14] In a robustness check, we also use the distance as a continuous measure instead of a dummy variable as an instrument.

[15] The data set covers the universe of firms in Germany including a municipality identifier. The earliest available representative year is 2000. Thus, we use the year 2000 as the pre-DSL year.

register data, the Integrated Employment Biographies (IEB) of the Federal Employment Agency provided by the IAB (for detailed information of a sub-sample of this data set, see e.g. Oberschachtsiek et al., 2008 and Table B.2 in Appendix B for a description of all labor market states). This administrative data set covers the universe of all individuals who have at least one entry in their social security records from 1975 on in West Germany and starting from 1992 in East Germany. The data cover approximately 80% of the German workforce and provide longitudinal information on individual employment biographies. Self-employed workers, civil servants, and individuals doing their military service are not included in the data set. For our empirical analysis, we use the universe of unemployed individuals who experienced at least one unemployment spell in the above defined subset of municipalities during our time period of consideration (1996-2008).[16]

The data provide daily information on employment records subject to social security contributions, unemployment records with transfer receipt as well as periods of job search. This permits us to precisely measure the duration of different labor market states and transitions between them, most notably transitions between unemployment and employment. The data do not allow for a distinction between voluntary and involuntary unemployment, though. We therefore follow Lee and Wilke (2009) and define involuntary unemployment as periods of registered job search and/or transfer receipt without a parallel employment relationship. Further information on the definition of un- and non-employment can be found in Appendix B. As the IEB are based on employers' notifications to the social security authorities, they are less prone to measurement error than comparable information from survey data, like e.g. the German Socio-Economic Panel (GSOEP). Additional advantages over survey data include the much lower extent of panel attrition and most notably the possibility to construct an inflow sample, which captures also shorter unemployment spells. To construct a measure of municipality-specific reemployment propensities, we link the universe of individuals with an employment to unemployment transition in every single year during the pre-DSL and DSL period (referred to as the *unemployment inflow sample*) with a municipality identifier at either the individual or establishment level. This allows us to merge the administrative data with information from other data sources (see Table B.1 in Appendix B).[17] In our analysis, we concentrate on individuals who were at least three months employed before they became unemployed. In doing so, we exclude individuals with short employment spells who may display a different pattern of search activity over their spells of employment and unemployment.

[16]When constructing the outcome variables as well as some control variables, we exploit the universe of individuals who experienced at least one unemployment spell in the above defined subset of municipalities during our time period of consideration as well as a random 50%-sample of employed individuals living in the above defined subset of municipalities.

[17]More specifically, the municipality identifier in the administrative data is based on individuals' place of residence. If the place of residence is missing, we use the municipality identifier of individual spells from the previous or subsequent five years or - in a final step - information on individuals' workplace (establishment) location.

Sample selection and main outcome variable. In our empirical analysis, the pre-DSL period covers the years 1998 and 1999, whereas the DSL period covers 2007 and 2008. We focus on these later DSL years for several reasons. First, as set out earlier, we will complement our analysis with individual-level survey data that are available from 2007 onwards. This restricts us in documenting first stage effects starting from 2007 only. Second, there is evidence that the early DSL years may be considered as transition years towards a new technology equilibrium. This appears to be particulary true for the less agglomerated municipalities, which typically have no own MDF and hence form the basis for our empirical analysis. To support this notion, Figure C.1 in Appendix C plots the distribution of DSL availability against time. Panel (A) of Figure C.1 displays the development for agglomerated municipalities, whereas Panel (B) shows the distributions for less agglomerated municipalities. The graphs illustrate that the transition phase among less agglomerated municipalities took apparently longer as compared to urban regions. Third, online search and recruiting technologies appear to have become more elaborated over the course of time. Some evidence for this consideration was documented in Section 2, pointing to some inefficiencies of the Federal Employment Agency's job board technology during the early DSL period. Some further evidence for improvements of the underlying technologies is given by the increasing importance of online recruiting among employers. According to figures from the IAB Vacancy Survey, between 2005 and 2008 the fraction of hirings that were preceded by online recruiting increased from about 45% to over 60% (see Figure A.1 in Appendix A).

As to our main outcome variable of interest, we compute reemployment propensities as the municipality-specific share of individuals reentering employment within m months after the inflow into unemployment, relative to the number of individuals at risk, i.e. those who are still unemployed. Cumulative reemployment probabilities are defined as the complement of the survival function, which is estimated by the non-parametric Kaplan-Meier estimator.[18] Figure C.2 (C.3) in Appendix C plots the distribution of the number of observed individuals in the data set by municipality and period (year). In the median municipality, 93 individuals were entering unemployment during the whole DSL period. The median over all pre-DSL years equals 87. To calculate meaningful averages at the municipality level, we further condition the sample on observing at least five individuals per year and municipality in our final unemployment inflow sample. Due to this condition, the final sample of municipalities (2,988) covers 90% of all available less agglomerated municipalities (3,339) that fulfill the requirements described above.

[18] Formally, the estimator is given by: $\hat{S}(m) = \prod\limits_{i:m_i \leq m} (1 - \frac{d_i}{n_i})$, where d_i is the number of spells that transit into employment in month, m_i, and n_i is the total number of individuals at risk during the time interval $[m_i, m_{i+1}]$.

7 Descriptive Statistics

Given that our empirical strategy focuses on less agglomerated municipalities without an own main distribution frame (MDF), we provide descriptive statistics for the above defined subset of 2,988 municipalities.

Municipality-level variables. Table 1 shows that in West Germany during the years 2007 and 2008 DSL was, on average, available for a fraction of 88% of households at the municipality level. In addition to broadband internet information, the table provides information on further regional characteristics at the municipality level.[19] Panel B of Table 1 shows the main control variables used in the empirical analysis. The first set of variables indicates that the population was aging, the average real daily wage increased over time and that the population became more skilled. The second set of variables refers to the occupational structure at the municipality level. The figures reveal that for less agglomerated Western German municipalities the occupational structure became more service oriented and less production-intensive. Panel C of Table 1 displays the main characteristics of the unemployment inflow sample. The average age exhibits a slight increase from 35.4 to 35.8 years. The same pattern is observed for the share of females among those entering unemployment. Moreover, as expected, low-skilled individuals and foreigners tend to be disproportionately represented in the inflow sample as compared to the overall average skill level and the share of foreigners at the municipality level (see Panel C of Table C.1 for further inflow characteristics).

Demand-side variables. Table C.1 in Appendix C displays firm and establishment information at the municipality level. The figures indicate that the average number of establishments increased in West Germany, whereas average establishment size decreased slightly and amounted to above six. As to firm entries and exits, the table documents that less firms entered and more firms exited the market, while total sales increased.

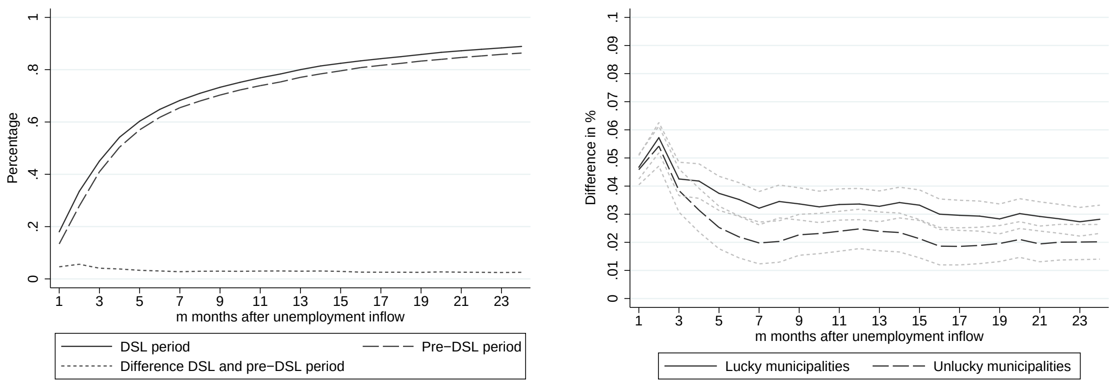
Cumulative reemployment probabilities. Based on the inflow sample at the municipality level, Panel (A) of Figure 2 shows cumulative reemployment probabilities at the municipality level for month, m, after the entry into unemployment, separately for the DSL (2007/08) and the pre-DSL years (1998/99). For example, the cumulative probability of having experienced a transition into employment by month 12 after entering unemployment was about 78% during the defined DSL years, whereas during the pre-DSL years the respective probability was about 75%.

[19] The descriptive statistics of the municipality characteristics shown in Panel B of Table 1 are based on re-weighted averages. As our sample consists of the universe of the unemployed and a 50% sample of employed individuals, we re-weight the averages to match the official unemployment rates. Some further regional characteristics for the pre-DSL and DSL years are also available from Falck et al. (2014) (see Table B.1 in Appendix B).

Table 1: Descriptive statistics

	pre-DSL years 1998/99	DSL years 2007/08
	(1)	(2)
Panel A: Broadband availability		
DSL	0.000	0.878
	(0.000)	(0.190)
Panel B: Municipality characteristics		
Inflow unemployed	30.983	32.022
	(32.195)	(33.774)
Population	1375.209	1384.957
	(1416.369)	(1436.977)
Female population share	0.500	0.502
	(0.018)	(0.037)
Population share aged 18-65	0.659	0.616
	(0.030)	(0.055)
Population share > 65	0.161	0.186
	(0.034)	(0.036)
Net migration rate	0.005	-0.001
	(0.021)	(0.018)
Unemployment rate	0.040	0.040
	(0.015)	(0.020)
Average real daily wage	97.526	98.631
	(12.002)	(17.088)
Low-skilled	0.169	0.151
	(0.045)	(0.037)
Medium-skilled	0.774	0.776
	(0.048)	(0.046)
High-skilled	0.056	0.073
	(0.034)	(0.038)
Foreign nationals	0.025	0.024
	(0.027)	(0.025)
Regional occupational structure		
Agriculture	0.025	0.025
	(0.023)	(0.022)
Production	0.361	0.298
	(0.088)	(0.076)
Salary	0.109	0.116
	(0.041)	(0.038)
Sale	0.066	0.071
	(0.023)	(0.022)
Clerical	0.205	0.212
	(0.057)	(0.055)
Service	0.226	0.270
	(0.063)	(0.073)
Panel C: Inflow characteristics		
Age	35.376	35.832
	(3.415)	(3.398)
Female share	0.370	0.416
	(0.140)	(0.133)
Low-skilled	0.201	0.214
	(0.112)	(0.109)
Medium-skilled	0.756	0.732
	(0.119)	(0.118)
High-skilled	0.043	0.053
	(0.057)	(0.060)
Foreign nationals	0.037	0.035
	(0.058)	(0.054)
Number of individuals in inflow sample	175,426	181,306
Number of municipalities	2,988	2,988

Notes: The table reports municipality-level descriptive statistics for West Germany. The pre-DSL period covers the years 1998 and 1999. The DSL period covers the years 2007 and 2008. The numbers are averaged within the pre-DSL and the DSL years, respectively. Panel A reports the DSL availability rate. Panel B reports municipality characteristics. Panel C reports age, female, education and nationality structure for the unemployment inflow sample. Further control variables are reported in Table C.1 in Appendix C.



(A) Overall *(B) Difference by treatment*

Notes: Panel (A) plots the cumulative probability of becoming reemployed within m months after an inflow into unemployment averaged at the municipality level, distinguishing between the DSL (2007/08) and the pre-DSL (1998/99) period. The bottom line plots the difference between the two upper lines against time. Panel (B) plots the same difference separately for lucky and unlucky municipalities. Grey dotted lines represent 95% confidence intervals.

Figure 2: Reemployment probability and difference between lucky and unlucky municipalities

At the end of the second year, we observe that the cumulative reemployment probability increased further by 10% points. This indicates that much of the dynamics already occurs during the first 12 months of unemployment. For this reason, we concentrate in our empirical analysis on the first year of unemployment.[20] The bottom line in Figure 2 (A) plots the difference between the two upper graphs against time. Overall, this line illustrates that during the DSL years the cumulative probability of experiencing a transition into employment is larger than in the pre-DSL period. Over the first 12 months, cumulative reemployment probabilities increased, on average, by 3.5% points.[21] Panel (B) of Figure 2 further distinguishes between lucky and unlucky municipalities. The graphs show that after the third month lucky municipalities show higher cumulative reemployment probabilities than their unlucky counterparts. This indicates, on a descriptive basis, that municipalities with higher DSL availability experienced a larger increase in reemployment probabilities and, as a result, a larger decline in unemployment durations over the two defined periods.

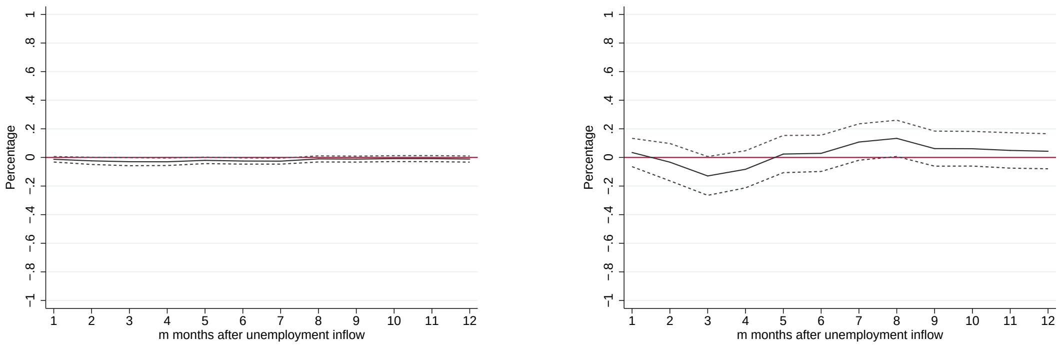
[20]A further reason is that after one year of unemployment, individuals are counted as long-term unemployed and experience different state-governed treatments, such as lower unemployment benefits and increased job search assistance.

[21]Throughout the analyses, we right-censor spells that are ongoing at the moment of the introduction of fast internet. An alternative approach would be to apply the methodology of Van den Berg et al. (2014) to identify and estimate average causal effects on hazard rates by exploiting such ongoing spells while taking dynamic selection due to unobserved heterogeneity into account. We do not pursue this approach because the fraction of such spells in the data is very low. Moreover, we suspect that the availability of DSL only leads to online search with a certain delay of which we do not know its length. Using ongoing spells while ignoring delays would severely underestimate the effects.

8 Empirical Results

8.1 Transitions from Unemployment to Employment

Baseline effects. We now turn to regression models in order to calculate standard errors and conduct hypothesis tests. We start our regression analysis by looking at differences in outcomes between the pre-DSL years (1998/99) and the DSL years (2007/08) over a constant time span. More specifically, we keep the differences between the periods constant at nine years, by connecting 2007 with 1998 and 2008 with 1999. We cluster standard errors at the municipality level as the identifying variation is measured at this level. Figure 3 displays the estimated effects of a 1% point increase in the municipality-specific share of households with DSL availability on the cumulative probability of reentering employment within m months after their inflow into unemployment. The left figure shows the ordinary least squares (OLS) estimates of the first difference model controlling for observable characteristics and MDF-by-year-fixed effects. The OLS coefficients are negative and partly significant at the 10% level during the first months after the inflow into unemployment. According to these estimates, a 1% point increase in DSL reduces the cumulative reemployment probability by about 0.03% points. The right figure shows the IV estimates. The Kleibergen-Paap F-Statistics is 84.0 and the first stage treatment coefficient equals 0.054, indicating that unlucky municipalities have on average 5% points lower DSL rates.



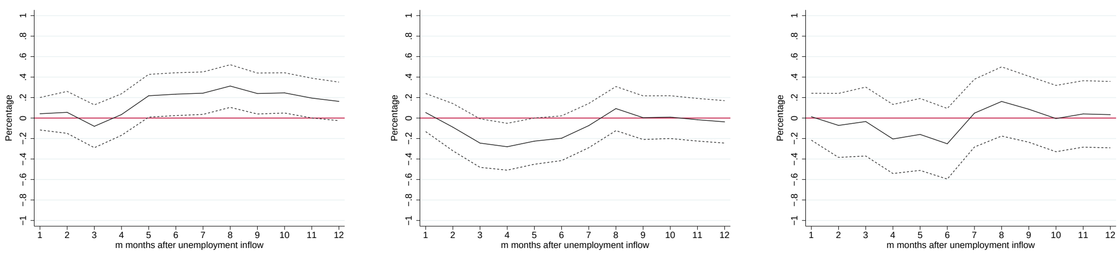
(A) OLS *(B) IV*

Notes: The figure shows the effects of a 1% point increase in the share of households with DSL availability on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment between 1998/1999 and 2007/2008. The regressions are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Dotted lines present the 90% confidence intervals. Standard errors are heteroskedasticity robust and clustered at the municipality level. Panel (A) plots the effects using OLS. Panel (B) corresponds to the IV model, where the distance is measured from the geographic centroid to the MDF and weighted by the location of the population. Regressions are based on 2,988 municipalities and 850 MDFs. The Kleibergen-Paap F-Statistic for the first stage in Panel (B) is 83.98.

Figure 3: IV regression results of DSL on unemployment-to-employment transitions

Therefore, weak identification issues do not apply here. In the IV model the point estimates become positive and partly significant after seven months in unemployment. In terms of magnitude, the coefficient amounts to 0.13 in month eight, which corresponds to up to 1.3% points higher cumulative reemployment probabilities after assigning an individual to a lucky instead of an unlucky municipality, where the unconditional difference in DSL rates (shown in Figure 1) is roughly 10% points.

Heterogeneous effects by socio-economic characteristics. The results from the pooled sample might mask heterogeneous effects across different subgroups. In particular, it might be conceivable that more skilled individuals or younger workers have greater exposure to the internet and thereby make more efficient use of online job search tools. We test this hypothesis by estimating the regressions for different subgroups of the unemployment inflow sample. We first break down the sample by gender as well as age, by distinguishing young ($<$ 35 years) and old workers ($\geq$ 35 years). We further test the hypothesis that the intensity with which employers use the internet for recruitment purposes may matter for its effectiveness in raising reemployment prospects for job seekers. Given that the descriptives from the IAB Job Vacancy Survey (see Section 2) suggested that vacancies for more skilled and white-collar occupations were more likely to be advertised online, we restrict our sample to these occupations. We do so by looking at skilled individuals (who have completed a vocational training or hold a university degree/technical school degree) entering unemployment from a *white-collar* job, with the latter comprising higher clerks, service, clerical or sales occupations.



(A) Male *(B) Young* *(C) Skilled white-collar*

Notes: The figure shows the effects of a 1% point increase in the share of households with DSL availability on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment between 1998/1999 and 2007/2008 separately for males, young individuals (below 35 years) and skilled white-collar individuals. The regressions are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Dotted lines present the 90% confidence interval. Standard errors are heteroskedasticity robust and clustered at the municipality level. The distance is measured from the geographic centroid to the MDF and weighted by the location of the population. Regressions are based on 2,551 municipalities and 803 MDFs for males, 2,359 municipalities and 765 MDFs for young individuals and 2,066 municipalities and 713 MDFs for skilled white-collar individuals. The Kleibergen-Paap F-Statistic for the first stage is 60.0, 53.4 and 35.6 for the three groups, respectively.

Figure 4: IV regression results of DSL on unemployment-to-employment transitions by socio-economic characteristics

Figure 4 plots the estimated coefficients along with their confidence intervals. Compared with the estimates from the pooled sample, Panel (A) of Figure 4 point to a clearer picture for unemployed males, for whom the positive effect of higher DSL availability is particularly pronounced after month four. In terms of magnitude, assigning an individual to a lucky instead of an unlucky municipality increases the cumulative reemployment probability by 2.3% points on average after four months in unemployment.[22] For skilled individuals who entered unemployment from white-collar jobs and young job seekers, we observe slightly negative effects during the first six months in unemployment with significant point estimates for young individuals. This negative effect may point to an inefficient use by the group of individuals below 35 years of age. During the second half of the first year in unemployment, the cumulative reemployment probability stays relatively close at zero. Overall, the comparison of the IV and OLS estimates points to different selection mechanisms. Males seem to be negatively selected, whereas the results for young individuals indicate a slightly positive selection.

Figure D.1 in Appendix D further plots the coefficients measuring the effects on monthly hazard rates rather than on cumulative probabilities. For males, the effects on monthly hazard rates exhibit a similar pattern as the effects on cumulative reemployment probabilities, as there are positive effects between 2%-4% points after four months in unemployment. For skilled white-collar workers and to some extent for young individuals, we document positive effects between 5% and 6% points in month seven and eight. These effects do not translate into much higher cumulative reemployment probabilities (see Figure 4). Still, the estimates indicate that - conditional on being at risk - especially skilled white-collar workers experience positive internet effects on their hazard rates later in their unemployment spells.

The results so far suggest that the increase in DSL availability appears to raise the cumulative reemployment probabilities especially for males. Moreover, a further finding is that the positive effect on reemployment probabilities shows up or becomes significant only with a certain time delay after entering unemployment. In Section 9, we will turn to the underlying mechanisms and address the question to what extent this finding may be explained by heterogeneous changes in job search related outcomes across subgroups, such as job seekers' adopted search channels and their application behavior.

8.2 Robustness Checks

Sample specification and weighting. In this subsection, we conduct several robustness checks. We start by providing regressions results for different sample specifications. First, we include all individuals in the inflow sample irrespectively of the length of their previous

[22]One may argue that these effects are small in magnitude. However, they have a similar order of magnitude as the effects of successful active labor market policies for the unemployed; see e.g. Crépon and Van den Berg (2016).

employment spell. Second, to address the issue that the results might be driven by small municipalities with few inflows into unemployment, we re-estimated our specifications by conditioning on municipalities with at least 500 inhabitants (in addition to conditioning on at least five individuals entering unemployment). As a third check, we allow for a non-employment gap of six months between two unemployment spells as well as between unemployment and reemployment and count this period as unemployment. Finally, we show the results without weighting the municipality-level variables by the number of inhabitants. The estimates shown in Figure E.1 in Appendix E suggest that the overall pattern of results remains unaltered. However, without conditioning on the length of the previous employment spell (Panel *2-A*), the negative effect for young job seekers becomes close to zero.

Demand-side effects. It is not inconceivable that DSL effects capture some product demand dynamics. In particular, an increase in broadband internet availability might affect labor demand, by altering the dynamics of firm entries and exits, the size of firms or total sales. In that case, unemployed individuals might experience different unemployment durations. Figure E.2 in Appendix E shows that the baseline results remain unaltered after excluding the above demand-side variables (i.e. firm entries and exits, the size of firms and total sales) from our regressions. Moreover, the results in Table E.1 in Appendix E indicate that there appears to be no causal effect of an increase in DSL availability at the municipality level on these variables. Note that the average radius of West-German municipalities is only 3.1 kilometers, hence firms' sales radius was likely to comprise unlucky as well as lucky municipalities in the pre-DSL period.

Recalls. A further concern could be that our estimates are affected by potential recalls, e.g. individuals who return to their pre-unemployment establishment.[23] In particular, it might be conceivable that unemployed individuals who are reemployed by the same employer do not actively search for a new job. There is evidence that individuals with recalls experience shorter unemployment durations and lower search intensities as compared to unemployed job seekers entering a new job (Nekoei and Weber, 2015, Fujita and Moscarini, 2013). This could be a potential explanation for the non-positive DSL effect at the beginning of the unemployment spell. Due to the endogeneity of recalls, we refrain from conditioning on this outcome, but rather re-estimate our model after excluding industries with a priori high recall rates. These industries include agriculture, construction, hotels and restaurant, passenger transport and delivery services. Figure E.3 in Appendix E presents the results. For males and young workers, the point estimates are higher than in the baseline specifications, with the estimates for males indicating a DSL effect of up to 5% points.

[23]In our sample, 23% of all individuals returned to their previous employer. The mean unemployment duration of recalls amounts to 98 days, with 75% of all spells being shorter than four months.

Empirical specification. We further conduct several robustness checks with respect to the empirical specification. In particular, we start by narrowing the distance around the threshold and excluding outlier municipalities in terms of their distance to the threshold and their broadband availability shares. In our baseline model, we have relied on 9-year differences in outcomes, by connecting e.g. 1998 and 2007 and 1999 and 2008. Given this procedure, a concern might be that our results are driven by (differences in) outcomes in specific years. To address this issue, we perform two robustness checks with respect to the definition of differences. We first average all variables within the pre-DSL and the DSL years, respectively, and then compute the difference between the averaged pre-DSL and DSL variables per municipality. This procedure is also likely to mitigate potential outlier values in specific years of our variables of interest. Second, to construct differences, we rely on 1998 as the only pre-DSL year, by taking the differences between 2007 and 1998 as well as 2008 and 1998. This robustness check gives rise to different lengths of the measured distances and provides a test of whether the distances and/or specific years matter for the estimated DSL effects. Figure E.4 in Appendix E gives the results for the three socio-economic groups. The figures corroborate the pattern of results that has been found earlier.

Treatment intensity - continuous instrument. The analysis so far has used a dichotomous treatment variable dividing municipalities into lucky and unlucky ones. Panel (B) of Figure 1 shows that the treatment intensity increases with higher distances. As a further robustness check, we therefore specify the first stage equation using the distance as a continuous measure of treatment intensity:

$$\Delta DSL_{it} = \gamma_0 + \gamma_1 \cdot PSTN_i \cdot distance_i + \Delta X_{it}' \cdot \gamma_2 + (MDF_i \times \delta_t) + \psi_{it}, \qquad (3)$$

where $PSTN$ takes on the value of *1* if a municipality is located more than 4,200 meters away from the MDF (unlucky) and zero otherwise. To measure different treatment intensities among the unlucky municipalities, the treatment dummy is interacted with the actual distance to the next MDF centered at the threshold value of 4,200 meters.[24] Figure E.5 in Appendix E presents the results. The positive effect for males stays at around 0.2. The results for young individuals and skilled white-collar workers are similar to the baseline results.

8.3 Effects During the Early DSL Years

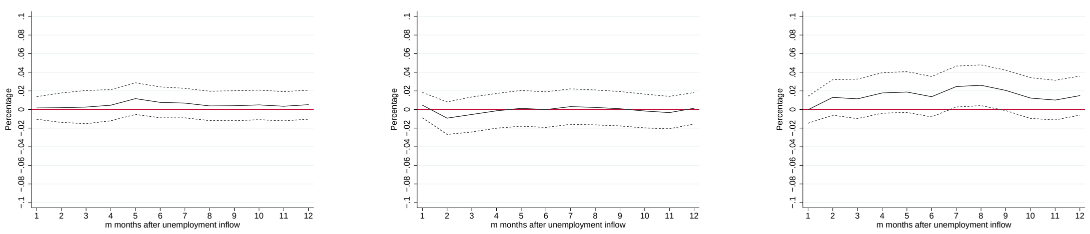
Appendix F presents the results for the early DSL years (2005/06), which have been shown to characterize a transition period towards a new technology equilibrium especially for the less agglomerated municipalities. Figure F.1 presents the baseline results. The overall pattern that emerges from the baseline estimates is that higher DSL availability does not

[24] As noted by Falck et al. (2014), using the distance as an instrument may violate the exclusion restriction. The value of this sensitivity analysis is therefore not clear.

affect the cumulative reemployment probabilities for all defined subgroups. For males, the estimates even point to *lower* cumulative reemployment probabilities during the first three months in unemployment.[25] Overall, the results point to the absence of causal internet effects on cumulative reemployment probabilities during the first 12 months in unemployment. A potential explanation for these findings may be that employers and job seekers were still adapting to the new technology and that job search technologies, such as that from the Federal Employment Agency, were still characterized by inefficiencies during the early DSL period. Taken together, the comparison of the early and late DSL years leads us to conclude that the effectiveness of the internet appears to have considerably improved across these periods. Note that this is in line with the findings of Kuhn and Mansour (2014), who showed that the relationship between internet job search and unemployment durations became more efficient over time.

8.4 Placebo Test

To test for the similarity or divergence in time trends across lucky and unlucky municipalities during the pre-DSL period, we further conduct a placebo test. In particular, we compute the differences in outcomes and covariates between 1999 and 1995 and regress the treatment dummy (and further controls including MDF fixed effects) on the change in the fraction of unemployed entering employment during the first 12 months after entering unemployment.



(A) Change 1999-1995 *(B) Change 1999-1995* *(C) Change 1999-1995*

Male *Young* *Skilled white-collar jobs*

Notes: The figure shows the effects of the treatment dummy on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment in 1995 and 1999 separately for males, young individuals (below 35 years) and skilled white-collar individuals. The endogenous variable is the change between 1999 and 1995. The regressions are population-weighted and performed separately for each month. The list of control variables includes the employment structure, occupational shares and industry shares (see Table B.1 in Appendix B). Due to data availability constraints we cannot control for firm dynamics, total population and age structure. Dotted lines present the 95% confidence interval. Robust standard errors in parentheses.
Number of municipalities: Male: (A): 2,529; Young: (B): 2,339; Skilled white-collar: (C): 2,049.

Figure 5: Placebo results

[25] This effect is relatively robust across the different specifications presented for the years 2007/08.

The results in Figure 5 show that the treatment dummy is insignificant and close to zero for each month after the inflow into unemployment for males and young workers. For skilled white-collar workers, results point to significant positive effects after six months indicating that during the pre-DSL period this group exhibits larger cumulative reemployment probabilities in unlucky municipalities as compared to their lucky counterparts. This trend during the pre-DSL years might lead to a downward bias in the estimated DSL coefficients. The placebo estimates for males and young workers point to a similar pre-treatment trend across lucky and unlucky municipalities and suggest that both groups performed similarly during the pre-DSL years. Overall, this suggests a causal interpretation of the DSL effect on cumulative reemployment probabilities.

9 Mechanisms

9.1 Individual-Level Job Search Strategies Based on Survey Data

Given that our strategy thus far identified an ITT, the question of to what extent the established effects arise from changes in individuals' job search behavior remains unanswered at this stage. To provide evidence on the underlying mechanisms, we complement our analysis by exploiting survey data on job search channels among job seekers from the survey *Panel Study on Labour Markets and Social Security* (PASS). A detailed description of the variables used in this study can be found in Appendix G (Table G.1). The survey started in 2007 as a panel, with the main purpose of surveying low-income households. We use the first waves of the data set, which correspond to the years 2007 to 2009 (see Trappmann et al., 2010 for a detailed description of the data).[26] For each individual we restrict attention to the observation in the first wave in which (s)he participated, and we ignore responses in subsequent waves. If respondents are looking for a job at the time of the relevant interview, they are asked to report their specific adopted job search channels. Possible categories include online job search, search via newspapers, friends/relatives, private brokers, the local employment agencies or further (non-specified) search channels. Moreover, the survey also asks whether a job seeker's household possesses a computer with an internet connection.[27] Table G.2 in Appendix G shows that home internet access is positively correlated with the incidence of online job search. Overall, the fraction of job seekers searching online is more than 25% points higher among job seekers with home internet access as compared to those with no home internet access.[28]

[26] The first wave is conducted mostly in 2007. 73% of all individuals used in our sample are interviewed in 2007. 23% are interviewed in 2008/09. The remaining 4% correspond to the year 2006.

[27] The survey does not specifically ask about broadband internet connection. This can induce misclassification of our explanatory variable. Depending on the extent of misclassification, IV estimates would therefore represent an upper bound.

[28] Analysis of the relationship between home internet access and online job search is based on both unemployed and employed job seekers. However, most individuals were unemployed at the time of the interview date (82%, see Table G.3 in Appendix G) while the employed were mostly in low-income precarious employment with high inflow rates into unemployment.

In what follows, we explore whether home internet access increases the incidence of online job search and changes the use of other job search channels. These results are mostly descriptive as they ignore the fact that the PASS subsamples of unemployed individuals are so-called stock samples of the unemployed in which individuals with unfavorable unobserved characteristics are overrepresented.[29] Similar to our empirical strategy at the municipality level, we again make use of regional identifiers provided by the Federal Employment Agency.[30] Apart from the municipality identifier, we are also able to take advantage of the postal codes provided by PASS. This is a particularly attractive feature of the data, as the combination of the municipality identifier and the postal code provides greater scope for variation in the treatment indicator that is needed for the IV regression (see Figure G.1 in Appendix G for a graphical illustration).

Survey evidence on search channels. Table 2 reports the estimates of the effect of home internet access on the probability of searching online for a job. The F-Statistic in the full sample is close to the benchmark value of 10. This value decreases when analyzing subsamples. While weak instruments in just-identified models are of no major concern as long as the first stage coefficient differs from zero, they are associated with higher standard errors (Angrist and Pischke, 2008, Angrist and Pischke, 2009). Overall, the IV estimates suggest that the OLS estimates are downward biased. This downward bias has also been documented in the analysis using the administrative data. Home internet access is associated with a strong and significant increase in the probability of online job search. Moreover, the results suggest that this effect is most pronounced among males, whereas the point estimate for young individuals is insignificant and lower as compared to that for the pooled sample. Note that the insignificant effect for young job seekers is broadly consistent with the municipality-level results suggesting no positive internet effects on the job finding prospects for this group. A potential explanation for the absent effect of home internet access on online job-search among the young might relate to time-consuming online activities other than job search.[31] Turning to our final subgroup, we are not able to condition on skilled individuals with white-collar occupations (if unemployed, in their previous job) due to sample size restrictions. For this reason, we provide separate estimations for skilled individuals and individuals whose (previous) occupation was a white-collar job. The results show that the point estimate for skilled individuals is of the same order of

[29]Note that this is the main reason for why we do not pursue a 2SIV or 2S2SLS approach. Conceptually, the latter approaches allow for identification of the effect of the use of online search channels on reemployment probabilities, by combining first-stage estimates based on the PASS data with the ITT from the administrative data. Implementing such an approach requires comparable samples. The restriction of our ITT analysis with register data to less agglomerated municipalities and, in particular, to a flow sample renders this approach infeasible.

[30]This empirical exercise is based on all West German municipalities.

[31]It has been shown that broadband internet leads to more entertainment consumption (Falck et al., 2014), music downloads and online shopping (Kolko, 2010), which is likely to be particulary relevant for younger individuals. There is also evidence that primarily young males spend a great deal of time playing computer games (e.g. first person shooter games) and fulfill their need for social interaction by participating in online networks (Jansz and Tanis, 2007, Frostling-Henningsson, 2009).

Table 2: Estimation results for home internet on online job search

	Full sample OLS (1)	Full sample IV (2)	Male IV (3)	Young IV (4)	Skilled IV (5)	White-collar jobs IV (6)
Home internet access	0.273***	0.674**	0.685**	0.517	0.699*	0.774*
	(0.018)	(0.317)	(0.346)	(0.530)	(0.391)	(0.426)
Threshold (first stage)		-0.118***	-0.160***	-0.123*	-0.112***	-0.117**
		(0.037)	(0.053)	(0.067)	(0.043)	(0.048)
F-statistic		10.00	9.06	3.41	6.67	5.99
Observations	2,914	2,914	1,478	1,133	1,884	1,624

Notes: The table reports regression results of home internet access on online job search for individuals in West Germany. The results are based on linear probability models. Home internet access is instrumented by a threshold dummy indicating whether the distance of the centroid of a person's home municipality to the next MDF is above 4,200 meters. The F-test of excluded instruments refers to the Kleibergen-Paap F-Statistic. Standard errors are heteroskedasticity robust and clustered at the household level. The number of observations (2,914) refers to the first observation of individuals during the first three waves. Thus, if we observe an individual multiple times during the first three waves, we use the first information only. The list of control variables includes individual characteristics, household information, father's education and information on the labor market history (see Table G.1 in Appendix G). Tables G.2 and G.3 provide descriptive statistics. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

magnitude as in the pooled sample and significant at the 10% level, whereas individuals whose last job was a white-collar job feature the highest point estimates. Consistent with our considerations in Section 2, this result lends support to the notion that the frequency with which employers' use the internet for recruiting purposes may matter for the intensity with which job seekers make use of online job search channels.

While the results from Table 2 thus far suggest that home internet access increases online job search, it might be conceivable that online job search crowds out non-online job search channels. To address this issue, we further analyze the effect of home internet access on job seekers' use of the remaining reported job search channels provided by the PASS data. Panel A of Table G.2 in Appendix G further reports the share of individuals adopting different search methods broken down by home internet access. The figures point to a slight negative correlation between home internet access and the incidence of non-online job search channels. On average, individuals without home internet access make use of 2.2 non-online search channels, whereas individuals with home internet access use 2.0 non-online channels, with the difference being significant. Note, however, that the internet's effect on job finding probabilities via possible substitution effects is, in general, ambiguous as the overall effect is likely to depend on the relative efficiency of the different channels. To explore which channels are potentially affected by crowding out effects, Table 3 reports the results from regressing search via newspapers, referrals of friends or relatives, the local employment agency and the job seekers own initiative on home internet access. The last column reports the effect on the sum of all non-online job search channels, which also includes private brokers and others.

Table 3: Estimation results for home internet on other job search channels

	Newspapers (1)	Referral (2)	Empl. Agency (3)	Own-initiative (4)	Sum non-online (5)
Panel A: Full sample					
Home internet access	0.228	-0.646*	-0.495	0.056	-1.006
	(0.261)	(0.355)	(0.345)	(0.060)	(0.773)
Panel B: Male					
Home internet access	0.157	-0.380	-0.068	0.063	-0.117
	(0.300)	(0.347)	(0.363)	(0.094)	(0.765)
Panel C: Young					
Home internet access	0.791	-0.567	-0.190	0.165	0.231
	(0.666)	(0.574)	(0.534)	(0.102)	(1.049)
Panel D: Skilled					
Home internet access	0.116	-0.398	-0.196	0.019	-0.504
	(0.296)	(0.394)	(0.379)	(0.077)	(0.899)
Panel E: White-collar jobs					
Home internet access	0.494	-0.584	-0.266	0.076	-0.498
	(0.385)	(0.423)	(0.402)	(0.050)	(0.962)

Notes: The table reports regression results of home internet access on various non-online job search channels for individuals in West Germany. Search via own-initiative comprises contacts to potential employers that were solely initiated by individual job seekers themselves, i.e. that do not reflect a response to a posted vacancy. The results are based on linear probability models. Home internet access is instrumented by a threshold dummy indicating whether the distance of the centroid of a person's home municipality to the next MDF is above 4,200 meters. The F-tests of excluded instruments refer to the Kleibergen-Paap F-Statistic and are equal to those reported in Table 2. Standard errors are heteroskedasticity robust and clustered at the household level. The number of observations is equal to that reported in Table 2. The number of observations (2,914) refers to the first observation of individuals during the first three waves. Thus, if we observe an individual multiple times during the first three waves, we use the first information only. The list of control variables includes individual characteristics, household information, father's education and information on the labor market history (see Table G.1 in Appendix G). Tables G.2 and G.3 provide descriptive statistics. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

The figures provide some weak evidence for a negative effect of home internet access on referrals by friends or relatives (column (2)). The estimated coefficient in the pooled sample is of the same order of magnitude as the corresponding effect on online job search from the previous table. Moreover, we find a negative but insignificant effect on job search via the federal employment agency (column (3)). For the subgroups, the effects on referrals and the employment agency are also negative but insignificant. On the other hand, the estimates indicate that job search via newspapers (column (1)) and own-initiative search (column (4)) are positively related to home internet access (accompanied by large standard errors). This suggests that home internet access induces individuals to search more proactively. Turning to the sum of all non-online job search channels in column (5), the figures reveal insignificant but negative effects (except for young individuals) of home internet access on non-online search. Overall, these findings suggest an (insignificant but sizeable) reduction in non-online job search especially for skilled and white collar jobs, whereas for men crowding out effects seem to play a minor role.

Survey evidence on application intensity. Apart from job search channels, the data set allows us to analyze the number of job applications as a measure of search intensity as well as the number of (realized) job interviews. While the number of applications may be considered as a further measure of search intensity, the number of job interviews is likely to be an important prerequisite of job offers and may therefore be viewed as a (weak) proxy for the arrival of job offers. Table 4 reports the estimation results of the effects of home internet access on these outcomes.[32] For the pooled sample, none of the coefficients from the IV regressions turn out to be significant in Panel A. Comparing the point estimates from the IV specification with the OLS results reveals that the OLS coefficients are downward biased. Turning to the subsamples shows that especially males exhibit a positive home internet access effect on the number of applications. In particular, the estimated coefficient shows that home internet raises the number of applications by more than 12. This substantial increase in search intensity does not translate into a larger number of realized job interviews, though. For the pooled sample as well as for the subgroups (except for young individuals), the figures from Panel B indicate that all estimated coefficients are either negative or very small and insignificant at conventional levels.

Table 4: Estimation results for home internet on application intensity

	Full sample OLS (1)	Full sample IV (2)	Male IV (3)	Young IV (4)	Skilled IV (5)	White-collar jobs IV (6)
Panel A: # Own-initiative applications						
Home internet access	-0.031	5.212	12.033**	0.688	5.832	3.147
	(0.229)	(3.781)	(4.805)	(7.279)	(4.805)	(4.376)
Panel B: # Job interviews						
Home internet access	0.007	0.040	-0.636	0.626	-0.126	-0.415
	(0.066)	(0.897)	(1.170)	(1.364)	(1.156)	(1.147)
Observations	2,914	2,914	1,478	1,133	1,884	1,624

Notes: The table reports regression results of home internet access on the number of applications and realized job interviews for individuals in West Germany. Own-initiative applications may result from using all available search channels. The results for indicator outcome variables are based on linear probability models. Home internet access is instrumented by a threshold dummy whether the distance of the centroid of a person's home municipality to the next MDF is above 4,200 meters. The F-test of excluded instruments refers to the Kleibergen-Paap F-Statistic and is the same as in Table 2. Standard errors are heteroskedasticity robust and clustered at the household level. The number of observations (2,914) refers to the first observation of individuals during the first three waves. Thus, if we observe an individual multiple times during the first three waves, we use the first information only. The list of control variables includes individual characteristics, household information, father's education and information on the labor market history (see Table G.1 in Appendix G). Tables G.2 and G.3 provide descriptive statistics. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

[32] More specifically, the survey asks respondents to report the number of *own-initiative* applications as well as the number of realized job interviews during *the last four weeks*.

9.2 Dynamics Within Individual Unemployment Spells

The results from the municipality analysis show that the positive effect on reemployment probabilities shows up or becomes significant only some time after entry into unemployment. In Section 3 we discussed possible explanations for duration-dependent effects. Along these lines, effects may only kick in after the individual has exhausted his or her informal search channels, where fast internet is thought to be more relevant for formal channels than for informal channels. Another explanation is that reemployment during the first months is driven by recalls at former employers. Yet another explanation is that newly unemployed individuals need time to get acquainted with online search tools. Registering a profile and engaging in online vacancy applications may only result in offers of employment that commences a few months later.

We have already seen that recalls are not responsible for the duration dependence. In the present subsection we use the PASS survey data to see if the other explanations are confirmed by data on the frequency of job interviews over the spell. In particular, we look at how the number of job interviews evolve over the elapsed length of an unemployment spell. As explained earlier, the number and incidence of job interviews is the only measure that is available to operationalize job offers in our data sources. A pattern that would support the above considerations would involve a delayed increase in the incidence of job interviews. Due to data restrictions, we provide the analysis on a purely descriptive basis, by comparing the outcomes of interest between individuals with different unemployment durations. Restricting the analysis to individuals who were unemployed for a maximum of one year reduces the sample size considerably and renders the above IV approach unfeasible.[33]

To rationalize the established delay of the internet's effect on reemployment probabilities, we need to document different time patterns of job interviews over the spell's duration across those with and without home internet access. In this regard, Table 4 has pointed to insignificant associations between home internet access and the number and incidence of job interviews. In what follows, we explore whether this might obscure time-varying effects over the duration of an unemployment spell. To address this issue, Figure G.3 plots the difference in the fraction of unemployed with job interviews by home internet access against different unemployment durations. Overall, the graphs illustrate that among those with home internet access the probability of job interviews is greater during the second to fourth quarter in unemployment as compared to their counterparts without home internet access. However, we wish to note that due to the small sample size

[33]We also show in Appendix G dynamics of online job search over the unemployment spell and document that the incidence of online job search increases during the first year of unemployment among individuals with home internet access. The relative increase is more pronounced among males after four months in unemployment. Among skilled white-collar workers, this increase starts after six months in unemployment (see Figures G.2 in Appendix G). This time pattern of online job search effort matches the results for the monthly hazard rates, indicating that reemployment hazards are 5-6% points higher in month 7 and 8.

these differences are estimated quite imprecisely. For males, home internet access raises the incidence of job interviews even more pronounced during the second to fourth quarter in unemployment - but again imprecisely estimated. The time gap is found to match that from the municipality level estimations. This may potentially account for the delay of the established positive effects of the internet on unemployed job seekers' reemployment probabilities. Overall, these patterns are consistent with the internet expansion raising job offer arrival rates with a certain time delay of at least one quarter in unemployment.

Figure G.3 in Appendix G also shows the corresponding graphs for the other three subgroups. For young individuals, job interviews seem to be lower during the first quarter. Along with the insignificant overall online job search incidence this result may provide a rationale for the negative DSL coefficient documented in Section 8. The increase in the incidence of job interviews during the second to fourth first quarter in unemployment is also visible for young and skilled white-collar workers, but less pronounced than for males.

9.3 Search Externalities

In this section, we address potential search externalities. A first source of spill-overs relates to interdependencies across lucky and unlucky municipalities. If the job finding prospects of unemployed job seekers located in lucky municipalities improve due to better online job search opportunities, this might, in turn, reduce the respective prospects of those located in unlucky municipalities. The underlying notion is that job seekers in lucky and unlucky municipalities are likely to compete for jobs in the same local labor market, such that those benefitting from the internet expansion may impose a congestion externality on their "unlucky" counterparts. The quantitative relevance of such spill-overs is likely to depend on individuals' and employers' search radius and the extent to which this radius has been altered by the internet expansion. As long as interdependencies arise from employers' behavioral changes, this should limit the scope for spill-overs. The reason is that employers' search radius was likely to comprise unlucky as well as lucky municipalities already in the pre-DSL period. At the same time, however, there is evidence that the pre-DSL restrictions in internet access were more likely to be binding for workers than for firms (see Section 2). Thus, we would expect that potential spill-over effects primarily arise from the behavior of individual job seekers, whose search radius was likely to be affected by the internet. Note that in the presence of such externalities, our estimated coefficients would have to be interpreted as effects inclusive of potential general equilibrium spill-overs.

While we are not able to directly deal with such kinds of externalities, we attempt to address externalities caused by a different group of job seekers, who are not included in our treatment and control group. As set out in Section 3, the internet expansion not only reduces search costs for the unemployed, but also for those searching on-the-job. To the extent that the internet also raises the job finding prospects of the employed, the resulting search externalities may mitigate or counteract the internet's effect on unemployed job seekers' job finding rates. To test this notion, we explore whether the expansion in broadband availability has led to an increase in job-to-job transitions among employed individuals. To rule out potential match quality effects, we confine our analysis to employment relationships that had already started prior to the DSL-period. To do so, we construct a stock sample of individuals who were employed at the cut-off date of 30th of June 2000 and who were still employed at the same employer at the start of 2007. For this sample, we then calculate the fraction of job-to-job transitions at the municipality level during the late DSL years 2007/08. To compare this outcome with the pre-DSL period, we construct an analogous sample and outcome variable for the pre-internet period, based on individuals who were employed at the cut-off date of 30th of June in 1991 and who were still employed at the same employer at the start of 1998 (see Table H.1 in Appendix H for basic descriptive statistics for both samples). This implies that we exclude individuals from our sample who experienced a transition from employment to unemployment or non-employment during the pre-DSL and DSL period, respectively. While this procedure allows us to rule out match quality effects, which - depending on the direction of the internet's effect on match quality - are also likely to affect the extent of job-to-job transitions, it comes at the cost of restricting the analysis to very stable employment relationships.

Columns (1) and (2) of Table 5 show the OLS and IV results for the full sample. The coefficients are negative and not significantly different from zero. An increase in

Table 5: Spill-over estimation results, job-to-job transitions

	Full sample		Male	Young	Skilled white-collar
	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)
ΔDSL	-0.016 (0.012)	-0.049 (0.063)	-0.101 (0.082)	-0.025 (0.108)	-0.026 (0.089)
Threshold (first stage)		-0.054*** (0.006)	-0.053*** (0.006)	-0.051*** (0.006)	-0.050*** (0.006)
F-Statistic		71.07	67.95	63.84	61.76
Municipalities	2,523	2,523	2,497	2,376	2,424

Notes: The table shows the effects of a 1% point increase in the share of households with DSL availability on the probability of job-to-job transitions for a stock sample of employed individuals (see Table H.1 in Appendix H). The estimates in columns (1) and (2) are based on a sample of individuals whose employment relationship started prior to the DSL/pre-DSL period. Columns (3)-(5) show the results separately for males, young individuals (below 35 years) and skilled white-collar individuals. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Standard errors are heteroskedasticity robust and clustered at the municipality level. The distance is measured from the geographic centroid to the MDF and weighted by the location of the population. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

DSL availability does not affect the probability of a direct job-to-job transition at the municipality level. If anything, the results point to slightly negative effects. A similar result holds if the regressions are performed separately by subgroups. Overall, these findings argue against the view that increased competition from employed job seekers should have played a significant role for the internet's effect on the job finding prospects of their unemployed counterparts. To the extent that employed individuals may have made use of their workplace internet access for job search, these results are consistent with the fact that the restrictions in internet access were less likely to be binding for employers than for private households during the DSL period.

10 Discussion and Conclusions

In this paper, we study the effects of the expansion in broadband internet (DSL) on reemployment probabilities among unemployed job seekers by exploiting regional peculiarities of the traditional public switched telephone network in West Germany. Overall, our results suggest that effects of the internet on the reemployment prospects of unemployed individuals based on OLS estimates are downward biased. After accounting for the endogeneity in internet availability, our estimates for the pooled sample point to slight positive internet advantages for unemployed job seekers with a certain time delay. Breaking down the analysis by socio-economic characteristics suggests that the internet's positive effect is particularly pronounced for male job seekers after spending four months in unemployment.

Given that the above strategy identifies an ITT, we also address first-stage effects by retrieving information on the adoption of job search channels from the PASS survey data. Using these data, we explore whether the availability of internet at home raises job seekers' *use* of the internet as a search channel. To gain further insights into potential crowding out effects, we also look at whether home internet access changes the use of alternative job search channels. The results, which are based on the same IV strategy as in the municipality-level analysis, indicate that home internet access is associated with an increase in online job search activities. Consistent with our municipality-level results, especially male and skilled white-collar job seekers are found to increase online job search if they have home internet access. The results provide also some evidence for crowding out effects on non-online job search, which are most pronounced (albeit insignificant) for white-collar and skilled workers and which appear to play less of a role for male job seekers. These findings lead us to conclude that the expansion of internet availability led to better reemployment prospects especially for males via raising the intensity with which this group has made use of the internet to search for jobs, without at the same time reducing their overall search effort.

The survey data also reveal that home internet access raises the number of own-initiative applications, especially for males. A further finding was that the positive effect on reemployment probabilities shows up or becomes significant only with a certain time delay after entering unemployment. To provide empirical support for a delayed positive effect on job offers, we further explore whether the incidence of job interviews across those with and without home internet access varies over the duration of an unemployment spell.

Our findings provide some tentative evidence that internet access appears to give rise to an increase in the incidence of job interviews with a certain time delay, which appears to match the delay found in the municipality level analysis. These results also offer potential directions for future research. Given that the internet raises the number of potential jobs that need to be evaluated against each other, future research should examine in more detail the internet's effect on job quality, e.g. whether the internet helps job seekers find a better job.

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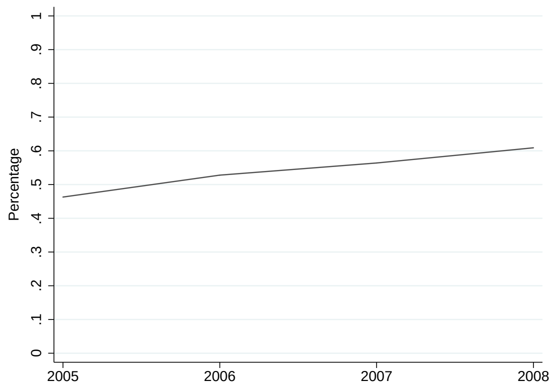
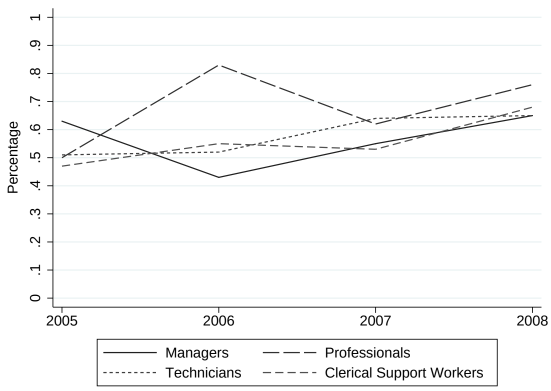
Appendix

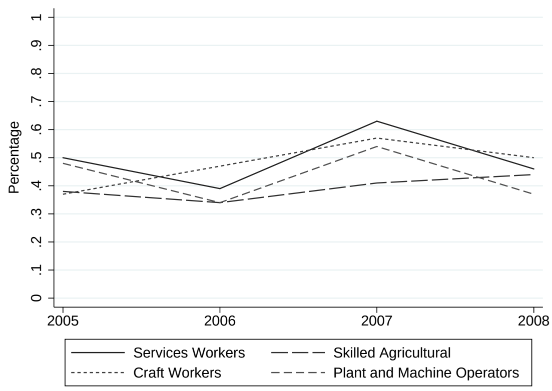
A Evolution of Online Recruiting



(A) Overall online recruiting



(B) Online recruiting by occupation - I



(C) Online recruiting by occupation - II

Notes: The plots show the fraction of vacancies being posted online among all successful hirings. Panel (A) shows the overall time trend. Panel (B) and Panel (C) show the trend by different occupational categories.

Figure A.1: Evolution of online recruiting

B Administrative Data Addendum

Table B.1: Definition of variables

Internet variables	
Broadband internet	Fraction of households in municipality i at year t with a subscription to DSL defined by an access speed of 384 kb/s or above. Documented numbers start in 2005.
	Source: Breitbandatlas Deutschland
Treatment	Equals 1 for municipalities in West Germany with a distance of more than 4,200 meters to the next main distribution frame (MDF). The distance is calculated using the geographic centroid weighted by the location of the population.
	Source: Falck et al. (2014)
Control variables	
Population	Number of inhabitants in municipality i at year t.
	Source: Falck et al. (2014)
Inflow unemployed	Number of individuals who became unemployed in municipality i at year t.
	Source: IEB, Federal Employment Agency
Female population share	Fraction of females in municipality i at year t. The female share is also measured for the inflow-specific sample.
	Source: Falck et al. (2014) and IEB, Federal Employment Agency
Population aged 18-65	Fraction of the population aged between 18 and 65 years in municipality i at year t. The pre-DSL fraction refers to the year 2001.
	Source: Falck et al. (2014)
Population aged > 65	Fraction of the population aged above 65 years in municipality i at year t. The pre-DSL fraction refers to the year 2001.
	Source: Falck et al. (2014)
Net migration	Net migration rate in municipality i at year t. The pre-DSL fraction refers to the year 2001.
	Source: Falck et al. (2014)
Unemployment rate	Unemployment rate in municipality i at year t. The pre-DSL fraction refers to the year 2001.
	Source: Falck et al. (2014)
Foreign nationals	Fraction of foreigners in municipality i at year t. The nationality is also measured for the inflow-specific sample.
	Source: IEB, Federal Employment Agency

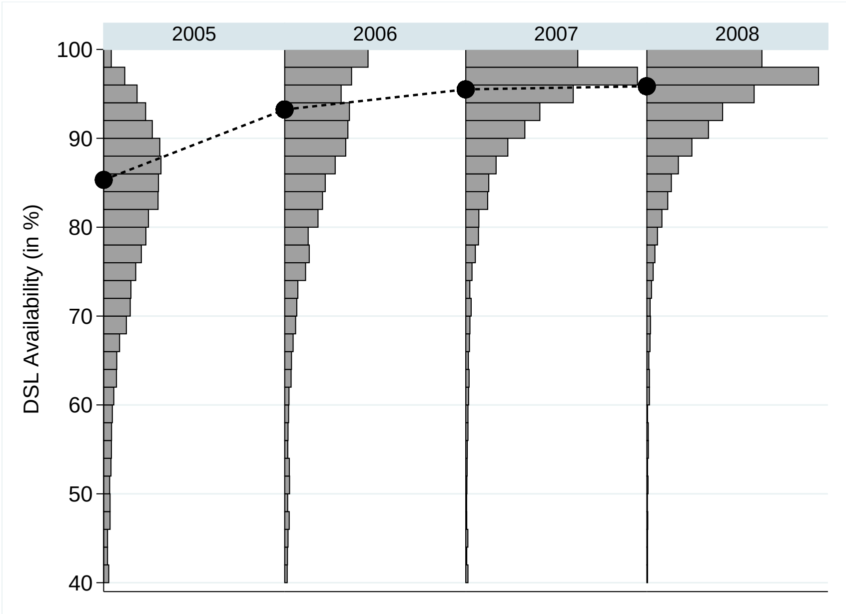
Table B.1: Definition of variables *(continued)*

Control variables	Description
Occupation	Occupational shares in municipality i at year t calculated for the categories agriculture, production, salary, sale, clerical and service (ref. service sector). The occupation is also measured for the inflow-specific sample. Source: IEB, Federal Employment Agency
Industry	Industry shares in municipality i at year t calculated for the categories agriculture/energy/mining, production, steel/metal/machinery, vehicle construction/apparatus engineering, consumer goods, food, construction, finishing trade, wholesale trade, retail trade, transport and communication, business services, household services, education/helth, organizations, public sector, else. Source: IEB, Federal Employment Agency
Skill level	Skill level in municipality i at year t. *Low skilled*: No degree/ highschool degree *Medium skilled*: Vocational training *High skilled*: Technical college degree or university degree. Skill level is also measured for the inflow-specific sample. Missing and inconsistent data on education are corrected according to the imputation procedure described in Fitzenberger et al. (2006). This procedure relies on the assumption that individuals cannot lose their educational degrees. Source: IEB, Federal Employment Agency
Real daily wage	Average real daily wage in municipality i at year t calculated among full-time employees. Gross daily wages are right-censored due to the upper social security contribution limit. To address this problem, we construct cells based on gender and year. For each cell, a Tobit regression is estimated with log daily wages as the dependent variable and age, tenure, age squared, tenure squared, full-time dummy, two skill dummies, occupational, sectoral as well as regional (Federal State) dummies as explanatory variables. As described in Gartner (2005), right-censored observations are replaced by wages randomly drawn from a truncated normal distribution whose moments are constructed by the predicted values from the Tobit regressions and whose (lower) truncation point is given by the contribution limit to the social security system. After this imputation procedure, nominal wages are deflated by the CPI of the Federal Statistical Office Germany normalised to 1 in 2010. Source: IEB, Federal Employment Agency
Number of establishments	Number of establishments in municipality i at year t. Source: Establishment History Panel, Federal Employment Agency
Size of establishments	Number of employees per establishment in municipality i at year t. Source: Establishment History Panel, Federal Employment Agency
Number of firm entries	Number of firms entering the market in municipality i at year t. The pre-DSL fraction refers to the year 2000. Source: Mannheim Enterprise Panel
Number of firm exits	Number of firms exiting the market in municipality i at year t. The pre-DSL fraction refers to the year 2000. Source: Mannheim Enterprise Panel
Total sales	Total sales based on firm information in municipality i at year t. The pre-DSL fraction refers to the year 2001. Source: Mannheim Enterprise Panel

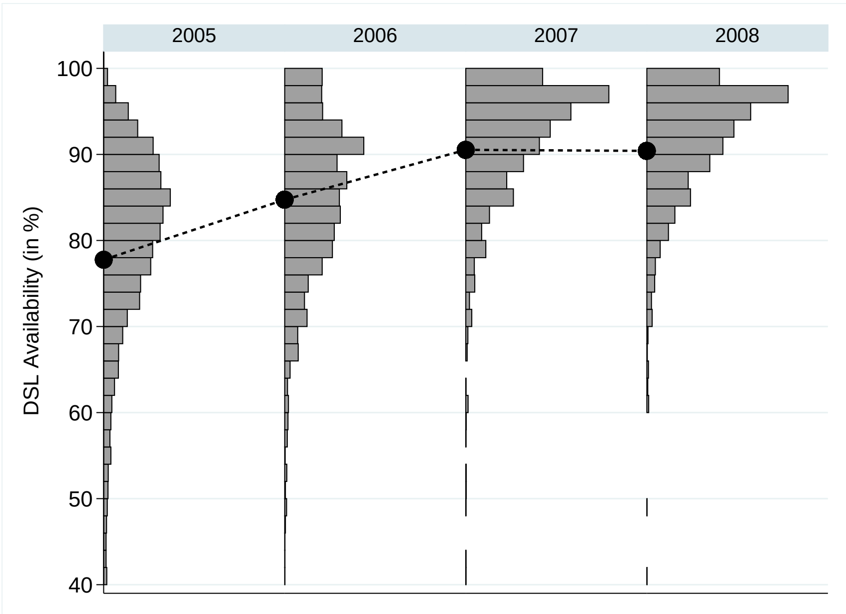
Table B.2: Description of labor market states

Employment: Employment spells include continuous periods of employment (allowing gaps of up to one month) subject to social security contributions and (after 1998) marginal employment. For parallel spells of employment and unemployment (e.g. for those individuals who in addition to their earnings receive supplementary benefits), we treat employment as the dominant labor market state.
Unemployment Unemployment spells include periods of job search as well as periods with transfer receipt. Prior to 2005, the latter include benefits such as unemployment insurance and means-tested unemployment assistance benefits. Those (employable) individuals who were not entitled to unemployment insurance or assistance benefits could claim means-tested social assistance benefits. However, prior to 2005, spells with social assistance receipt may be observed in the data only if the job seekers' history records social assistance recipients as searching for a job. After 2004, means-tested unemployment and social assistance benefits were merged into one unified benefit, also known as 'unemployment benefit II' (ALG II). Unemployment spells with receipt of ALG II are recorded in the data from 2007 onwards, such that the data provide a consistent definition of unemployment only for the period 2007-2010.
Distinction between un- and non-employment Extending the procedure proposed by Lee and Wilke (2009), involuntary unemployment is defined as comprising all continuous periods of registered job search and/or transfer receipt. Gaps between such unemployment periods or gaps between transfer receipt or job search and a new employment spell may not exceed three months, otherwise these periods are considered as non-employment spells (involving voluntary unemployment or an exit out of the social security labor force). Similarly, gaps between periods of employment and transfer receipt or job search are treated as involuntary unemployment as long as the gap does not exceed six weeks, otherwise the gap is treated as non-employment.

C Descriptive Statistics



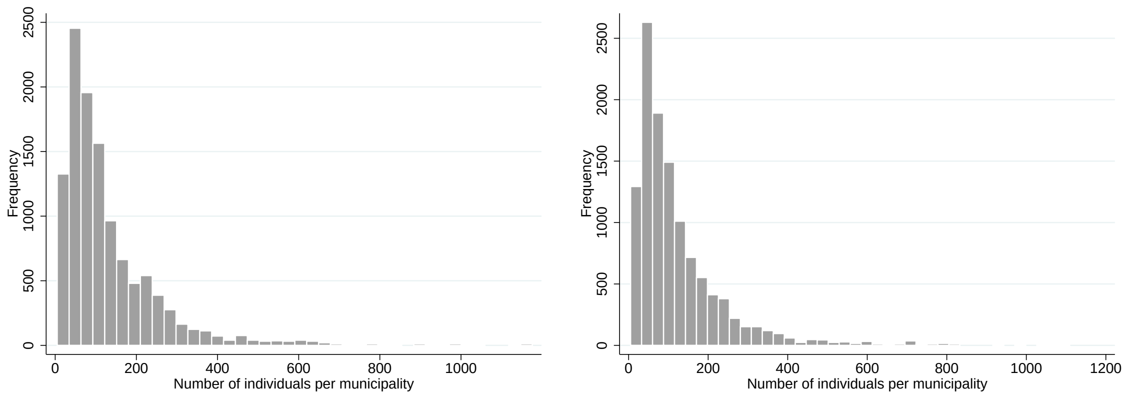
(A) Agglomerated municipalities



(B) Less agglomerated municipalities

Notes: The figures show histograms of DSL availability (measured as a percentage of households for which DSL is technically available) in German municipalities for the defined DSL years 2005 to 2008. Panel (A) shows the development for agglomerated municipalities. Panel (B) shows the results for less agglomerated municipalities (used in the IV approach) without an own MDF and no closer MDF available. The graphs are truncated at 40%. The dotted line connects the population-weighted mean availabilities for all years.

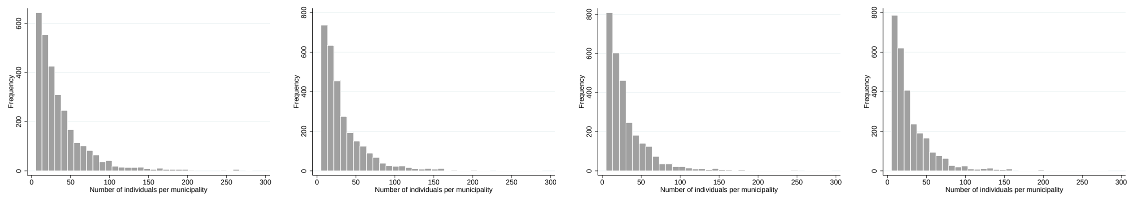
Figure C.1: Empirical distribution of DSL availability by sample



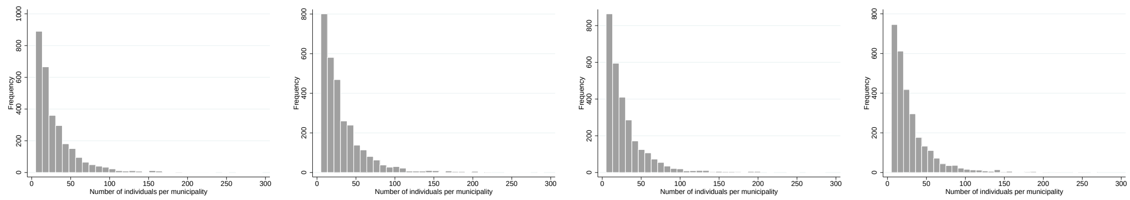
(A) DSL period *(B) Pre-DSL period*

Notes: The figures plot the distribution of the number of individuals in the unemployment inflow sample per municipality for the DSL (2005-2008) and the pre-DSL period (1996-1999). The median over all DSL years equals 93. The median over all pre-DSL years equals 87.

Figure C.2: Observed individuals per municipality by period



(1-A) 2005 *(1-B) 2006* *(1-C) 2007* *(1-D) 2008*



(1-A) 1996 *(2-B) 1997* *(3-C) 1998* *(4-D) 1999*

Notes: The figures plot the distribution of the number of individuals in the unemployment inflow sample per municipality for each pre-DSL and DSL year.

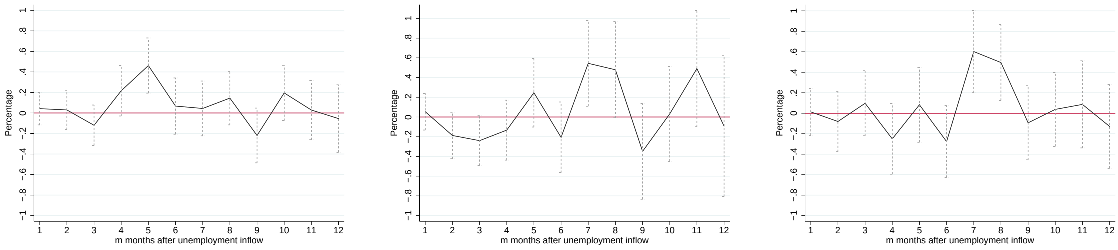
Figure C.3: Observed individuals per municipality during all DSL and pre-DSL years

Table C.1: Further descriptive statistics

	Pre-DSL years 1998/99 (1)	DSL years 2007/08 (2)
Panel A: Demand-side variables		
Number of establishments	30.167	40.939
	(39.655)	(52.480)
Establishment size	6.244	6.121
	(5.213)	(4.572)
Number of firm entries	2.742	2.378
	(3.773)	(3.284)
Number of firm exits	1.867	3.290
	(3.010)	(4.478)
Sales	30.089	64.663
	(413.700)	(568.570)
Panel B: Sector composition		
Agriculture/Energy/Mining	0.034	0.033
	(0.027)	(0.026)
Production	0.065	0.049
	(0.052)	(0.040)
Steel/Metal/Machinery	0.091	0.085
	(0.062)	(0.060)
Vehicle construction/Apparatus engineering	0.041	0.038
	(0.044)	(0.039)
Consumer goods	0.055	0.042
	(0.039)	(0.028)
Food	0.035	0.033
	(0.024)	(0.022)
Construction	0.068	0.042
	(0.040)	(0.027)
Finishing trade	0.049	0.037
	(0.023)	(0.018)
Wholesale trade	0.052	0.049
	(0.027)	(0.024)
Retail trade	0.093	0.098
	(0.033)	(0.030)
Transport and communication	0.047	0.054
	(0.026)	(0.023)
Business services	0.084	0.105
	(0.034)	(0.037)
Household services	0.066	0.081
	(0.039)	(0.036)
Education/Health	0.120	0.136
	(0.045)	(0.045)
Organizations	0.018	0.021
	(0.013)	(0.013)
Public sector	0.057	0.056
	(0.026)	(0.023)
Panel C: Inflow characteristics		
Occupation		
Agriculture	0.056	0.043
	(0.075)	(0.060)
Production	0.452	0.391
	(0.159)	(0.144)
Salary	0.074	0.073
	(0.072)	(0.068)
Sale	0.061	0.073
	(0.062)	(0.065)
Clerical	0.142	0.146
	(0.100)	(0.096)
Service	0.215	0.274
	(0.112)	(0.122)

Notes: The table reports municipality-level descriptive statistics for West Germany. The numbers are averaged within the pre-DSL and the DSL years, respectively. Panel A reports demand-side variable. Panel B report the sector structure. Panel C reports occupational for the unemployment inflow sample.

D Empirical Hazard Rates

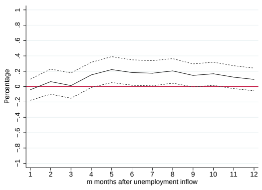


(A) Male *(B) Young* *(C) Skilled white-collar*

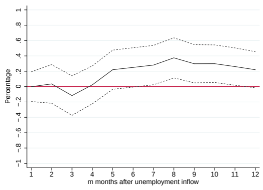
Notes: The figure shows the effects of a 1% point increase in the share of households with DSL availability on the transition probability from unemployment to employment in month m for an inflow sample of individuals who entered unemployment between 1998/1999 and 2007/2008 separately for males, young individuals (below 35 years) and skilled white-collar individuals. The regressions are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Dotted lines present the 90% confidence interval. Standard errors are heteroskedasticity robust and clustered at the municipality level. The distance is measured from the geographic centroid to the MDF and weighted by the location of the population. Regressions are based on 2,551 municipalities and 803 MDFs for males, 2,359 municipalities and 765 MDFs for young individuals and 2,066 municipalities and 713 MDFs for skilled white-collar individuals. The Kleibergen-Paap F-Statistic for the first stage is 60.0, 53.4 and 35.6 for the three groups, respectively.

Figure D.1: IV regression results of DSL on unemployment-to-employment transitions by socio-economic characteristics

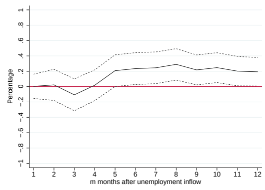
E Sensitivity and Robustness Results



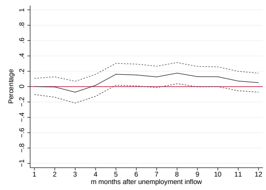
(1-A) All tenure, Male



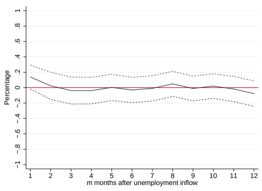
(1-B) Population 500+, Male



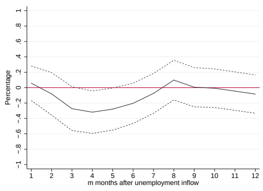
(1-C) 6 month gap, Male



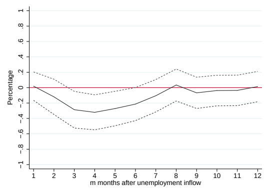
(1-D) Without weighting, Male



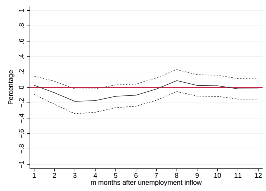
(2-A) All tenure, Young



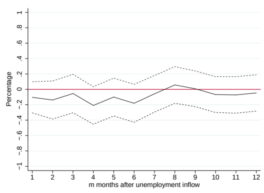
(2-B) Population 500+, Young



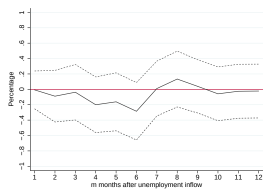
(2-C) 6 month gap, Young



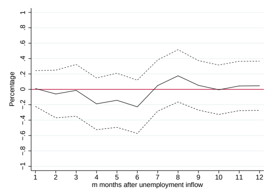
(2-D) Without weighting, Young



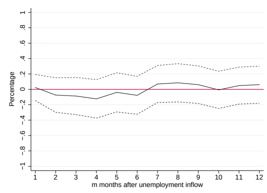
(3-A) All tenure, Skilled white-collar



(3-B) Population 500+, Skilled white-collar



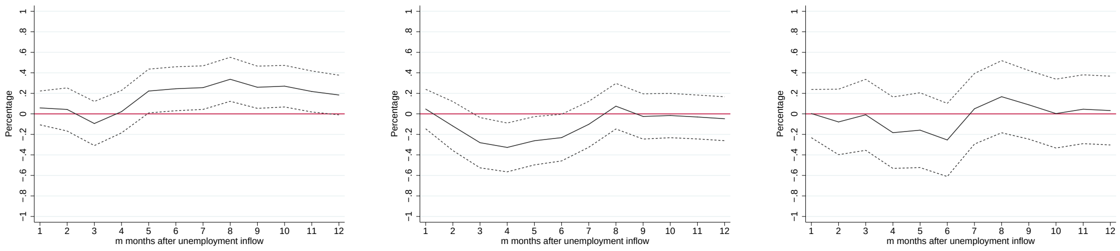
(3-C) 6 month gap, Skilled white-collar



(3-D) Without weighting, Skilled white-collar

Notes: The figure shows the effects of a 1% point increase in the share of households with DSL availability on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment between 1998/1999 and 2007/2008 separately for males, young individuals (below 35 years) and skilled white-collar individuals. Panel (A) performs the analysis for an inflow sample of individuals without excluding persons who have been less than three months employed before entering unemployment. Panel (B) performs the analysis conditional on the local municipality size of at least 500 inhabitants. Panel (C) performs the analysis for an inflow sample by allowing for gaps in the administrative records between unemployment and another labor market state of at most six months. Panel (D) performs the analysis without population-weighting. The regressions in Panel (A) - (C) are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Dotted lines present the 90% confidence interval. Standard errors are heteroskedasticity robust and clustered at the municipality level.
Number of municipalities: Male: (1-A): 2,812, (1-B): 2,046, (1-C): 2,553, (1-D): 2,551; Young: (2-A): 2,688, (2-B): 2,009, (2-C): 2,363, (2-D): 2,359; Skilled white-collar: (3-A): 2,405, (3-B): 1,842, (3-C): 2,072, (3-D): 2,066.

Figure E.1: IV regression results of DSL on unemployment-to-employment transitions, sample specification



(A) Male *(B) Young* *(C) Skilled white-collar*

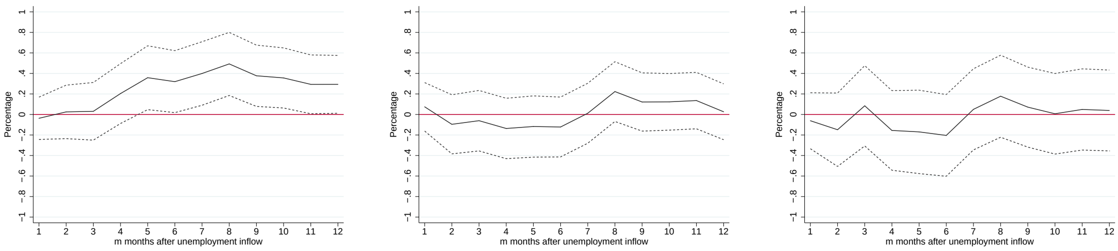
The figure shows the effects of a 1% point increase in the share of households with DSL availability on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment between 1998/1999 and 2007/2008 separately for males, young individuals (below 35 years) and skilled white-collar individuals. The regressions are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares and industry shares (see Table B.1 in Appendix B). Dotted lines present the 90% confidence interval. Standard errors are heteroskedasticity robust and clustered at the municipality level.
Number of municipalities: Male: (A): 2,551; Young: (B): 2,359; Skilled white-collar: (C): 2,066.

Figure E.2: IV regression results of DSL on unemployment-to-employment transitions, excluding demand-side control variables

Table E.1: Estimation results analyzing demand-side effects

	Net firm creation (1)	# Firm entries (2)	# Firm exits (3)	Total sales (4)	Size of establishments (5)
Δ DSL	0.363	-0.090	-0.541	473.1	0.011
	(0.563)	(0.403)	(0.415)	(640.3)	(1.932)
F-Statistic (first stage)	112.1	112.7	112.1	112.7	112.7
Observations	6,514	6,616	6,514	6,616	6,616
Number of Municipalities	3,278	3,331	3,278	3,331	3,331

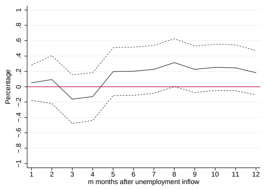
Notes: The figure shows the effect of a 1% point increase in the share of households with DSL availability on selected demand-side variables. Sales are measured in million euro. The pre-DSL year refers to the year 2000. The DSL period covers the years between 2007 and 2008. The regressions are population-weighted. The number of firm entries and firm exits are measured in logs. The list of control variables includes population structure, employment structure, occupational shares and industry shares. The F-test of excluded instruments refers to the Kleibergen-Paap F-Statistic. Standard errors are heteroskedasticity robust and clustered at the municipality level. The distance is measured from the geographic centroid to the MDF and weighted by the location of the population.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.



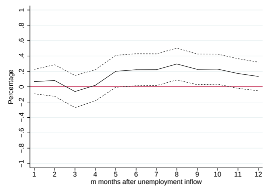
(A) Male *(B) Young* *(C) Skilled white-collar*

The figure shows the effects of a 1% point increase in the share of households with DSL availability on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment between 1998/1999 and 2007/2008 separately for males, young individuals (below 35 years) and skilled white-collar individuals. The regressions exclude individuals entering unemployment from sectors with a priori high recall rates (e.g. agriculture, construction, hotel and restaurant, passenger transport and delivery service). The regressions are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Dotted lines present the 90% confidence interval. Standard errors are heteroskedasticity robust and clustered at the municipality level.
Number of municipalities: Male: (A): 2,529; Young: (B): 2,350; Skilled white-collar: (C): 2,064.

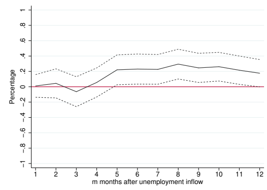
Figure E.3: IV regression results of DSL on unemployment-to-employment transitions, excluding recall industries



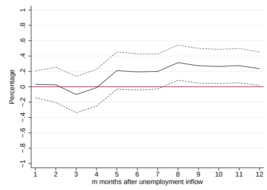
(1-A) 2000m,
Male



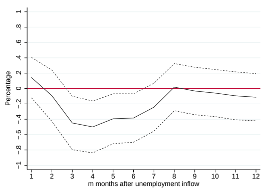
(1-B) Outlier,
Male



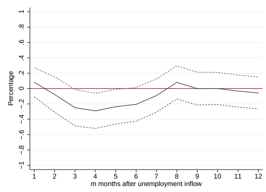
(1-C) Mean,
Male



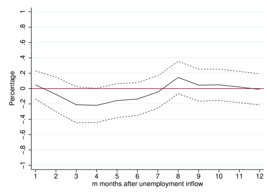
(1-D) Pre-DSL year 1998,
Male



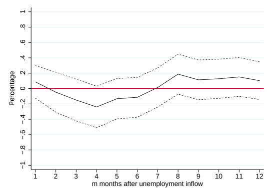
(2-A) 2000m,
Young



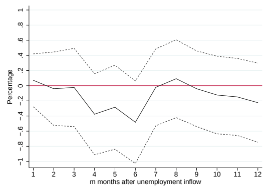
(2-B) Outlier,
Young



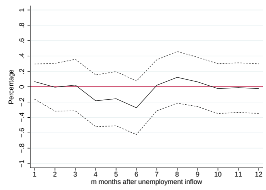
(2-C) Mean,
Young



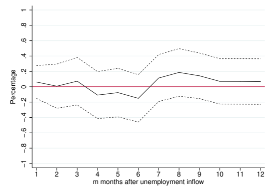
(2-D) Pre-DSL year 1998,
Young



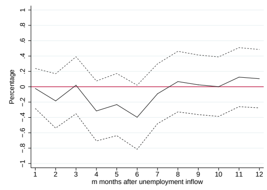
(3-A) 2000m,
Skilled white-collar



(3-B) Outlier,
Skilled white-collar



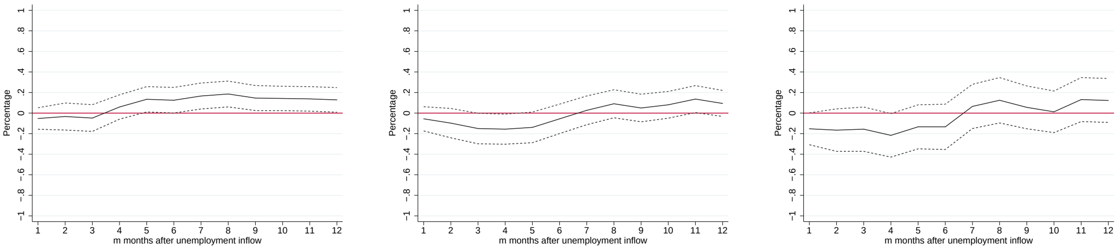
(3-C) Mean,
Skilled white-collar



(3-D) Pre-DSL year 1998,
Skilled white-collar

Notes: The figure shows the effects of a 1% point increase in the share of households with DSL availability on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment between 1998/1999 and 2007/2008 separately for males, young individuals (below 35 years) and skilled white-collar individuals. Panel (A) performs the analysis on municipalities whose distance to the next MDF is less than 2,000 meters from the threshold. Panel (B) performs the analysis by excluding outlier municipalities (see above). Panel (C) performs the analysis by averaging over the single years within the DSL and pre-DSL period. Panel (D) performs the analysis by assigning the year 1998 to every DSL year and then calculate the differences. The regressions are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Dotted lines present the 90% confidence interval. Standard errors are heteroskedasticity robust and clustered at the municipality level.
Number of municipalities: Male: (1-A): 1,928, (1-B): 2,537, (1-C): 2,812, (1-D): 2,455; Young: (2-A): 1,785, (2-B): 2,347, (2-C): 2,359, (2-D): 2,254; Skilled white-collar: (3-A): 1,545, (3-B): 2,054, (3-C): 2,066, (3-D): 1,902.

Figure E.4: IV regression results of DSL on unemployment-to-employment transitions, empirical specification

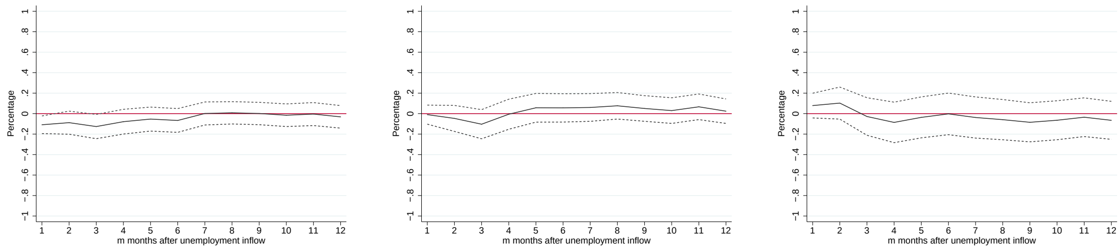


(A) Male *(B) Young* *(C) Skilled white-collar*

Notes: The figure shows the effects of a 1% point increase in the share of households with DSL availability on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment between 1998/1999 and 2007/2008 separately for males, young individuals (below 35 years) and skilled white-collar individuals. All regressions include a continuous instrument by interacting the treatment dummy with the actual distance. The regressions are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Dotted lines present the 90% confidence interval. Standard errors are heteroskedasticity robust and clustered at the municipality level.
Number of municipalities: Male: (A): 2,551; Young: (B): 2,359; Skilled white-collar: (C): 2,066.

Figure E.5: IV regression results of DSL on unemployment-to-employment transitions, continuous instrument specification

F Estimation Results for the Years 2005/06



(A) Male *(B) Young* *(C) Skilled white-collar*

Notes: The figure shows the effects of a 1% point increase in the share of households with DSL availability on the cumulative transition probability from unemployment to employment within m months for an inflow sample of individuals who entered unemployment between 1996/1997 and 2005/2006 separately for males, young individuals (below 35 years) and skilled white-collar individuals. The regressions are population-weighted and performed separately for each month. The list of control variables includes the population structure, employment structure, occupational shares, industry shares and firm structure (see Table B.1 in Appendix B). Dotted lines present the 90% confidence interval. Standard errors are heteroskedasticity robust and clustered at the municipality level. The distance is measured from the geographic centroid to the MDF and weighted by the location of the population. Regressions are based on 2,724 municipalities and 820 MDFs for males, 2,541 municipalities and 790 MDFs for young individuals and 2,127 municipalities and 724 MDFs for skilled white-collar individuals. The Kleibergen-Paap F-Statistic for the first stage is 110.6, 101.6 and 76.6 for the three groups, respectively.

Figure F.1: IV regression results of DSL on unemployment-to-employment transitions by socio-economic characteristics 2005/06

G PASS Data Addendum

Table G.1: Definition of variables

Outcomes	Description
Job search	Dummies for job search channels used by individuals who are looking for a job at the interview date: online job search, search via newspapers, friends/relatives, private broker, the local employment agency, own-initiative or non-specified search channels
Number of applications	Number of own-initiative applications during last four weeks
Number of job interviews	Number of job interviews during last four weeks
Individual characteristics	
Main employment status	Dummies for main employment status at interview date: employed, program participant, reference category: unemployed
Age	Dummies for age groups: age 26 - 35 years, age 36 - 45 years, age 46 - 55 years, age 56 - 65 years, reference category: age $\leq$ 25 years
Immigrant	Dummy for being an immigrant
Female	Dummy for being female
Professional qualification	Dummies for highest professional qualification level: certificate of secondary education (*Hauptschulabschluss*, *Realschulabschluss*) without vocational training, high school diploma (*Fachhochschulreife*, *Hochschulreife*) without vocational training, certificate of secondary education with vocational training, high school diploma with vocational training, Foreman (*Meister, Techniker*) or diploma of Berufsakademie (BA), technical college (TC) or university degree, reference category: no degree
Married	Dummy for being married
Attitudes to work	Dummies for work attitude based on four item-scale ranging from 1 (disagree) to 4 (totally agree) to valuate four statements ("Work is only a means to earn money", "Having a job is the most important thing in life", "Work is important, because it gives you the feeling of being part of society", "I would like to work even if I didn't need the money"): high ($\geq$ 4), medium ($>$ 0 and $<$ 4), missing, reference category: low ($\leq$ 0)
Household information	
HH income	Dummies for household income per month in €: 1,000 - 1,499, 1,500 - 1,999, 2,000 - 2,999, 3,000 - 3,999, 4,000 - 4,999, $\geq$ 5,000, reference category: $\leq$ 1,000
Means-tested HH	Dummy for household receiving unemployment benefits II
HH size	Dummies for household size: two persons, three persons, more than three persons, reference category: single household
Housing situation	Dummy for being home owner, for living in a shared flat, reference category: rent
Father's education	
Professional qualification	Dummies for highest professional qualification level: certificate of secondary education (*Hauptschulabschluss*, *Realschulabschluss*) or high school diploma (*Fachhochschulreife*, *Hochschulreife*) without vocational training, certificate of secondary education or high school diploma with vocational training, Foreman (*Meister, Techniker*) or diploma of Berufsakademie, technical college or university degree, father's education is missing, reference category: no degree
Labor market history	
Unemployment duration	Dummies for cumulative unemployment duration in months: categories are spitted according to percentiles: 0 - 25, 25 - 50, 50 - 75, $>$ 75, reference category: 0
Tenure	Dummies for length of last employment spell (with social security contributions) in months: categories are spitted according to percentiles: 0 - 25, 25 - 50, 50 - 75, $>$ 75, reference category: 0
Daily wage	Daily wage of last employment spell (with social security contributions) in 2010 €
History missing	Dummy for information on labor market history based on administrative data is missing

Table G.2: Home internet access, job search methods and application intensity

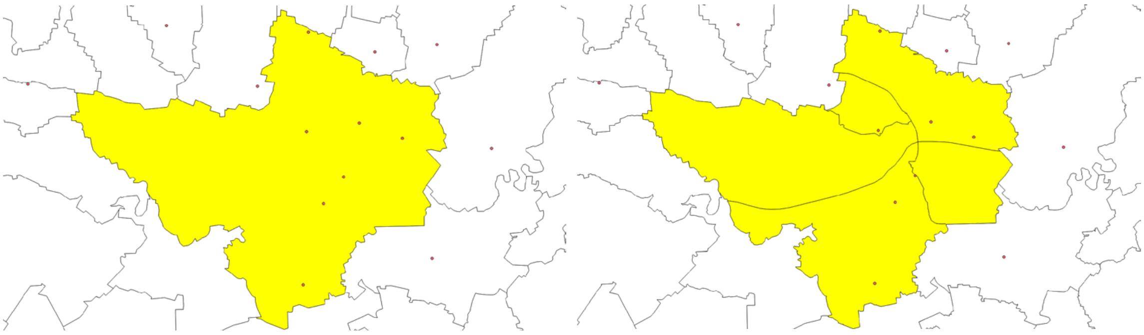
	N (1)	No home internet (2)	Home internet (3)	p-value (4)
Panel A: Job search				
Job search: online	2,914	0.578	0.848	0.000
Job search: newspaper	2,914	0.864	0.813	0.000
Job search: referral	2,914	0.669	0.601	0.000
Job search: empl. agency	2,914	0.423	0.342	0.000
Job search: private broker	2,914	0.151	0.139	0.349
Job search: own-initiative	2,914	0.018	0.013	0.225
Job search: else	2,914	0.129	0.100	0.013
Sum non-online search	2,914	2.255	2.008	0.000
Panel B: Application				
No. of applications (own-initiative)	2,914	2.525	2.465	0.781
No. of job interviews	2,914	0.597	0.600	0.967

Notes: The number of observations refers to individuals observed during the first three waves (2006/07, 2008 and 2009).

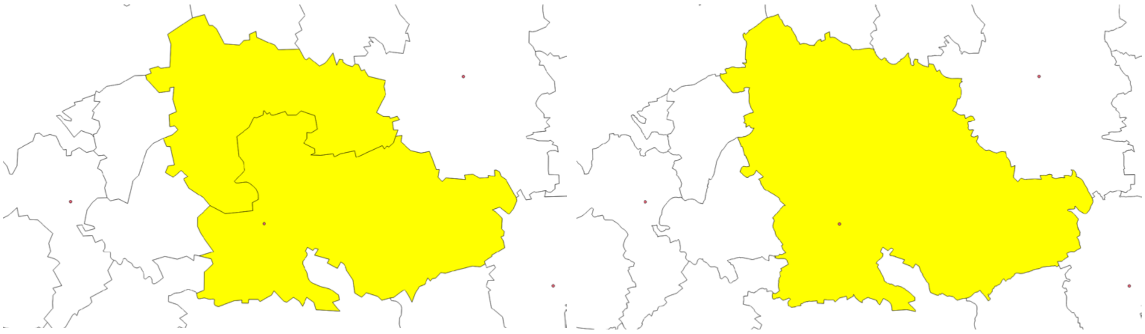
Table G.3: Descriptive statistics of individual characteristics

	N (1)	Mean (2)	No home internet (3)	Home internet (4)	p-value (5)
Employed	2,914	0.177	0.105	0.232	0.000
Program participant	2,914	0.122	0.128	0.117	0.399
Age $\leq$ 25	2,914	0.140	0.142	0.138	0.757
Age 26-35	2,914	0.249	0.232	0.263	0.055
Age 36-45	2,914	0.314	0.290	0.333	0.014
Age 46-55	2,914	0.230	0.253	0.212	0.010
Age 56-65	2,914	0.067	0.083	0.054	0.002
Immigrant	2,914	0.125	0.149	0.107	0.001
Female	2,914	0.493	0.473	0.508	0.068
No degree	2,914	0.061	0.098	0.033	0.000
Sec./Interm. no training	2,914	0.257	0.289	0.232	0.001
TC/Abitur no training	2,914	0.035	0.024	0.044	0.003
Sec./Interm. with training	2,914	0.407	0.438	0.384	0.003
TC/Abitur with training	2,914	0.058	0.040	0.072	0.000
Foremen/BA	2,914	0.076	0.055	0.092	0.000
TC, University	2,914	0.105	0.056	0.143	0.000
Married	2,914	0.315	0.251	0.364	0.000
Female and married	2,914	0.122	0.084	0.151	0.000
Work attitude: missing	2,914	0.136	0.124	0.145	0.103
Work attitude: low	2,914	0.235	0.215	0.250	0.027
Work attitude: medium	2,914	0.394	0.423	0.371	0.004
Work attitude: high	2,914	0.236	0.238	0.235	0.841
Household information					
HH income less 1000	2,914	0.414	0.556	0.306	0.000
HH income 1000 - 1500	2,914	0.286	0.289	0.284	0.798
HH income 1500 - 2000	2,914	0.144	0.102	0.175	0.000
HH income 2000 - 3000	2,914	0.102	0.048	0.142	0.000
HH income 3000 - 4000	2,914	0.038	0.006	0.063	0.000
HH income 4000 - 5000	2,914	0.009	0.000	0.015	0.000
HH income more 5000	2,914	0.010	0.001	0.016	0.000
Means-tested HH	2,914	0.721	0.814	0.650	0.000
HH = 1	2,914	0.284	0.392	0.202	0.000
HH = 2	2,914	0.269	0.282	0.260	0.185
HH = 3	2,914	0.221	0.174	0.257	0.000
HH = 4-11	2,914	0.225	0.152	0.281	0.000
Home owner	2,914	0.133	0.069	0.181	0.000
Flat-sharing	2,914	0.071	0.079	0.066	0.192
Father's education					
Degree missing	2,914	0.263	0.300	0.234	0.000
No degree	2,914	0.060	0.086	0.041	0.000
School degree no training	2,914	0.080	0.092	0.070	0.031
School degree with training	2,914	0.432	0.411	0.448	0.043
Foremen/BA	2,914	0.083	0.062	0.099	0.000
TC, University	2,914	0.083	0.049	0.108	0.000
Labor market history					
Unemployment duration	2,315	67.206	76.124	60.352	0.000
Tenure	2,315	15.856	14.906	16.587	0.232
Daily wage	2,022	48.529	44.389	51.700	0.000
History missing	2,914	0.206	0.202	0.208	0.697

Notes: The number of observations refers to individuals observed during the first three waves (2006/07, 2008 and 2009).



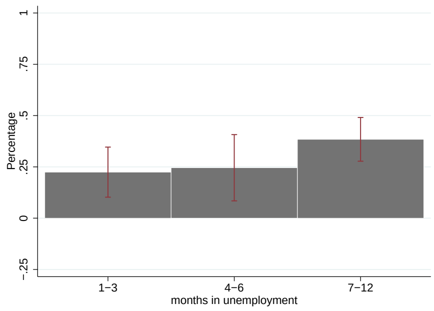
(1-A) Ingolstadt - municipality region *(1-B) Ingolstadt - postal codes*



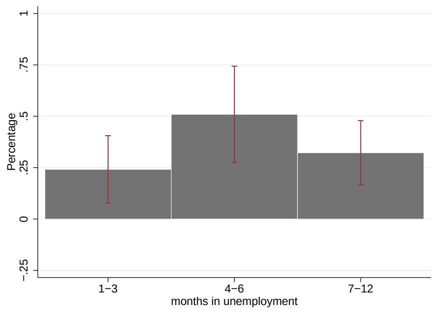
(2-A) Ingelfingen/Kränzelsau - municipality region *(2-B) Ingelfingen/Kränzelsau - postal codes*

Notes: The figures present examples, where the smallest regional unit is either the postal code or the municipality. The combination of the municipality identifier and the postal code provides greater scope for variation in the treatment indicator that is needed for the IV regression. To illustrate this, the figure provides two examples where the municipality identifier is preferred over the postal code and vice versa. Panels (1-A) and (1-B) show the borders from Ingolstadt. Panel (1-A) depicts the municipality and (1-B) the postal code borders. The dots represent the main distributions frames. For the example of Ingolstadt, using the postal code would provide an advantage over using the municipality as the geographic centroid of the western postal code region is more than 4,200 meters away from the next MDF. The lower figures draw the borders of a less agglomerated region, where two municipalities share the same postal code. In this setting, the municipality ID would be preferred over the postal code.

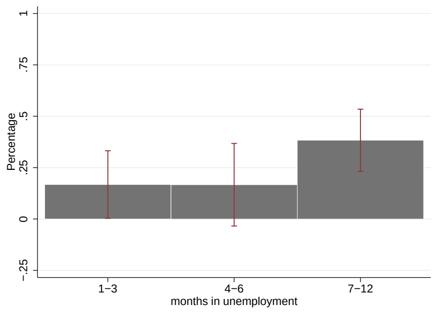
Figure G.1: Exploiting municipality and postal code information for the instrument



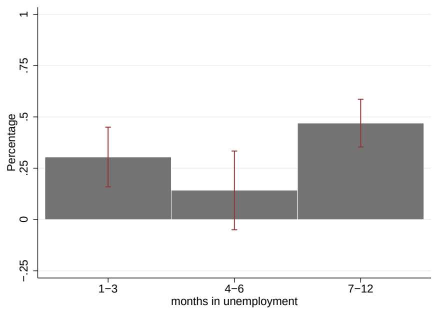
(1) Full sample



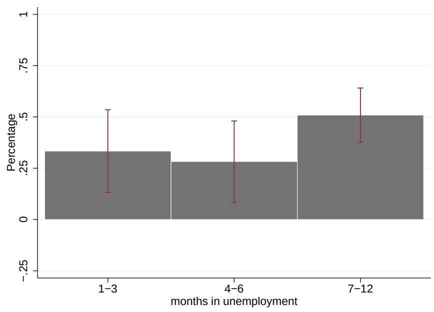
(2-A) Male



(2-B) Young



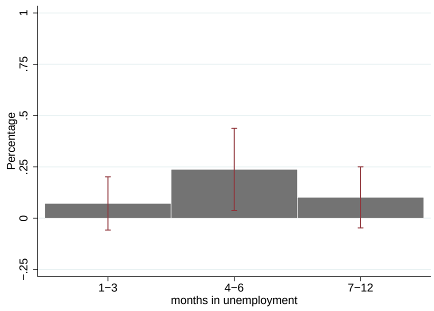
(2-C) Skilled



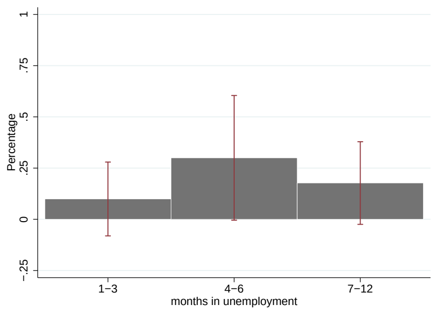
(2-D) White-collar jobs

Notes: The figures plot the difference in the share of individuals searching online for a job by home internet access dependent on the elapsed unemployment duration. Panel (1) shows the results for the full sample. Panel (2) shows the results by socio-economic characteristics. 90% confidence interval at the top of each bar.
Number of individuals: 1^{st} category (1-3 months): Full sample: 155, Male: 83, Young: 86, Skilled: 99, White-collar jobs: 58; 2^{nd} category (4-6 months): Full sample: 68, Male: 32, Young: 36, Skilled: 49, White-collar jobs: 49; 3^{rd} category (7-12 months): Full sample: 133, Male: 68, Young: 67, Skilled: 92, White-collar jobs: 82.

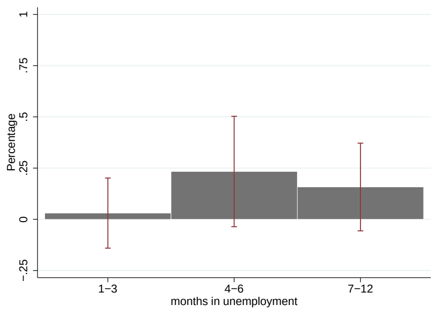
Figure G.2: Difference in online job search by home internet access, three unemployment intervals



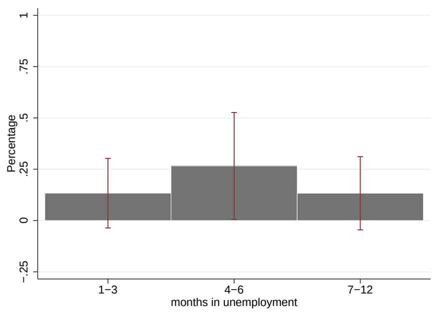
(1) Full sample



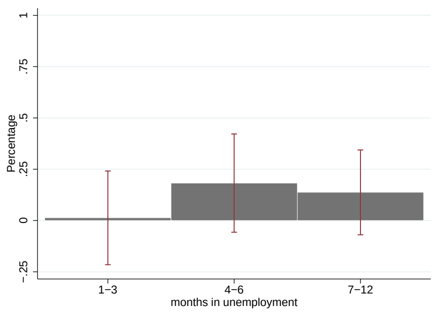
(2-A) Male



(2-B) Young



(2-C) Skilled



(2-D) White-collar jobs

Notes: The figures plot the difference in the share of individuals with job interviews by home internet access dependent on the elapsed unemployment duration. Panel (1) shows the results for the full sample. Panel (2) shows the results by socio-economic characteristics. 90% confidence interval at the top of each bar.
Number of individuals: 1^{st} category (1-3 months): Full sample: 155, Male: 83, Young: 86, Skilled: 99, White-collar jobs: 58; 2^{nd} category (4-6 months): Full sample: 68, Male: 32, Young: 36, Skilled: 49, White-collar jobs: 49; 3^{rd} category (7-12 months): Full sample: 133, Male: 68, Young: 67, Skilled: 92, White-collar jobs: 82.

Figure G.3: Difference in interview probability by home internet access, three unemployment intervals

H Search Externalities

Table H.1: Descriptive statistics from the sample of employed individuals

	Pre-DSL years 1998/99 (1)	DSL years 2007/08 (2)
Panel A: Sample construction		
Sampling date	June 30, 1991	June 30, 2000
Number of individuals per municipality	72.757	89.676
	(80.129)	(93.422)
Panel B: Outcome variable		
Job-to-job transitions	0.325	0.222
	(0.098)	(0.077)
Panel C: Baseline characteristics		
Age	35.629	39.121
	(2.027)	(1.652)
Female share	0.329	0.419
	(0.092)	(0.080)
Low-skilled	0.131	0.104
	(0.072)	(0.054)
Medium-skilled	0.815	0.824
	(0.079)	(0.067)
High-skilled	0.055	0.073
	(0.049)	(0.054)
Foreign	0.033	0.031
	(0.051)	(0.045)
Occupation		
Agriculture	0.014	0.015
	(0.027)	(0.026)
Production	0.406	0.329
	(0.127)	(0.107)
Salary	0.121	0.136
	(0.068)	(0.063)
Sale	0.046	0.056
	(0.039)	(0.038)
Clerical	0.241	0.246
	(0.091)	(0.082)
Service	0.171	0.217
	(0.077)	(0.077)

Notes: The table reports basic municipality-level descriptive statistics for West Germany on the sample used to estimate the effects of broadband internet availability on job-to-job transitions. Job-to-job transitions are defined as employer changes allowing gaps of up to one month. The pre-DSL period covers the years 1998 and 1999. The DSL period covers the years 2007 and 2008. The numbers are averaged within the pre-DSL and the DSL years, respectively. The sample for the DSL period is based on employed individuals at the reference date 30th June 2000 who are still employed at the same employer at the start of the year 2007. The sample for the pre-DSL period is based on employed individuals at the reference date 30th June 1991 who are still employed at the same employer at the start of the year 1998. Individuals who experience a transition from employment to unemployment or non-employment in the pre-DSL and DSL period, respectively are excluded from the analysis.