The Impact of the Internet on Worker Flows

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The Internet has increased the ease and availability of employment information, but a question remains as to how, and if, this increased information has changed employment outcomes. This research examines the impact of the Internet on worker flows and job matching. While previous research found a negative impact of the Internet on unemployment duration, this research demonstrates the importance of including flows between employment to employment in an analysis of the impact of Internet. Over 80 percent of online job seekers are employed at the time of their job seeking and Internet users, conditional on observables, are more likely to change jobs and are less likely to transition to unemployment. Furthermore, those who use the Internet have greater wage growth when changing jobs. I use several approaches to attempt to isolate an exogenous source of Internet use in order to isolate the causal relationship between the Internet, job change, and wage growth. The first is to examine state-level aggregate data. As states' Internet penetration rates rose differentially through the 1990's so did employer-to-employer worker flows with a 10 percentage point rise in state-level internet penetration leading to a 5% increase in employer-to-employer flows. While it can be difficult to disentangle whether changes in state labor markets reflect Internet usage or drive Internet adoption, I find a useful instrument that isolates the causal mechanism: the Internet has diffused in much the same way as past innovations, and hence average state ownership rates of household appliances in 1960 describe Internet adoption patterns over the past decade.

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1. Introduction

As dot-coms proliferated and at home Internet use sky-rocketed, many economists began to speculate on how this new technology would change the labor market. In 2000 Alan Krueger wrote that "The Internet is rapidly changing the way workers search for jobs and employers recruit workers… [with] significant implications for unemployment, pay, and productivity." Autor (2000) outlines several of the ways in which the Internet might improve matching and provides evidence on the use of the Internet for job search. In the ensuing years the Internet has become an important part of people's lives and jobs: in 2004 73% of households had access to the Internet and 58% and 28% of adults used the Internet at home and work, respectively.[1] Yet, we still know very little about how the Internet has impacted employment.

While the potential for the Internet to affect employment is vast, this research focuses on one specific aspect – the role of the Internet in matching workers and firms. The innovation of the Internet is both an increase in access to a vast amount of information and improved communication. Workers can gather information about both the availability and characteristics of jobs from information on the Internet or through email-based communication (in this way personal networks are a compliment to the Internet). They can then apply for openings and communicate with potential employers. All of which can be done 24 hours a day, without ever leaving one's home or work desk.

Workers have turned to the Web to take advantage of this new wealth of employment information with more than one in four online adults visiting job or career information sites in 2004.[2] And workers believe that the Internet is helping them find jobs. Figure 1 shows that among those that found a job in mid-2002 22% credited the Internet as the primary means by which they found their job. Yet none of this is evidence that the Internet has improved worker-firm matching. Ultimately, assessing how the Internet's job search capabilities have changed worker-firm matching

[1] Data calculated from Forrester Research's 2005 Technographics Benchmark. 86% of those who use the Internet at work also use the Internet at home, however the majority (59%) of those who use the Internet at home don't have access at work.
[2] Data are from Forrester Research's 2005 Technographics Benchmark. Individuals who use the Internet were asked how often they use certain types of Web sites. This data is comparable to that found using the 1998, 2000, and 2001 CPS Computer Supplements which finds that among those with Internet access, online job search is used by a fifth of the employed and over half of the unemployed.

requires ascertaining whether it has changed important labor market outcomes such as wages, job satisfaction, and the duration of unemployment.[3]

The research to date is not promising -- research measuring the effect of the Internet on job search found that unemployment duration is not lower for Internet job searchers, and may even be higher.[4] The authors conclude that perhaps those who searched on the Internet are negatively selected on unobservables. Alternatively, the negative effects of the Internet – the cheap cost of application leading to a plethora of applications for which employers have no useful sorting mechanism – may be greater than any beneficial effect. Or perhaps, there is a lengthy learning process whereby both employees and employers adjust to the new technology before it can be beneficial. And finally, perhaps the Internet changes search differentially for employed and unemployed job seekers; changing both who becomes unemployed and the subsequent matching process. In this case, examining only unemployment duration may give a very incomplete picture.

Introspection leads one to suspect that the Internet may be more important for on-the-job search. The Internet's anytime, anywhere aspect allows search to take place both outside of the regular work day and during the work day (workers use the Internet for many personal reasons during the work day, including job search). The unemployed face fewer time constraints and may therefore benefit less from the technology.

This research examines how the Internet has impacted job transitions, from employment-to-employment, employment-to-unemployment, and unemployment-to-employment. If on-the-job search has risen, we should see an increase in employment-to-employment flows. Furthermore, we might see fewer employment-to-unemployment transitions if employed workers who search using the Internet are more successful at locating new work before their current job ends. In this case, the negative selection of those who do move from employment-to-unemployment would bias any analysis of unemployment duration upwards. In other words, it is not that those who search the Internet for employment are negatively selected on unobservables, but that those who search the Internet *conditional on being unemployed* are negatively selected on unobservables.

This research uses data from the 1998, 2000, and 2001 CPS Computer Supplements to examine the relationship between employment transitions and use of the Internet both generally and specifically for job search purposes. The CPS Supplements also allow examination of wage

[3] Job satisfaction may capture an overall sense of the match including improvements in non-wage compensation.
[4] Kuhn and Skuterod (2004) find that, conditional on observables, unemployment duration may be higher for Internet job searchers, something that they attribute to sorting on unobservables.

changes. If the Internet facilitates better matches then productivity may increase leading to higher wages. Alternatively, the increased access to information about outside offers may simply represent a shift in bargaining power toward workers, leading to an increase in wages without changing jobs.

In sum, the Internet has changed the process by which firms and workers match, however there has been little evidence that the Internet has improved matching. This research esamines worker mobility patterns using the longitudinal aspect of the CPS to follow employed workers in the CPS Computer Supplements. These data provide information on current employer, household and individual computer and internet use, and whether or not they have changed employers in subsequent months. We find that workers who are online are 15% to 30% more likely to change jobs than those who are not online, controlling for observable worker and job characteristics. Similarly, workers who are online are 25% more likely to change jobs within the same firm. An alternative specification considers the timing of Internet diffusion across states. This aggregate state-level data shows that a 10 percentage point increase in a state's Internet penetration leads to a 5% increase in state-level employer-to-employer flows and a more than 15% increase in job changing by the college educated. These findings provide the first evidence that the Internet has fundamentally changed the matching process.

2. Data and Descriptive Statistics

The August 2000 and September 2001 Current Population Statistics (CPS) Computer and Internet Use Supplements ask respondents about their and their households' computer and Internet use in addition to the usual battery of employment questions. These data reveal that a tremendous amount of online job search is being done by the employed and unemployed. Table 1 shows descriptive statistics for home online usage and online job search among the employed, unemployed, and those not in the labor force. Among those employed, 49% were online and 11.3% searched for a job online. While only 39% of the unemployed have online access at home, they are much more likely to search for work online (29%). However, the large difference in the stock of the employed relative to the unemployed means that the unemployed are a very small share of online job searchers. The unemployed represent only 9% of those searching for a job online, while the employed comprise 81%. These descriptive statistics illustrate the importance of the employed in assessing the potential overall effect of the Internet on job matching.

Additionally, the benefits of Internet job search may be greater for the employed; reducing the cost of on-the-job search more than it increases the efficiency of search by the unemployed. The technology allows ads to be scanned quickly, detailed job information can be gained without physically visiting the firm, and communication can occur during non-business hours via email. This both reduces the need to take time off from work and, potentially, reduces the probability that the current employer overhears the job seeking behavior.[5] Furthermore, "surfing" the Web may be more enjoyable or may be done more efficiently by taking advantage of slow periods at the office, making on-the-job online job search less expensive in terms of foregone leisure. Finally, as previously mentioned, the Internet has made it easier for firms and headhunters to identify potential candidates among those who are not actively searching.

The longitudinal component of the CPS allows approximately 75% of the respondents to the Computer and Internet Use Supplements to be examined in the subsequent month.[6] I followed all people who were employed in the August 2000 and September 2001 Supplements into the September 2000 and October 2001 monthly surveys, respectively. The CPS (since 1994) employs a dependent interviewing technique in which interviewees are read back their employment details from the proceeding month and asked to confirm them. These questions allow employment flows to be calculated including those who are still employed with the employer from the previous month and those who are still employed, albeit with a new employer.

Table 2 shows the one-month employment flows of those employed in August 2000 and September 2001 broken into those who had searched for a job online in the previous month and those who had not. The first column reports results for the 88.7% who had not searched for a job online in the proceeding month: 93.3% are employed in the same job one month later, 2.7% are employed with a new employer, 1.0% are unemployed, and 2.9% are no longer in the labor force. The second column shows the employment flows for the 11.3% of workers who were looking for a job online in the first month: 91.2% are employed in the same job one month later, 4.5% are employed with a new employer, 1.9% are unemployed, and 2.4% are no longer in the labor force.

Comparing the first two columns in Table 2 reveals that those who were searching for a job online were more likely to change jobs and slightly more likely to become unemployed. However,

[5] In contrast, posting resumes online is likely to increase the probability that one's current employer discovers the job seeking activity relative to mailing resumes to select employers.
[6] While the survey is designed to be able to follow 75%, roughly only 95% of the 75% can actually be matched from one month to the next. For more information on matching in the CPS see Madrian and Lefgren (1999). Details about the match used in this paper are available from the author by request.

this comparison ignores the counterfactual of offline job search. To compare online on-the-job search with offline on-the-job search we turn to the February 1997 and February 1999 CPS Contingent Worker Supplement. Fallick and Fleischman (2004) use the Contingent Worker Supplements to examine the difference in employer flows for those who engage in offline on-the-job search.[7] Their findings are shown in the third and fourth columns of Table 2. The third column shows employment flows for the 95.6% of workers who were not engaged in on-the-job search: 95.0% are employed in the same job one month later, 2.1% are employed with a new employer, 0.9% are unemployed, and 2.0% are no longer in the labor force. While these results are similar to those found for workers who had not engaged in online on-the-job search, striking differences arise in the fourth column when examining employment flows for the 4.4% of workers who were seeking a job the previous period. Among these seekers only 80.9% remained with their previous month's employment, 11.3% were employed with a new employer, 5.6% were unemployed, and 2.3% were no longer in the labor force. Clearly those who are searching for a job while employed are negatively selected—in other words searchers seem to have private information about the possibility of their job ending.

Taken together Table 1 illustrates that online job search is different in a number of dimensions. A higher percentage of workers engage in online on-the-job search compared with offline on-the-job search behavior and offline on-the-job seekers appear to be more negatively selected on likely future employment outcomes as they transition to unemployment much more frequently than do online on-the-job seekers. However, those engaged in online on-the-job search are also quite likely to have negative information about the likelihood of their employment continuing into the future. As such we would expect to see those searching for a job online more likely to change employers, more likely to become unemployed, and quite likely, more likely to suffer wage losses.

[7] The contingent worker surveys use similar definitions as the monthly CPS uses to assess unemployed job search activity. The questions are not designed to capture method of action (for instance, emailing versus postal mailing of resumes). However it seems reasonable for this period to assume that much of this search activity is done offline.

3. Worker Flows and Internet Access

The difficulty with looking at workers who are searching online is that there is no direct way to measure the counterfactual – what would have happened had they not been able to search online. One way to get around this is simply to compare employment outcomes for those who use the Internet with those who don't. To the extent that Internet use itself is uncorrelated with the unobserved characteristics that cause on-the-job search (such as private information about current match quality), then comparing employment outcomes among Internet users with non-users (controlling for observables) will capture the effect of the additional search induced by the Internet on employment outcomes. However, this introduces a similar selection problem if those who use the Internet are more (less) likely to change employers for reasons unrelated to the Internet, this will bias the coefficient upward (downward). An additional benefit of this measure is that it captures the total net effect of using the internet on employer-to-employer flows, regardless of whether a worker perceives him or herself to be actively searching online (those who communicate by email with a friend about a potential job lead and then submit an application online may very well be more likely to change jobs as a result of the Internet, but may not answer "yes" to a survey question regarding online job search).

To test whether Internet use itself is associated with a change in the probability of changing employers we follow workers in the 2000 and 2001 CPS Computer Use Supplements and assess whether the probability of moving from one employer to another employer in the subsequent month (EE) depends on Internet use in the previous month (I) controlling for demographics (current age, age-squared, marital status, race, education, gender, income, family type), industry and occupation, and state and year fixed effects. That is, probit regressions were run for:

$$EE_{i,t} = \alpha + \beta I_{i,t} + X_{i,t}\phi + \sum_k \chi_k Occupation_k + \sum_p \varphi_p Industry_p + + \sum_s \eta_s State_s + \sum_t \lambda_t Year_t + \varepsilon_{i,t}$$

where EE=1 if the worker changed employers in the subsequent month, I=1 if the worker uses the Internet, and X is a vector of demographic variables. The parameter of interest is β.

The regression results are reported in Table 3. Column 1 reports the results for the entire sample of those who were employed in the Supplement surveys. The coefficient on Internet represents the change in the probability for a discrete change from no Internet use to using the Internet evaluated at the mean of the dependent variable. The coefficient evaluated at the predicted mean implies that those who use the Internet are 18% more likely to have changed employers the following month.

In addition to individual behavior the CPS Computer and Internet Supplement asks respondents about the use of computers and the Internet by anyone in the household. This allows one to examine Internet use within households that have a computer and those that have Internet access. Among the employed who live in a household with a computer 75% use the Internet and among those who live in a household with Internet access 83% use the Internet. The last two columns in Table 3 show coefficients that are larger, albeit not statistically different from, that shown in the first column. Evaluating the effect of Internet use at the mean of the dependent variable shows that Internet use is associated with a 28% increase in job changing. While the last two columns potentially reduce selection problems at the household level, they also potentially exacerbate individual selection issues.

Table 4 looks at whether those who use the Internet are more or less likely to become employed if they are unemployed and whether they are more or less likely to become unemployed if they are employed. These results show that coefficients that indicate that those who use the Internet are 7% less likely to become unemployed conditional on being employed. Examining those who are unemployed we see a positive, yet statistically insignificant relationship between Internet use and the likelihood of becoming employed. This result is consistent with the findings in Kuhn and Skuterod (2004).

4. State-Level Variation in Internet Penetration and Worker Flows

Individual data suggests that the Internet is affecting worker flows, yet it is difficult to know if any of this is causal. One potential source of exogenous variation in Internet access comes from the different rates at which the Internet diffused across US states. While the literature on Internet adoption has largely focused on its rapid adoption or differences across demographic groups, there exists tremendous variation in online penetration rates across state economies. Proprietary data obtained from Forrester Research provides data from large annual surveys on whether an individual is actively online (defined as accessing the Web at least 3 times in the past 3 months). While the Forrester data is quite similar to the CPS computer supplement data, it provides a larger time period over which to examine online access. The Forrester surveys commenced in 1997 and contain roughly 100,000 respondents per year through 2001 and 60,000 per year thereafter. Additionally, Forrester captures retrospective information about when a person first went online allowing data to be constructed back to 1994. I combine current and retrospective data from these surveys to measure annual state online penetration rates.[8] Measurements for 1992 and 1993 are interpolated following Goolsbee and Brown (2002).[9] Prior to 1992, Internet penetration, while unmeasured, is effectively zero.

Table 5 shows the mean, standard deviation, minimum, and maximum of state online penetration rates defined to include those who regularly used the Internet.[10] By 2002 70% of the US used the Internet, but across states this varied from 53% to 80%. Much of the variation in Internet use at the state level reflects long-standing patterns in their speeds of technological adoption. However using variation in state online penetration rates over time to identify changes in worker flows rests on an assumption that the changes in state online penetration rates are not themselves caused by something that would be correlated with changes in worker flows. Section 4 will explore potential confounding mechanisms.

For state level variation we measure employment-to-employment flows using the March CPS from 1988 to the present. The March CPS asks the employed "For how many employers did ... work in [previous year]?"[11] To measure individual employment-to-employment flows at a monthly rate for each person i, I calculated[12]:

$$\textit{Job-to-job flow}_i = (\textit{Number of employers last year}_i \ -1)/12$$

where the sample was restricted to those who worked full-year. Aggregating this measure to state-year averages, I then ran: [13]

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[8] Forrester provides data for 48 states plus the District of Columbia, omitting Hawaii and Alaska from their surveys.
[9] Goolsbee and Brown calculated rates for 1992 and 1993 by scaling 1994 online usage by the overall rate of growth of domain names. I applied their scaling to my estimates of 1994 online usage; my estimate differs from theirs because I obtained access to a larger set of surveys.
[10] Those who regularly use the Internet can do so either at home or work, but much of the variation occurs because of differences across states in home use.
[11] Respondents are given instructions that if they have more than one employer at same time, they should only count it as one employer.
[12] This measure follows Shimer (2003).
[13] State demographic characteristics include the proportion of the population who are white, female, married, ages 18 to 30, ages 30 to 50, ages 50 to 65, over age 65, and the share by years of education completed for those with less than 12, 12, 13-15, 16, and 17-20

$$Job-to-job\ flows_{s,t} = \beta\ Online\ Penetration_{s,t} + \sum_{i=0}^{2}\mu_i\ unemployment\ rate_{s,t-i} + \sum_{k} State\ demographics_{s,t} + \psi\ \%\ of\ workers\ \ in\ large\ firms_{s,t} + \sum_{s}\eta_s State_s + \sum_{t}\chi Year_t + \varepsilon_{s,t} \tag{2}$$

Table 6 shows estimates for both the population-weighted and unweighted OLS regressions. The results yield coefficients that are similar in magnitude and statistically significant. The results for all full-year employed workers suggest that an increase in Internet penetration of 10 percentage points led to a nearly .06 percentage point increase in monthly employment to employment flows, which is roughly a 5% increase. The second row restricts the sample to full-year workers who work in the private sector, slightly increasing the estimated response to .08.

It is unlikely that Internet job search has affected the employment-to-employment flows of all workers equally. For instance, low skill workers already operate in thick labor markets, and the returns to search are unlikely to be large. Additionally, there is substantial variation in the types of jobs that are advertised online, and again there are few low-skill jobs advertised, potentially reflecting the fact that not all workers have similar access to the Internet and, therefore, propensities to search for jobs online. Thus, if Internet job search is the mediating mechanism for the increase in employment-to-employment flows, we should see a much smaller effect, or no effect, on those with a high school degree or lower and we should see a larger effect for those with some college education and beyond.

Panel A of Table 7 runs these regressions for those full-year employed in the private sector by education level while continuing to control for state-level worker demographics. The estimated effects of Internet access on employment-to-employment job flows are largely as expected, with large effects on those who have been to college and smaller effects on high school graduates. A 10 percentage point increase in Internet access for a full-year employed college graduate working in the private sector leads to more than 15% increase in job change.

Similarly, we should expect that the Internet has had a larger impact on younger workers who have adopted the Internet more rapidly. Panel B of Table 7 runs the regression for those full-year employed in the private sector by age group. The largest effect is seen on those ages 30-39, with large standard errors around the estimate for those ages 18-29. Taken together, these results suggest an increase in employment-to-employment flows resulting from higher state-level Internet penetration particularly for those with college degrees.

5. **Instrumenting for State-Level Variation in Internet Penetration**

The empirical strategy used in Section 3 raises several questions. The first is whether state consumer Internet use merely reflects state commercial Internet usage. If this were true then the mediating mechanism explaining any association between changes in state Internet penetration and changes in job market outcomes may simply reflect the adoption of Internet technology by industry. For example, states with bigger changes in Internet penetration might be states with faster productivity growth due to commercial use.

The second question this strategy raises is whether the mediating mechanism is simply variation in regional business cycles. For example, states with faster growing economies may have citizens with more rapidly increasing purchasing power, some of which may be used to acquire Internet access. In this case, a finding of more employment-to-employment flows, for example, may be caused by macroeconomic conditions rather than Internet job search.

To address the first concern I compare the adoption of the Internet by consumers with that by firms.[14] While adoption by both consumers and firms has occurred at a rapid pace, the adoption patterns have not been at all similar.[15] Forman, Goldfarb, and Greenstein (2002) construct a measure of commercial adoption using the Harte Hanks Market Intelligence Survey. They construct two measures of commercial adoption: "participation" and "enhancement". The former represents investment in and adoption of Internet technology by firms while the latter captures the use of technology specifically for competitive advantage such as electronic commerce. Neither of the measures is particularly well-correlated with consumer use: Figure 1 illustrates the relationship between commercial and consumer Internet adoption in 2000 using the more broadly defined "participation" measure of commercial adoption.[16] Regressions of consumer online participation for each year from 1994 through 2003 on commercial penetration in 2000 show no statistically significant relationship, confirming that commercial adoption neither leads nor lags consumer adoption.[17]

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[14] Data on commercial penetration refer to the measure of commercial participation developed in Forman, Goldfarb, and Greenstein (2002).
[15] Not surprisingly, Web domain registration and household Internet use are also correlated; the more people there are online the more firms there are trying to capture their attention. But Web domain registration does not represent commercial Internet use more generally.
[16] The finding that commercial participation is uncorrelated to household adoption using data from Forrester Research's Technographics Benchmark data matches that found by Forman, Goldfarb, and Greenstein using NTIA estimates of Internet household use.
[17] Earlier years actually show a negative, albeit insignificant, relationship between the two.

The second concern is less easily resolved. While controls can help resolve whether Internet usage is a cause or consequence of changing conditions, the best solution is to develop an instrument that would be correlated with changes in Internet penetration, but not correlated with changes in the business cycle (or other potential mediating mechanisms). To identify a potential instrument, I consider the hypothesis that consumer Internet adoption would follow long-standing patterns in the adoption of household appliances. To test this hypothesis, I examine the relationship between Internet use and adoption of other basic consumer technological improvements. In 1960 only 23% of households had an automatic washer and 76% had a telephone. Figure 3a shows state Internet penetration rates in 2000 graphed against the predicted Internet penetration using a linear combination of state ownership rates of automatic washing machines and telephones in 1960.[18] The predictive power of these historical patterns of adoption of household appliances for Internet penetration is remarkable. This figure strongly suggests that the Internet is diffusing to households in a pattern similar to other household innovations. As a communication technology, it is unsurprising that Internet penetration closely mirrors that of the telephone (moreover, most Interact access occurs over telephone lines). However, because telephones were further along in the adoption process, the diffusion of automatic washing machines, which were a newer technology in 1960 and therefore were much earlier in the adoption process, provides separate, useful variation.

The fact that automatic washing machine and telephone diffusion in 1960 predict state-level Internet adoption in a given year suggests that there are some state-characteristics that impact household technology diffusion that are relatively stable over time, this naturally raises the question of what those characteristics are. One hypothesis for why diffusion patterns emerge is because of neighborhood effects. The purchase and use of new technology may be influenced by the degree to which the state housing characteristics facilitate diffusion. As such we can look at states where houses are farther apart because they are on large plots of land and see if diffusion is slower in such states.

Figure 3b shows a relationship similar to that seen in Figure 3a, Internet penetration rates in 2000 are now graphed against that predicted by a linear combination of the percentage of

[18] Automatic washers differ from manual washing machines. The 1960 census captured information about washing machine ownership and categorized ownership into auto or semi-automatic and those with a wringer or separate spinner. Television and radio are both predictive of Internet use, but are sufficiently correlated with telephone penetration as to add no marginal predictive power. Other appliances, such as dryers and air conditioners were not considered because of the influence of climate on their adoption.

people in a state living on plots of land between one and ten acres and the percentage of people in a state living on farms. Not surprisingly, states with more people on large acres have less Internet access, while farms mitigate some of this effect.

The relationships shown in Figures 3a and 3b exist for all years of Internet penetration. But a useful instrument to test the results in Section 4 needs a time-varying component. As such, I use the 1960s measures interacted with year effects to instrument for online access. Appendix Table 1 shows the first stage of this regression. The instrument resulting from using automatic washing machines and telephones in 1960 interacted with year fixed effects is a stronger instrument and results in coefficients that are similar in magnitude to those seen in the OLS. Disaggregating by education level yields results that are consistent with the OLS; showing a large and significant increase in flows among college graduates and little, if any, effect for those with less than a college degree.

Table 8 shows these results for all full-year employed, those in the private sector, and by education and age using the acre and farm measures in 1960 interacted with year fixed effects to instrument for online access. The coefficients are broadly similar, although slightly larger. An 10 percentage point in Internet access results in a .1 percentage point increase in employment-to-employment flows for those employed in the private sector full-year. For educational groups, the coefficients are broadly consistent with the OLS, but with larger standard errors. The results among age groups are also similar, with the results for those 30-39 remaining both the largest and most statistically significant.

In sum, the IV results yield results that are less precise although broadly consistent with the OLS results providing weak, yet supporting, evidence for their findings.

6. Concluding Remarks

In the past ten years Internet usage has risen from effectively zero to 70% of the population. This rapid rise in information technology has the potential to dramatically alter labor market outcomes by making job search more efficient for workers, yet research has yet to confirm this popular perception. This paper points to the importance of employed online job search – showing that the employed represent over 80% of those searching for a job online – and highlights the difficulties in comparing online and offline on-the-job search metrics. By focusing on Internet access rather than online job search we avoid the endogeneity issue of those who choose to search for a job online while employed. We show an economically and statistically significant increase in job changing for those who use the Internet. Additionally we show that state-level rises in Internet penetration are associated with state-level rises in employer-to-employer worker flows. This finding suggests that the Internet may be leading to better job matches for the employed and highlights the need for further work to examine the overall effect of the Internet on the labor market and match quality.

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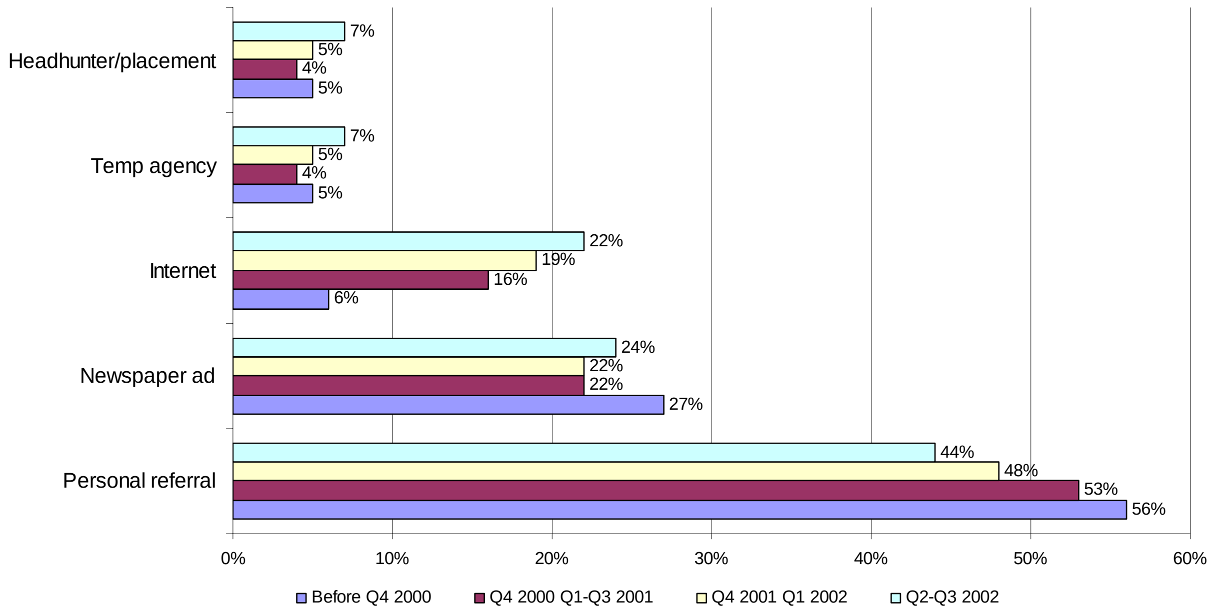
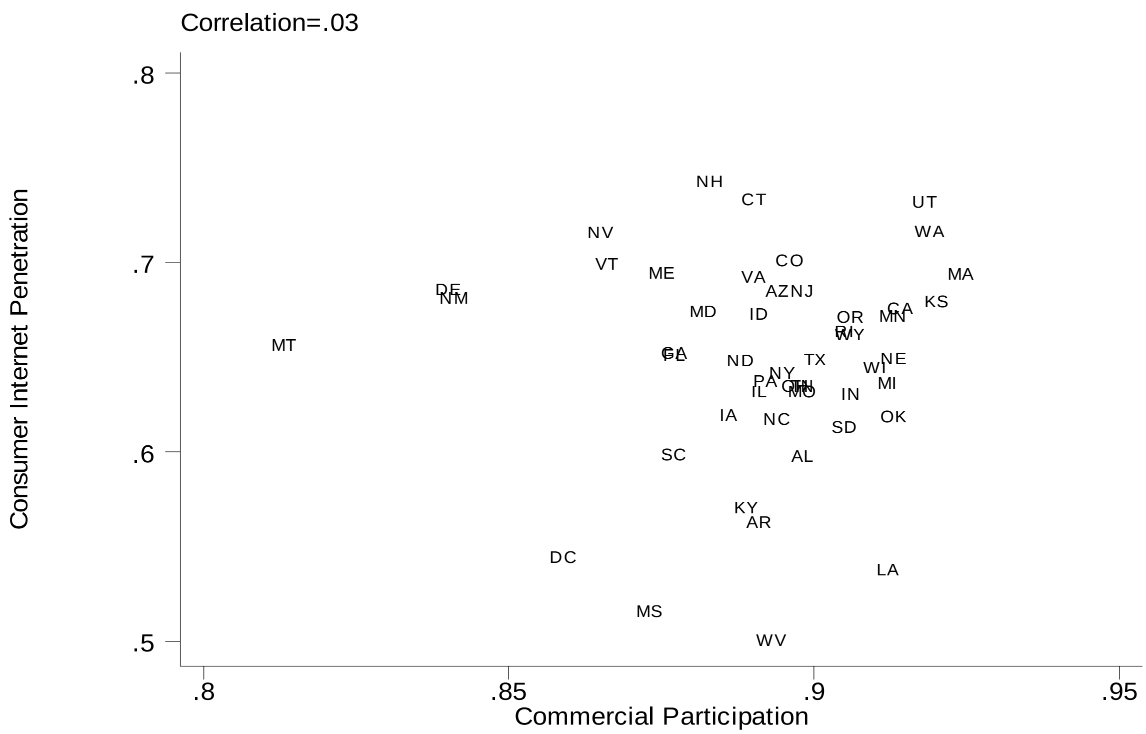
Figure 1: Primary Method Used to Find Current Job



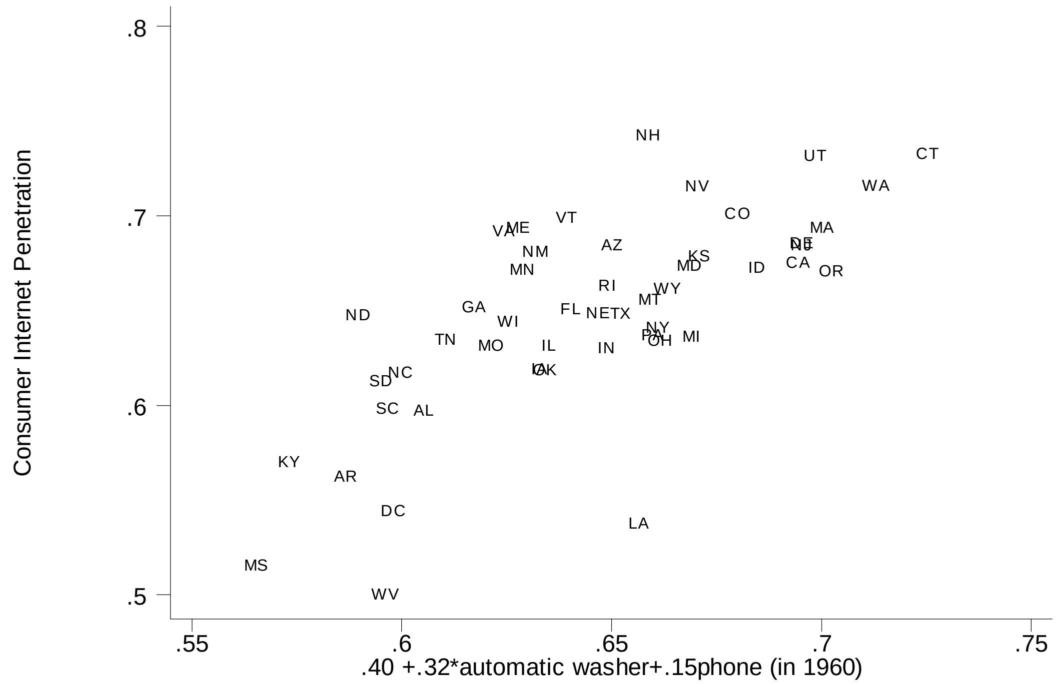
Source: Forrester Research survey (November 2002). Question was only asked to those who were currently employed and use the Internet. Individuals are divided by when they started their current job.

Figure 2: Internet Use: Consumers Versus Firms



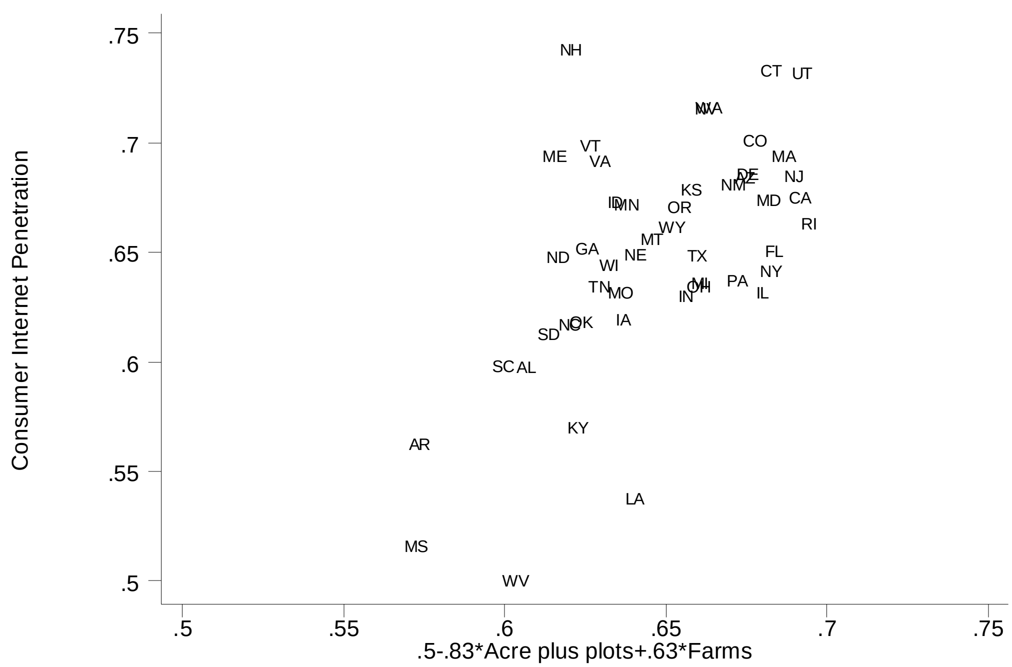
Source: Consumer online penetration is state average online use by individuals for 2000 using data from Forrester Research. Commercial Internet participation rates are from Forman, Goldfarb, Greenstein (2002).

Figure 3a: Consumer Internet Penetration Predicted by 1960 Phone and Automatic Washing Machine Ownership Rates



The graph compares actual online penetration measured in 2000 (shown on the y-axis) with that predicted by the following regression shown on the x axis: Online $_{s, t=2000} = \alpha + \beta$*Own Phone$_{s, t=1960} + \delta$*Own Automatic Washing Machine$_{s, t=1960} + \varepsilon$

Figure 3b: Consumer Internet Penetration Predicted by 1960 Land Characteristics



The graph compares actual online penetration measured in 2000 (shown on the y-axis) with that predicted by the following regression shown on the x axis: Online $_{s, t=2000} = \alpha + \beta$*Live on 1-10 acre plot$_{s, t=1960} + \delta$*Live on farm$_{s, t=1960} + \varepsilon$

Source: Online penetration is from Forrester Research's proprietary Technographics Benchmark 2001 data. Online is defined to be "online at least 3 times in the last three months" from any location. Automatic washer, phone penetration, plot size and farm data are from the Public Use Micro Sample (PUMS) of the 1960 Census of Population.

TABLE 1: Descriptive Statistics: Internet Use and Online Job Search

	Percent Online	Percent Searching Online	Proportion of adult population	Share of online job searchers
Employed	49%	11%	65%	81%
Unemployed	39%	29%	3%	9%
Not in the Labor Force	26%	3%	32%	10%

Source: August 2000 and September 2001 CPS computer supplements matched with the September 2000 and October 2001 monthly CPS, respectively.

TABLE 2: Employment Flows By Previous Months On-the-Job Search Status for Online and Offline Search

	2000 & 2001 CPS Computer Supplements		**1997 & 1999 CPS Contingent Worker Supplement** (Fallick and Fleischman 2004)	
Employment Status One Month Later	No online on-the-job search	Online on-the-job search	No traditional on-the-job search	Traditional On-the-job Search
% of Total Employed in the First Month	88.7%	11.3%	95.6%	4.4%
Same Employer	93.3%	91.2%	95%	80.9%
New Employer	2.7%	4.5%	2.1%	11.3%
Unemployed	1.0%	1.9%	0.9%	5.6%
Not in the Labor Force	2.9%	2.4%	2.0%	2.3%

Source: August 2000 and September 2001 CPS computer supplements matched with the September 2000 and October 2001 monthly CPS, respectively. The Fallick and Fleischman (2004) columns are from Table 6 and reflect results from the February 1997 and February 1999 Contingent Worker Supplements matched with March 1997 and 1999 data. Flows represent employment status one month later for those employed in the original supplement month.

TABLE 3: Probit Estimates of Employer Changes and Internet Use

Independent Variable	All Workers	Households With Computers	Households With Internet Access
Individual Internet Use Dummy	$.003^{***}$	$.005^{*}$	$.004^{**}$
	(.002)	(.002)	(.002)
Pseudo R^2	.036	.042	.045
Number of observations	88,681	61,136	52,673
Mean of Dependent Variable	.024	.023	.024
Percent Effect of Internet Use on Job Changing Evaluated at X bar	15%	28%	28%

Notes: Each column is a probit regression evaluating the probability that a worker changes jobs between the two months conditional on Internet use in the first month and control variables. The dependent variable =1 if the respondent uses the internet. Coefficients represent the change in the probability for a discrete change from no Internet use to use evaluated at the mean of the dependent variable. Robust standard errors are in parentheses. *, **, and *** indicate statistically discernible from zero at the 1%, 5%, and 10% levels respectively. Controls include state and year fixed effects, occupation and industry, and demographics. Demographic controls include age, age squared, marital status, race, family type, income, education, and gender. Source: August 2000 and September 2001 CPS computer supplements matched with the September 2000 and October 2001 monthly CPS, respectively.

TABLE 4: Probit Estimates of the Likelihood of having an Unemployment Spell

	Dependent variable: Prob. Of experiencing an unemployment spell	Dependent variable: Prob. of becoming employed
Sample	Workers who were employed in September 2001	Workers who were unemployed in September 2001
Independent Variable:		
Individual Internet Use Dummy	-.002*	.026
	(.001)	(.060)
Pseudo R^2	.110	.099
Number of observations	15,506	628
Mean of Dependent Variable	.036	.509
Percent Effect of Internet Use on Unemployment Evaluated at X bar	-7%	5%

Notes: Each column is a probit regression evaluating the probability that a worker either becomes unemployed or becomes employed between the two months conditional on Internet use in the first month and control variables. The coefficient of interest=1 if the respondent uses the internet. Coefficients represent the change in the probability for a discrete change from no Internet use to use evaluated at the mean of the dependent variable. Robust standard errors are in parentheses. *, ** and *** indicate statistically discernible from zero at the 1%, 5%, and 10% levels respectively. Controls include state and year fixed effects, occupation and industry, and demographics. Demographic controls include age, age squared, marital status, race, family type, income, education, and gender. Source: September 2001 CPS computer supplements matched with the October 2001 monthly CPS, respectively.

TABLE 5: State Online Penetration Rates

	Mean	Standard Deviation	Minimum	Maximum
1992	2%	1%	1%	3%
1993	4%	1%	2%	7%
1994	7%	2%	4%	12%
1995	12%	3%	7%	18%
1996	20%	4%	12%	27%
1997	30%	5%	19%	39%
1998	44%	5%	31%	54%
1999	56%	5%	41%	65%
2000	65%	5%	50%	74%
2001	68%	5%	54%	77%
2002	70%	6%	53%	80%

Source: Online penetration numbers are from come from Forrester Research's proprietary data where online is defined to be "online at least 3 times in the last three months" from any location. State-year penetration numbers are calculated from 5 years of survey data including retrospective data on how long the respondent had been online. For example, state data for 1999 is calculated by combining current reports in 1999 and retrospective reports in 2000-2003. Data for 1992 and 1993 is interpolated following Goolsbee and Brown (2002): by scaling 1994 online usage by the overall rate of growth of domain names. I applied their scaling to my estimates of 1994 online usage.

TABLE 6: Employment-to-Employment Flows

$$Job-to-job\ flows_{s,t} = \beta\ OnlinePenetration_{s,t} + \sum_{i=0}^{2}\mu_i\ unemployment\ rate_{s,t-i} + \sum_k State\ demographics_{s,t} + \psi\ \%\ of\ workers\ in\ large\ firms_{s,t} + \sum_s \eta_s State_s + \sum_t \chi Year_t + \varepsilon_{s,t}$$

	All Full-year Employed		Full year employed in the private sector	
Regression coefficients are multiplied by 100 to aid interpretability. [19]	**States weighted equally**	**Population-weighted**	**States weighted equally**	**Population-weighted**
	Column A	*Column B*	*Column C*	*Column D*
Mean Flow				
Online Penetration Rate	.582** (.257)	.528* (.287)	.773*** (.308)	.729** (.331)
State unemployment rates	-.031** (.014)	-.020* (.012)	-.025** (.012)	-.013 (.010)
R^2	1.71*** (.575)	1.39*** (.619)	1.94** (.950)	1.69* (.981)
Controls				
State fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Demographic characteristics of labor force	√	√	√	√
Percent of state workers in firms with 1,000 or more employees	√	√	√	√
Two lags of the state unemployment rate	√	√	√	√

*** and ** indicate statistically discernible from zero at the 1% and 5% levels, respectively.

Robust standard errors are in parentheses. State-level demographic characteristics control for the fraction of the state's employed population who are white, female, married, ages 18 to 30, ages 30 to 50, ages 50 to 65, over age 65, and the share by educational attainment for those with a high school degree or less and for those with a college degree or above.

Source: Job changing data reflect annual data from 1988 through 2003 created from the March CPS. Online penetration numbers are from come from Forrester Research's proprietary data.

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TABLE 7: Employment-to-Employment Flows by Age and Education

Sample	Mean[20]	OLS Result
Panel A: By education Status (full-time employed in private sector)		*Coefficient on Online Penetration*
High School Graduate	1.0%	-.030 (.449)
Some college	1.3%	1.23** (.625)
College degree or higher	1.1%	1.71*** (.575)
Panel B: By age (full-time employed in private sector)		
Ages 18-29	1.9%	.815 (.722)
30-39	1.0%	1.03** (.439)
40-49	0.7%	.846* (.443)
50 and over	0.5%	-.058 (.459)
Controls		
State fixed effects		√
Year fixed effects		√
Demographic characteristics of labor force		√
Percent of state workers in firms with 1,000 or more employees		√
State unemployment rate		√
Two lags of the state unemployment rate		√

*** and ** indicate statistically discernible from zero at the 1% and 5% levels, respectively.

Robust standard errors are in parentheses. State-level demographic characteristics control for the fraction of the state's employed population who are white, female, married, ages 18 to 30, ages 30 to 50, ages 50 to 65, over age 65, and the share by educational attainment for those with a high school degree or less and for those with a college degree or above.

Source: Job changing data reflect annual data from 1988 through 2003 created from the March CPS. Online penetration numbers are from come from Forrester Research's proprietary data.

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[20]Regression coefficients are multiplied by 100 to aid interpretability.

TABLE 8: Employment-to-Employment Flows: Instrumental Variables

Panel A: Aggregate Results	All full-year employed	Full-year employed in private sector *Column B*	*By education*	*By age*
	0.995 (.630)	1.22* (.741)		
High School Graduate			.340 (.968)	
Some college			1.15 (1.38)	
College degree or higher			1.84 (1.23)	
Ages 18-29				1.90 (1.65)
30-39				2.20** (1.10)
40-49				1.35 (1.02)
50 and over				.325 (.930)
Controls				
State fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Demographic characteristics of labor force	√	√	√	√
Percent of state workers in firms with 1,000 or more employees	√	√	√	√
State unemployment rate	√	√	√	√
Two lags of the state unemployment rate	√	√	√	√

*** and ** indicate statistically discernible from zero at the 1% and 5% levels, respectively.

Robust standard errors are in parentheses. State-level demographic characteristics control for the fraction of the state's employed population who are white, female, married, ages 18 to 30, ages 30 to 50, ages 50 to 65, over age 65, and the share by educational attainment for those with a high school degree or less and for those with a college degree or above.

Appendix Table 1: First Stage: Instrumental Variables Approach

$$Online\ Penetration_{s,t} = \alpha + \sum_t \eta_t Year_t * Percent\ on\ 1\text{-}10\ acre\ plots + \sum_t \eta_t Year_t * Percent\ on\ farms + \varepsilon_{s,t}$$

	Column A	*Column B*
	First stage without additional controls	First stage with all controls included in second stage
Acre*Year=1994	-1.51** (.633)	-.134 (.161)
Acre*Year=1995	-1.02 (.665)	-.203 (.161)
Acre*Year=1996	-.353 (.651)	-.268* (.159)
Acre*Year=1997	.788 (.690)	-.305* (.165)
Acre*Year=1998	2.49*** (.678)	.367** (.165)
Acre*Year=1999	3.22*** (.615)	.465*** (.160)
Acre*Year=2000	3.83*** (.665)	.534*** (.164)
Acre*Year=2001	4.62*** (.662)	.573*** (.163)
Acre*Year=2002	4.20*** (.692)	.675*** (.167)
Farm*Year=1994	-1.51** (.633)	.094 (.177)
Farm*Year=1995	-1.02 (.665)	.155 (.179)
Farm*Year=1996	-.353 (.651)	.150 (.177)
Farm*Year=1997	.788 (.690)	.147 (.182)
Farm*Year=1998	2.49*** (.678)	.151 (.183)
Farm*Year=1999	3.22*** (.615)	. .264 (.174)
Farm*Year=2000	3.83*** (.665)	.418*** (.18)
Farm*Year=2001	4.62*** (.662)	.539*** (.177)
Farm*Year=2002	4.20*** (.692)	.676*** (.183)
Adjusted R^2	.67	.99

*** and ** indicate statistically discernible from zero at the 1% and 5% levels, respectively.
Robust standard errors are in parentheses.

Source: Online penetration numbers are from come from Forrester Research's proprietary data. Plot size and farm data are from the Public Use Micro Sample (PUMS) of the 1960 Census of Population.