Applying Behavioral Insights to Inform Job Seekers: Experimental Evidence from Online Job Search

Ariella Kahn-Lang Spitzer, *Mathematica Policy Research*

Chris O'Leary, *W.E. Upjohn Institute*

Greg Chojnacki, *Mathematica Policy Research*

Bill Congdon, *Urban Institute*

Nima Rahimi, *University of Texas at Austin*

Abstract

We explore if additional information intended to cause behavioral changes in the way job seekers conduct online job search led to efficiency or wage gains for job seekers. Counter to the behavioral literature, we find evidence that additional information in online job search did not cause job seekers to increase the breadth of their search. We find evidence that job seekers assigned to receive the additional information treatment were 4.2 percentage points less likely to select a job listing and clicked on 20.7% fewer job listings on their first visit. On average, we find no evidence that the additional information changed the extent or breadth of job search, or the hourly wage of explored job listings. These effects seem to be at least partially driven by job seekers using the additional information to lessen certain cognitive search biases to more efficiently scan job listings.

We are grateful to...

1 Introduction

How workers search for and match to jobs is fundamental to the operation of labor markets—affecting outcomes for workers, employers, and the broader economy. When workers can efficiently find jobs that are a good fit for their skills, they can earn higher wages, firms can be more productive, and the overall labor market operates more efficiently (Mortensen and Pissarides 2011). Conversely, when job search and matching are not quick or smooth, this imposes costs on the job seeker and employers. For example, unemployed workers who cannot quickly return to work may struggle to meet their basic needs or the needs of their household (Ganong and Noel 2019). Although some portion of unfilled job openings can be explained by a mismatch in skills (Kahn 2015), some are driven by search frictions (i.e., the availability of information about job openings) impeding job seekers from quickly or easily finding opportunities for which they are qualified (Bartik and Stuart 2022).

Today, most job search is conducted online (Faberman and Kudlyak 2019). Despite the potential of online job search to connect job seekers to substantially more opportunities, evidence is mixed on the degree to which online search improves matching between job seekers and job openings (Kircher 2020). Despite the improved access to job listings, job seekers are likely still missing promising opportunities. One possibility is that job seekers are searching too narrowly. While job seekers may be open to a diverse set of opportunities, they tend to focus their job search on sectors and occupations they have worked in previously (Belot et al. 2019). Job seekers searching in an overly narrow manner might not be aware of the transferability of their skills to sectors and occupations they have not worked in before. Thus, strategies encouraging qualified job seekers to consider job opportunities across a broader set of sectors and occupations could raise the number of job applications and job offers—potentially increasing the job finding rate or improving match more generally (Moscarini 2001).

We explore if additional information designed to change the behavior of online job seekers causes job seekers to optimize their search. We focus on four cognitive biases from the behavioral literature—information overload, status quo bias, identity mismatch, and hassle factors. Cognitive biases may lead job seekers apply to jobs in an overly narrow manner, leading them to miss promising opportunities. Mitigating search frictions generated by information overload, status quo bias, identity mismatch, and hassle factors could alleviate a substantive barrier to employment. Targeted behaviorally informed interventions designed to address systematic cognitive biases narrowing job search could encourage qualified job seekers to apply to a broader set of sectors and occupations. Prior research has suggested

that even small behavioral interventions may affect behavior (Nagtegaal et al. 2019).

We test the impact of a behaviorally informed intervention using the West Michigan Works (WMW) Weekly Hot Jobs! page. The WMW Weekly Hot Jobs! page is an online list of job postings providing job seekers with quick links to relatively higher-paying job opportunities within in-demand industries. Job listings are presented as a set of industry-specific tables. Within each industry-specific table, each job listing shows the county, city, employer, job title, and a link to a more detailed description. Job seekers must select the link that directs them to a more detailed description of the job listing to apply for the job.

The behaviorally informed intervention in this study included two nudges that were designed to prompt job seekers to consider the transferability of their skills to occupations and industries outside of their main search. First, we added a column to the regularly updated job listings which provided information about relevant transferable experience alongside the existing information. Second, we included a prompt reminding job seekers to review job listings in industries other than the job listings presented in the first industry-specific table that appears when the WMW Weekly Hot Jobs! page loads.

Our results suggest the additional information had the opposite effect from what the existing behavioral literature would have predicted. We find the additional information decreased the breadth of job search for online job seekers. Job seekers were 4.2 percentage points ($p < 0.01$) less likely to click on at least one job description and on average clicked on 20.7% or 0.11 ($p < 0.01$) fewer job descriptions on their first visit. On average, we found no evidence the additional information treatment increased the breadth of search, changed the likelihood of returning to the WMW Weekly Hot Jobs! page, or the hourly wage of explored job listings. However, job seekers towards the upper tail of the wage distribution increased their hourly wage of explored job listings by as much as 17.2% or roughly $3.76 per hour.

We contribute broadly to the literature on behavioral interventions, assistance for job search activities, and the behavioral mechanisms behind job search. Much of the literature on job search assistance focuses on interventions more time, labor, and financially intensive than ours. For example, Alfonsi et al. (2025), Cheung et al. (2023), and Caria et al. (2023) all require some form of directly administered job search counseling provided by a professional or peer. Our study is one of a small number specifically aimed at reducing cognitive job search frictions through the use of additional information in a cost effective and easy to scale manner. Belot et al. (2019) provided advice to job seekers using an online tool. The tool recommends additional occupations based on the similarity and success of prior job seekers, skills, and labor market tightness. Altmann et al. (2018) created a brochure providing

job search information, strategies, motivation, and consequences of unemployment for job seekers. Both found some form of increase in job search breadth, employment, or earnings.[1]

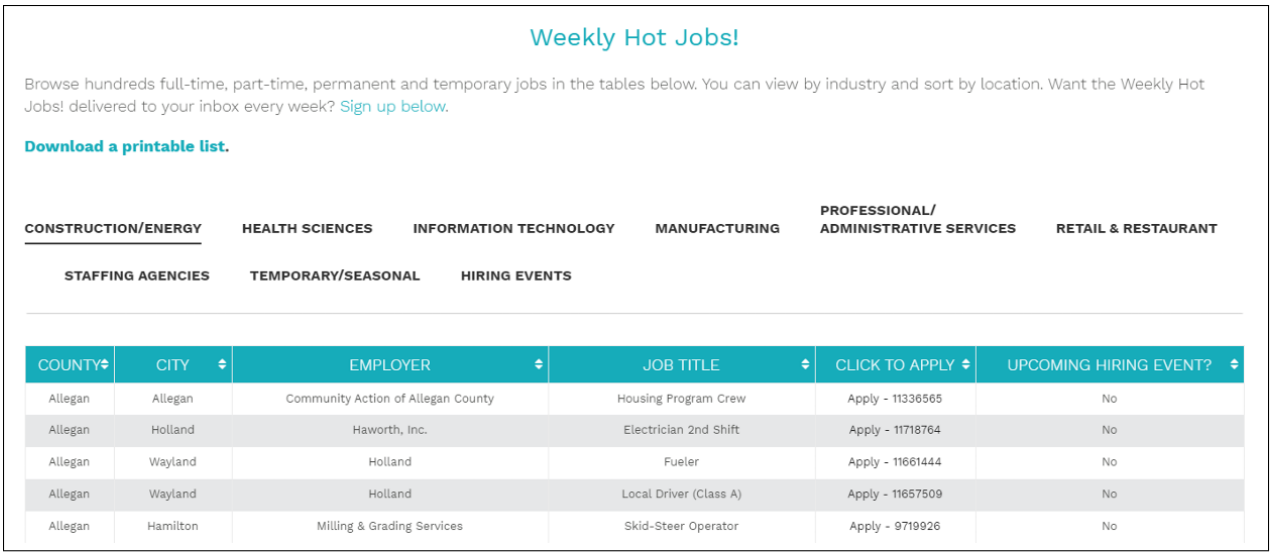
2 Background and Setting

This paper presents the results of an experiment run on the WMW Weekly Hot Jobs! page which is hosted on the WMW site. WMW is the workforce agency covering seven counties in West Michigan (Allegan, Barry, Ionia, Kent, Montcalm, Muskegon, Ottawa). WMW operates American Jobs Centers called Michigan Works Offices in each of the seven counties. American Job Centers are designed to provide comprehensive assistance to all job seekers. American Job Centers were established under the Workforce Investment Act and reauthorized in the Workforce Innovation and Opportunities Act (WIOA) of 2014. WMW is one of 16 Michigan Works agencies in the state of Michigan. Except for the Detroit metropolitan area, the WMW area is the most densely populated region in Michigan (State of Michigan 2020).

WMW aims to promote economic growth in West Michigan by connecting job seekers with employers and developing the local workforce to meet employer needs. WMW provides a range of services and supports to employers, employees, and job seekers. Some services provided by WMW include hosting job fairs and industry councils for employers, offering career coaching and employability services for job seekers, and identifying incumbent worker training and up-skilling opportunities for individuals who are already employed. The largest industries in West Michigan are health care and social assistance, manufacturing, and retail trade (State of Michigan 2021). The Appendix includes detailed statistics by industry, demographics, and individual characteristics for the U.S., Michigan, and West Michigan.

The WMW Weekly hot Jobs! page is managed by WMW and provides quick links to relatively higher-paying job opportunities within in-demand industries. WMW partners with local employers to identify some of the highest-growing and most in-demand jobs in West Michigan. For a job to be included on the WMW Weekly Hot Jobs! page the job must pay at least $13 per hour. Jobs must be determined to be in-demand in West Michigan as a result of high projected growth or in short-term demand due to the COVID-19 pandemic. The WMW Weekly Hot Jobs! page is updated every Friday. Over the course of the intervention an average of 438 job listings were posted each week. Jobs posted on the WMW Weekly

[1]Belot et al. (2019) found an increase of 0.2 standard deviations in the set of occupations job seekers were exposed to and a 44% increase in the total number of interviews. Altmann et al. (2018) estimated an increase of 4% in both earnings and employment.



Weekly Hot Jobs!

Browse hundreds full-time, part-time, permanent and temporary jobs in the tables below. You can view by industry and sort by location. Want the Weekly Hot Jobs! delivered to your inbox every week? Sign up below.

Download a printable list.

CONSTRUCTION/ENERGY | HEALTH SCIENCES | INFORMATION TECHNOLOGY | MANUFACTURING | PROFESSIONAL/ ADMINISTRATIVE SERVICES | RETAIL & RESTAURANT

STAFFING AGENCIES | TEMPORARY/SEASONAL | HIRING EVENTS

COUNTY	CITY	EMPLOYER	JOB TITLE	CLICK TO APPLY	UPCOMING HIRING EVENT?
Allegan	Allegan	Community Action of Allegan County	Housing Program Crew	Apply - 11336565	No
Allegan	Holland	Haworth, Inc.	Electrician 2nd Shift	Apply - 11718764	No
Allegan	Wayland	Holland	Fueler	Apply - 11661444	No
Allegan	Wayland	Holland	Local Driver (Class A)	Apply - 11657509	No
Allegan	Hamilton	Milling & Grading Services	Skid-Steer Operator	Apply - 9719926	No

Figure 1: Original WMW Weekly Hot Jobs! page (control)

Hot Jobs! page can be full-time, part-time, permanent, or temporary. Within each industry-specific table on the web page job seekers are able to sort by city and county. The Appendix includes graphs detailing the number of jobs posted each month at the aggregate and industry level. Figure 1 is the default WMW Weekly Hot Jobs! page that job seekers assigned to the control group see.

We tested this intervention from August 7, 2021, through March 3, 2022. While the impacts of the pandemic were still present during this period, the stark negative impacts on the labor market had largely dissipated. Both the U.S. and West Michigan labor market was particularly tight over the intervention. The unemployment rate across West Michigan had fallen from its peak of 21.4% in April 2020 to an average of 3.9% over the course of the intervention (U.S. DOL Bureau of Labor Statistics 2022a, 2022c). Notably, requirements for Unemployment Insurance (UI) beneficiaries to register with WMW were waived before the intervention and reinstated in November 2021. Also, enhanced UI benefits from the pandemic continued through early September 2021. Changes to UI and other policies concurrent with the intervention may have influenced the beliefs, behaviors, and actions of job seekers surrounding job search and career exploration. The Appendix includes detailed graphs characterizing the employment dynamics of Michigan over the intervention using the Job Openings and Labor Turnover Survey (JOLTS) and the Current Population Survey (CPS).

3 Experimental Design and Data

3.1 Behavioral intervention

Applying for a job on the WMW Weekly Hot Jobs! page requires accessing the WMW Weekly Hot Jobs! page, viewing the job listings presented on each industry-specific table, selecting a link directing job seekers to a detailed description of the job listing (including the application), and submitting an application.

The treatment WMW Weekly Hot Jobs! page incorporates two sets of changes motivated by the behavioral theory described in section two. The first set of changes were designed to prompt job seekers about the transferability of their skills. The second set of changes were designed to remind job seekers to explore job listings across other industries. Figure 2 is the enhanced WMW Weekly Hot Jobs! page that job seekers assigned to the treatment group see. We conducted a series of user tests from March 15–19, 2021, with nine current WMW job seekers. In each of the user testing sessions, we observed users as they navigated through the treatment web page. We then asked a series of questions about their experience and perceptions to better understand how users and potential job seekers interact with the treatment web page. The purpose of the user testing was to identify any improvements to the treatment page that could increase job search efficiency by broadening the industries and occupations that job seekers considered.

An additional column on the far right of each industry-specific table. The additional column contains three job titles for each job listing. The three additional job titles are dynamic and correspond to a specific job listing. The three additional job titles are intended to inform job seekers that they are qualified for the job listing if they have held one of the three additional job titles displayed in the column. The three additional job titles were developed using the O*NET career changers matrix. The O*NET career changers matrix was developed by the U.S. Department of Labor (DOL) to assist job seekers looking to easily transfer to a new occupation matching their current skills, education and prior work experience. Underneath the three additional job titles, job seekers see a bright red prompt. Job seekers see three additional job titles by hovering over the red prompt. A bright red and bold box with a prompt encouraging job seekers to search for job opportunities across all industry tables. The box is displayed above each industry-specific table. Also, bold and emphasized industry tabs.

The treatment WMW Weekly Hot Jobs! page is intended to address cognitive behavioral

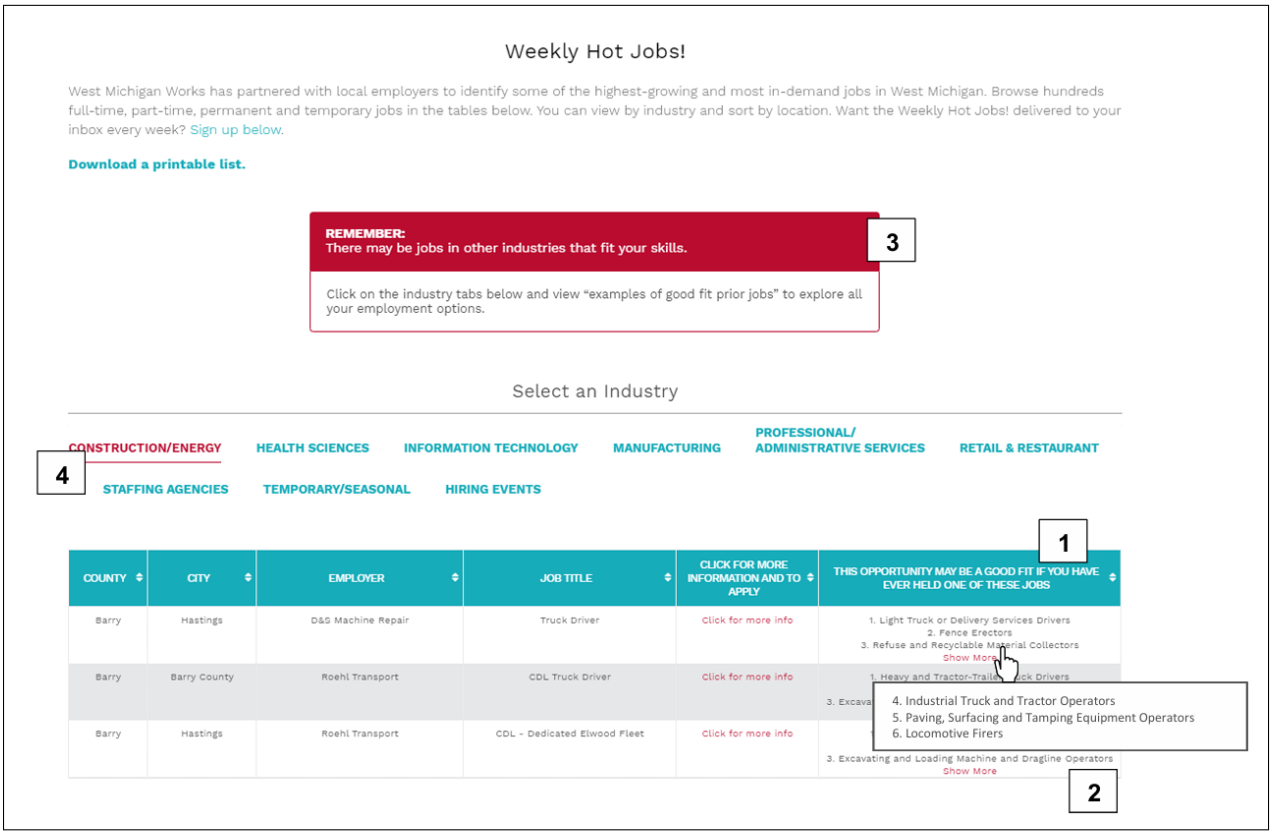


Figure 2: Enhanced WMW Weekly Hot Jobs! page (treatment)

barriers that could generate search frictions for online job seekers. Job seekers may click through to the application page for several job listings. However, job seekers may not reach the application pages to job listings they are best matched for given their skills and experience. The hassle of wading through less-suitable job listings could result in job seekers applying to a fewer number of job opportunities than would be ideal. Job seekers may also feel the WMW Weekly Hot Jobs! page does not display relevant information or feel overwhelmed if they cannot determine whether their skills or experience make them a good match for a job opportunity. Making information about relevant experience for each job listing more salient and easier to access, by presenting it alongside the job title and above each industry-specific table, could encourage job seekers to click through to a larger number of job descriptions—potentially leading to more high quality job applications. Additionally, job seekers may refrain from browsing jobs for which they might be qualified because of the belief the job title is inconsistent with their self-perceptions of work or experience. Inclusion of an additional column containing three relevant job titles, a prompt encouraging job seekers to explore all industry tabs, additional job title information, and an industry prompt are intended to prompt job seekers to consider that their skills and experience may be more transferable or relevant than they had originally considered.

3.2 Fielding the experiment

The intervention, a randomized control trial (RCT), ran from August 7, 2021, through March 3, 2022. To determine the length of the study, we completed power calculations to estimate the minimum detectable effects based on predicted users and baseline outcome rates. The control group received the original (default) WMW Weekly Hot Jobs! page and the treatment group received the enhanced WMW Weekly Hot Jobs! page with the two sets of behaviorally motivated changes. Job seekers were automatically assigned to the treatment or control group the first time they accessed the WMW Weekly Hot Jobs! page during the intervention period. Table 1 shows that the treatment and control groups are balanced across all observable characteristics. Job seekers were randomly assigned using Google Optimize (Optimize Resource Hub 2023). Once job seekers have been assigned to the treatment or control group, they continued to see the same version of the WMW Weekly Hot Jobs! page for every return visit from the same browser. Google Optimize randomizes users into treatment and control groups based on the device and browser they use. However, if a job seeker visited the WMW Weekly Hot Jobs! page on more than one device or browser, there is a possibility the job seeker was randomized into both the treatment and control group. It is possible a job seeker randomized into both groups would select the version of

the WMW Weekly Hot Jobs! page they preferred or potentially alter their behavior in some way due to their exposure of multiple versions of the WMW Weekly Hot Jobs! page. Data on job seeker behavior on the WMW Weekly Hot Jobs! page was collected from the Google Analytics application programming interface (API). Due to the terms of our Google Optimize account we were required to restart the experiment twice throughout the intervention. The experimental portion was restarted on November 4, 2021, and February 2, 2022.

Table 1: Balance Table

	Control	Treated	Difference	S.E.
Device type				
Desktop device	0.506	0.499	0.008	0.016
Mobile device	0.468	0.475	-0.007	0.016
Tablet device	0.026	0.026	-0.000	0.005
Hour of first visit				
Hour of first visit: 10pm-4am	0.097	0.095	0.002	0.009
Hour of first visit: 5am-11am	0.489	0.477	0.011	0.016
Hour of first visit: 12pm-5pm	0.323	0.338	-0.015	0.015
Hour of first visit: 6pm-9pm	0.091	0.090	0.001	0.009
Month of first visit: January	0.136	0.134	0.002	0.011
Month of first visit				
Month of first visit: August	0.133	0.142	-0.009	0.011
Month of first visit: September	0.132	0.143	-0.011	0.011
Month of first visit: October	0.154	0.151	0.003	0.011
Month of first visit: November	0.174	0.162	0.012	0.012
Month of first visit: December	0.134	0.135	-0.001	0.011
Month of first visit: January	0.136	0.134	0.002	0.011
Month of first visit: February/March	0.137	0.132	0.005	0.011

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

The terms of our Google Optimize account required us to restart the experimental portion of the intervention twice during the intervention period. The experimental portion was restarted on November 4, 2021, and February 2, 2022. All users were randomly assigned again every time the experimental portion was restarted. However, since our primary outcomes

are focused on the first site visit, reassignment does not impact our primary outcomes. Regardless, job seekers whose treatment status changed over the experiment were weighted to zero, for our primary estimates, using response weights due to secondary outcomes estimated across all visits.

The WMW Weekly Hot Jobs! page had 4,150 unique users over the intervention period. 2,060 users were randomly assigned to the treatment group and 2,090 were randomly assigned to the control group. Our primary data source on job seeker behavior on the WMW Weekly Hot Jobs! page comes from the Google Analytics API. The sample is winsorized and does not include 88 users whom we believed could bias our estimates (users with atypical site visit patterns). Users were removed who clicked on an atypical number of job descriptions on their first visit or returned to the WMW Weekly Hot Jobs! page an atypical number of times. Users with atypical site visit patterns are unlikely to be job seekers and more likely to be professionals assisting others with job search or automated browsers. Identifying outliers in the context of our intervention is challenging given that outcomes are skewed right, making the presence of extreme values consistent with the distribution of the data (National Institute of Standards and Technology 2012). We considered values to be outliers if they were in the top 1.22% of values—a percentile threshold associated with a z-score of 2.24. This is a standard cutoff used in the literature (Aguinis et al. 2013). Based on this rule, client identifiers associated with WMW Weekly Hot Jobs! page visits on more than 19 unique dates or over eight job description clicks on their first visit were removed. All users with client identifiers associated with a member of the study team were removed. We further removed 72 individuals who accessed both the treatment and control web pages.

Our primary sample is composed of 3,987 unique job seekers. 1,975 unique job seekers assigned to the treatment group and 2,012 unique job seekers assigned to the control group. However, our primary estimates utilize response weights that down-weight job seekers whose treatment status changed due to the experiment restart to zero. There are 93 job seekers down-weighted to zero. Thus, the sample used to generate our primary estimates is composed of 3,984 unique job seekers. The treatment and control groups are similar on all observable characteristics, as seen in Table 1. There are no meaningful or statistically significant differences between the treatment and control groups by device type, time of first visit, or the month of their first visit.

Data collected from the Google Analytics API include information on visit date and time, links clicked, device type, and whether the job seeker saw the treatment or control site. A job seeker is defined as a user with a unique client ID that identifies a unique browser and IP address combination. Because it is not possible to differentiate between multiple

sessions in a day, we defined a visit as a unique date on which the job seeker visited the site. We supplement our primary data collected through the Google Analytics API with monthly JOLTS data from the Bureau of Labor Statistics (BLS), daily Google Search data from Google Trends, and yearly data from the American Community Survey (ACS). Data from the JOLTS survey and Google Trends are for the state of Michigan. Data from the ACS are only for the seven counties in West Michigan covered by WMW.

JOLTS data allows us to control for the job-open rate, hire rate, separation rate, quit rate, and layoff rate in Michigan on the first month they accessed the WMW Weekly Hot Jobs! page. The Google search data from Google Trends allows us to control for the saliency of employment related factors potentially affecting online job search in Michigan. These data are normalized to the intervention period and to Michigan—capturing the relative intensity of individuals searching employment related topics on Google in Michigan over the period of the intervention. Google Trends controls are assigned based on the first day the job seeker accessed the WMW Weekly Hot Jobs! page. We use the ACS from 2021 and 2022 to estimate the hourly wage of each job listing on the WMW Weekly Hot Jobs! page. We use the classified O*NET codes for each job listing and the Standard Occupational Classification (SOC) codes from the ACS to merge each job listing to the average hourly wage of the seven counties in Michigan covered by WMW based on their SOC code. Job listings with an estimated hourly wage less than $13 were recoded to $13 because a job must pay at least $13 to be included on the WMW Weekly Hot Jobs! page. The average hourly wage is used for job seekers who selected multiple job listings over a single visit date.

4 Behavioral Theory

Conversations with WMW staff revealed their belief that online job seekers were searching too narrowly, therefore missing promising opportunities. We hypothesized that four primary cognitive biases, central to the behavioral literature, could lead job seekers to search in an overly narrow manner. The four cognitive biases we focus on throughout the intervention are status quo bias, identity mismatch, hassle factors, and information overload. Table 2 summarizes the mechanisms through which each cognitive bias could lead to an overly narrow search and how the additional information treatment was intended to combat them.

Table 2: Behavioral Bottlenecks in Job Search and Design Implications

Intended Job-Seeker Process	Hypothesized Behavioral Bottlenecks	Design Implications
Panel A. Restricting Feature: Job Listings Sorted by Industry		
Select each industry to browse	Identity mismatch; status quo bias; information overload; hassle factors	Add a prompt reminding users to search across industries
Browse all jobs within an industry	Identity mismatch; status quo bias; hassle factors; information overload	Provide skill-match information (e.g., relevant job experience) directly in each job listing
Panel B. Skills Match Information Embedded in Application Link Page		
Click on each potentially relevant job title	Identity mismatch; status quo bias; hassle factors	Provide skill-match information (e.g., relevant job experience) directly in each job listing
Apply for relevant jobs	Hassle factors	Provide skill-match information (e.g., relevant job experience) directly in each job listing

4.1 Status quo bias

Status quo bias, in a job search context, describes the tendency of individuals to rely on prior experience and stay in their comfort zone of familiar job opportunities, rather than exploring new ones — job seekers tend to search for positions in the same industries or occupations in which they have previously worked (Samuelson and Zeckhauser 1988). A strong tendency for individuals and job seekers to maintain the status quo could be that the perceived disadvantages of change seem larger than the potential advantages (Kahneman et al., 1991). For example, it's well researched that some form of status quo bias affects healthcare enrollees with employer sponsored health insurance plans (Afendulis et al., 2015; Handel 2013; Sinaiko and Hirth 2011; Strombom et al., 2002). Many healthcare enrollees will choose to stay in their current plan even though they are presented with another clearly preferred plan and are able to switch.

A simplified description from Dean et al., (2017) illustrates the relationship between the job seekers preferences and choice given the limited attention each job seeker can allocate. Assume a job seeker is facing a choice, c, of jobs x, y, z in set $\mathcal{X} = \{x, y, z\}$, attention function $\mathcal{A}(\{x, y, z\}) = \{x\}$, and preferences $z \succ y \succ x$. Thus, $c(\{x, y, z\}, x) = \{x\}$. In this overly simplified setting of status quo bias, the job seeker is familiar and comfortable with job x. However, the job seeker prefers both job z and y to job x. When presented all job

opportunities at once, given the limited and constrained attention of the job seeker, the job seeker will choose a less preferred opportunity by defaulting to choosing job x.

Geng (2016) found that one factor contributing to status quo bias is that people spend more time considering a default option than the alternatives. Job seekers facing status quo bias could be given additional information regarding the transferability of their skills to different jobs or industries. Job seekers presented with additional information could experience a positive form of informational crowd out where job seekers are less able to consider the default option. Revisiting the simplified example from Dean et al., (2017), job seekers receiving the additional information treatment no longer face a constraint on their attention. Effectively, the choice set of the job seeker is limited to x and y. Now $c(\{x, y\}, x) = \{y\}$ and the job seeker chooses y, their most preferred job, over their default x.

4.2 Identity mismatch

Identity mismatch occurs when an individual perceives that their identity is not consistent with the social perceptions of a group (Rodríguez-García et al. 2021). Bettman et al. (1991) link the evaluation of social categories (Fiske and Pavelchak 1986) to decision making heuristics. Specifically, they hypothesize that decision makers draw on recognizable social categories as part of a heuristic that allows them to evaluate each option based on the category it belongs to, rather than assessing the characteristics of each option. For example, a disproportionate share of women in nursing is partially explained by the perception that nursing is a job for women (O'Connor 2015). Identity mismatch can be so extreme in certain contexts that Oh (2023) found that just over two-fifths of surveyed Indian workers would be willing to forgo 10 times their daily wage to avoid spending even 10 minutes on work associated with other castes.

A simplified adaptation of the framework from Akerlof and Kranton (2005) where job seekers maximize utility, U, via wages, w, or search effort, e, gives: $U(w, e; g) = w - e + I_g - t_g|e^*(g) - e|$. g represents the job seeker's social group or background, I_g is the job seeker's identity utility from being in social group g, and $t_g|e^*(g) - e|$ is the penalty or disutility of diverging from the optimal effort for social group g. In our setting, $I_g - t_g|e^*(g) - e|$, is effectively the cost of the identity mismatch bias. This mismatch can cause job seekers to behave in irrational ways and search for less suitable jobs due to their current sense of self or self image — understanding how identity can negatively affect job seekers reveals how preferences can be changed (Akerlof and Kranton 2000).

Our understanding was that job seekers using the WMW Weekly Hot Jobs! page may be searching in an overly narrow manner due to the belief that their skills may not be transferable to other industries. Therefore, job seekers receiving the additional information treatment could see their cost of identity mismatch, $I_g - t_g|e^*(g) - e|$, decrease or even go to zero. Without the penalty coming from the job seeker's identity, the job seeker is free to search across any industry.

4.3 Hassle factors

Hassle factors are aspects of a process that seem like minor inconveniences but are nonetheless substantive enough to dissuade users from engaging (Bertrand et al. 2004). For example, in the context of applying for a government program, even when the time and mental effort required by an application process are easily outweighed by subsequent benefits in a rational cost benefit analysis, these hassles (time spent and cognitive burden) can deter individuals from applying for the benefit program (Babcock et al. 2012).

Small steps such as having to click a link directing you to a new web page to view information about a job opening could dissuade individuals from taking the next steps in their job search. Providing information in a format that is easy to access and use can mitigate perceived inconveniences (Simpson and Prusak 1995). Providing job seekers, assigned to the additional information treatment, with emphasized application buttons and easily accessible information on other relevant jobs was intended to decrease hassle-costs. A decrease in hassle-costs could see job seekers utilize more of the WMW job resources (e.g., employment support from a specialist, mock-interviews).

4.4 Information overload

Finding a job often requires an individual to gather and assess large amounts of information about job characteristics, their own skills, and how competitive and time-consuming each application might be (Grubb 2002). Information overload is when individuals become overwhelmed when faced with more information than they can feasibly digest. The additional or excessive information raises the job seekers processing burden relative to the value of the additional information (Persson 2018). Once overwhelmed, due to an excessive quantity of information, decision quality can deteriorate. (Hanka and Fuka 2000, Eppler and Mengis 2004).

The deterioration of decision quality causes individuals to experience information avoidance and can be explained by individuals choosing to stop considering new information (Bawden and Robinson 2020; Hiltz and Turoff 1985). When individuals face information overload in the process of informing a decision, the individual must choose between different available strategies, known as heuristics (Bettman et al. 1991; Payne et al. 1992). These heuristics may involve detailed consideration of the characteristics of each option ("elimination by aspects," Tversky 1972) or they might avoid assessing characteristics of options altogether, by simply recalling how one felt about each option last time they were evaluated ("affect referral," Wright 1975; Lynch et al. 1988). Individuals may choose to stop considering new information, or they may implement a heuristic allowing them to filter the excessive information presented to them in stages (Bettman et al. 1991; Payne 1976).

Job seekers experiencing information overload can be given tools allowing them to implement their own filtering heuristics. Job seekers who start with a narrow search will search more broadly after receiving recommendations of occupations related to their initial search (Belot et al. 2019). Similarly, providing additional information designed to help individuals distinguish between more and less attractive options (Malhotra 1984). If this information is presented at the point in time when needed and with guidance on how to use it, it can be particularly helpful (Simpson and Prusak 1995). Mitigating frictions from information overload should result in some form of increase in search or engagement on the WMW Weekly Hot Jobs! page for job seekers assigned to the treatment group.

5 Theoretical Framework

The traditional understanding from the behavioral literature is that job seekers in our setting would use the additional information and increase their engagement on the WMW Weekly Hot Jobs! page throughout their search. However, we found the opposite — job seekers decreased their overall engagement with no change in the breadth or extent of their job search. We believe this is because the additional information caused job seekers to experience a form of information overload. We extend the theoretical framework on behavior and information overload from Persson (2018) as a way to formalize why our estimates depart from the conventional interpretation of the behavioral literature.

Assume the job seeker has a fixed stock of cognitive attention $\overline{a}$ across two information bundles s_c and s_d. Core job information that is the most important to the job seeker is denoted by s_c while all other information is denoted by s_d. Let the attention allocated to

each bundle be $a_c, a_d \geq 0$ with $a_c + a_d \leq \overline{a}$. Attention improves job match quality s.t. the job seeker maximizes Equation 1.

$$\underset{a_c,a_d}{max}\ U(a_c, a_d; N_d) = V_c(a_c) + \underbrace{V_d(\frac{a_d}{\varphi_d(N_d)})}_{\equiv V_d(a_d;N_d)} - C(a_c + a_d) \tag{1}$$

$V_c(a_c), V_d(a_d; N_d)$ are the values, increasing and concave utility functions, of information for the attention allocated to each bundle a_c, a_d, respectively. $C(a_c + a_d)$ is the increasing and convex cost of attention, N_d indexes the volume or complexity of the additional bundle, and φ_d is the intensity of the information friction where $\varphi_d(N_d) \geq 1$ and the effective attention per additional information is $a_d/\varphi_d(N_d)$. Let the values of information for the attention allocated to each bundle preserve standard diminishing returns assumptions with increasing costs s.t. $V_b'(a_b) > 0, V_b''(a_b) < 0$ for $b \in \{c, d\}$ and $C'(\overline{a}) > 0, C''(\overline{a}) > 0$. In addition to standard normality assumptions, in equilibrium, the marginal value of each information bundle is equal to the marginal attention of cost.[2]

$$\underbrace{V_c'(a_c^*)}_{\text{Marginal Benefit } (MB_c)} = \underbrace{V_d'(\frac{a_d^*}{\varphi_d(N_d)})\frac{1}{\varphi_d(N_d)}}_{\text{Marginal Benefit } (MB_d)} = \underbrace{C'(a_c^* + a_d^*)}_{\text{Marginal Cost } (MC)} \tag{2}$$

Intuitively, job seekers have limited attention, face multiple information signals, and those multiple information signals can reduce the ability of the job seeker to react to information relevant signals. Our treatment raises N_d without changing other aspects of the job seekers maximization problem — affecting job seekers optimal attention allocation due to an increase in the disclosure or complexity of information (Persson 2018).

[2]Full derivation of optimality conditions from the constrained optimization problem:
$\mathcal{L} = V_c(a_c) + V_d(a_{d;N_d}) - C(a_c + a_d) + \lambda(\overline{a} - a_c - a_d) + \theta_c a_c + \theta_d a_d$;

Assume standard Karush–Kuhn–Tucker (KKT) conditions where multiplier $\lambda \geq 0$, non negativity constraints $\theta_c, \theta_d \geq 0$, and $V_d(a_{d;N_d}) \equiv V_d(\frac{a_d}{\varphi_d(N_d)})$;

First order conditions (FOCs):
$\frac{\partial \mathcal{L}}{\partial a_c} = V_c'(a_c) - C'(\overline{a}) - \lambda + \theta_c = 0$, $\frac{\partial \mathcal{L}}{\partial a_d} = V_d'(a_d; N_d) - C'(\overline{a}) - \lambda + \theta_d = 0, \theta_c a_c = 0, \theta_d a_d = 0$;

Suppose $a_c > 0, a_d > 0$, $\theta_c = \theta_d = 0$, and $\lambda \geq 0$; $V_c'(a_c^*) - C'(\overline{a}) = V_d'(a_d^*; N_d) - C'(\overline{a})$;

Thus: $V_c'(a_c^*) = V_d'(a_d^*; N_d) \equiv V_d'(\frac{a_d^*}{\varphi_d(N_d)})\frac{1}{\varphi_d(N_d)}$

Set MB_d equal to MC and simplify by multiplying each side by $\varphi_d(N_d)$:

$$\varphi_d(N_d)\left[\underbrace{V_d'(\frac{a_d^*}{\varphi_d(N_d)})\frac{1}{\varphi_d(N_d)}}_{\text{Marginal Benefit } (MB_d)} = \underbrace{C'(a_c^*+a_d^*)}_{\text{Marginal Cost } (MC)}\right] \Rightarrow V_d'(\frac{a_d^*}{\varphi_d(N_d)}) = C'(a_c^*+a_d^*)\varphi_d(N_d) \quad (3)$$

$$\underbrace{V_d'(\frac{a_d^*}{\varphi_d(N_d)})}_{\substack{\text{Marginal Benefit of Information } (MBI_d) \\ \equiv\ \rho}} = \underbrace{C'(a_c^*+a_d^*)\varphi_d(N_d)}_{\text{Marginal Cost of Information } (MCI_d)} \quad (4)$$

Rearrange to get κ:

$$\underbrace{\kappa}_{\text{Degree of Information Overload}} \equiv \frac{C'(a_c^*+a_d^*)\varphi_d(N_d)}{V_d'(\frac{a_d^*}{\varphi_d(N_d)})} \quad (5)$$

We summarize the information overload tradeoff in Equation 5 where κ represents the degree of information overload. When N_d rises due to an increase in the disclosure of information or φ_d rises due to the complexity of the disclosure, marginal returns to the additional attention bundle, a_d, fall. The marginal benefit of information (MBI_d), compactly noted as ρ, is shifted downward. Overall search and engagement is reduced and κ increases. Alternatively, an increase in ρ decreases κ.[3]

Formally, k represents the degree of information overload faced by the treatment group and $\tilde{\kappa}$ the degree of information overload faced by the control group. $\kappa > \tilde{\kappa}$ indicates the treatment increased information overload. Changing the optimal allocation for each attention bundle. The treatment group's allocation to the core attention bundle, a_c, is now crowded out relative to the control group, $\tilde{a_c}$, where $a_c < \tilde{a_c}$. Resulting in lower overall search, engagement, or ineffective-use of the additional information on the Weekly Hot Jobs! page relative to the control group. Using Equation 4 we can further decompose the marginal benefit and costs of the additional information treatment. To ease interpretation, we subtract $\tilde{\rho}$ from ρ s.t. an increase in the value from the information treatment is interpreted via a positive coefficient. For example, a scenario where $(\tilde{\kappa} - \kappa) < 0$ and $(\rho - \tilde{\rho}) \leq 0$ could indicate that job seekers in the treatment group experienced information overload with no increase in the value of the additional information shown. Therefore, the disclosure of the additional information from the treatment or the complexity of the disclosure magnified the attention costs already faced

[3]The direction of κ is a function of ρ and MCI_d: $\kappa < 1$ when $\rho > MCI_d$; $\kappa = 1$ when $\rho = MCI_d$; $\kappa > 1$ when $\rho < MCI_d$.

by the job seeker.

6 Methods

To estimate the impact of the intervention on job seekers, we considered a total of 11 outcomes. Three primary outcomes: (1) number of job descriptions clicked on at first visit, (2) at least one job description clicked on at first visit, (3) hourly wage of explored job listings at first visit. Nine secondary outcomes: (4) number of job descriptions clicked on across all visits, (5) at least one job description clicked on across all visits, (6) hourly wage of explored job listings across all visits (7) number of industry buttons clicked at first visit, (8) accessed website more than once, (9) total number of times the website was accessed, (10) contacting a WMW talent development specialist at first visit, (11) scheduling a mock interview at first visit.

Our primary estimation strategy is an ordinary least squares (OLS) linear regression equation estimated in Equation 6 and Equation 7. The only difference between Equation 6 and Equation 7 is the outcome variable and interpretation of the treatment coefficient. We estimate the same equation for all secondary outcomes as well. Our preferred specification controls for observable characteristics associated with each job seeker and response weights.

$$\underbrace{y_i{}^{1,2}}_{\substack{\text{(1) Number of job descriptions clicked (first visit)}\\ \text{(2) At least one job description clicked (first visit)}}} = \alpha + \underbrace{\{\tilde{\kappa} - \kappa\}}_{\beta^{1,2}} T_i + X_i'\gamma + \Theta_i'\delta + \lambda O_i + \epsilon_i \qquad (6)$$

$$\underbrace{y_i{}^{3}}_{\text{(3) Hourly wage of explored job listings (first visit)}} = \alpha + \underbrace{\{\rho - \tilde{\rho}\}}_{\beta^{3}} T_i + X_i'\gamma + \Theta_i'\delta + \lambda O_i + \epsilon_i \qquad (7)$$

The dependent variable, $y_i{}^{1,2}$, in Equation 6 measures engagement on the WMW Weekly Hot Jobs! page for for individual i. Engagement is measured by the number of job descriptions clicked on at first visit and whether at least one job description was clicked on at first visit. $\beta^{1,2}$ or $(\tilde{\kappa} - \kappa)$ is the coefficient of interest and represents the effect of the additional information treatment on WMW Weekly Hot Jobs! page engagement. The dependent variable, $y_i{}^{3}$, in Equation 7 is the hourly wage of the explored job listings at first visit. The

hourly wage is a proxy for the value of the additional information treatment presented to the job seeker. β [3] or $(\rho - \tilde{\rho})$ is the coefficient of interest and captures if the additional information treatment caused an increase in the job seekers value of the additional information.

T is an indicator equal to one if the individual was assigned to the treatment group. X_i' is a vector of controls for individual-level job seeker characteristics from the RCT, Θ_i' is a vector of controls from the JOLTS survey, O_i controls for the intensity of employment related topics from Google Trends, and ϵ_i is an error term. Controls from the JOLTS survey and Google Trends are assigned based on the first month and day the job seeker accessed the web page, respectively. Controls from the RCT include fixed effects for device type (desktop, laptop, tablet) and the hour of the day the web page was first accessed, the first month the web page was accessed, and the average hourly wage and number of job postings on the WMW Weekly Hot Jobs! page the week the job seeker first accessed the web page. Controls from the JOLTS survey include the rate of hires, job openings, layoffs, quits, and separations over the first month the job seeker accessed the web page.

Our preferred estimates include the full set of controls and response weights. Response weights are to adjust for the experiment restart. Individuals who saw both the treatment and control page are weighted to zero and individuals assigned to either the treatment or control without switching treatment status receive a one. Those consistently assigned in two experiments receive twice the weight as those in a single experiment and those in three experiments receive double the weight of those in two experiments. We also calculate normalized inverse-probability weights (Hirano et al., 2003; Hirano and Imbens 2001) scaled by our response weights. Estimates with normalized inverse probability weights (IPWs) are substantively identical to our preferred estimates and are included for all outcomes in the Appendix.[4]

We also estimate the causal effect of the treatment throughout the hourly wage distribution using unconditional quantile regressions (UQRs) and the recentered influence function (RIF) (Autor et al., 2023; Borah and Basu 2013; Firpo et al., 2009). Traditional quantile regression estimates are conditional on treatment status. Conditional quantile regressions will not consistently identify the effect unconditional of the treatment T if any unconditional quantile τ for the outcome y is different than the conditional distribution of $y|T$ (Firpo et al., 2009). The influence function IF is a tool from the robust statistics literature (Hampel et al., 1986) assessing the effect of adding or removing a single observation from a statistic. In our setting

[4]Full weights calculations: Γ = Response weights ; $log(\frac{\pi(X')}{1-\pi(X')}) = \alpha + X_i'\gamma + \epsilon_i$; $\pi(X') = \mathbb{P}(T_i = 1|X') = \frac{exp(\alpha + X_i'\gamma + \epsilon_i)}{1+exp(\alpha + X_i'\gamma + \epsilon_i)}$; $\hat{\beta} = (\frac{1}{N}\sum_{i=1}^{N}[\frac{y_i T_i}{\hat{\pi}(X')} - \frac{y_i(1-T_i)}{1-\hat{\pi}(X')}]) \cdot \Gamma$

the IF asses' the effect of adding or removing a single observation from a specific quantile. The RIF is calculated by adding the initial statistic to its IF.[5]

$$RIF(y; q_\tau) = q_\tau + \underbrace{\frac{\tau - I\{Y \leq q_\tau\}}{f_Y(q_\tau)}}_{IF(y;q_\tau)} \tag{8}$$

Once the RIF is calculated Equation 9 can be estimated using OLS. Following Autor et., (2023), our primary estimates use bootstrapped standard errors calculated with 1,000 replications. We also include the full set of controls and response weights.

$$RIF({y_i}^3; q_\tau) = \alpha + \underbrace{\{\rho_\tau - \tilde{\rho_\tau}\}}_{{\beta_\tau}^3} T_i + X_i'\gamma_\tau + \Theta_i'\delta_\tau + \lambda_\tau G_i + \epsilon_i \tag{9}$$

7 Impact

The results of our intervention provide empirical evidence suggesting that providing additional information intended to mitigate behavioral search frictions for online job seekers had the opposite effect from what the behavioral literature would have predicted. Job seekers assigned to the treatment WMW Weekly Hot Jobs! page clicked on fewer job listings instead of more. Our main results for our three primary outcomes are summarized in Table 3.

We found that job seekers assigned to the treatment WMW Weekly Hot Jobs! page decreased their engagement with job opportunities relative to job seekers assigned to the control WMW Weekly Hot Jobs! page. In their first visit, job seekers assigned to the treatment group were 4.2 percentage points less likely to click on at least one job description and clicked on an average of 0.11 fewer job descriptions. Both estimates are statistically significant ($p < 0.01$). The inclusion of outliers from our non-winsorized sample increased the magnitude of the decline that job seekers clicked on at least one job description in their first visit from 4.2 percentage points to 4.6 percentage points ($p < 0.01$). The effect on the number of job descriptions clicked in their first visit is no longer statistically significant. The Appendix

[5]We calculate the IF by evaluating the indicator function $I\{Y \leq q_\tau\}$ where q_τ is the τth quantile by treatment status of the unconditional distribution of the hourly wage of explored job listings on first visit Y. The indicator function denotes whether the hourly wage of explored job listings is less than or equal to q_τ. The difference of quantile τ and $I\{Y \leq q_\tau\}$ is divided by $f_Y(q_\tau)$, the probability density function of the average hourly wage of explored job listings at q_τ. The RIF is then the sum of q_τ, or the average hourly wage of explored job listings at the τth quantile by treatment status, and the IF.

Table 3: Impacts of Additional Information Treatment on WMW Weekly Hot Jobs!

	$\tilde{\kappa} - \kappa$		$\rho - \tilde{\rho}$
	(1) Number of job descriptions clicked (first visit)	(2) At least one job description clicked (first visit)	(3) Hourly wage of explored job listings (first visit)
Treatment effect	-0.114**	-0.042**	0.754
	(0.041)	(0.014)	(0.553)
Control group mean	0.550	0.262	21.89
% effect	-20.727	-16.031	—
Constant	-3.349	1.057	89.329
	(4.120)	(1.670)	(62.120)
Response Weights	YES	YES	YES
RCT-Controls	YES	YES	YES
JOLTS-Controls	YES	YES	YES
Google-Controls	YES	YES	YES
Response Weights*IPWs	NO	NO	NO
Observations	3,894	3,894	771
R^2	0.025	0.025	0.086

Robust standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

includes estimates for all non-winsorized regression results.

Across all visits, job seekers assigned to the treatment group were 4.4 percentage points ($p < 0.01$) less likely to click on at least one job description and clicked on an average of 0.16 ($p < 0.05$) fewer job descriptions. We do not interpret the coefficient on the treatment indicator for contacting a WMW specialist. While statistically significant, only 14 job seekers in total selected the contact a WMW specialist option. All other secondary outcomes are not statistically significant at traditional significance cutoffs. Most notably, job seekers were no more or no less likely to return to the WMW Weekly Hot Jobs! page or to explore other industry tabs. Thus, job seekers assigned to receive the additional information treatment decreased their engagement on the page but not the breadth or duration of their search. Estimates and frequency counts for all outcomes are included in the Appendix.

Our results contradict traditional interpretations of the behavioral literature—additional information prompting online job seekers to think more broadly about how their experience may be relevant to other positions would encourage them to explore additional job openings. Instead, our results suggest an alternative behavioral interpretation. Job seekers assigned to the treatment group were no less likely to return to the WMW Weekly Hot Jobs! page but, on average, were less likely to click on at least one job description. We believe the additional

information caused job seekers to experience some form of information overload. Thus, the behavioral literature notes two possible responses. Job seekers either completely avoided the additional information or developed a heuristic using the additional information to filter in stages. Since the treatment had no effect on the likelihood of job seekers returning to the web page, we believe our results provide empirical evidence that job seekers responded to the additional information by filtering in stages. Possibly indicating the additional information allowed job seekers to more efficiently scan job listings without clicking on the description link.

7.1 Heterogeneity

We check for potential heterogeneity across device type and throughout the distribution of the hourly wage of explored job listings. We find that the effect of the treatment varied by the type of device used to access the WMW Weekly Hot Jobs! page. Tables with estimates for all outcomes across device type can be found in the Appendix. None of our outcomes are statistically significant for tablet or mobile device users.

Differences among job seekers assigned to the treatment and control group are substantially larger in magnitude (more negative) for desktop users. Table 4 summarizes the effect of the treatment for our primary outcomes and preferred specification for desktop users. Among desktop users, job seekers assigned to the treatment page clicked on an average of 0.20 ($p < 0.01$) or 28.4% fewer job listings and 5.9 ($p < 0.01$) percentage points less likely to click on at least one job description on their first visit relative to job seekers assigned to the control page. Across all visits, job seekers assigned to the treatment page clicked on an average of 0.26 ($p < 0.05$) fewer job listings and were 6.0 ($p < 0.01$) percentage points less likely to click on at least one job description across all visits. There was no statistically significant effect on the hourly wage of explored listings on first visit or across all visits for desktop users. A potential explanation for the heterogeneity across device type could be related to the different way the WMW Weekly Hot Jobs! page displays on a desktop versus mobile or tablet device. Job seekers using a desktop will see the added column with three additional job titles on their initial screen. However, job seekers using a mobile or tablet device must scroll to the right to see the additional columns.

Table 4: Desktop Device: Impacts of Additional Information Treatment on WMW Weekly Hot Jobs!

	$\tilde{\kappa} - \kappa$		$\rho - \tilde{\rho}$
	(1) Number of job descriptions clicked (first visit)	(2) At least one job description clicked (first visit)	(3) Hourly wage of explored job listings (first visit)
Treatment effect	-0.198**	-0.059**	0.202
	(0.068)	(0.021)	(0.775)
Control group mean	0.696	0.303	22.49
% effect	-28.448	-19.472	—
Constant	7.005	4.337	42.724
	(13.344)	(2.885)	(79.206)
Response Weights	YES	YES	YES
RCT-Controls	YES	YES	YES
JOLTS-Controls	YES	YES	YES
Google-Controls	YES	YES	YES
Response Weights*IPWs	NO	NO	NO
Observations	1,947	1,947	439
R^2	0.032	0.033	0.087

Robust standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

On average, we found no statistically significant effect of the treatment on the hourly wage of explored job listings. However, UQRs suggest the treatment had a differential effect towards the tails of the hourly wage distribution. Figure 3 illustrates the differential effect of the additional information treatment throughout the hourly wage distribution on first visit.

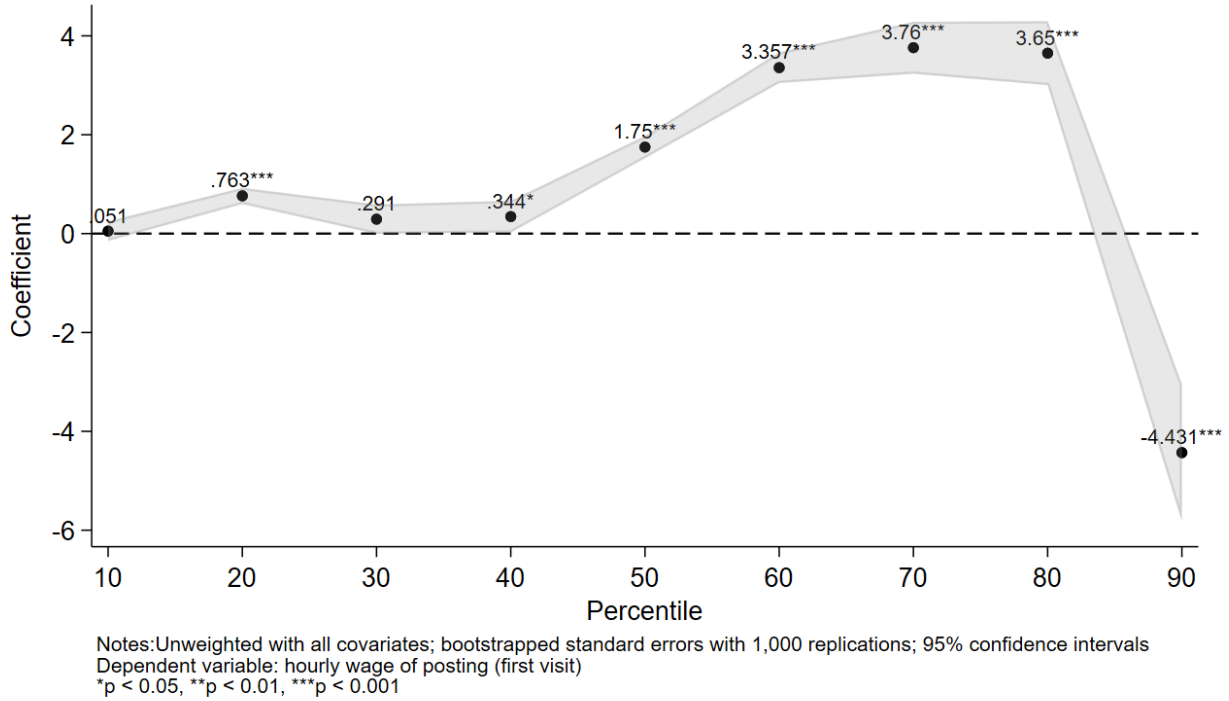


Figure 3: Unconditional Quantile Regressions (UQRs) for the Hourly Wage of Explored Job Listings (first visit)

The effect of the treatment is small to nonexistent at the lower end of the hourly wage distribution. Job seekers at the median, or 50th percentile, to the 80th percentile experience large and statistically significant increases in the hourly wage of explored job listings, on first visit, from the additional information treatment. Table 5 summarizes the effect of the additional information treatment throughout the hourly wage distribution of explored job listings on first visit. Panel A of Table 5 displays the treatment effects and Panel B of Table 5 displays the wage levels at each percentile.

The effect peaks at the 70th percentile resulting in an increase of \$3.76 per hour or %17.2 relative to the control group. Contextualizing the per hour increase results in an increase of $\$7,821$ a year (assuming a 40 hour work week and 52 weeks a year). At the 90th percentile of the hourly wage distribution we estimate a decrease in the hourly wage of explored job listings, on first visit, of \$4.43 per hour or %20.2. Resulting in a decrease of $\$9,214$ a year. The hourly wage on first visit for jobs on the WMW Weekly Hot Jobs! page at the median is \$20.67 per hour or $\$42,994$ a year. The hourly wage at the 80th percentile is \$27.08 per hour or $\$53,326$ a year and \$33.74 per hour or $\$70,179$ a year at the 90th percentile. Our estimates show that job seekers, roughly, at the yearly income level between $\$42,994$ and

$53,326 a year may have found some sort of value from the additional information treatment. However, job seekers at or above the $70,179 a year income level may have experienced a large decline in value due to the additional information.

Table 5: Treatment Effects Throughout the Wage Distribution and Wage Levels

Panel A: Treatment Effects

	(1) Hourly effect ($)	(2) Hourly % effect (%)	(3) Yearly effect ($)
10th percentile	0.05	—	104
20th percentile	0.76***	3.47	1,581
30th percentile	0.29	—	603
40th percentile	0.34*	1.55	707
50th percentile	1.75***	7.99	3,640
60th percentile	3.36***	15.35	6,989
70th percentile	3.76***	17.18	7,821
80th percentile	3.65***	16.67	7,592
90th percentile	-4.43***	-20.24	-9,214

Panel B: Wage Levels

	(4) Hourly wage ($)	(5) Yearly income ($)
10th percentile	13.91	28,933
20th percentile	16.01	33,301
30th percentile	17.71	36,837
40th percentile	19.35	40,248
50th percentile	20.67	42,994
60th percentile	22.06	45,885
70th percentile	24.58	51,126
80th percentile	27.08	56,326
90th percentile	33.74	70,179

Notes: Panel A reports estimated treatment effects (per hour, percent, and per year) for each percentile of the hourly wage on first visit. Panel B reports wage levels and implied yearly income for each percentile across the hourly wage distribution. Yearly income calculations assume a 40 hour work week and 52 weeks a year. Control group hourly wage is $21.89. Significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Hourly effect estimates in Panel A use the full set of controls and bootstrap SEs calculated with 1,000 replications.

7.2 Behavioral Interpretation and Discussion

The additional information treatment on the WMW Weekly Hot Jobs! page is intended to address cognitive behavioral barriers that could generate search frictions for online job seekers. Job seekers may click through to the application for several job listings but never reach the jobs where they would be the best match given their skills and experience. Cognitive behavioral barriers can generate search frictions negatively impacting the search process. Job seekers may default towards searching for jobs they have held in the past or industries consistent with their own identity. Job seekers may also feel they are unable to find job relevant information or overwhelmed if they cannot determine whether their skills or experience make them a good match for a job opportunity. The treatment was intended to provide more job relevant information in a manner easily accessible for job seekers.

Our results suggest the additional information added to job listings had the opposite effect from what the behavioral literature predicted, leading job seekers to click on fewer job listings with no change in the breadth or duration of their search. From our theoretical framework, our estimates for engagement on the WMW Weekly Hot Jobs! page show that $(\tilde{\kappa} - \kappa) < 0$ indicating that job seekers assigned to the additional information treatment experienced a form of information overload. On average, we did not find an increase in the value of the additional information. Potentially indicating the disclosure and amount of information or complexity of the additional information was the cause of the information overload — interviews with job seekers provide some evidence for this. Job seekers using the WMW Weekly Hot Jobs! page indicate the additional job title information displayed on the treatment web page was helpful while the bright red prompt to explore other industries was not. The bold and red color of the prompt unexpectedly caused job seekers to perceive the industry prompt as an advertisement or other irrelevant information. This would also explain the larger declines in web page engagement for desktop device users. Since mobile and tablet users were not instantly displayed the additional information (due to how the page loads on mobile and tablet devices) the additional information disclosure was more pronounced for desktop device users.

We did not find an average increase in the value, or marginal benefit of information, of the additional information for job seekers. However, we find evidence that the additional information may have been valuable for some job seekers. We use the hourly wage of explored job listings as a proxy for the value of the additional information treatment. Our estimates for the hourly wage show that $(\rho - \tilde{\rho}) > 0$ for some job seekers, indicating an increase in the value of information, depending on where they are in the hourly wage distribution.

Roughly, job seekers at the lower tail to median of the distribution found small or no value while job seekers at the upper tail of the distribution found negative value in the additional information. However, job seekers from the median to 80th percentile seem to have found some value in the additional information. Experiencing large and statistically significant increases in the hourly wage of explored job listings.

The heterogeneity in the value of the additional information throughout the wage distribution could be explained due to the nature of jobs hosted on the WMW Weekly Hot Jobs page! or the actual transferability of skills associated with job seekers at different wage levels. Both explanations are likely affected to some degree by the industry composition in West Michigan. WMW operates American Job Centers established under WIOA, a workforce development system, possibly displaying job listings catered more towards individuals at certain wage levels. Research has shown the importance of soft skills in the labor market and their importance on wages (Barrera-Osorio et al., 2023; Heckman and Kautz 2012). Higher wage job seekers using the WMW Weekly Hot Jobs page! may have come from jobs or industries where their primary set of skills were related to communication, teamwork, or general interpersonal skills. Recommendations for some of those job seekers may have pushed them towards more customer service oriented roles. Whereas job seekers just above the median hourly wage may have more general manufacturing skills and realized their skills in one manufacturing occupation easily translate to another higher paying manufacturing occupation. The largest industries in West Michigan are educational and health care services and manufacturing which employ %22.2 and %19.5 of the population, respectively. Only %5.3 of the population is employed in the finance and real estate industry.[6] It's plausible treated job seekers coming from an industry similar to the finance and real estate industry may have seen the additional information and explored relatively lower wage job listings in an industry such as education or health care services. The combination of the workforce development nature of the WMW Weekly Hot Jobs! page, the manner of the transferability of skills associated with each wage level, and the industry composition of West Michigan are likely to be, at least, partially responsible for why certain job seekers saw value in the additional information while others did not.

We find evidence that the disclosure or complexity of the additional information caused job seekers to experience some form of information overload. Job seekers decreased their engagement but not the breadth or duration of their search. It's possible job seekers may have responded to the additional information by developing criteria they can use to quickly scan jobs to reduce the cognitive difficulty of the online search process (Payne 1976). Filtering out

[6]The Appendix includes detailed employment statistics by industry for West Michigan.

most job listings with one or two simple criteria would allow job seekers to carefully compare the remaining listings they have prioritized for review (Roberts and Lattin 1991; Manduca 2024). For example, job seekers may have incorporated the additional information into their initial filtering criteria allowing them to more efficiently evaluate the potential fit of each job listing. Alternatively, job seekers may have filtered on a different set of initial criteria and disregarded the additional information. Interviews with job seekers provide evidence in support of both interpretations. Some job seekers noted they only considered opportunities in one or two counties and seemingly ignored the additional information. On the other hand, some job seekers reported finding the additional information helpful for quickly focusing on the most promising opportunities.

Our results add to the job search literature by clearly identifying how differing types and quantities of information can cause online job seekers to adopt different behavioral strategies to cope with additional information. Adjusting the quantity of the information disclosure, the complexity of the information, or the industries targeted may all affect job seeker behavior. Removing any bold or highlighted text may reduce the complexity of an additional information disclosure. Limiting any additional information to only a single addition would decrease the dimensionality of an additional information disclosure by limiting the quantity of information. Both sets of adjustments could see a decrease in information overload resulting in increased web page engagement. Tailored information disclosures for specialized online job boards could also increase the value of an additional information disclosure for job seekers.

The context of the intervention may not apply to all job search scenarios. During the period of the intervention, the West Michigan labor market was particularly tight. A low unemployment rate may have impacted the behavior of job seekers. Job seekers visiting the WMW Weekly Hot Jobs! page may not be representative of the average online job seeker. Our study is limited to job seekers in West Michigan who are aware of the WMW Weekly Hot Jobs! page and opted to use it for job search. We are also unable to directly estimate the impact of the intervention on employment or match quality. In total, only 4% of job seekers who selected a job description link clicked through to the application page. As a result, even with available data on employment outcomes, we would not have sufficient power with our sample to detect an effect. Furthermore, our experimental design is limited by the capabilities of Google Optimize. Randomization occurs at the device and browser level. If a job seeker visited the WMW Weekly Hot Jobs! page on more than one device or browser, there is a possibility the job seeker was randomized into both the treatment and control group and selected the version of the WMW Weekly Hot Jobs! page they preferred

or potentially alter their behavior in some way due to their exposure of multiple versions of the WMW Weekly Hot Jobs! page.

8 Conclusion

We find evidence that the additional information added to the WMW Weekly Hot Jobs! page allowed job seekers to more efficiently scan available job listings. Efficiently filtering out potentially less suitable job listings to focus on those most closely aligned with their skills. The empirical and qualitative evidence seem to indicate that the additional information added to the treatment page, while helpful, caused job seekers to experience a type of information overload. On average, we find job seekers responded to the additional information by employing a filtering information in stages heuristic. We believe this allowed job seekers to identify relevant job opportunities without having to select the additional job description link. Future interventions could decrease the amount of information online job seekers interact with. Potentially leading job seekers to consider more options or engage with more job descriptions.

The different ways job seekers respond to new information can have distinct implications for job search. Our results lead us to believe that job seekers used the additional information from the treatment page to filter job listings into a priority set for review. Job search outcomes may have improved for job seekers if they were able to use the additional information from the treatment page to more efficiently filter out job opportunities where they would be a poor match. In contrast, job seekers could experience worse job search outcomes if the additional information from the treatment page overwhelmed them and caused them to completely avoid relevant information. Job seekers ignoring additional information during their job search could potentially experience a less efficient job search with worse employment outcomes, increased search time, and worse match quality. However, job seekers using the additional information to effectively filter job opportunities could experience better employment outcomes, decreased search time, and improvements in match quality.

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9 Appendix

9.1 Tables and Graphs

Table 6: Summary Statistics by Treatment Status

	All	Control	Treated
Desktop device	0.503	0.506	0.499
	(0.500)	(0.500)	(0.500)
Mobile device	0.471	0.468	0.475
	(0.499)	(0.499)	(0.499)
Tablet device	0.026	0.026	0.026
	(0.159)	(0.159)	(0.160)
Hour of first visit: 10pm-4am	0.096	0.097	0.095
	(0.295)	(0.297)	(0.294)
Hour of first visit: 5am-11am	0.483	0.489	0.477
	(0.500)	(0.500)	(0.500)
Hour of first visit: 12pm-5pm	0.330	0.323	0.338
	(0.470)	(0.468)	(0.473)
Hour of first visit: 6pm-9pm	0.090	0.091	0.090
	(0.287)	(0.288)	(0.286)
Month of first visit: January	0.135	0.136	0.134
	(0.342)	(0.343)	(0.341)
Month of first visit: August	0.138	0.133	0.142
	(0.345)	(0.340)	(0.349)
Month of first visit: September	0.138	0.132	0.143
	(0.345)	(0.339)	(0.350)
Month of first visit: October	0.152	0.154	0.151
	(0.359)	(0.361)	(0.358)
Month of first visit: November	0.168	0.174	0.162
	(0.374)	(0.379)	(0.369)
Month of first visit: December	0.135	0.134	0.135
	(0.341)	(0.341)	(0.342)
Month of first visit: January	0.135	0.136	0.134
	(0.342)	(0.343)	(0.341)
Month of first visit: February/March	0.135	0.137	0.132
	(0.341)	(0.344)	(0.339)
Observations	3987	2012	1975

Means in cells and standard deviations in parentheses.

Table 7: Frequency by Treatment Status

	All			Treated			Control		
	count	min	max	count	min	max	count	min	max
Unique job listings (number) clicked, first visit	970	1	8	443	1	7	527	1	8
Job listing (at least one) clicked, first visit	970	1	1	443	1	1	527	1	1
Hourly wage of posting, first visit	796	13	60	364	13	60	432	13	52
Unique job listings (number) clicked, ever	1083	1	33	502	1	21	581	1	33
Job listing (at least one) clicked, ever	1083	1	1	502	1	1	581	1	1
Hourly wage of posting, ever	912	13	60	422	13	60	490	13	52
Unique industry tabs (number) clicked, first visit	1004	1	7	517	1	7	487	1	7
Returned on at least two distinct dates	589	1	1	301	1	1	288	1	1
Number of visits to page (unique dates)	3987	1	19	1975	1	19	2012	1	19
Clicked contact WMW specialist, first visit	14	1	1	3	1	1	11	1	1
Clicked schedule mock-interview, first visit	364	1	1	169	1	1	195	1	1
Desktop device	2004	1	1	985	1	1	1019	1	1
Mobile device	1879	1	1	938	1	1	941	1	1
Tablet device	104	1	1	52	1	1	52	1	1
Hour of first visit: 10pm-4am	384	1	1	188	1	1	196	1	1
Hour of first visit: 5am-11am	1926	1	1	943	1	1	983	1	1
Hour of first visit: 12pm-5pm	1317	1	1	667	1	1	650	1	1
Hour of first visit: 6pm-9pm	360	1	1	177	1	1	183	1	1
Month of first visit: January	538	1	1	265	1	1	273	1	1
Month of first visit: August	549	1	1	281	1	1	268	1	1
Month of first visit: September	549	1	1	283	1	1	266	1	1
Month of first visit: October	607	1	1	298	1	1	309	1	1
Month of first visit: November	670	1	1	320	1	1	350	1	1
Month of first visit: December	537	1	1	267	1	1	270	1	1
Month of first visit: January	538	1	1	265	1	1	273	1	1
Month of first visit: February/March	537	1	1	261	1	1	276	1	1

Table 8: Outcomes - Means

	Treated	Control	Difference	S.E.
Primary outcomes				
Unique job listings (number) clicked, first visit	0.452	0.550	-0.098***	0.037
Job listing (at least one) clicked, first visit	0.224	0.262	-0.038***	0.014
Hourly wage of posting, first visit	22.478	21.890	0.588	0.526
Secondary outcomes - Engagement across all visit				
Unique job listings (number) clicked, ever	0.623	0.771	-0.149**	0.061
Job listing (at least one) clicked, ever	0.254	0.289	-0.035**	0.014
Hourly wage of posting, ever	22.452	21.878	0.574	0.479
Secondary outcomes - Exploration				
Unique industry tabs (number) clicked, first visit	0.498	0.541	-0.043	0.036
Returned on at least two distinct dates	0.152	0.143	0.009	0.011
Number of visits to page (unique dates)	1.571	1.564	0.008	0.056
Secondary outcomes - Additional engagement				
Clicked contact WMW specialist, first visit	0.002	0.005	-0.004**	0.002
Clicked schedule mock-interview, first visit	0.086	0.097	-0.011	0.009

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 9: Outcomes - Means, Non-winsorized

	Treated	Control	Difference	S.E.
Primary outcomes				
Unique job listings (number) clicked, first visit	0.596	0.668	-0.073	0.060
Job listing (at least one) clicked, first visit	0.232	0.272	-0.040***	0.014
Hourly wage of posting, first visit	22.458	21.809	0.649	0.496
Secondary outcomes - Engagement across all visit				
Unique job listings (number) clicked, ever	0.843	1.076	-0.232**	0.109
Job listing (at least one) clicked, ever	0.263	0.303	-0.040***	0.014
Hourly wage of posting, ever	22.454	21.888	0.566	0.452
Secondary outcomes - Exploration				
Unique industry tabs (number) clicked, first visit	0.523	0.584	-0.060	0.038
Returned on at least two distinct dates	0.160	0.156	0.003	0.011
Number of visits to page (unique dates)	1.836	2.002	-0.166	0.124
Secondary outcomes - Additional engagement				
Clicked contact WMW specialist, first visit	0.001	0.005	-0.004**	0.002
Clicked schedule mock-interview, first visit	0.086	0.098	-0.011	0.009

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 10: Desktop Device: Outcomes - Means

	Treated	Control	Difference	S.E.
Primary outcomes				
Unique job listings (number) clicked, first visit	0.529	0.696	-0.167**	0.059
Job listing (at least one) clicked, first visit	0.251	0.303	-0.052**	0.020
Hourly wage of posting, first visit	22.369	22.492	-0.124	0.713
Secondary outcomes - Engagement across all visit				
Unique job listings (number) clicked, ever	0.743	0.960	-0.217*	0.094
Job listing (at least one) clicked, ever	0.286	0.334	-0.047*	0.021
Hourly wage of posting, ever	22.439	22.495	-0.056	0.643
Secondary outcomes - Exploration				
Unique industry tabs (number) clicked, first visit	0.932	1.024	-0.092	0.064
Returned on at least two distinct dates	0.146	0.118	0.028	0.015
Number of visits to page (unique dates)	1.750	1.602	0.149	0.094
Secondary outcomes - Additional engagement				
Clicked contact WMW specialist, first visit	0.002	0.003	-0.001	0.002
Clicked schedule mock-interview, first visit	0.084	0.085	-0.001	0.012

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 11: Regressions of the Treatment Coefficient for All Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unique job listings (number) clicked, first visit	-0.098**	-0.115**	-0.111**	-0.118**	-0.115**	-0.114**	-0.114**
	(0.037)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Job listing (at least one) clicked, first visit	-0.038**	-0.041**	-0.041**	-0.043**	-0.041**	-0.042**	-0.042**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Hourly wage of posting, first visit	0.588	0.680	0.796	0.689	0.649	0.754	0.753
	(0.526)	(0.538)	(0.550)	(0.532)	(0.542)	(0.553)	(0.553)
N	796	771	771	771	771	771	771
Unique job listings (number) clicked, ever	-0.149*	-0.159*	-0.156*	-0.165*	-0.159*	-0.161*	-0.161*
	(0.061)	(0.073)	(0.073)	(0.072)	(0.073)	(0.072)	(0.072)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Job listing (at least one) clicked, ever	-0.035*	-0.043**	-0.043**	-0.045**	-0.043**	-0.044**	-0.044**
	(0.014)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Hourly wage of posting, ever	0.574	0.514	0.639	0.474	0.497	0.568	0.566
	(0.479)	(0.499)	(0.511)	(0.496)	(0.501)	(0.514)	(0.513)
N	912	863	863	863	863	863	863
Unique industry tabs (number) clicked, first visit	-0.043	-0.045	-0.040	-0.046	-0.045	-0.038	-0.039
	(0.036)	(0.039)	(0.035)	(0.039)	(0.039)	(0.035)	(0.035)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Returned on at least two distinct dates	0.009	-0.001	-0.001	-0.003	-0.001	-0.004	-0.004
	(0.011)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Number of visits to page (unique dates)	0.008	-0.024	-0.024	-0.032	-0.023	-0.035	-0.035
	(0.056)	(0.065)	(0.064)	(0.064)	(0.065)	(0.063)	(0.063)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Clicked contact WMW specialist, first visit	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Clicked schedule mock-interview, first visit	-0.011	-0.014	-0.015	-0.014	-0.014	-0.016	-0.016
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
N	3,987	3,894	3,894	3,894	3,894	3,894	3,894
Response Weights	NO	YES	YES	YES	YES	YES	NO
RCT-Controls	NO	NO	YES	NO	NO	YES	YES
JOLTS-Controls	NO	NO	NO	YES	NO	YES	YES
Google-Controls	NO	NO	NO	NO	YES	YES	YES
Response Weights*IPWs	NO	NO	NO	NO	NO	NO	YES

Winsorized sample; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; Robust standard errors in parentheses

Table 12: Regressions of the Treatment Coefficient for All Outcomes, Non-winsorized

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unique job listings (number) clicked, first visit	-0.073	-0.096	-0.096	-0.096	-0.097	-0.093	-0.093
	(0.061)	(0.064)	(0.062)	(0.064)	(0.064)	(0.064)	(0.064)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Job listing (at least one) clicked, first visit	-0.040**	-0.045**	-0.045**	-0.047***	-0.045**	-0.046**	-0.046**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Hourly wage of posting, first visit	0.649	0.691	0.768	0.634	0.662	0.703	0.702
	(0.497)	(0.509)	(0.519)	(0.505)	(0.513)	(0.524)	(0.523)
N	852	819	819	819	819	819	819
Unique job listings (number) clicked, ever	-0.232*	-0.253*	-0.254*	-0.252*	-0.253*	-0.250*	-0.250*
	(0.109)	(0.128)	(0.129)	(0.126)	(0.128)	(0.127)	(0.127)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Job listing (at least one) clicked, ever	-0.040**	-0.051***	-0.050***	-0.052***	-0.051***	-0.051***	-0.051***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Hourly wage of posting, ever	0.566	0.480	0.574	0.366	0.460	0.466	0.465
	(0.451)	(0.477)	(0.485)	(0.475)	(0.480)	(0.489)	(0.488)
N	982	916	916	916	916	916	916
Unique industry tabs (number) clicked, first visit	-0.060	-0.063	-0.057	-0.065	-0.064	-0.056	-0.056
	(0.038)	(0.041)	(0.037)	(0.041)	(0.041)	(0.037)	(0.037)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Returned on at least two distinct dates	0.003	-0.008	-0.008	-0.010	-0.008	-0.010	-0.010
	(0.011)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Number of visits to page (unique dates)	-0.166	-0.239	-0.224	-0.247	-0.237	-0.235	-0.235
	(0.123)	(0.225)	(0.219)	(0.218)	(0.224)	(0.208)	(0.208)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Clicked contact WMW specialist, first visit	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Clicked schedule mock-interview, first visit	-0.011	-0.016	-0.017	-0.016	-0.016	-0.018	-0.018
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
N	4,075	3,957	3,957	3,957	3,957	3,957	3,957
Response Weights	NO	YES	YES	YES	YES	YES	NO
RCT-Controls	NO	NO	YES	NO	NO	YES	YES
JOLTS-Controls	NO	NO	NO	YES	NO	YES	YES
Google-Controls	NO	NO	NO	NO	YES	YES	YES
Response Weights*IPWs	NO	NO	NO	NO	NO	NO	YES

Non-winsorized sample; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; Robust standard errors in parentheses

Table 13: Desktop Device: Regressions of the Treatment Coefficient for All Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unique job listings (number) clicked, first visit	-0.167**	-0.198**	-0.198**	-0.201**	-0.200**	-0.198**	-0.198**
	(0.059)	(0.068)	(0.068)	(0.067)	(0.068)	(0.068)	(0.068)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Job listing (at least one) clicked, first visit	-0.052**	-0.058**	-0.059**	-0.060**	-0.059**	-0.059**	-0.059**
	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Hourly wage of posting, first visit	-0.124	0.120	0.290	0.173	0.104	0.202	0.203
	(0.710)	(0.731)	(0.773)	(0.732)	(0.730)	(0.775)	(0.774)
N	457	439	439	439	439	439	439
Unique job listings (number) clicked, ever	-0.217*	-0.251*	-0.257*	-0.257*	-0.252*	-0.260*	-0.260*
	(0.093)	(0.121)	(0.121)	(0.120)	(0.121)	(0.121)	(0.121)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Job listing (at least one) clicked, ever	-0.047*	-0.058**	-0.059**	-0.061**	-0.058**	-0.060**	-0.060**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Hourly wage of posting, ever	-0.056	0.060	0.109	-0.007	0.036	-0.038	-0.039
	(0.641)	(0.667)	(0.705)	(0.677)	(0.667)	(0.708)	(0.708)
N	524	489	489	489	489	489	489
Unique industry tabs (number) clicked, first visit	-0.092	-0.099	-0.106	-0.101	-0.099	-0.103	-0.103
	(0.064)	(0.068)	(0.069)	(0.068)	(0.069)	(0.069)	(0.068)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Returned on at least two distinct dates	0.028	0.023	0.023	0.020	0.023	0.020	0.020
	(0.015)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Number of visits to page (unique dates)	0.149	0.107	0.102	0.090	0.105	0.086	0.086
	(0.094)	(0.106)	(0.107)	(0.106)	(0.106)	(0.105)	(0.105)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Clicked contact WMW specialist, first visit	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Clicked contact WMW specialist, first visit	-0.001	-0.008	-0.009	-0.008	-0.008	-0.009	-0.009
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
N	2,004	1,947	1,947	1,947	1,947	1,947	1,947
Response Weights	NO	YES	YES	YES	YES	YES	NO
RCT-Controls	NO	NO	YES	NO	NO	YES	YES
JOLTS-Controls	NO	NO	NO	YES	NO	YES	YES
Google-Controls	NO	NO	NO	NO	YES	YES	YES
Response Weights*IPWs	NO	NO	NO	NO	NO	NO	YES

Winsorized sample; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; Robust standard errors in parentheses

Table 14: Mobile Device: Regressions of the Treatment Coefficient for All Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unique job listings (number) clicked, first visit	-0.045	-0.049	-0.054	-0.055	-0.049	-0.061	-0.061
	(0.044)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Job listing (at least one) clicked, first visit	-0.029	-0.032	-0.035	-0.034	-0.032	-0.037	-0.037
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Hourly wage of posting, first visit	1.698*	1.599*	1.584*	1.339	1.604*	1.485	1.480
	(0.787)	(0.800)	(0.798)	(0.799)	(0.813)	(0.831)	(0.831)
N	306	301	301	301	301	301	301
Unique job listings (number) clicked, ever	-0.106	-0.098	-0.098	-0.106	-0.098	-0.109	-0.109
	(0.080)	(0.081)	(0.080)	(0.082)	(0.081)	(0.081)	(0.081)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Job listing (at least one) clicked, ever	-0.026	-0.033	-0.036	-0.036	-0.033	-0.038	-0.038
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Hourly wage of posting, ever	1.536*	1.171	1.265	1.011	1.179	1.179	1.177
	(0.733)	(0.775)	(0.773)	(0.771)	(0.780)	(0.781)	(0.781)
N	350	338	338	338	338	338	338
Unique industry tabs (number) clicked, first visit	0.000	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Returned on at least two distinct dates	-0.010	-0.025	-0.024	-0.025	-0.024	-0.026	-0.026
	(0.017)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Number of visits to page (unique dates)	-0.118	-0.133	-0.133	-0.134	-0.132	-0.142	-0.142
	(0.061)	(0.075)	(0.074)	(0.075)	(0.075)	(0.074)	(0.073)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Clicked contact WMW specialist, first visit	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.008*	-0.008*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Clicked contact WMW specialist, first visit	-0.022	-0.020	-0.022	-0.021	-0.021	-0.024	-0.024
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
N	1,879	1,846	1,846	1,846	1,846	1,846	1,846
Response Weights	NO	YES	YES	YES	YES	YES	NO
RCT-Controls	NO	NO	YES	NO	NO	YES	YES
JOLTS-Controls	NO	NO	NO	YES	NO	YES	YES
Google-Controls	NO	NO	NO	NO	YES	YES	YES
Response Weights*IPWs	NO	NO	NO	NO	NO	NO	YES

Winsorized sample; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; Robust standard errors in parentheses

Table 15: Tablet Device: Regressions of the Treatment Coefficient for All Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unique job listings (number) clicked, first visit	0.327	0.365	0.175	0.347	0.326	0.143	0.143
	(0.265)	(0.271)	(0.278)	(0.285)	(0.280)	(0.292)	(0.292)
N	104	101	101	101	101	101	101
Job listing (at least one) clicked, first visit	0.115	0.132	0.085	0.119	0.133	0.069	0.068
	(0.096)	(0.096)	(0.100)	(0.099)	(0.097)	(0.100)	(0.100)
N	104	101	101	101	101	101	101
Hourly wage of posting, first visit	1.084	0.710	3.413	2.032	0.727	9.022	8.970
	(3.371)	(3.563)	(8.344)	(3.679)	(3.708)	(27.154)	(27.159)
N	33	31	31	31	31	31	31
Unique job listings (number) clicked, ever	0.481	0.573	0.574	0.546	0.497	0.534	0.535
	(0.406)	(0.412)	(0.457)	(0.408)	(0.399)	(0.474)	(0.474)
N	104	101	101	101	101	101	101
Job listing (at least one) clicked, ever	0.077	0.095	0.048	0.081	0.095	0.040	0.040
	(0.098)	(0.099)	(0.102)	(0.100)	(0.099)	(0.104)	(0.104)
N	104	101	101	101	101	101	101
Hourly wage of posting, ever	1.142	1.086	0.508	2.494	0.947	4.472	4.418
	(2.858)	(3.009)	(6.656)	(3.108)	(3.113)	(11.796)	(11.781)
N	38	36	36	36	36	36	36
Unique industry tabs (number) clicked, first visit	0.404	0.427	0.347	0.387	0.421	0.293	0.295
	(0.239)	(0.244)	(0.306)	(0.249)	(0.253)	(0.276)	(0.277)
N	104	101	101	101	101	101	101
Returned on at least two distinct dates	-0.019	-0.054	-0.015	-0.057	-0.063	0.001	0.001
	(0.070)	(0.070)	(0.075)	(0.068)	(0.069)	(0.071)	(0.071)
N	104	101	101	101	101	101	101
Number of visits to page (unique dates)	-0.385	-0.532	-0.277	-0.518	-0.561	-0.231	-0.230
	(0.323)	(0.319)	(0.232)	(0.316)	(0.322)	(0.220)	(0.220)
N	104	101	101	101	101	101	101
Clicked contact WMW specialist, first visit	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
N	104	101	101	101	101	101	101
Clicked contact WMW specialist, first visit	-0.019	-0.018	-0.017	-0.010	-0.018	-0.011	-0.011
	(0.042)	(0.043)	(0.049)	(0.045)	(0.042)	(0.051)	(0.051)
N	104	101	101	101	101	101	101
Response Weights	NO	YES	YES	YES	YES	YES	NO
RCT-Controls	NO	NO	YES	NO	NO	YES	YES
JOLTS-Controls	NO	NO	NO	YES	NO	YES	YES
Google-Controls	NO	NO	NO	NO	YES	YES	YES
Response Weights*IPWs	NO	NO	NO	NO	NO	NO	YES

Winsorized sample; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; Robust standard errors in parentheses

Table 16: Unconditional Quantile Regression (UQRs) for the Hourly Wage of Job Listings (first visit)

	(1)	(2)	(3)	(4)	(5)	(6)
10th percentile, hourly wage, first visit	0.051	0.051	0.049	0.059	0.052	0.051
	(0.090)	(0.094)	(0.090)	(0.088)	(0.089)	(0.091)
N	3,987	3,987	3,987	3,987	3,987	3,987
20th percentile, hourly wage, first visit	0.749***	0.749***	0.750***	0.773***	0.749***	0.763***
	(0.126)	(0.131)	(0.127)	(0.127)	(0.129)	(0.124)
N	3,987	3,987	3,987	3,987	3,987	3,987
30th percentile, hourly wage, first visit	0.281*	0.281*	0.284*	0.301*	0.281*	0.291*
	(0.132)	(0.137)	(0.130)	(0.136)	(0.134)	(0.128)
N	3,987	3,987	3,987	3,987	3,987	3,987
40th percentile, hourly wage, first visit	0.333*	0.333*	0.335**	0.352**	0.334*	0.344**
	(0.131)	(0.130)	(0.128)	(0.135)	(0.131)	(0.128)
N	3,987	3,987	3,987	3,987	3,987	3,987
50th percentile, hourly wage, first visit	1.736***	1.736***	1.737***	1.765***	1.736***	1.750***
	(0.147)	(0.150)	(0.149)	(0.148)	(0.146)	(0.148)
N	3,987	3,987	3,987	3,987	3,987	3,987
60th percentile, hourly wage, first visit	3.339***	3.339***	3.344***	3.375***	3.341***	3.357***
	(0.189)	(0.193)	(0.183)	(0.188)	(0.191)	(0.184)
N	3,987	3,987	3,987	3,987	3,987	3,987
70th percentile, hourly wage, first visit	3.739***	3.739***	3.748***	3.784***	3.740***	3.760***
	(0.254)	(0.255)	(0.256)	(0.252)	(0.244)	(0.251)
N	3,987	3,987	3,987	3,987	3,987	3,987
80th percentile, hourly wage, first visit	3.620***	3.620***	3.635***	3.677***	3.623***	3.650***
	(0.348)	(0.341)	(0.347)	(0.343)	(0.346)	(0.352)
N	3,987	3,987	3,987	3,987	3,987	3,987
90th percentile, hourly wage, first visit	-4.450***	-4.450***	-4.470***	-4.301***	-4.437***	-4.431***
	(1.015)	(1.031)	(1.008)	(1.022)	(0.985)	(1.006)
N	3,987	3,987	3,987	3,987	3,987	3,987
Robust SEs	YES	NO	NO	NO	NO	NO
Bootstrap SEs	NO	YES	YES	YES	YES	YES
RCT-Controls	NO	NO	YES	NO	NO	YES
JOLTS-Controls	NO	NO	NO	YES	NO	YES
Google-Controls	NO	NO	NO	NO	YES	YES

Winsorized sample; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; Bootstrap standard errors calculated with 1,000 replications

Table 17: Unconditional Quantile Regression (UQRs) for the Hourly Wage of Job Listings (ever)

	(1)	(2)	(3)	(4)	(5)	(6)
10th percentile hourly wage, ever	0.042	0.042	0.039	0.050	0.042	0.041
	(0.097)	(0.097)	(0.096)	(0.096)	(0.099)	(0.096)
N	3,987	3,987	3,987	3,987	3,987	3,987
20th percentile hourly wage, ever	0.523***	0.523***	0.527***	0.551***	0.522***	0.539***
	(0.132)	(0.133)	(0.131)	(0.134)	(0.132)	(0.133)
N	3,987	3,987	3,987	3,987	3,987	3,987
30th percentile hourly wage, ever	0.509***	0.509***	0.514***	0.531***	0.508***	0.522***
	(0.130)	(0.126)	(0.130)	(0.132)	(0.129)	(0.136)
N	3,987	3,987	3,987	3,987	3,987	3,987
40th percentile hourly wage, ever	0.410**	0.410**	0.415**	0.433**	0.410**	0.424**
	(0.134)	(0.134)	(0.127)	(0.134)	(0.134)	(0.132)
N	3,987	3,987	3,987	3,987	3,987	3,987
50th percentile hourly wage, ever	1.763***	1.763***	1.767***	1.795***	1.762***	1.781***
	(0.152)	(0.150)	(0.148)	(0.150)	(0.154)	(0.153)
N	3,987	3,987	3,987	3,987	3,987	3,987
60th percentile hourly wage, ever	3.363***	3.363***	3.369***	3.405***	3.362***	3.390***
	(0.200)	(0.200)	(0.204)	(0.195)	(0.196)	(0.194)
N	3,987	3,987	3,987	3,987	3,987	3,987
70th percentile hourly wage, ever	2.911***	2.911***	2.922***	2.966***	2.910***	2.944***
	(0.271)	(0.266)	(0.273)	(0.263)	(0.280)	(0.266)
N	3,987	3,987	3,987	3,987	3,987	3,987
80th percentile hourly wage, ever	1.355***	1.355***	1.374***	1.425***	1.354***	1.406***
	(0.348)	(0.342)	(0.340)	(0.342)	(0.353)	(0.335)
N	3,987	3,987	3,987	3,987	3,987	3,987
90th percentile hourly wage, ever	-7.529***	-7.529***	-7.558***	-7.316***	-7.535***	-7.453***
	(1.111)	(1.098)	(1.144)	(1.083)	(1.124)	(1.111)
N	3,987	3,987	3,987	3,987	3,987	3,987
Robust SEs	YES	NO	NO	NO	NO	NO
Bootstrap SEs	NO	YES	YES	YES	YES	YES
RCT-Controls	NO	NO	YES	NO	NO	YES
JOLTS-Controls	NO	NO	NO	YES	NO	YES
Google-Controls	NO	NO	NO	NO	YES	YES

Winsorized sample; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; Bootstrap standard errors calculated with 1,000 replications

Table 18: ACS Balance Table for US and Hot Jobs Counties

	US	Hot Jobs	Difference	S.E.
Wages, work, and employment				
Employed	0.600	0.638	-0.038	0.013
Unemployed	0.033	0.027	0.007	0.007
Not in Labor Force	0.367	0.335	0.031*	0.006
Hourly Wage	26.603	23.305	3.297	1.104
Usual Hours Worked	20.222	20.765	-0.543	0.376
Demographics, education, and the household				
College Graduate	0.265	0.253	0.012	0.003
White	0.574	0.755	-0.181***	0.003
Black	0.121	0.075	0.046**	0.002
Hispanic	0.190	0.098	0.092***	0.001
Asian	0.061	0.025	0.036***	0.001
Access to Internet	0.954	0.961	-0.007	0.004
Female	0.505	0.503	0.002*	0.000
Age	39.401	38.233	1.168*	0.146
Married	0.394	0.413	-0.019	0.007
Family Size	3.156	3.148	0.009	0.050

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 19: ACS Balance Table by Industry for US and Hot Jobs Counties

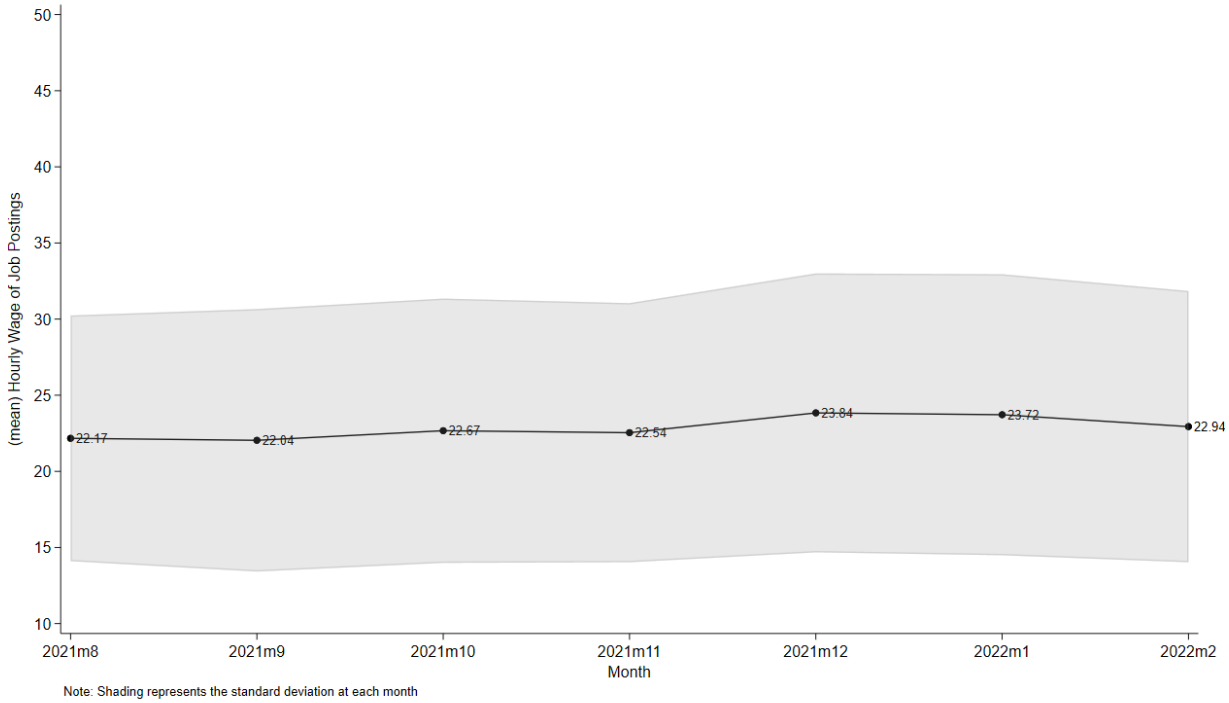
	US	Hot Jobs	Difference	S.E.
Manufacturing	0.092	0.195	-0.103***	0.002
Agriculture and Mining	0.084	0.069	0.015	0.006
Wholesale Trade	0.021	0.024	-0.002	0.002
Retail Trade	0.115	0.122	-0.007	0.002
Transportation and Utilities	0.059	0.046	0.013**	0.001
Information	0.018	0.011	0.007*	0.001
Finance and Real Estate	0.063	0.053	0.010	0.003
Professional, Admin, and Waste Services	0.121	0.095	0.026*	0.005
Educational and Health Care Services	0.226	0.222	0.004	0.002
Arts and Hospitality	0.095	0.086	0.008	0.002
Public Administration	0.046	0.024	0.022**	0.002
Military	0.008	0.000	0.007***	0.000
Other	0.047	0.048	-0.000	0.001

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

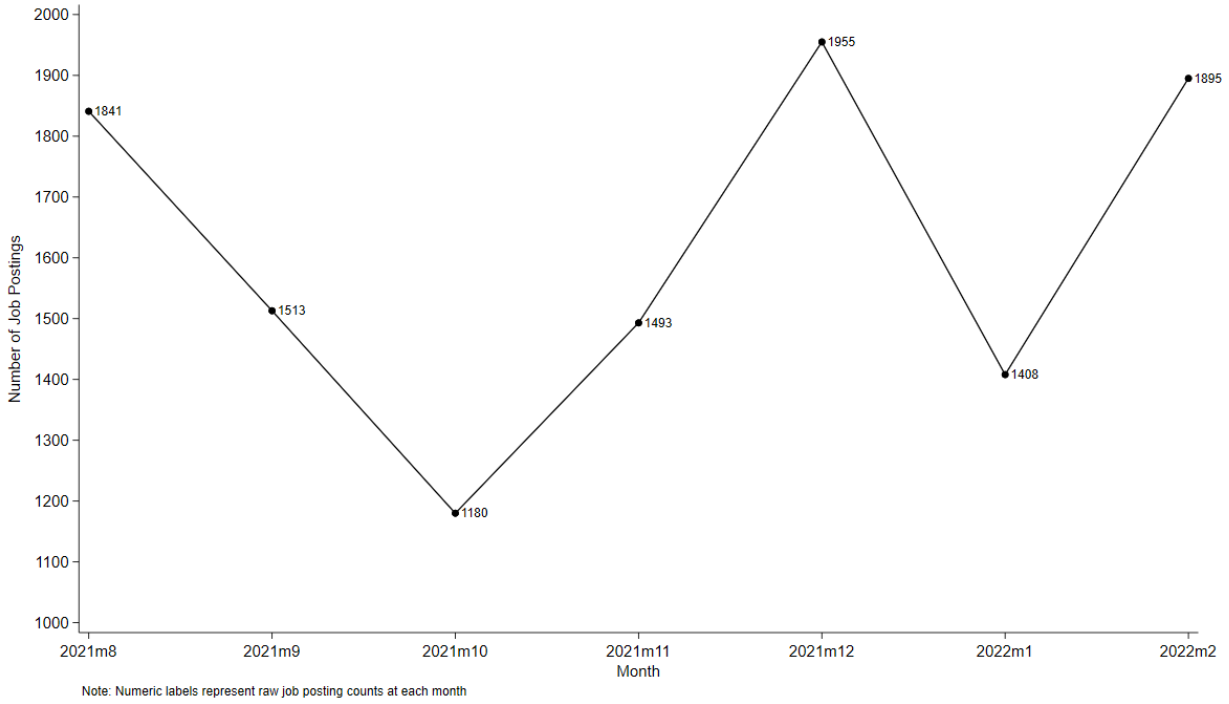
Table 20: ACS - Summary Statistics for US, MI, and Hot Jobs Counties

	US	Michigan	Hot Jobs
Employed	0.600	0.568	0.638
	(0.012)	(0.017)	(0.013)
Unemployed	0.033	0.037	0.027
	(0.009)	(0.009)	(0.005)
Not in Labor Force	0.367	0.395	0.335
	(0.004)	(0.008)	(0.008)
Hourly Wage	26.603	23.711	23.305
	(1.210)	(1.259)	(0.986)
Usual Hours Worked	20.222	19.545	20.765
	(0.359)	(0.376)	(0.393)
College Graduate	0.265	0.239	0.253
	(0.004)	(0.004)	(0.000)
White	0.574	0.724	0.755
	(0.003)	(0.002)	(0.003)
Black	0.121	0.141	0.075
	(0.001)	(0.001)	(0.002)
Hispanic	0.190	0.049	0.098
	(0.001)	(0.001)	(0.001)
Asian	0.061	0.034	0.025
	(0.001)	(0.001)	(0.001)
Access to Internet	0.954	0.950	0.961
	(0.005)	(0.002)	(0.004)
Female	0.505	0.505	0.503
	(0.000)	(0.000)	(0.000)
Age	39.401	40.650	38.233
	(0.169)	(0.190)	(0.118)
Married	0.394	0.391	0.413
	(0.001)	(0.001)	(0.010)
Family Size	3.156	3.025	3.148
	(0.019)	(0.019)	(0.068)

Means in cells and standard deviations in parentheses.

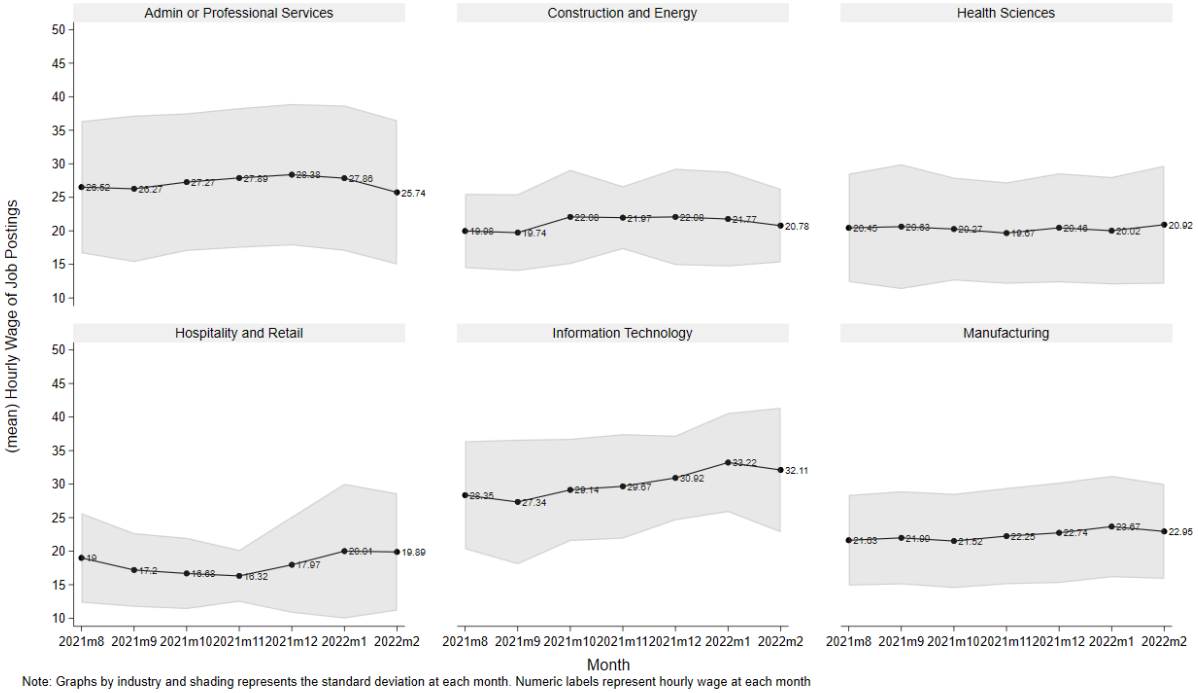


(a) Hourly wage of weekly job listings

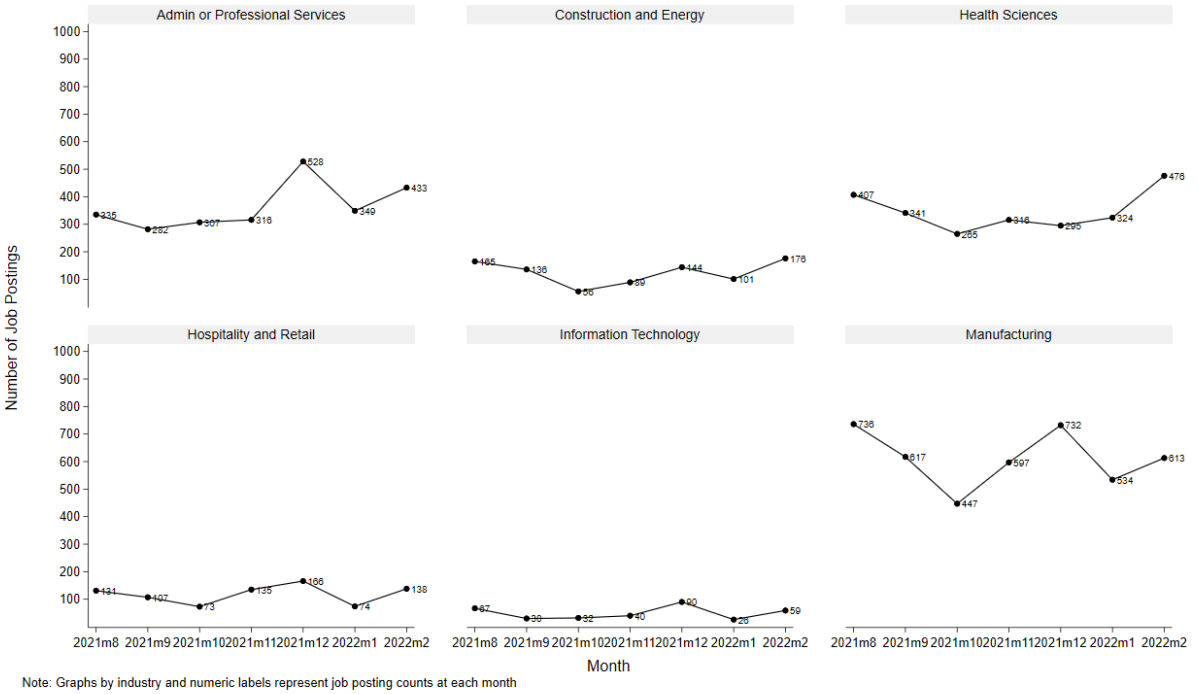


(b) Number of weekly job listings

Figure 4: Aggregate WMW Weekly-Hot-Jobs Listing Statistics

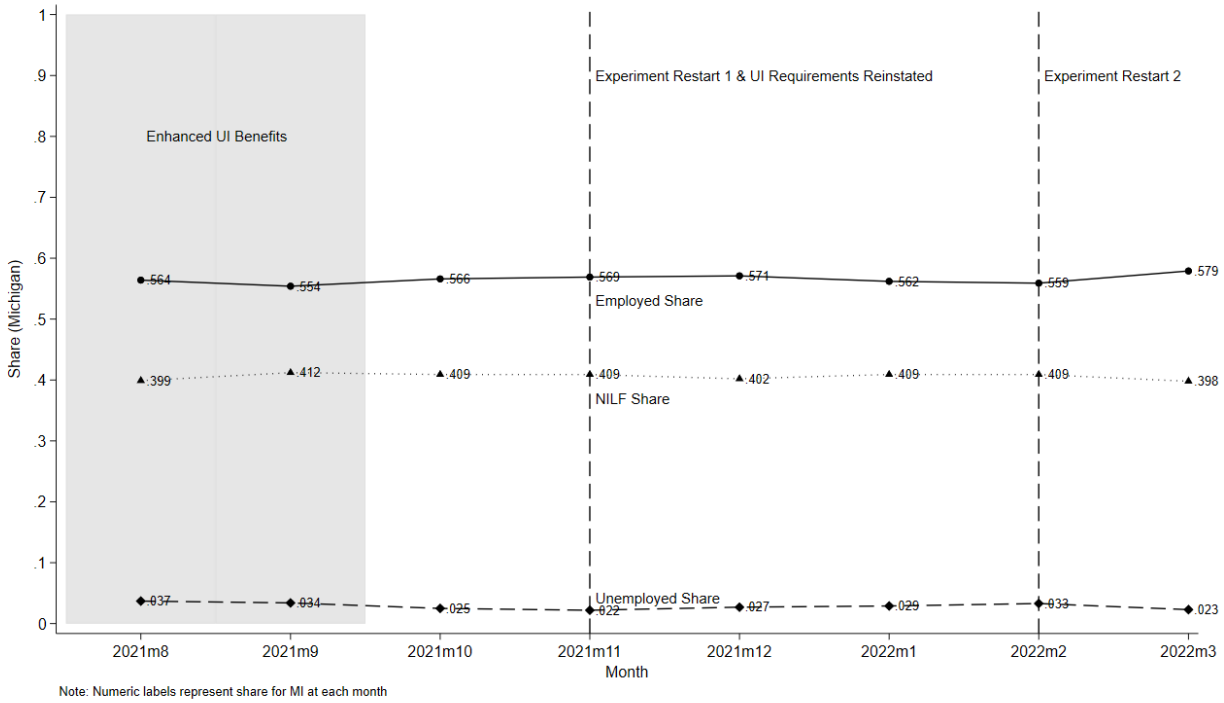


(a) Hourly wage of weekly job listings by industry

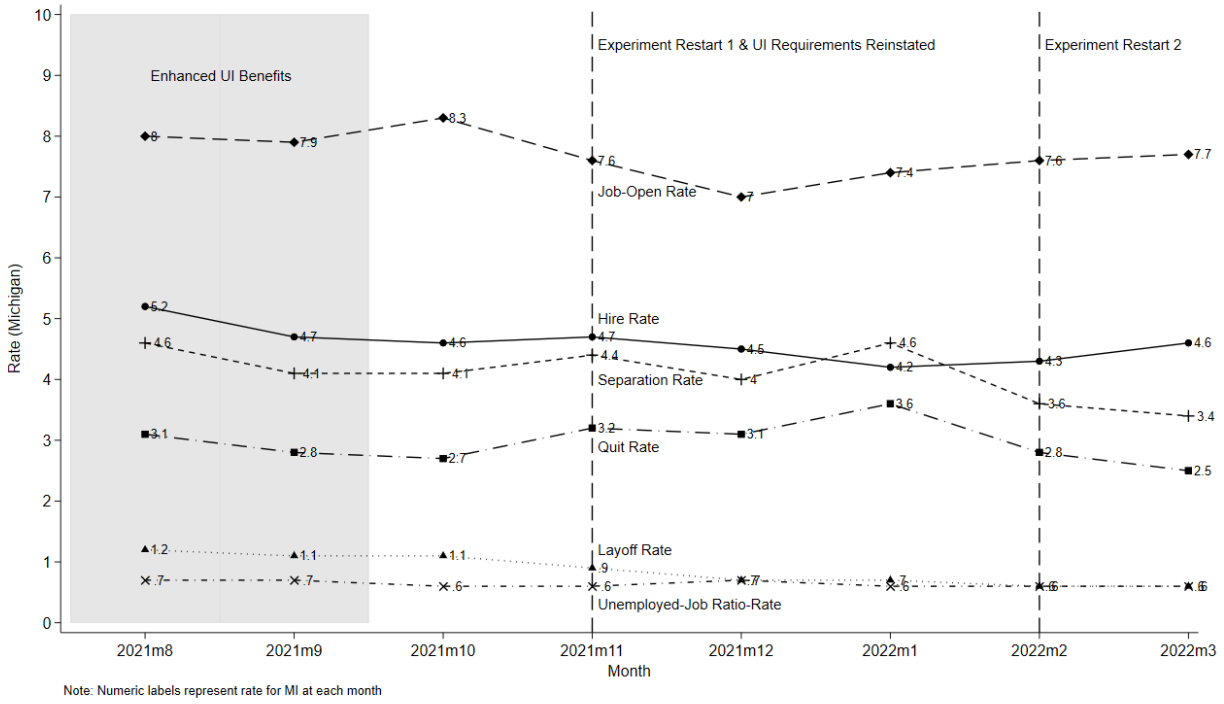


(b) Number of weekly job listings by industry

Figure 5: WMW Weekly-Hot-Jobs Posting Statistics

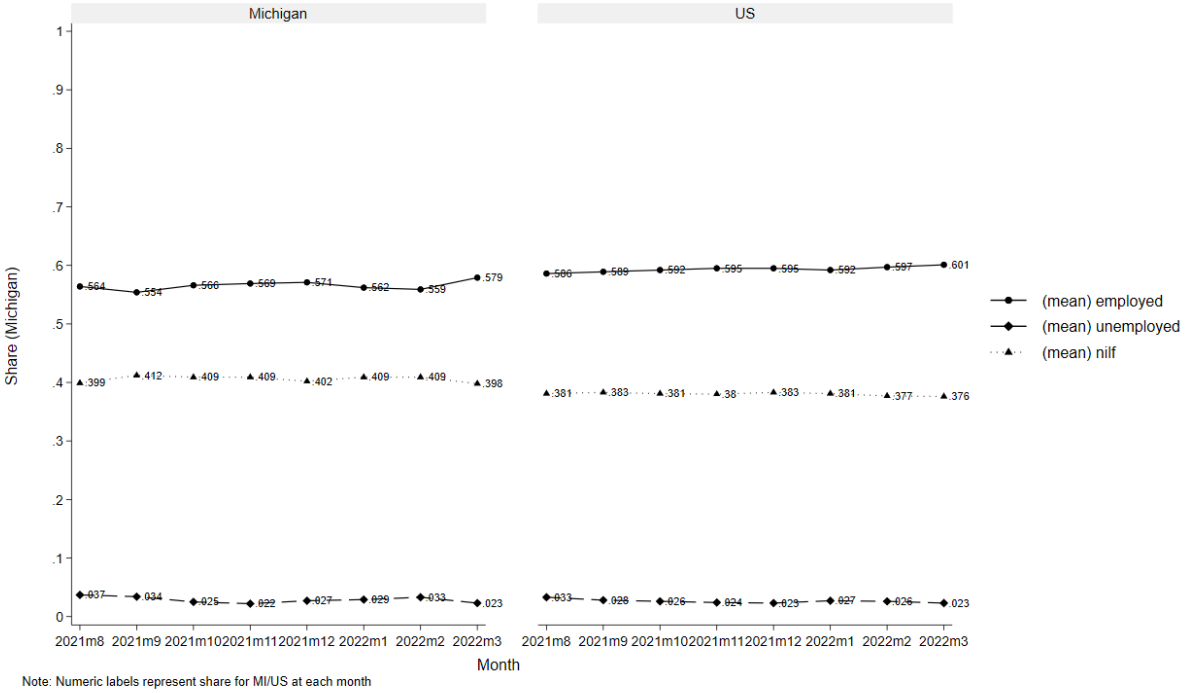


(a) Current Population Survey (CPS)

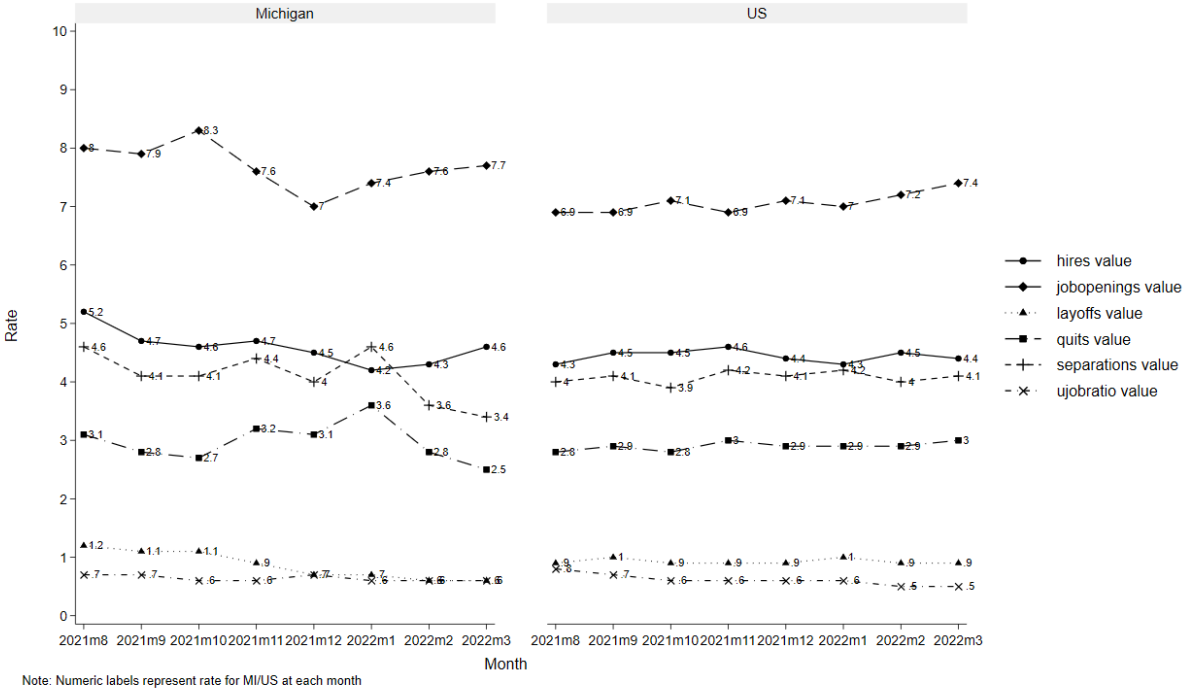


(b) Job Openings and Labor Turnover Survey (JOLTS)

Figure 6: Michigan Employment Characteristics

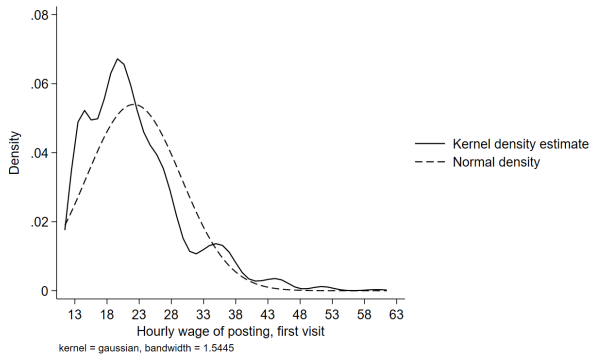


(a) Current Population Survey (CPS)

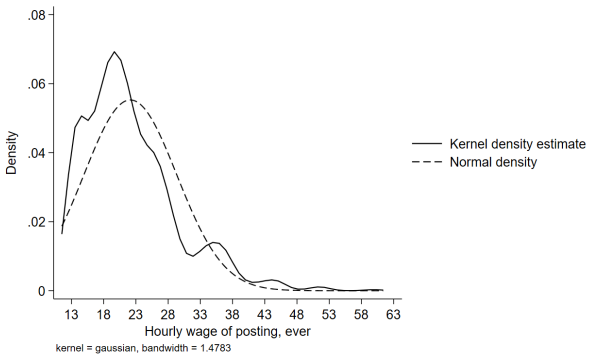


(b) Job Openings and Labor Turnover Survey (JOLTS)

Figure 7: Employment Characteristics for Michigan and U.S.

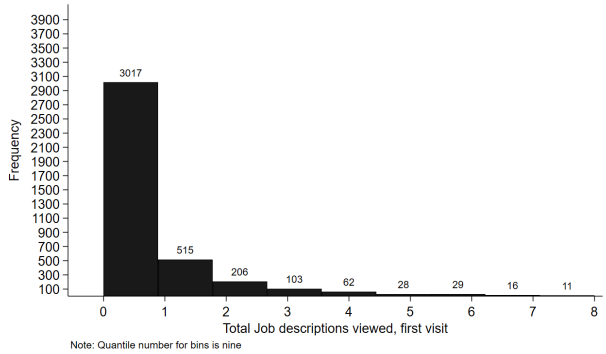


(a) Hourly wage of job listing (first visit)

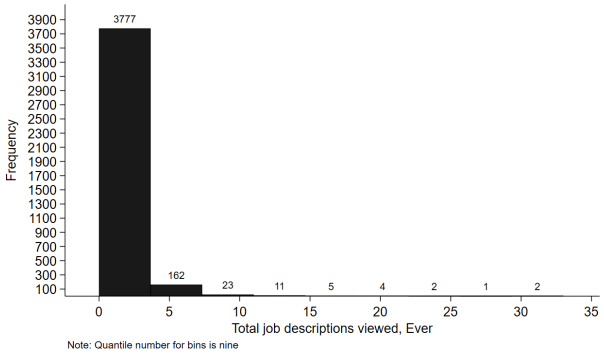


(b) Hourly wage of job listing (ever)

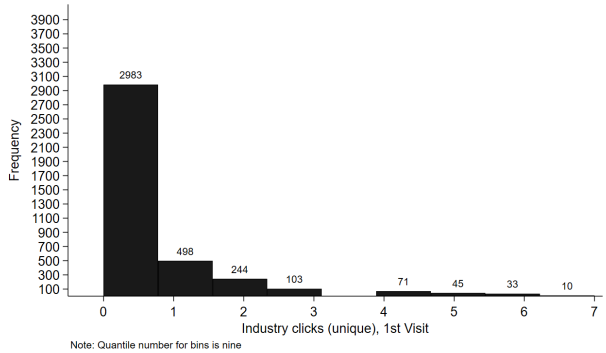
Figure 8: Kernel Density Plots



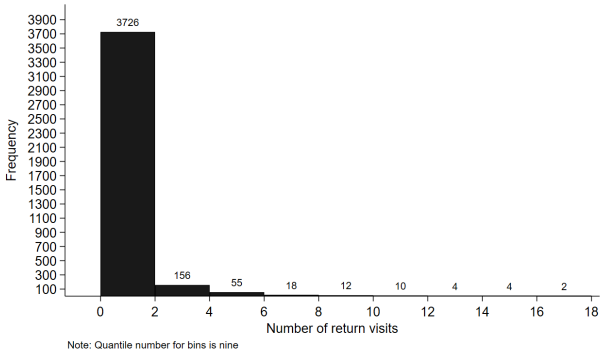
(a) Total job descriptions viewed, first visit



(b) Total job descriptions viewed, ever



(c) Industry clicks (unique), first visit



(d) Number of return visits

Figure 9: Histograms for Non-Binary Outcomes

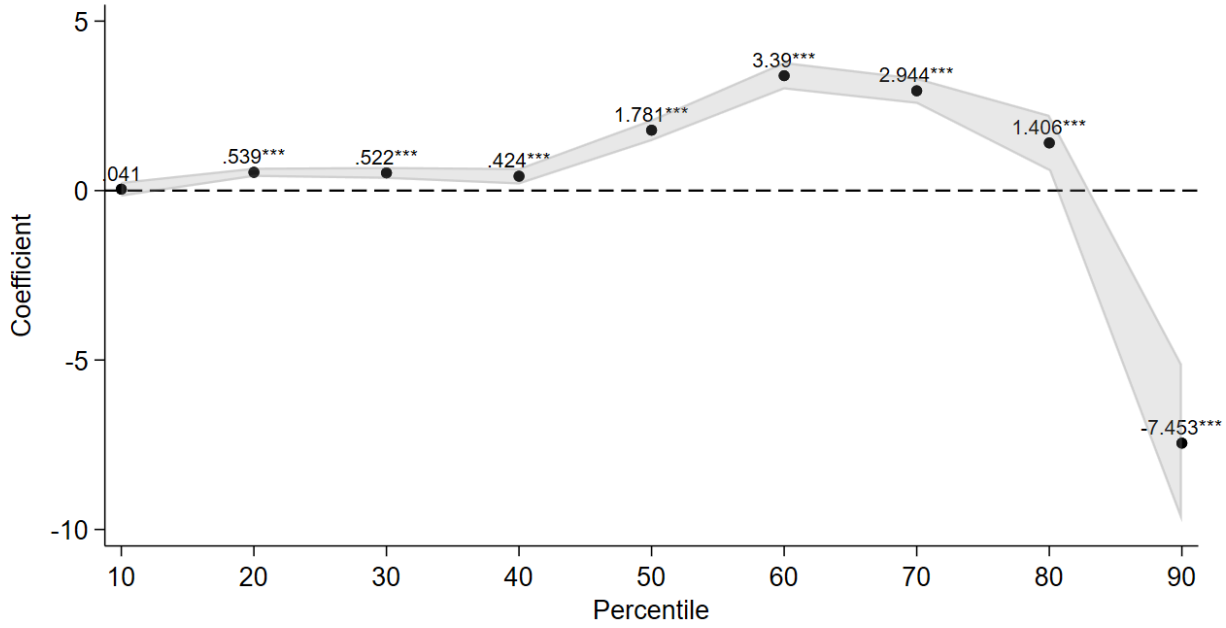


Figure 10: Unconditional Quantile Regressions (UQRs) for the Hourly Wage of Explored Job Listings (ever)

9.2 Interviews

Throughout the study we conducted sets of interviews with potential WMW job seekers and WMW staff to supplement our empirical findings and better understand the potential effects of the intervention.

9.2.1 WMW staff interviews

We conducted semi-structured discussions with four WMW staff who assisted us with the design and implementation of the web page. Discussions with WMW staff took place in February and March 2022. Each discussion lasted approximately one hour. We asked WMW staff to describe the level of effort involved in implementing the intervention, their ability to successfully implement the intervention, key features regarding the context of the implementation, and general thoughts and lessons learned.

9.2.2 WMW job seeker interviews

We conducted interviews and observations with five potential WMW job seekers in March 2022. We initially aimed to recruit nine job seekers to participate in interviews and observations; however, recruitment was challenging. For example, some job seekers who were identified to participate never selected a time. Additionally, we asked WMW to restrict their selection of job seekers to those who previously used the WMW Weekly Hot Jobs! page. Though we later relaxed this restriction, WMW staff were not optimistic they would find additional participants.

We recruited participants who were diverse in terms of age, occupation, and industry. Each discussion lasted approximately 45 minutes, and job seekers received a $50 electronic gift card for their participation. The discussions gathered information on three primary topics: (1) the job seekers' work search goals, (2) the differences they noticed between the treatment and control web pages, and (3) the extent to which the changes to the web page were useful and encouraged the customer to search more broadly.

We first asked job seekers to describe whether they were searching for work and, if applicable, their work search goals. Each job seeker then explored either the treatment or control web page. Three job seekers began with the treatment web page and two began with the control web page. We asked them to imagine that they were visiting the web page to search for

a job and to narrate what they were doing as we observed via screen-share. After they explored the treatment web page, we asked an initial set of questions focused on their goals for using the treatment page and the extent to which it met their expectations. After job seekers had explored both web pages, we asked them to describe the differences they noticed between the two pages and their reactions to those differences. For any differences they did not mention, we then pointed them out and asked for their reflections on the salience and usefulness of those differences. Finally, we asked job seekers to reflect on the extent to which the changes to the web page were useful and encouraged them to search more broadly. We probed to understand whether they would recommend other changes, whether the column listing relevant experience felt applicable to their level of experience, and whether they were open to searching for work in multiple industries.