Does the Internet Help the Unemployed Find Jobs?*

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Abstract

This paper investigates whether using the Internet for job search helps unemployed workers find jobs. The self-selection of Internet job searchers is addressed by the instrumental variable (IV) estimation strategy. I isolate potentially exogenous variation in individuals' Internet job search status by exploiting variation in adoption of the Internet across occupations. The fraction of unemployed workers using the Internet to search for jobs increased more rapidly in occupations with higher computer use rates before the introduction of the Internet. The analysis sample consists of unemployed workers from the September 1992 Basic Monthly Current Population Survey (CPS) and the December 1998, August 2000, and September 2001 CPS Computer and Internet Use Supplements. The unemployed workers are longitudinally matched with their employment outcomes from the subsequent CPS files. The panel structure of the CPS enables us to follow the individuals for up to subsequent 15 months. The IV results suggest that unemployed workers searching for jobs online are around 14 percentage points more likely to be employed during the 15 month follow-up period than unemployed workers who do not engage in Internet job search. This implies that using the Internet for job search raises the 15-month job finding rate by around 26 percent at the mean.

Keywords: Internet job search, employment outcomes
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1 Introduction

The Internet has become an essential job search and recruitment tool since the mid 1990s. An employer survey conducted in March 2007 indicates that 44 percent of new hires in 2006 by respondent organizations in the private and public sector is through online recruiting.[1] The use of the Internet for job search and recruitment has expanded rapidly especially during the early years from mid-1990s to early 2000s.[2] Table 1 shows that the fraction of unemployed job seekers looking for work online more than doubled from 15 percent in 1998 to 32 percent in 2001. This fraction almost tripled from 5 percent in 1998 to 14 percent in 2001 among unemployed workers on layoff. During the same period, the fraction of Global 500 companies with corporate websites that used their websites for recruiting purposes also increased dramatically from 29 percent to 88 percent.[3]

As Internet job search and recruitment have grown increasingly popular, its consequence on unemployment has been the focus of much attention among researchers. As pointed out by Krueger (2000); Autor (2001); Freeman (2002), whether the expansion of the Internet would lead to more successful search outcomes is theoretically ambiguous. On the one hand, the Internet makes job search and recruitment process more efficient by lowering job search costs for both workers and firms and enabling them to consider more potential matches more quickly. On the other hand, the Internet could make workers and firms choosier by raising their reservation match quality. When we also consider a general equilibrium effect of the lower cost of online search as discussed in Autor (2001), it is even harder to predict employment outcomes of using the Internet for job search. The cheaper and easier it gets to learn about and apply for jobs, the worse the adverse selection in the applicant pool could become. This is because in the lower cost regime many people including even some non-serious ones who would not consider looking for jobs otherwise would apply for many more jobs. This could lead to a lower job finding rate among online applicants. Therefore, the faster and cheaper job searches enabled by the Internet may or may not lead to lower unemployment. Whether the use of the Internet leads to better search outcomes is an empirical question.

This paper investigates whether using the Internet for job search helps unemployed workers find jobs. Kuhn and Skuterud (2004) is the first and widely cited empirical study looking at the relationship between

[1] From the 2007 report of the Society for Human Resource Management cited by Nakamura et al. (2009).

[2] Monster.com, CareerBuilder.com, and hotjobs.yahoo.com, the three leading commercial US job sites, were launched in 1995, 1996, and 1997, respectively. America's Job Bank is founded by the US government in 1995. Craigslist.org and JobCentral.com, the two other well-known non-profit job sites, are launched in 1995 and 2001, respectively.

[3] See Table 1.3 in Nakamura et al. (2009).

the use of the Internet for job search and employment outcomes. They use data from the December 1998 and August 2000 Current Population Survey (CPS) Computer and Internet Use Supplements matched with the subsequent CPS files. Their descriptive analysis finds that Internet job searchers do not have shorter unemployment spells (but have longer spells in some specifications) when the difference in observable characteristics between Internet job searchers and non-Internet searchers is controlled for. They conclude that their findings imply either "(a) Internet job search is ineffective in reducing unemployment durations or (b) Internet job searchers are adversely selected on unobservable characteristics." They leave it to future research to extract the causal effect of Internet job search on employment outcomes and to disentangle the two possibilities.

Aside from Kuhn and Skuterud (2004), there is little other empirical evidence on the effect of using the Internet for job search on employment.[4] This is because it is quite challenging to find exogenous variation in individuals' Internet job search status from observational data in which Internet job searchers are usually self-selected. I find only two papers addressing the endogeneity problem. Both of the papers study the effect of an expansion of a specific job search engine. One of the two recent studies finds a positive effect of the Internet on labor market efficiency while the other finds a zero effect. Kroft and Pope (2008) exploit geographical variation in the expansion of Craigslist, a non-profit search engine for jobs, housing, personals, for sale, services, etc., between 2005 and 2007 and find no measurable impact on local area unemployment rates. Bagues and Labini (2009) study an expansion of *AlmaLaurea*, a job search engine founded by an inter university consortium of Italian universities to help university graduates find jobs, in 1996 and 1997, when some of Italian universities joined the membership while others did not. They conclude that *AlmaLaurea* reduced the unemployment rate among graduates of *AlmaLaurea* member universities. Thus, the results are mixed and no consensus has been reached regarding the sign and magnitude of the effect of online job search on employment outcomes in the existing literature.

The main goal of this paper is to estimate the causal effect of Internet job search on employment probability using a representative sample of the unemployed population in the US. Thus, Kuhn and Skuterud (2004) is the starting point of this paper. The self-selection of Internet job searchers is addressed by the instrumental variable (IV) estimation strategy. I isolate potentially exogenous variation in individuals' Internet job search status by exploiting variation in adoption of the Internet across occupation groups. The

[4]Fountain (2005) finds a positive correlation between Internet job search and job finding rates in 1998 but a negative correlation in 2000 from a similar descriptive analysis using the same data as Kuhn and Skuterud (2004).

fraction of unemployed workers using the Internet to search for jobs increased more rapidly in occupations with a higher computer use rate before the introduction of the Internet. Based on this reasoning, whether an unemployed person searched for jobs online is instrumented by the interaction between time and the occupational computer use rate in a baseline year. The time component of the instrument represents the exogenous introduction of the Internet as a job search tool, relying on the fact that the Internet was not available for most of people until late 1994 when Netscape's Navigator program was released. Note that the Internet adoption speed is constructed to be the same among all individuals within an occupation. Thus, whether an individual decided to be quicker than others at adopting online job search methods does not affect the instrument. Nonetheless, the exclusion restriction may be violated when the baseline occupational computer use rates are correlated with changes in individuals' employment outcomes during the analysis period. To avoid potential biases from the violation of the exclusion restriction, I include a large set of control variables as well as occupation, industry, and state fixed effects in the regression equations. No other studies have used this type of instrument with individual level US data to measure the effect of Internet job search on employment probability.

I use repeated cross-section data from the September 1992 Basic Monthly file and the December 1998, August 2000, and September 2001 Computer and Internet Use Supplements to the CPS. The Computer and Internet Use Supplement surveys asked respondents whether they had searched for jobs online. None of the respondents to the September 1992 Basic Monthly survey were using the Internet to look for work because the Internet was not introduced among general public until late 1994. Following Kuhn and Skuterud (2004), I construct the analysis sample of this paper by restricting the data to unemployed persons. I track the employment outcomes of the unemployed individuals in the analysis sample by matching the four main CPS files with the subsequent CPS Basic Monthly files longitudinally. The panel structure of the CPS enables us to follow the individuals for up to subsequent 15 months. I focus on whether the unemployed individuals become employed one month, two months, twelve months, or in any month after their job search status was observed. The occupational computer use rate, a key component of the instrument, comes from the October 1993 School Enrollment Supplement to the CPS.

I start by showing that descriptive analysis results are comparable to findings in Kuhn and Skuterud (2004). The average probability of finding a job is significantly higher among unemployed workers using the Internet for job search, and Internet job searchers have observable characteristics associated with a higher employment probability. When the difference in the observable characteristics are controlled, Internet job

searchers are not more likely (but less likely in the first two months) to find a job than non-Internet searchers. The regression coefficient estimates on the Internet job search indicator variable from my analysis sample are very similar to the ones from data used in Kuhn and Skuterud (2004).

The first stage results show that the interaction between the 1993 occupational computer use rate and time well predicts whether an unemployed individual engaged in Internet job search. The first stage estimates imply that a 10 percentage point higher baseline occupational computer use rate is associated with a 0.52-0.60 percentage point faster yearly increase in the Internet job search rate among the unemployed.

The IV results suggest that unemployed workers using the Internet to search for jobs are around 14 percentage points more likely to find a job at any point during the 15 month follow-up period. The IV coefficient estimates on Internet job search status are positive and at least five times larger than the Ordinary Least Squares (OLS) estimates. The results do not change much when I look at employment outcomes at four different follow-up points or add additional controls to the regression. Although the IV estimates are insignificant or marginally significant at the 10 percent level due to the loss of precision, the positive and large estimates robust to different specifications provide evidence that using the Internet for job search raises job finding rates among the unemployed when self-selection of Internet job searchers is properly addressed.

The remainder of the paper is organized as follows. Section 2 describes the econometric model for the relationship between Internet job search and employment outcomes as well as its IV estimation framework. Section 3 describes the data sets used for the analysis and shows summary statistics. Section 4 presents the estimation results, including the OLS and IV estimates of the effect of Internet job search on employment probability, as well as the first-stage estimates. Section 5 concludes.

2 Econometric Model and Estimating Framework

2.1 Econometric Model

The econometric model for the relationship between employment outcome and Internet job search status can be written as

$$E_i = \beta S_i + \mathbf{X}_i \gamma + \varepsilon_i, \tag{1}$$

where E_i is individual i's employment outcome and S_i is whether the person searched for work online. $\mathbf{X}_i$ is a vector including individual characteristics that affect employment outcomes, such as education level

and activities prior to unemployment, as well as labor market conditions that person i is facing, such as state and occupation unemployment rates. In the usual limited dependent variable set-up, we can think of Y_i, a continuous unobservable latent variable such that a worker becomes employed ($E_i = 1$) if and only if $Y_i \geq 0$, and remains unemployed ($E_i = 0$) if and only if $Y_i < 0$. The coefficient β is the parameter of interest indicating whether searching for jobs online affects employment outcomes or not.

An individual i uses the Internet for her job search when the net benefits of using the Internet to look for work exceeds the net benefits of not doing so. The net benefits can be monetary or psychological benefits of the employment outcomes net of search costs associated with an individual's Internet job search status.[5] The econometric model for the Internet job search status can be expressed as

$$S_i = 1\left[\mathbf{Z}_i\boldsymbol{\pi} \geq u_i\right], \tag{2}$$

where $\mathbf{Z}_i$ is a vector of covariates that affect costs and benefits associated with an individual i's Internet job search status.

Notice that OLS estimates of β in equation (1) can be biased when S_i is endogenously determined, i.e. $\text{Cov}(\varepsilon_i, u_i|\mathbf{X}_i) \neq 0$. For example, Internet job searchers may have unobservable characteristics associated with higher employment chances. For example, the fact that a person uses the Internet to search for jobs could indicate that the person is familiar with modern information technology, or does not mind adopting or learning new technology.[6] People progressively adopting these technologies could usually be the ones more attractive to potential employers. In this case, β would be biased upward due to the pseudo positive correlation between the likelihood of using the Internet for job search and the likelihood of becoming employment through unobservable characteristics.

Alternatively, Internet job searchers may be negatively selected based on unobservable characteristics as pointed out by other researchers. For example, Autor (2001) emphasizes the adverse selection among Internet job searchers due to the very low costs associated with using the Internet for job search. The low cost aspect attracts more job seekers including unqualified ones to online job search activities relative to the traditional offline job search methods. Because it is almost free to read online ads, search job listings,

[5]The unit of benefits and costs can be utility levels or dollars. Kuhn and Skuterud (2004) use dollar unit implicitly assuming linear utility function.

[6]This may not sound plausible nowadays when the Internet is no longer something new and the Internet access rate is very high. However, data come from 1998-2001. Over 70 percent of US population did not have home Internet access in 1998. The Internet had become popular very rapidly during the analysis period of this paper between 1998 and 2001 as seen in Table 1.

or post a resume on a job listing site, even individuals with low expected benefits, i.e. low employment chances, can engage in online job search. Casual job seekers, who do not actively look for work or do not know exactly what they are looking for, would be searching for jobs online rather than engaging in other job search methods, since they can see all the job listings on the Internet at once without spending much money and time. The adverse selection can occur in other aspects as well. Kuhn and Skuterud (2004) mention that persons who engage in online job search may be doing so because of their poor informal contacts and social networks, or because of health or disability limitations. The increasing concerns about identity theft on the Internet can also exacerbate adverse selection. If this is the case, β would be biased downward.

In order to figure out the true effect of engaging in online job search on employment outcomes, the endogeneity of Internet job search status has to be addressed properly. A way to obtain consistent estimates of β is to use instrumental variables.[7] A valid instrument should be a variable in $\mathbf{Z}_i$ that is neither included in $\mathbf{X}_i$ nor correlated with ε_i . Next, I provide more details on my IV estimation strategy.

2.2 IV Estimation Framework

To isolate potentially exogenous variation in individuals' Internet job search status, I exploit the fact that the Internet itself or as a job search tool had been adopted in different speeds across different occupation groups. The fraction of Internet job searchers had increased more rapidly among the unemployed workers in occupations in which the use of computer at work was more common before the introduction of the Internet. This is plausible because individuals who had a job in computer intensive occupations would have been more likely to become familiar with the Internet and consequently more likely to use the Internet for job search when they became unemployed. The online job search methods became available as the use of the Internet rapidly expanded among general public after the introduction of Netscape's Navigator program in 1994.[8] Before the Internet was introduced and became popular among general public, there was considerable variation in the fraction of workers using a computer at work across different occupations. In 1993, for example, over 95 percent of Mathematical and Computer Scientists and Computer Equipment Operators used a computer at work, while less than 5 percent of Construction Laborers and workers in Forestry and Fishing Occupations or Private Household Service Occupations did so. About 45 percent of workers in all occupations used a computer at work in 1993. The average computer use rate was similar to the computer

[7] The IV estimator is asymptotically consistent but biased in finite samples.

[8] The Internet use was not popular until the introduction of Netscape's Navigator program in 1994 [Card and DiNardo (2002)].

use rate among Teachers, Except College and University (49 percent), and workers in Protective Service Occupations (43 percent) or Health Diagnosing Occupations (49 percent). I therefore expect variation in the Internet job search adoption rate in different occupations would depend on the baseline distribution of the computer use at work. The computer use rates at work by detailed CPS occupation categories in 1993 are presented in Appendix Table 1. For example, the fraction of Internet job searchers should have increased more rapidly among unemployed Mathematical and Computer Scientists or Computer Equipment Operators than among unemployed workers in Forestry and Fishing Occupations or Private Household Service Occupations. Figure 1 illustrates this by plotting the fraction of unemployed workers looking for jobs online over time in occupations with four different initial (in 1993) computer use rate. It shows the Internet job search rate started from zero in all the occupations but increased more steeply in occupations with higher computer use rate in 1993.

Motivated by this reasoning, my instrument is constructed as

$$Z_{ct} = C_c^{93} \cdot t, \tag{3}$$

where C_c^{93} is the fraction of workers using a computer at work in occupation c in 1993 and t is a linear time trend.[9]

Using Z_{ct} as an instrument for the Internet job search variable in (1), I posit the following linear probability models for the IV estimation in Section 4. The empirical specification for the relationship between employment outcomes and online job search status can be expressed as,

$$E_{it} = \beta S_{it} + \mathbf{X}_{it}\gamma + \alpha_c + \zeta_d + \eta_s + \mu_t + \varepsilon_{it}. \tag{4}$$

And, the first-stage relationship can be written as

$$S_{it} = \theta Z_{ct} + \mathbf{X}_{it}\delta + \alpha_c + \zeta_d + \eta_s + \mu_t + u_{it}. \tag{5}$$

Here, E_{it} is equal to 1 if individual i (in occupation c, industry d, and state s[10]) who are unemployed at

[9] I also tired a more generalized version, $Z_{ct} = C_c^{93} \cdot \mu_t$, where μ_t is a set of time dummy variables. $C_c^{93} \cdot t$ has a much stronger prediction power for the Internet job search status than $C_c^{93} \cdot \mu_t$. Table 7 shows the IV estimates using $C_c^{93} \cdot \mu_t$ as a set of instruments in the main specification. Results in other specifications are available upon request.

[10] All the variables that vary in individual (i) level also vary in occupation (c), industry (d), and state (s) levels. The additional subscripts, c, d, and s, are suppressed from the equations for notational convenience.

time t becomes employed within a certain time interval after t. S_{it} equals one if individual i searches for jobs online. $\mathbf{X}_{it}$ are other time-varying individual characteristics.α_c is a a set of occupation dummies, ζ_d is a set of industry dummies, and η_s is a set of state dummies. These fixed effects control for time invariant occupation, industry, and state characteristics. μ_t is a general time trend incorporating time-varying factors common across individuals. This model is estimated using repeated cross section data from Monthly CPS files in 1992 (before the introduction of the Internet among general public), 1998, 2000, and 2001 as explained in Section 3.

I work with the linear probability model instead of a duration model or a non-linear binary choice model. This is because it is easier to deal with endogenous regressors when both outcome (employment outcome equation (4) in this paper) and treatment (Internet job search status equation (5) in this paper) processes are normal and linear. When models for outcome and treatment are from nonnormal and nonlinear processes, and especially from different statistical families, tractable multivariate distributions for a joint model of outcome and treatment often do not exist.[Cameron and Trivedi (2005)] Duration outcomes with binomial treatment is a typical example with no analytic joint distribution.

Note that including the fixed effects, α_c, ζ_d, and η_s, in equations (4) and (5) is important, because C_c^{93} may be correlated with labor market conditions in occupation, industry, and state levels. For example, individuals having occupations with traditionally high computer use rate could be more likely to be in high-technology industries or in states with high-technology economy, where the labor demand patterns might be different compared to the other industries or states.

The only source of variation in the instrument, Z_{ct}, is the interaction of the baseline distribution of occupational computer use rate with time. Note that the time component represents the exogenous introduction of the Internet and online job search methods. Since the Internet adoption speed is the same among all individuals within an occupation, whether an individual had been quick at adopting the Internet or online job search methods has no effect on Z_{ct}. This makes the exclusion restriction, $\text{Cov}(Z_{ct}, \varepsilon_{it}) \neq 0$, plausible.

3 Data and Descriptive Analysis

The primary data in this study come from the December 1998, August 2000, and September 2001 Computer and Internet Use Supplements to the CPS.[11] The Supplement surveys asked respondents whether they had

[11]The Internet job search question appeared in the December 1998 Supplement for the first time and disappeared after October 2003. The October 2003 Supplement is not included in the analysis sample because the occupation classification system, which

used the Internet (at any location) to search for jobs. The December 1998 and August 2000 supplements include two questions: "Does ... REGULARLY use the Internet to search for jobs?" and "Internet use outside the home, to search for jobs, y/n." The former was asked to people with home Internet access, while the latter was asked to those used the Internet outside their homes. The Internet job search indicator variable is equal to one when a respondent answered yes to either of the two questions in the two supplements. The September 2001 Supplement combined the two Internet job search questions in the two previous surveys into one: "This year, (has NAME/have you) used the Internet to search for a job?" The wording of the question slightly changed, and it asked whether respondents had engaged in the Internet job search in the survey year specifically. I ignore the slight difference in the Internet job search questions across years. I assume that if a person used the Internet to search for a job in the survey year, the person regularly searched for jobs online. The assumption implies that Internet job search is a time invariant individual characteristic.

The employment outcomes of the individuals in the Supplements are from the subsequent Basic Monthly CPS files. I longitudinally match individuals in the December 1998, August 2000, and September 2001 Supplements with the common survey respondents in the ten subsequent Basic Monthly Surveys by exploiting the panel structure of the CPS. The December 1998 Supplement is merged to the January-March 1999, September-December 1999, and January-March 2000 Basic Monthly Surveys. Similarly, the August 2000 (September 2001) Supplement is matched to the September-November 2000 and May-November 2001 (October-December 2001 and June-December 2002) Basic Monthly Surveys. When matching the CPS respondents, I follow the procedure proposed by Madrian and Lefgren (1999).[12] I restrict the sample to individuals who were unemployed, i.e. laid off or looking for work, in December 1998, August 2000, and September 2001. This approach enables me to find out whether Internet job search facilitated employment throughout the 15 months of the follow-up period after an individual had been observed as unemployed. When constructing my analysis sample, I only include the civilian noninstitutional population with age 16 or above. My analysis sample consists of 8,191 individuals including 1,887 Internet job searchers.[13]

The analysis sample also includes a group of non-Internet job searchers, whose Internet job search

is essential in constructing the instrument, in the October 2003 Supplement is substantially different from the ones in the previous supplements. The 2002 Census occupational and industry classification systems were newly adopted to the CPS in January 2003 and it is not straightforward to construct a crosswalk linking the CPS occupation categories before and after January 2003.

[12]The merged observations are tagged as bad matches for which (1) gender differs, (2) race differs, (3) the age difference is less than -1 or greater than 3, or (4) the person type changes from an adult to a child across the CPS files. The tagged observations are not included in the estimations in Section 4 if the bad match occurs before the person becomes employed as in Kuhn and Skuterud (2004).

[13]By year, there are 2,457 observations (including 330 Internet job searchers) in 1998, 2,480 observations (including 588 Internet job searchers) in 2000, and 3,254 observations (including 969 Internet job searchers) in 2001.

status was exogenously determined, from the September 1992 Basic Monthly CPS. They did not in online job search activities, not because they optimally decided not to, but because the Internet access and various online activities including job search were not available back then. The October-December 1992 and June-December 1993 Basic Monthly CPS files are merged to the 1992 Basic Monthly CPS to collect information on their employment status in the follow-up period. Note that the entire follow-up period is before 1994 when Netscape's Navigator program was introduced and the Internet started getting popular among the general public. For this reason, it is fair to assume that employment outcomes in any follow-up months were not affected by the introduction of the Internet. Among the respondents to the September 1992 Basic CPS, I keep 4,975 individuals who were unemployed. In total, the analysis sample consists of 13,166 unemployed persons, including 1,887 Internet job searchers and 11,279 non-Internet searchers.

The fraction of workers using a computer at work in each occupation, C_c^{93} in equation (3), is constructed from the October 1993 School Enrollment Supplement to the CPS.[14] It is calculated as the weighted fraction of currently employed workers aged 16 or above within 45 detailed occupation categories, who answered yes to the question, "Does ... use a computer directly at work?"[15]

Table 2 gives means and standard deviations of the variables used for the estimations in this study. The first six columns report summary statistics for the 1998, 2000, and 2001 Supplements by Internet job search status and for the overall supplement sample. It appears that Internet job search may reflect sorting on observable individual characteristics as pointed out by Kuhn and Skuterud (2004); Fountain (2005); Stevenson (2006, 2009). Kuhn and Skuterud (2004) find "unemployed workers who search for a job online have observable characteristics that are usually associated with greater job search success than other unemployed workers" from their descriptive analysis using the December 1998 and August 2000 Supplements to the CPS. This pattern still exists in my sample which includes the more recent round of the Computer and Internet Supplement. The unemployed workers who looked for work online had occupations with lower unemployment rates than non-Internet searchers. Higher fraction of Internet job searchers worked prior to the current unemployment spell relative to other unemployed people. Online job searchers were more likely to be between ages of 26 and 55, better educated, less likely to be black or Hispanic, and more likely to be homeowners than those who did not engage in online job search activities. Internet job searchers were

[14]The question asking about computer use at work is available from the October Supplements in the following selected years: 1984, 1989, 1993, and 1997. I choose to use the October 1993 data because it is before the Internet became popular among the general public and not far from September 1992, the starting year of my analysis sample.

[15]To calculate these frequencies, 70,350 observations are used.

more actively using various traditional job search methods[16], which indicates that online job searchers were usually the ones looking for work more actively.

Along with the fast penetration of the Internet from 1998 to 2001, using the Internet for job search also became popular. This can be seen from the fact that the fraction of unemployed workers engaging in online job search more than doubled from 13 percent in 1998 to 30 percent in 2001.[17] It is reiterated on the top block of Table 2. About a half of Internet job searchers are from the 2001 Supplement, while the proportion of each of the three Supplements is about one third among non-Internet searchers. Nonetheless, the popularity of online job search did not dilute the positive selection on observable characteristics of online job searchers over the three year period.

The second block from the bottom of Table 2 shows that online job searchers were living in an environment with a better access to the information technology and had more opportunities to use a computer and the Internet than non-Internet searchers. People who looked for work online were over three times more likely to have an access to the Internet from home than people who didn't use the Internet for job search. Also, online job seekers were more concentrated in occupations in which computer use was traditionally more prevalent.

The last two columns of Table 2 present the means and standard deviations of the observable characteristics of unemployed workers from the 1992 Basic Monthly CPS. Many of the average observable characteristics in the seventh column are significantly different at the 5% level from those of the Supplement sample in the fifth column. Especially, retrospective unemployment duration from the 1992 sample is about a month longer than from the Supplement sample. The state unemployment rate and occupation unemployment rate are 3.2 and 2.5 percentage points higher respectively in 1992 relative to 1998, 2000, and 2001. This is because September 1992 was under adverse labor market conditions after the July 1990 - March 1991 recession while the three supplement months were under more favorable economic conditions.

The bottom block of Table 2 reports the fraction of individuals employed at various follow-up points after December 1998, August 2000, September 2001, and September 1992. The numbers indicate the fraction of the employed among the individuals whose labor force status was observed at each follow-up point.

[16]The six traditional search methods were listed in the September 1992 CPS: 1) Contacted employer directly, 2) Contacted public employment agency, 3) Contacted private employment agency, 4) Contacted friends or relatives, 5) Placed or answered ads, and 6) Other search methods. The six additional search methods listed in the December 1998, August 2000, and September 2001 CPS are reclassified as 6) Other search methods to make the search method categories consistent with the September 1992 file. Note that these methods may or may not involve using the Internet.

[17]From author's calculation.

Among the analysis sample, 8,926 people's labor force status was observed a month after the four initial months. The number of persons with observed labor force status decreases to 5,669 two months after, and to 4,171 a year after the initial months. In any post-initial months, 10,532 people's labor force status was observed after excluding the bad matches. These observations are used for the estimation analysis in Section 4. In the Supplement sample, employment rates were not significantly different between the Internet job searchers and other unemployed individuals one or two months after the Supplement months. After 12 months, however, persons who looked for jobs using the Internet were 10 percentage points more likely to be employed than non-Internet searchers and the difference is statistically significant at the 5 percent level. In any post-Supplement months, the employment chances were higher for Internet job searchers than for job seekers not using the Internet. The difference is 3 percentage points and statistically significant at the 5 percent level. However, it would be premature to conclude whether or not Internet job search was effective in raising employment probability. Internet job search status is correlated with an individual's observable and unobservable characteristics associated with both higher and lower employment chances. Unemployed workers from the 1992 Basic Monthly Survey sample had lower employment chances at various follow-up points than the ones in the Supplement sample. It is due to the adverse labor market conditions in 1992.

4 Results

4.1 OLS Estimates

Table 3 and 4 present OLS estimates of the effect of Internet job search on employment probability conditional on various control variables. Although controlling for observable characteristics would not sufficiently resolve the endogeneity of Internet job search status, I present the OLS estimates as a benchmark for comparison with the IV estimates. The OLS estimates also demonstrate that they are comparable to results in Kuhn and Skuterud (2004).

Table 3 reports OLS regression results of equation (4) for employment outcomes in one month, two months, twelve months, and at any months after individuals' job search status was observed. The results in Table 3 are from the main specification and the set of control variables therein are also included in the IV analysis in the subsequent sections. The estimated effects of online job search on employment probability in four columns are ranging from -0.032 in column (2) to 0.036 in column (3), and none of them are statistically different from zero at the conventional level. Note that the strong positive correlation between searching for

jobs online and finding a job a year after the initial month or any time within the 15 month follow-up period appeared in the univariate results in the bottom block of Table 2 and panel A of Table 4, no longer exists once individual characteristics and labor market conditions are held constant. When we look at the relationship between Internet job search and employment probability one and two months after the initial month, the zero and small positive correlations in the univariate results no longer survive and become negative with additional controls although the estimated effect is not significant at the conventional levels.

The relationship between other covariates and employment probability in Table 3 are qualitatively similar across four employment outcomes at various follow-up points. One additional month of retrospective unemployment duration is associated with a one percentage point lower employment probability. People on layoff are 18-20 percentage points more likely to become employed. With one percentage point higher unemployment rate in the resident state, unemployed workers are less likely to find a job by 1-4 percentage points. Individuals who worked or went to school prior to the current unemployment spell are generally more employable than the ones who did not. The younger one is, the more likely one is to find a job. Married males are 4-12 percentage points more likely to become employed than single males. The difference in the job finding rate is neither as pronounced nor significant between single male and single female or between single female and married female. Better educated ones are generally more likely to get a job. Blacks have 5-11 percentage points lower chances to be employed than whites and other races.

Table 4 shows that my OLS results are comparable to Kuhn and Skuterud (2004) by reporting the OLS coefficient on the Internet job search variable in different specifications from my analysis sample and the sample used in Kuhn and Skuterud (2004). Kuhn and Skuterud (2004) and its working paper version, Kuhn and Skuterud (2002), only report estimates from their probit and duration analysis and the marginal effects for the probit results are not reported either. To have coefficient estimates from Kuhn and Skuterud (2004) that can be compared to estimates in this paper, I reproduce the OLS version of Kuhn and Skuterud (2004)'s results using the same data and variables as in their paper.[18] Most of the variables in my analysis sample are generated in the same manner as Kuhn and Skuterud (2004) did. There are several variables not identical to the Kuhn-Skuterud counterparts since some CPS questions were not consistent between 1992 and the other years. Even for those variables, I constructed them as close as possible to the ones in the Kuhn-Skuterud sample. The coefficients on Internet job search produced from the Kuhn-Skuterud sample are reported in

[18]The data and variables used in Kuhn and Skuterud (2004) are available from http://www.econ.ucsb.edu/~pjkuhn/Data/DataIndex.html. I was also able to replicate the Kuhn-Skuterud sample, which is a subset of my analysis sample.

the first row on each panel.

Panel A shows the beneficial effects of Internet job search on employment probability when there are no other covariates included in the regressions. The coefficient estimates from my sample are similar to the ones obtained from the Kuhn-Skuterud sample. Panel B shows the effect of online job search on job finding rate when covariates in the main specification are included in the regressions. Note that the coefficient estimates in the third row of panel B are identical to the ones in the first row of Table 3. I also report the results from the specification without occupation, industry, and state dummies in the second row of panel B because Kuhn and Skuterud (2004) do not include those indicator variables in their analysis. The coefficient estimates are similar in terms of the sign and magnitude within column. As pointed out in Table 2, the effect of Internet job search becomes more negative or smaller if it remains positive relative to the univariate results in panel A. Following Kuhn and Skuterud (2004), Panels C, D, and E report results from specifications with additional control variables. The effect of online job search reported in panel C are conditional on individual's home Internet access. We can see that the negative estimates in panel B are now more pronounced and the small positive coefficient in column (3) becomes slightly smaller in panel C. The coefficient estimates in panel D are from regressions controlling for the traditional search methods listed in Table 2, and panel E reports results from the regressions controlling for both home Internet access and the traditional search methods. In all panels, the coefficient estimates are comparable in terms of the sign and magnitude within column. Thus, if my IV results are substantially different from the results in the well established study by Kuhn and Skuterud (2004), it is not because my analysis sample and some of the covariates are not identical to theirs, but because endogeneity of Internet job search is addressed in this paper whereas it is not in their work.

4.2 First-Stage Estimates

Before presenting the IV results, this section estimates the first stage, showing that $C_c^{93} \cdot t$, the interaction between time and 1993 occupational computer use rate, is a good predictor of unemployed individuals' Internet job search status.

Table 5 shows the first-stage relationship in a regression form by estimating equation (5). Each column presents the first-stage of the relationship between online job search status and employment outcomes in one month, two months, twelve months, or in any months after individuals' job search status was observed. Each column of Table 3 corresponds to each of the main IV regressions in Table 6. All the regressions include occupation, industry, and state dummies, and heteroskedasticity robust standard errors are reported.

In all four columns, estimates of θ, the coefficient on $C_c^{93} \cdot t$ in equation (5), are very similar from 0.052 to 0.060 and statistically significant at the less than the 1 percent level.[19] These estimates imply that unemployed individuals in an occupation with 10 percentage points higher baseline computer use rate at work experienced 0.52-0.60 percentage points additional increase in Internet job search rate each year. Unemployed individuals in an occupation with the computer use rate a standard deviation above (29 percentage point higher) from the average computer use rate (32.6 percent) would have experienced 13.5-15.7 percentage points higher increase in Internet job search rate from 1992 to 2001. Given that the Internet job search rate was zero for everyone in 1992, this implies 13.5-15.7 percentage points higher Internet job search rate than the average in 2001, which is about one third of the standard deviation of the 2001 Internet job search rate (45.7 percent). Therefore, the estimated effect of $C_c^{93} \cdot t$ on Internet job search rate is quite substantial.

The coefficient estimates on other variables in the first-stage regressions confirm that online job searchers generally have attributes associated with higher job finding rates. Unemployed persons living in states with higher unemployment rate are less likely to search for jobs online. Persons who worked or went to school are more likely to use the Internet for job search than those who did not. The Internet job search rates are substantially higher among younger workers relative to those in older age groups. The difference is about 10 percentage points between the youngest group with age 16-25 and the oldest group with age 56 and above. The Internet job search rate is positively associated with educational attainment. Unemployed workers with college degree are about 20 percentage points more likely to search for jobs online than unemployed workers whose highest educational attainment is primary school. The coefficients on Black and Hispanic are both negative and significant.

At the bottom of Table 5, I report diagnostic statistics that are useful for testing whether $C_c^{93} \cdot t$ is a relevant instrument. The adjusted R^2 from the first stage regressions are around 0.27-0.31, which are not low. But, we can expect that the IV estimates would suffer from some loss of precision relative to OLS. Testing the significance of the instrument, i.e. $H_0 : \theta = 0$, yields the F-statistics of very large values, ranging from 141 in column (3) to 410 in column (4).[20] Therefore, we can strongly reject the null hypothesis that the instrument is weak. The F-statistics of over 100 also suggest that the finite sample bias of IV estimates would be less than 1 percent that of OLS.[21] As Bound et al. (1995) propose, I also report partial R^2 coefficient

[19] It is not surprising that the coefficient estimates are similar in all four columns because observations contributed to the regression results in column (1), (2), (3) are subsets of observations used for the regression in column (4).

[20] The first-stage F-statistics of over 100 are substantially larger than 10, the widely cited threshold.

[21] See Staiger and Stock (1997); Stock et al. (2002); Stock and Yogo (2005) for more details on formal tests for weak instruments and the finite-sample bias of the IV estimator with weak instruments.

between $C_c^{93} \cdot t$ and the Internet job search rate as another measure of the instrument's strength.[22] It has values around 0.03-0.04, which predicts that the standard errors around the coefficient estimates on Internet job search rate in the IV regressions of equation (4) will be inflated by five to six times according to the simple formula, $\text{var}(\hat{\beta}_{IV}) = \text{var}(\hat{\beta}_{OLS})/\text{partial } R^2$. Although there is no standard critical values for using partial R^2 as a diagnostic, the partial R^2 of 0.03-0.04 is not low compared to the values reported in the IV literature using individual data. Therefore, I can conclude that the instrument, $C_c^{93} \cdot t$, is free from the weak instrument problem.

Next, I present Durbin-Wu-Hausman F-statistics testing the null hypothesis that the OLS and IV estimates are the same. In all columns except column (3), the null hypothesis is rejected at the 10 percent level with p-values 0.072 in column (1), 0.050 in column (2), and 0.100 in column (4). This result suggests that the OLS estimates suffer from the endogeneity problem given the assumption that the instrument is valid.

4.3 IV Estimates

Table 6 presents the main results of this paper, the IV estimation results of the effect of using the Internet for job search on employment probability. The structure of the table is identical to that of Table 3, but now endogeneity of S_{it} in equation (4) is addressed by instrumenting it by $C_c^{93} \cdot t$ as in equation (5). Again, all the regressions include occupation, industry, and state dummies, and heteroskedasticity robust standard errors are reported.

The IV estimates of β are all positive and at least five times larger but less efficient than corresponding OLS estimates in Table 3. Standard errors around the IV estimates of β are also five to six times larger than the standard errors around the corresponding OLS estimates as anticipated in Section 4.2. Column (1) shows that Internet job searchers are 12.2 percentage points more likely to be employed one month after their job search status is observed relative to people who does not use the Internet for job search. The estimated effect is not significant with p-value $= 0.133$. After two months, searching for jobs online is associated with 16.0 percentage points higher employment probability as shown in column (2). The estimate is marginally insignificant at the 10 percent level with p-value $= 0.106$. The difference in job finding rates between Internet job searchers and non-Internet searchers increases to 17.6 percentage points (with p-value $= 0.198$) in 12 months, which is presented in column (3). The effect of Internet job search on job finding rate gets slightly bigger as we follow individuals for longer horizon. This pattern is also observed in OLS estimates.

[22] Since there is only one endogenous variable, the partial R^2 is equal to Shea (1997) 's partial R^2.

Among all the individuals whose employment status are observed in any post-initial months, Internet job search raises employment probability by 14.1 percentage points on the average. The effect is statistically significant at the 10 percent level with p-value $= 0.097$.

The coefficient estimates and their standard errors of the other control variables, on the other hand, are very similar to those from the OLS estimations in Table 3. It is not surprising because other regressors, which are exogenous in my IV model, are instrumented by themselves and therefore have a very high partial R^2 from the first stage. Note that it is a partial R^2, rather than R^2, that influences the precision of an endogenous regressor.[23]

The estimated effect of searching for jobs online is quite large considering that the average employment rate among non-Internet searchers are 29.8 percent in a month, 37.0 percent in two months, 52.2 percent in twelve months, and 54.4 percent in any month after their job search status is observed. Using the Internet for job search increases the job finding rates by 41 and 43 percent for one and two month outcomes and by 34 percent for twelve month outcomes. For any post-initial month outcomes, searching for jobs online leads to 26 percent higher job finding rate.

Table 7 reports the IV coefficient estimates on Internet job search from other specifications of equations (5) and (4). In panel A, other specifications of (4) presented in Table 4 are estimated with the IV strategy. The first row in panel A estimates equation (4) with no other covariates, including X_{it} and all the fixed effects. Note that the the exclusion restriction is likely to be violated when these covariates are omitted from the regression because the occupational computer use rate might be correlated with individual characteristics as well as occupation, industry, and state level labor market conditions. Nonetheless, I report the estimates so that they can be compared to the OLS estimates in the second row in panel A of Table 4. The next three rows in panel A are the IV version of the regressions in the third row of panels C, D, and E in Table 4, additionally controlling for home Internet access, traditional job search method use, or both. The estimated effects of Internet job search in these various specifications are all positive although their corresponding OLS estimates are negative for one or two month outcomes. They are generally larger than the corresponding IV estimates from the main specification in Table 6 by around 2-5 percentage points. Therefore, the positive and large IV estimate of β is robust to additional control variables.

Panel B of Table 7 repeats the IV estimation of the main specification as in Table 6, but with a slightly different set of instruments. Now, the Internet job search variable is instrumented by $Z_{ct} = C_c^{93} \cdot \mu_t$, where

[23] See Section 4.9.3 of Cameron and Trivedi (2005) for more on low precision of IV estimators.

μ_t is a set of time dummy variables. Although the standard errors are high, the new IV estimates are also positive and larger than the OLS estimates, but smaller than the original IV estimates in Table 6. With the new instruments, the first-stage results are not as strong as the original instrument, $C_c^{93} \cdot t$. For example, the first-stage F-statistics are smaller although still much larger than 10, and the IV estimates (except the one in column (2)) are not different from the OLS estimates according to Durbin-Wu-Hausman test results. Nonetheless, the estimates indicating a 10-12 percentage point increase in job finding rate due to Internet job search are consistent with the positive and large effect of Internet job search reported in Table 6.

5 Conclusion

This paper investigates whether using the Internet for job search helps unemployed workers find jobs. I address self-selection of Internet job searchers by exploiting the fact that the Internet was adopted more rapidly among individuals in occupations with the higher computer use rate before the introduction of the Internet. The IV results suggest that unemployed workers searching for jobs online are around 14 percentage points more likely to be employed during the 15 month follow-up period than unemployed workers who do not engage in Internet job search. This implies that using the Internet for job search raises the 15-month job finding rate by around 26 percent at the mean. Given the prevailing ideas of the two mechanisms by which Internet access can affect job search – 1) job search and recruitment process become more efficient, and 2) workers and firms become choosier as their reservation match quality increases, the results here suggest that the latter effect dominates the former.

A possible threat to the internal validity of the IV estimates is the possible correlation between the baseline occupational computer use rates and the changes in unemployed individuals' job finding rates throughout the analysis period between 1992 and 2001. To test whether it is likely to be the case, we can conduct a falsification exercise showing if the instrument has a predictive power for the changes in employment outcomes before the analysis period, for example, from 1983 to 1992.

Another caveat of the analysis in this paper is that a general equilibrium effect is ignored. Therefore, it is hard to claim that the results found in the partial equilibrium analysis would imply lower frictional unemployment rate. By making it easier and cheaper for employed workers to search for jobs, the availability of the Internet as a job search tool could lead to more job separations. This implies a larger pool of job seekers and higher competition among them. The positive partial equilibrium effect of Internet job search

on employment probability found among unemployed workers is likely to be neutralized by this general equilibrium effect. Therefore, in future research, it would be interesting to find out how the results would change when the general equilibrium effects are taken into account.

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Figure 1. Fraction of Unemployed Workers Searching for Jobs Online in Occupations with Different Computer Usage Rates

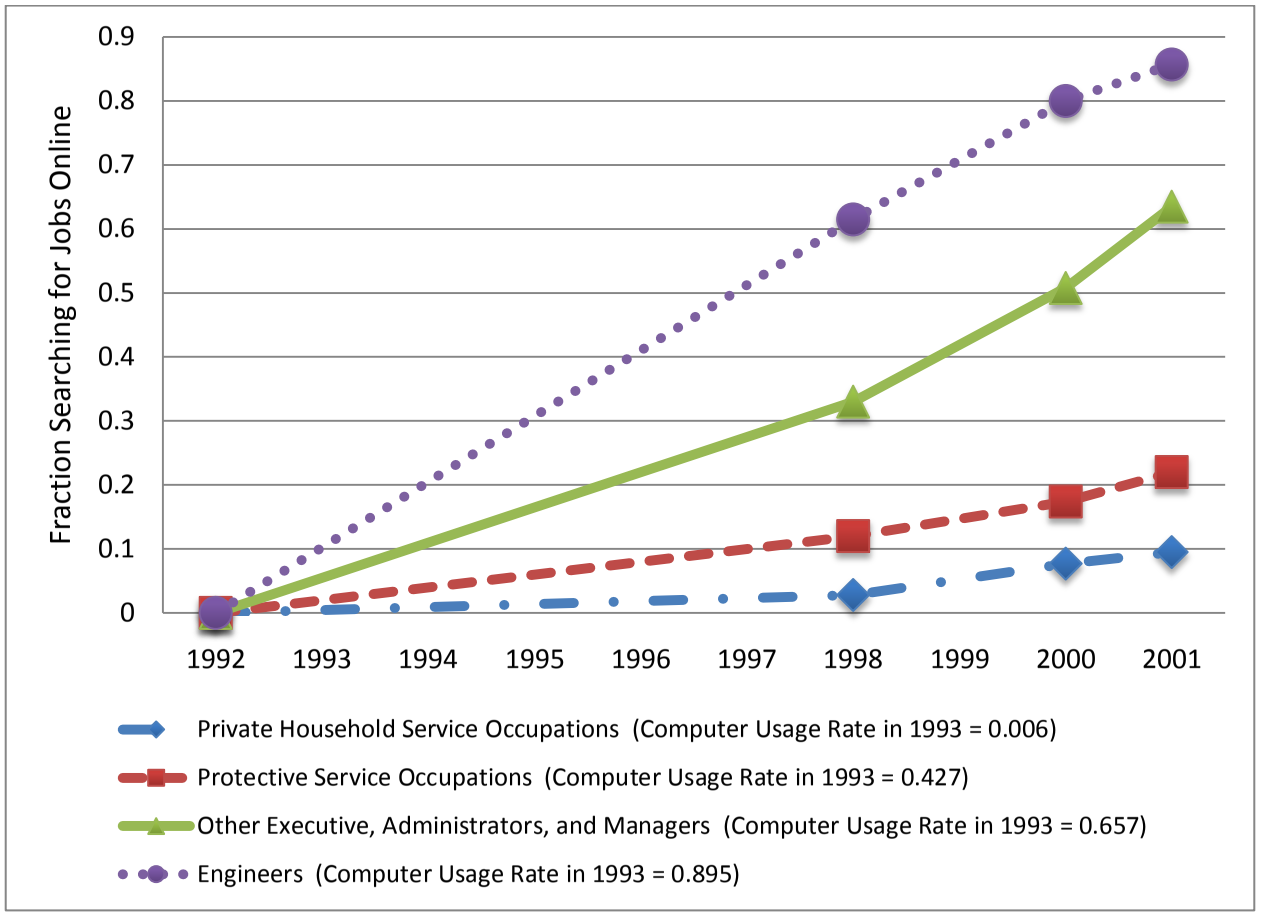

Table 1. Fraction of Persons with Internet Access and Engaging in Internet Job Search, by Labor Force Status

December 1998, August 2000, and September 2001 (Replicated and Extended from Kuhn and Skuterud (2004))

	Fraction with home Internet access			Fraction looking for work online			Fraction looking for work online, given home Internet access		
	1998	2000	2001	1998	2000	2001	1998	2000	2001
Employed									
at work	0.347	0.521	0.627	0.071	0.112	0.113	0.159	0.183	0.153
absent	0.338	0.610	0.649	0.070	0.105	0.108	0.165	0.150	0.143
Unemployed									
on layoff	0.164	0.392	0.434	0.048	0.101	0.142	0.174	0.206	0.263
looking	0.221	0.396	0.515	0.149	0.257	0.319	0.497	0.542	0.534
NILF									
retired	0.122	0.237	0.315	0.003	0.005	0.005	0.023	0.021	0.015
disabled	0.105	0.204	0.277	0.014	0.022	0.018	0.104	0.097	0.059
other	0.319	0.465	0.584	0.039	0.063	0.069	0.090	0.117	0.104
Total	0.294	0.457	0.555	0.055	0.089	0.092	0.146	0.165	0.142

Notes: All means are calculated from the December 1998, August 2000, and September 2001 Computer and Internet Use Supplements to the CPS using the CPS final weights.

Table 2. Summary Statistics

	1998, 2000, 2001 Computer/Internet Supplements							
	Internet job search						1992 Basic	
	Yes		No		All		Monthly	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Retrospective duration in months	3.379	4.509	3.322	4.884	3.335	4.800	4.536*	5.785
2001 Supplement	0.514	0.500	0.362	0.481	0.397*	0.489	0.000*	0.000
2000 Supplement	0.312	0.463	0.300	0.458	0.303	0.459	0.000*	0.000
1998 Supplement	0.175	0.380	0.337	0.473	0.300*	0.458	0.000*	0.000
On layoff	0.059	0.235	0.173	0.378	0.146*	0.354	0.108*	0.310
State unemployment rate	4.543	0.903	4.548	0.942	4.547	0.933	7.722*	1.417
Occupational unemployment rate	4.232	2.130	5.523	2.675	5.226*	2.617	7.697*	2.972
Worked prior to unemployment	0.599	0.490	0.419	0.493	0.461*	0.498	0.523*	0.500
School prior to unemployment	0.178	0.383	0.178	0.383	0.178	0.383	0.048*	0.215
Quit job	0.168	0.374	0.122	0.327	0.133*	0.339	0.118*	0.323
Private sector	0.817	0.387	0.809	0.393	0.811	0.392	0.781*	0.414
Public sector	0.107	0.309	0.073	0.261	0.081*	0.273	0.087	0.281
Self-employed	0.041	0.199	0.038	0.192	0.039	0.194	0.028*	0.164
Age 16-25	0.291	0.454	0.367	0.482	0.350*	0.477	0.343	0.475
Age 26-35	0.252	0.434	0.207	0.405	0.217*	0.412	0.272*	0.445
Age 36-45	0.220	0.414	0.207	0.405	0.210	0.407	0.198	0.399
Age 46-55	0.178	0.382	0.128	0.334	0.139*	0.346	0.114*	0.318
Male	0.485	0.500	0.510	0.500	0.505	0.500	0.524*	0.499
Married	0.426	0.495	0.341	0.474	0.360*	0.480	0.410*	0.492
Male and married	0.208	0.406	0.159	0.366	0.170*	0.376	0.213*	0.410
Spouse employed	0.312	0.463	0.235	0.424	0.253*	0.435	0.272*	0.445
Primary school	0.004	0.065	0.076	0.264	0.059*	0.236	0.052	0.223

Incomplete high school	0.083	0.276	0.268	0.443	0.225*	0.418	0.218	0.413
Complete high school	0.246	0.431	0.382	0.486	0.351*	0.477	0.371*	0.483
Incomplete college	0.234	0.423	0.147	0.354	0.167*	0.373	0.181*	0.385
Associate degree	0.087	0.283	0.042	0.200	0.052*	0.223	0.053	0.223
Black	0.118	0.322	0.194	0.395	0.176*	0.381	0.175	0.380
Hispanic	0.069	0.253	0.165	0.371	0.143*	0.350	0.110*	0.313
Home owner	0.594	0.491	0.542	0.498	0.554*	0.497	0.538	0.499
Contacted employer directly	0.600	0.490	0.530	0.499	0.547*	0.498	0.652*	0.476
Contacted public employment agency	0.229	0.421	0.158	0.365	0.175*	0.380	0.201*	0.401
Contacted private employment agency	0.123	0.329	0.049	0.215	0.066*	0.248	0.082*	0.275
Contacted friends or relatives	0.162	0.369	0.106	0.308	0.119*	0.324	0.211*	0.408
Placed or answered ads	0.224	0.417	0.101	0.302	0.129*	0.336	0.376*	0.485
Other search method	0.758	0.429	0.522	0.500	0.576*	0.494	0.043*	0.203
Number of search methods	2.097	1.174	1.467	1.058	1.612*	1.118	1.566*	1.011
Internet access at home	0.826	0.380	0.265	0.441	0.394*	0.489	0.000*	0.000
Occupational computer use rate in 1993	0.507	0.294	0.279	0.268	0.332*	0.291	0.317*	0.290
Internet job search	1.000	0.000	0.000	0.000	0.230	0.421	0.000*	0.000
Employed 1 month after initial month	0.295	0.456	0.319	0.466	0.314	0.464	0.270*	0.444
Employed 2 months after initial month	0.394	0.489	0.399	0.490	0.398	0.490	0.330*	0.470
Employed 12 months after initial month	0.637	0.481	0.534	0.499	0.559*	0.497	0.508*	0.500
Employed in any post- initial month	0.597	0.491	0.566	0.496	0.573*	0.495	0.515*	0.500
Number of months observed	2.732	2.196	2.622	2.188	2.648	2.190	2.486*	2.183
Number of Obs	1887		6304		8191		4975	

Notes: * in the fifth column indicates means are statistically different between Internet job searchers and non-Internet searchers at the 5-percent significance level. * in the seventh column indicates means are statistically different between the supplement sample from 1998, 2000, and 2001 and the 1992 sample at the 5-percent significance level.

Table 3. Effect of Internet Job Search on Employment Probability – OLS Results

	Dependent Variable							
	Employed 1 mon after initial month		Employed 2 mon after initial month		Employed 12 mon after initial month		Employed in any post-initial mon	
	(1)		(2)		(3)		(4)	
Internet job search	-0.023	(0.015)	-0.032	(0.021)	0.036	(0.024)	0.002	(0.015)
1998 Supplement	-0.078	(0.029)**	-0.074	(0.039)*	-0.066	(0.046)	-0.034	(0.029)
2000 Supplement	0.042	(0.033)	0.040	(0.045)	-0.123	(0.053)**	0.027	(0.033)
2001 Supplement	-0.034	(0.027)	-0.024	(0.037)	-0.118	(0.043)**	-0.034	(0.028)
Retrospective duration in months	-0.008	(0.001)**	-0.008	(0.001)**	-0.010	(0.001)**	-0.009	(0.001)**
On layoff	0.198	(0.018)**	0.192	(0.024)**	0.193	(0.026)**	0.184	(0.017)**
State unemployment rate	-0.012	(0.008)	-0.024	(0.010)**	-0.036	(0.012)**	-0.016	(0.008)**
Occupational unemployment rate	-0.005	(0.004)	-0.001	(0.006)	-0.003	(0.007)	-0.000	(0.004)
Worked prior to unemployment	0.009	(0.013)	0.032	(0.017)*	0.140	(0.021)**	0.052	(0.014)**
School prior to unemployment	-0.019	(0.018)	0.017	(0.023)	0.080	(0.029)**	0.021	(0.018)
Quit job	0.041	(0.016)**	0.035	(0.022)	0.007	(0.027)	0.018	(0.017)
Private sector	-0.190	(0.173)	0.087	(0.203)	0.173	(0.222)	-0.174	(0.175)
Public sector	-0.170	(0.174)	0.055	(0.205)	0.110	(0.226)	-0.220	(0.176)
Self-employed	-0.049	(0.175)	0.188	(0.206)	0.167	(0.226)	-0.085	(0.176)
Age 16-25	0.127	(0.020)**	0.132	(0.028)**	0.235	(0.032)**	0.173	(0.021)**
Age 26-35	0.102	(0.019)**	0.093	(0.026)**	0.228	(0.030)**	0.145	(0.020)**
Age 36-45	0.071	(0.018)**	0.038	(0.026)	0.197	(0.029)**	0.132	(0.020)**
Age 46-55	0.069	(0.020)**	0.047	(0.028)*	0.133	(0.031)**	0.107	(0.021)**
Male	-0.015	(0.013)	-0.027	(0.018)	0.001	(0.022)	0.001	(0.014)
Married	-0.012	(0.019)	-0.009	(0.026)	0.030	(0.030)	-0.016	(0.020)
Male and married	0.035	(0.020)*	0.072	(0.027)**	0.116	(0.031)**	0.053	(0.020)**
Spouse employed	0.001	(0.017)	-0.009	(0.023)	-0.024	(0.026)	0.021	(0.017)
Primary school	-0.064	(0.027)**	-0.111	(0.035)**	-0.100	(0.043)**	-0.121	(0.028)**
Incomplete high school	-0.101	(0.020)**	-0.131	(0.027)**	-0.086	(0.032)**	-0.129	(0.020)**
Complete high school	-0.058	(0.018)**	-0.062	(0.024)**	-0.040	(0.028)	-0.074	(0.018)**

Incomplete college	-0.032	(0.019)*	-0.045	(0.025)*	-0.020	(0.029)	-0.051	(0.018)**
Associate degree	-0.044	(0.025)*	-0.039	(0.034)	0.028	(0.038)	-0.045	(0.025)*
Black	-0.054	(0.014)**	-0.047	(0.019)**	-0.105	(0.022)**	-0.068	(0.014)**
Hispanic	-0.020	(0.016)	-0.004	(0.022)	0.009	(0.027)	0.001	(0.017)
Home owner	0.021	(0.010)**	-0.005	(0.014)	0.018	(0.017)	0.050	(0.010)**
Constant	0.289	(0.079)**	0.386	(0.109)**	0.470	(0.125)**	0.437	(0.082)**
Adjusted R-squared	0.071		0.068		0.095		0.063	
N	8926		5669		4171		10284	

Notes: Robust standard errors in parentheses. * p<0.10 ** p<0.05 All regressions include occupation dummies, industry dummies, and state dummies.

Table 4. Comparability to Kuhn and Skuterud (2004) – OLS Coefficient on Internet Job Search

	Dependent Variable							
	Employed 1 mon after initial month (1)		Employed 2 mon after initial month (2)		Employed 12 mon after initial month (3)		Employed in any post-initial mon (4)	
A. Mean difference (without controls)								
Kuhn-Skuterud sample	0.009	(0.021)	0.048	(0.028)*	0.113	(0.032)**	0.069	(0.021)**
My sample	-0.003	(0.014)	0.024	(0.018)	0.114	(0.021)**	0.053	(0.014)**
B. Main specification								
Kuhn-Skuterud sample	-0.038	(0.023)*	-0.023	(0.031)	0.024	(0.033)	-0.001	(0.022)
My sample (no fixed effects)	-0.038	(0.015)**	-0.043	(0.020)**	0.022	(0.023)	-0.009	(0.015)
My sample (with fixed effects)	-0.023	(0.015)	-0.032	(0.021)	0.036	(0.024)	0.002	(0.015)
C. Controlling for home Internet access								
Kuhn-Skuterud sample	-0.070	(0.025)**	-0.052	(0.034)	0.016	(0.039)	-0.035	(0.025)
My sample (no fixed effects)	-0.060	(0.017)**	-0.074	(0.022)**	0.024	(0.026)	-0.031	(0.017)*
My sample (with fixed effects)	-0.042	(0.017)**	-0.059	(0.023)**	0.029	(0.027)	-0.019	(0.017)
D. Controlling for traditional job search methods								
Kuhn-Skuterud sample	-0.032	(0.023)	-0.017	(0.031)	0.016	(0.033)	0.001	(0.023)
My sample (no fixed effects)	-0.028	(0.015)*	-0.031	(0.020)	0.015	(0.023)	-0.007	(0.015)
My sample (with fixed effects)	-0.018	(0.016)	-0.027	(0.021)	0.028	(0.024)	0.001	(0.016)
E. Controlling for home Internet access and traditional search methods								
Kuhn-Skuterud sample	-0.061	(0.026)**	-0.045	(0.035)	0.003	(0.039)	-0.031	(0.025)
My sample (no fixed effects)	-0.051	(0.017)**	-0.064	(0.022)**	0.015	(0.026)	-0.030	(0.017)*
My sample (with fixed effects)	-0.037	(0.017)**	-0.054	(0.023)**	0.020	(0.027)	-0.020	(0.017)

Notes: Robust standard errors in parentheses. * p<0.10 ** p<0.05

Table 5. First Stage Results

	Dependent Variable: Internet Job Search							
	Corresponding Second Stage Dependent Variable							
	Employed 1 mon after initial month		Employed 2 mon after initial month		Employed 12 mon after initial month		Employed in any post-initial mon	
	(1)		(2)		(3)		(4)	
1993 Occupational Computer Use Rate * (Year-1992)	0.055	(0.003)**	0.060	(0.004)**	0.052	(0.004)**	0.055	(0.003)**
1998 Supplement	0.034	(0.018)*	0.025	(0.022)	0.037	(0.027)	0.034	(0.016)**
2000 Supplement	0.079	(0.022)**	0.075	(0.027)**	0.098	(0.034)**	0.078	(0.021)**
2001 Supplement	0.108	(0.018)**	0.110	(0.022)**	0.114	(0.028)**	0.104	(0.017)**
Retrospective duration in months	0.000	(0.001)	0.001	(0.001)	-0.001	(0.001)	0.000	(0.001)
On layoff	-0.066	(0.010)**	-0.064	(0.013)**	-0.068	(0.015)**	-0.061	(0.009)**
State unemployment rate	-0.011	(0.005)**	-0.009	(0.006)	-0.006	(0.007)	-0.010	(0.004)**
Occupational unemployment rate	0.007	(0.003)**	0.009	(0.003)**	0.004	(0.004)	0.006	(0.002)**
Worked prior to unemployment	0.029	(0.009)**	0.034	(0.011)**	0.044	(0.013)**	0.035	(0.008)**
School prior to unemployment	0.045	(0.013)**	0.032	(0.016)**	0.025	(0.020)	0.042	(0.012)**
Quit job	0.001	(0.012)	0.005	(0.015)	0.000	(0.019)	-0.001	(0.011)
Private sector	0.096	(0.047)**	0.096	(0.072)	0.172	(0.066)**	0.098	(0.044)**
Public sector	0.115	(0.050)**	0.099	(0.075)	0.157	(0.069)**	0.110	(0.046)**
Self-employed	0.081	(0.051)	0.080	(0.077)	0.157	(0.072)**	0.082	(0.048)*
Age 16-25	0.089	(0.014)**	0.100	(0.017)**	0.103	(0.019)**	0.091	(0.012)**
Age 26-35	0.083	(0.013)**	0.095	(0.016)**	0.116	(0.018)**	0.084	(0.012)**
Age 36-45	0.056	(0.013)**	0.067	(0.016)**	0.077	(0.017)**	0.059	(0.012)**
Age 46-55	0.050	(0.015)**	0.062	(0.018)**	0.073	(0.019)**	0.056	(0.013)**
Male	-0.007	(0.009)	-0.012	(0.011)	-0.007	(0.015)	-0.004	(0.008)
Married	0.021	(0.013)	0.011	(0.017)	0.011	(0.020)	0.021	(0.013)*
Male and married	0.029	(0.014)**	0.024	(0.017)	0.023	(0.021)	0.028	(0.013)**
Spouse employed	-0.011	(0.012)	-0.011	(0.015)	0.006	(0.017)	-0.010	(0.011)
Primary school	-0.200	(0.016)**	-0.196	(0.020)**	-0.186	(0.024)**	-0.205	(0.015)**
Incomplete high school	-0.187	(0.015)**	-0.184	(0.019)**	-0.179	(0.022)**	-0.191	(0.014)**

Complete high school	-0.152	(0.014)**	-0.152	(0.018)**	-0.159	(0.021)**	-0.160	(0.013)**
Incomplete college	-0.088	(0.015)**	-0.090	(0.019)**	-0.098	(0.023)**	-0.094	(0.014)**
Associate degree	-0.071	(0.021)**	-0.076	(0.027)**	-0.062	(0.031)**	-0.073	(0.019)**
Black	-0.036	(0.009)**	-0.030	(0.012)**	-0.031	(0.014)**	-0.031	(0.009)**
Hispanic	-0.058	(0.011)**	-0.049	(0.013)**	-0.056	(0.016)**	-0.050	(0.010)**
Home owner	-0.008	(0.007)	-0.008	(0.009)	0.011	(0.011)	-0.004	(0.006)
Constant	0.118	(0.051)**	0.076	(0.065)	0.118	(0.075)	0.126	(0.048)**
Adjusted R-squared	0.288		0.309		0.274		0.285	
F-statistic on instrument	353.144		277.643		141.004		409.869	
Partial R-squared	0.0339		0.042		0.030		0.034	
Durbin-Wu-Hausman F-statistic	3.240		3.856		1.059		2.746	
N	8926		5669		4171		10284	

Notes: Robust standard errors in parentheses. * p<0.10 ** p<0.05 All regressions include occupation dummies, industry dummies, and state dummies.

Table 6. Effect of Internet Job Search on Employment Probability – IV Results

	Dependent Variable							
	Employed 1 mon after initial month		Employed 2 mon after initial month		Employed 12 mon after initial month		Employed in any post-initial mon	
	(1)		(2)		(3)		(4)	
Internet job search	0.122	(0.081)	0.160	(0.099)	0.176	(0.137)	0.141	(0.085)*
1998 Supplement	-0.102	(0.031)**	-0.106	(0.042)**	-0.089	(0.051)*	-0.057	(0.032)*
2000 Supplement	0.006	(0.038)	-0.011	(0.051)	-0.160	(0.064)**	-0.008	(0.039)
2001 Supplement	-0.076	(0.035)**	-0.084	(0.047)*	-0.159	(0.058)**	-0.074	(0.036)**
Retrospective duration in months	-0.008	(0.001)**	-0.008	(0.001)**	-0.010	(0.001)**	-0.009	(0.001)**
On layoff	0.208	(0.019)**	0.207	(0.024)**	0.204	(0.028)**	0.194	(0.018)**
State unemployment rate	-0.010	(0.008)	-0.022	(0.010)**	-0.034	(0.012)**	-0.014	(0.008)*
Occupational unemployment rate	-0.008	(0.005)*	-0.006	(0.006)	-0.006	(0.007)	-0.003	(0.005)
Worked prior to unemployment	0.005	(0.013)	0.026	(0.017)	0.134	(0.021)**	0.048	(0.014)**
School prior to unemployment	-0.023	(0.018)	0.015	(0.023)	0.080	(0.029)**	0.018	(0.018)
Quit job	0.041	(0.016)**	0.034	(0.022)	0.007	(0.026)	0.018	(0.016)
Private sector	-0.200	(0.169)	0.077	(0.207)	0.151	(0.225)	-0.184	(0.172)
Public sector	-0.181	(0.170)	0.047	(0.209)	0.091	(0.227)	-0.230	(0.173)
Self-employed	-0.057	(0.171)	0.183	(0.210)	0.148	(0.227)	-0.093	(0.174)
Age 16-25	0.113	(0.021)**	0.110	(0.029)**	0.219	(0.035)**	0.159	(0.023)**
Age 26-35	0.089	(0.020)**	0.073	(0.028)**	0.210	(0.033)**	0.133	(0.022)**
Age 36-45	0.062	(0.019)**	0.024	(0.026)	0.186	(0.030)**	0.123	(0.021)**
Age 46-55	0.060	(0.020)**	0.033	(0.028)	0.122	(0.032)**	0.098	(0.022)**
Male	-0.014	(0.013)	-0.025	(0.018)	0.002	(0.022)	0.002	(0.013)
Married	-0.015	(0.019)	-0.011	(0.025)	0.028	(0.030)	-0.019	(0.020)
Male and married	0.030	(0.020)	0.067	(0.027)**	0.113	(0.031)**	0.049	(0.020)**
Spouse employed	0.003	(0.017)	-0.007	(0.022)	-0.024	(0.025)	0.022	(0.017)
Primary school	-0.034	(0.032)	-0.071	(0.040)*	-0.073	(0.049)	-0.092	(0.033)**
Incomplete high school	-0.073	(0.025)**	-0.094	(0.033)**	-0.061	(0.040)	-0.102	(0.026)**
Complete high school	-0.036	(0.022)	-0.032	(0.028)	-0.018	(0.035)	-0.051	(0.022)**

Incomplete college	-0.019	(0.020)	-0.027	(0.027)	-0.006	(0.032)	-0.038	(0.020)*
Associate degree	-0.034	(0.025)	-0.025	(0.034)	0.037	(0.038)	-0.035	(0.026)
Black	-0.049	(0.014)**	-0.042	(0.019)**	-0.102	(0.022)**	-0.064	(0.015)**
Hispanic	-0.011	(0.017)	0.006	(0.023)	0.017	(0.027)	0.008	(0.017)
Home owner	0.022	(0.010)**	-0.004	(0.014)	0.016	(0.017)	0.051	(0.010)**
Constant	0.293	(0.079)**	0.404	(0.109)**	0.473	(0.123)**	0.439	(0.081)**
Adjusted R-squared	0.062		0.053		0.087		0.056	
N	8926		5669		4171		10284	

Notes: Robust standard errors in parentheses. * p<0.10 ** p<0.05 All regressions include occupation dummies, industry dummies, and state dummies.

Table 7. Additional IV Results – Coefficient on Internet Job Search

	Dependent Variable							
	Employed 1 mon after initial month (1)		Employed 2 mon after initial month (2)		Employed 12 mon after initial month (3)		Employed in any post-initial mon (4)	
A. Other specifications								
Without other covariates	0.084	(0.030)**	0.210	(0.038)**	0.278	(0.048)**	0.188	(0.030)**
Controlling for home Internet access	0.142	(0.118)	0.182	(0.143)	0.224	(0.198)	0.153	(0.122)
Controlling for traditional search methods	0.148	(0.084)*	0.186	(0.101)*	0.166	(0.140)	0.155	(0.087)*
Controlling for home Internet access and traditional search methods	0.178	(0.122)	0.217	(0.147)	0.210	(0.203)	0.174	(0.126)
B. Other instrument								
1993 Occupational Computer Use Rate * Year Dummies used as instruments	0.095	(0.078)	0.124	(0.096)	0.113	(0.127)	0.117	(0.081)

Notes: Robust standard errors in parentheses. * p<0.10 ** p<0.05

Appendix Table 1. Computer Use at Work by Occupations

Recode (PRDTOCC1)	CPS Detailed Occupation	Computer Usage Rate at Work
05	Mathematical and Computer Scientists	0.984
22	Computer Equipment Operators	0.965
15	Technicians, Except Health Engineering, and Science	0.897
04	Engineers	0.895
06	Natural Scientists	0.874
03	Management Related Occupations	0.872
21	Supervisors - Administrative Support	0.868
23	Secretaries, Stenographers, and Typists	0.862
01	Administrators and Officials, Public Administration	0.862
24	Financial Records, Processing Occupations	0.801
26	Other Administrative Support Occupations,Including Clerical	0.744
17	Sales Representatives, Finance, and Business Service	0.732
09	Teachers, College and University	0.725
14	Engineering and Science Technicians	0.691
02	Other Executive, Administrators, and Managers	0.657
11	Lawyers and Judges	0.646
08	Health Assessment and Treating Occupations	0.596
12	Other Professional Specialty Occupations	0.581
16	Supervisors and Proprietors, Sales Occupations	0.571
18	Sales Representatives, Commodities, Except Retail	0.560
13	Health Technologists and Technicians	0.554
07	Health Diagnosing Occupations	0.490
10	Teachers, Except College and University	0.490
28	Protective Service Occupations	0.427
35	Other Precision Production Occupations	0.347
33	Mechanics and Repairers	0.304
19	Sales Workers, Retail and Personal Services	0.298
25	Mail and Message Distributing	0.259
20	Sales Related Occupations	0.231
37	Fabricators, Assemblers, Inspectors, and Samplers	0.175
36	Machine Operators and Tenders, Except Precision	0.175
30	Health Service Occupations	0.175
41	Freight, Stock and Material Handlers	0.158
39	Other Transportation Occupations and Material Moving	0.144
43	Farm Operators and Managers	0.137
42	Other Handlers, Equipment Cleaners, and Laborers	0.126
38	Motor Vehicle Operators	0.121
29	Food Service Occupations	0.108

Appendix Table 1. (Continued)

Recode (PRDTOCC1)	CPS Detailed Occupation	Computer Usage Rate at Work
32	Personal Service Occupations	0.102
34	Construction Trades	0.079
44	Farm Workers and Related Occupations	0.059
31	Cleaning and Building Service Occupations	0.053
40	Construction Laborer	0.036
45	Forestry and Fishing Occupations	0.029
27	Private Household Service Occupations	0.006
	All Occupations	0.452

Note: Calculated from October 1993 School Enrollment Supplement to the CPS