Search Effort and the Minimum Wage*

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Abstract

I assess the impact of the minimum wage on the search effort of the unemployed. Using machine learning methods, and leveraging the richness of the American Time Use Survey (ATUS) together with the large sample size of the Current Population Survey (CPS), I build measures of search effort and exposure to the minimum wage for unemployed workers. I exploit 49 state-level minimum wage changes in the US over 1999-2019 in a stacked-event study design to examine whether the highly exposed unemployed change their search effort in response to the policy. I find that a 12% increase in the minimum wage leads to a 6.1% increase in search effort. Yet, the individuals increasing effort do not find jobs faster. Interpreting the estimates through the lens of a standard DMP model with search effort, I find that the observed effort increase should have raised employment by 4 p.p. ceteris paribus. However, market tightness declines in equilibrium so that the return per unit of effort in terms of job finding gets reduced, ultimately leading to an overall null employment effect. Moreover, this setup allows me to investigate the welfare impact of the policy in a transparent way, revealing that the minimum wage increases welfare for exposed individuals.

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1 Introduction

After extensive economics research, and given the patterns of growing inequality and stagnant wages at the bottom of the distribution observed in recent decades, the minimum wage continues to be a deeply debated policy tool. A prominent view among its opponents in the minimum wage debate is that employment is determined by the demand side of the market, and an increase in wages will come at the cost of fewer jobs. Nevertheless, this narrative contrasts with the view often exhibited when analyzing other economic policies like unemployment insurance, where it is postulated that the supply side influences employment (Manning, 2021).

Bringing this alternative scenario to the minimum wage setting, in a context of imperfect labor markets with frictions, the impact of the policy is theoretically ambiguous. When firms post vacancies and unemployed individuals search for jobs, an increase in the minimum wage may lead to firms reducing vacancies, but this can be compensated by increased search effort by the unemployed, which can lead to employment remaining constant in equilibrium.
Despite the theoretical relevance of this search effort mechanism (e.g., Pissarides, 2000; Acemoglu, 2001), there is very limited empirical evidence on how effort reacts to the minimum wage. In order to estimate the effort response to the minimum wage by the unemployed, one needs at least three features in a context with minimum wage variation: (i) large sample size on unemployed individuals; (ii) measure of search intensity; and (iii) measure of exposure to the minimum wage. The lack of these three features in the same dataset for a context with substantial minimum wage variation may be behind the lack of evidence.

This paper overcomes the empirical challenges in the following way. First, I use data from the CPS Basic to get a large sample of unemployed individuals in the United States. Second, in order to obtain a measure of search intensity, I combine data from the CPS Basic and from Time Use data (ATUS). In particular, I exploit the fact that a set of questions on search methods used by the unemployed are present in both datasets. I apply machine learning methods to train a model in the ATUS data that predicts search intensity using information on search methods and demographics. After that, I use the estimated model to predict search intensity back in the CPS in order to make use of the large sample size. Third, given the importance of assessing the impact of the minimum wage on potentially affected individuals, I obtain a measure of exposure to the minimum wage for unemployed individuals. For this exercise, I apply machine learning methods following Cengiz et al. (2022) in a sample of employed individuals where wage information is available (CPS MORG) in order to predict minimum wage status based on demographic characteristics. I then use this trained model to predict exposure based on demographics among my unemployed individuals in the CPS Basic.

Having constructed these measures, I then estimate the impact of the minimum wage on the search effort of unemployed individuals most affected by it, using 49 state-level minimum wage events in a stacked event-study specification over the years 1999-2019 in the United States. I find that an increase of the minimum wage by 12% leads to an increase of search effort by 6.1%. This finding is robust to several concerns, including confounding state-level shocks, and provides the first evidence on an important mechanism often highlighted in search models, which is crucial to explain the employment effect documented by the literature.

At the same time, I also find that individuals who increase effort are not more likely to find a job quicker, which is consistent with the zero employment effect in the literature.

In order to interpret the estimates, I take a standard random search model (DMP) and introduce unemployed's search effort. The employment response in this framework can be decomposed between a partial equilibrium response of effort when market tightness is held constant, and a market-level adjustment term where effort is held fixed but tightness is allowed to adjust. In this context, the effort response found predicts that employment should have increased by 4 p.p. in response to the minimum wage if tightness did not adjust. However, the fact that, in equilibrium, vacancies may go down and effort goes up, makes that the return to every unit of effort in terms of job finding decreases, and so equilibrium employment remains unchanged.

Moreover, the proposed setup allows me to study the welfare impact of the minimum wage in a very transparent way. The key idea is that the search effort response by unemployed individuals reveals information about their welfare. Specifically, the observed increase in effort allows me to obtain an upper bound for the negative welfare impact due to higher search cost. I then compare this cost with the welfare benefit due to increased expected wages, which results in an unambiguously positive impact on welfare.

My paper contributes to several strands of the literature. First it relates to work on the employment effects of the minimum wage (e.g., Card and Krueger, 1994; Giuliano, 2013; Dube et al., 2016; Cengiz et al., 2019; 2022; Godøy et al., 2021; Dustmann et al., 2022) . This large empirical literature documents a pervasive near zero employment effect. I provide an alternative explanation for this observed equilibrium outcome.

Second, it relates to the literature on job search and the minimum wage (e.g., Burdett and Mortensen, 1998; Pissarides, 2000; Acemoglu, 2001; Flinn, 2006; Ahn et al., 2011; Kudlyak et al., 2022). This is a more theoretical literature that emphasizes the importance of the search effort channel. I present the first empirical evidence for this core mechanism in search models.

Third, it relates to work on job search and unemployment, and in particular to the one employing Time Use data (e.g., Krueger and Mueller, 2010; 2012; DellaVigna et al., 2017; Mukoyama et al., 2018; Faberman and Kudlyak, 2019; Marinescu and Skandalis, 2021; DellaVigna et al., 2022; Faberman et al., 2022; Adams et al., 2022). Two papers in this area are particularly related to my work. First, I relate to Mukoyama et al. (2018) who combine information in CPS and ATUS data to build a measure of search effort, and investigate how it varies over the business cycle. Second, I relate to Adams et al. (2022) who investigate the impact of the minimum wage on search effort. This latter paper uses ATUS data and an event-study approach and do not find that effort responds to the minimum wage. However, this finding may not be very surprising. On the one side, their sample size is small, so it is not clear whether they are able to detect an effect even if there was one. On the other side, in most specifications they focus on all workers/unemployed, so given that the minimum wage workers are a small share of the labor force it is not clear that one can detect an effect by looking at all the individuals[1]. I contribute by combining the richness of Time Use data with the large sample size of the CPS Basic using machine learning methods, and using this setup to learn about the causal impact of the minimum wage.

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 explains the empirical methodology. Section 4 presents the results. Section 5 interprets the estimates through the lens of a standard search model and assesses the welfare impact of the policy, and Section 6 concludes.

2 Data

Current Population Survey - Basic. I use the CPS Basic files over the years 1999-2019. This is a monthly survey containing around 60,000 households in the United States. The demographics of interest used are age, race, Hispanic, gender, education, veteran status, marital status and rural residency. Furthermore, if unemployed, the dataset also includes information on whether individuals used a variety of methods to search for jobs.

[1]They also investigate effects for some demographic groups more likely to be affected by the minimum wage, but they do not find an effect presumably due to the even smaller sample size in these specifications.

Current Population Survey - Merged Outgoing Rotation Group. I also use the CPS-MORG files, which corresponds to a subset of the sample present in the CPS Basic. Specifically, these observations correspond to individuals who are in their fourth or eight month in the sample, when usual hourly wages, weekly earnings and weekly hours worked are asked. I exclude observations with imputed values for hourly wages, weekly earnings or hours worked. As is standard in the literature, I use reported hourly wage for hourly workers and define hourly wage as usual weekly earnings divided by usual weekly hours for other workers.

American Time Use Survey. I leverage information from ATUS over the years 2003-2019. Respondents fill a daily diary where they register the amount of time devoted to different detailed activities, including job search. Moreover, individuals in this sample are also asked the same demographic and job search methods questions that are asked in the CPS Basic.

Minimum Wages. I use data on state-level minimum wages over 1979-2019 from Vaghul and Zipperer (2016) and updated by Cengiz et al. (2022).

3 Empirical Methodology

In order to assess the impact of the minimum wage on unemployed's search effort, I proceed in three steps. First, I construct a variable capturing exposure to the minimum wage in order to know what individuals are potentially affected by the minimum wage. Second, I build a search effort measure that can be used in a large sample size like the CPS Basic. Third, I present the regression model used to estimate the causal impact of the minimum wage.

3.1 Exposure to the Minimum Wage

The first step needed to investigate how the minimum wage affects search behavior by the unemployed is to know who the unemployed that would potentially earn the minimum wage upon employment are. This is important since the minimum wage workers are a small share of the labor force, and thus one needs to zoom in on the set of workers that will potentially respond to the policy in case there is a response. Otherwise one can find that effort does not react in the whole population even when there is a significant effect among the treated population. However, wages for the unemployed are not observed, which complicates classification of unemployed into minimum wage individuals. In order to address this challenge, I follow the machine learning approach proposed by Cengiz et al. (2022).

Prediction Algorithm. The algorithm employed to classify unemployed individuals into being affected by the minimum wage is based on gradient-boosted decision trees. To operationalize this approach, I work with datasets from CPS-ORG and CPS-Basic. Using the wage information in the CPS-ORG, I define being exposed to the minimum wage as earning less than 125% of the minimum wage. Focusing on the periods before state-level changes occur, I divide the sample into a training and a test sample. Then, I apply the prediction algorithm where a set of demographics (age, education, gender, rural residency, marital status, race, Hispanic and veteran status) are used to predict whether individuals are exposed to the minimum wage. The tuning parameters are set using 5-fold cross validation. Once the model is trained in the training dataset of the CPS-ORG, I use it to predict exposure to the minimum wage on the sample of unemployed individuals in the CPS Basic, using the same set of demographics as predictors.

Assessing Model Performance. A standard way to assess performance in the machine learning literature is to analyze precision-recall curves. For a given subsample of individuals, precision refers to the number of true minimum workers contained in that subsample as a proportion of the number of people in the subsample. Recall refers to the number of true minimum wage workers in a subsample as a proportion of the total number of minimum wage workers in the population. For example, if a subsample contains one observation with a true minimum wage worker, theprecision rate is 1 but the recall rate is very small since all but one minimum workers in the population are not in this subsample. For my sample, the precision-recall curve is shown in Figure 1. When recall is around 10%, the share of true minimum wage workers in the sample is above 70%. As we increase recall, precision tends to decline since generally there exists a trade off between precision and recall when choosing a sample.

For my main analysis, I define the group of individuals highly exposed to the minimum wage as those above the 90^{th} percentile in the distribution of the predicted probability of being a minimum wage worker, and everyone else as not exposed to the policy. The characteristics of both groups are shown in Table 1. The group of minimum wage individuals has a precision rate around 70%, and is generally younger and less educated than the rest of the unemployed.

3.2 Search Effort Measurement

The second step is to obtain a measure of search effort that can be used for causal inference. Given the limited sample size of the ATUS data where detailed search effort information is present, this dataset cannot be succesfully used directly to assess the impact of the minimum wage. However, it can be used in combination with the larger sample size of the CPS Basic to learn about the search behavior of the unemployed, given that the questions on the search methods the unemployed are present in both datasets. I build on Mukoyama et al. (2018) who exploit both datasets to understand job search behavior over the cycle. I deviate from them by applying machine learning methods for the prediction model, which allows me to obtain higher precision. Specifically, I start by dividing the ATUS data into a training and a test dataset and apply a gradient-boosted decision trees algorithm. Using the information provided by unemployed individuals in their diary, I code as daily searchers those who report a positive amount of time spent on job search activities in a given day. This is the main outcome, which the model predicts based on a set of demographics (age, education, gender, marital status, race, Hispanic) and search methods (listed in Table 2). Tuning parameters are chosen using a 5-fold cross-validation method. Once the model is estimated, I use it to predict the probability of daily search on the sample of unemployed individuals in the CPS Basic sample. As a descriptive exercise for comparison with Mukoyama et al. (2018), I find similar results on the behavior of this variable over the business cycle as shown in Figure A1.

3.3 Impact of the Minimum Wage

The third step, once we know who unemployed individuals affected by the minimum wage are and how much search effort their exert, is to assess the impact of the minimum wage. To do so, I follow the stacked regression approach proposed by Cengiz et al. (2019). I select 49 minimum wage events where the treated states did not experience a (non-trivial) minimum wage increase in the 3 years prior before and where the control states did not have a (non-trivial) minimum wage increase within the 7-year window. I create event-datasets, stack them by event time, and estimate a model of the following form:

$$Y_{hst} = \sum_{\tau=-3}^{3} \beta_\tau \cdot treat_{hst}^{\tau} + \Omega_{hst} + \mu_{hs} + \rho_{ht} + u_{hst} \tag{1}$$

where Y_{hst} corresponds to outcome in event-dataset h, state s and event-time t, and Ω_{hst} captures small and federal MW changes. This design uses only within event variation, which prevents negative weighting issues highlighted in the recent DiD literature (e.g., Callaway and Sant'Anna, 2021; Borusyak et al., 2022).

4 Results

Main Results. Figure 2 shows the main results. Panel (a) depicts that for the period considered, the statutory minimum wage increased persistently by around 12%. At the same time, as shown in Panel (b), search effort of the highly exposed unemployed individuals increased by around 6.1%. The outcome of interest presents similar trends in treated and control states prior to the reform, and suddenly reacts when the minimum wage is enacted.

In Panel (c), I study whether the change in search effort led to increased job finding. For that exercise, I exploit the panel structure of the CPS and define a 2-month job finding as the probability that an individual found a job within the next two months. I find that the higher search effort did not lead to increased job finding.

Effect on Individuals Not Exposed to the Minimum Wage. One possibility is that the increase in search effort is driven by a confounding shock that hits treated states at the same time as the minimum wage. In order to alleviate this concern, here I repeat the same analysis as above but focus on the rest of unemployed individuals who are not predicted to earn the minimum wage upon employment. For them, the increase in the minimum wage should not lead to large effort responses since they are not directly affected by the policy. Figure 3 shows the results. Reassuringly, individuals located in treated states but less exposed to the minimum wage do not change their search behavior relative to control states (Panel b). Moreover, job finding remains also constant for these individuals (Panel c).

Selection. With heterogeneity in search effort, the observed increase in effort could be driven by a selection effect where individuals who search harder are more likely to remain unemployed after the reform. However, this concern appears to have little empirical relevance. First, evidence from Cengiz et al. (2022) shows that there are not responses along the participation margin so that changes in the unemployed composition driven by different people entering the labor market are not quantitatively important. Second, I find that job finding does not change in response to the minimum wage, which means that the search effort response seems to come from a similar set of individuals.

In addition, as shown in Figure 4, I assess the robustness of the main effect to iterative inclusion of several controls, where I find that the main effect remains approximately constant once these covariates are accounted for. The first row shows the baseline specification. The second adds a control for the predicted probability of being a minimum wage individual to assess whether the composition of affected unemployed changes towards more/less exposed individuals. The third row adds a state-level unemployment rate control. The fourth column adds several demographic controls (age, sex, race, rural status, education). Overall, results remain robust to the inclusion of a variety of controls.

High Frequency. Here I consider 6-month periods in order to assess whether the observed pattern is driven by unexpected underlying dynamics. Although results are somewhat more noisy, Figure A2 reveals that search effort remains flat prior to the reform and reacts in a permanent way as soon as the minimum wage is enacted.

Search Time. So far, the main outcome of interest has been the probability of daily search. As an alternative outcome, I also investigate search behavior along daily time spent on job search activities. This outcome is much more skewed and has a large proportion of individuals searching zero minutes. I apply a Poisson model in this case to predict search time in the ATUS data, and then follow a similar procedure as before to predict in the CPS Basic. This variable is somewhat predicted with less precision but, as shown in Figure A3, event-study results show a similar qualitative and quantitative pattern relative to the outcome used in the main analysis.

Search Methods. Here I assess to what extent my approach that combines datasets and applies machine learning methods improves upon a method that only uses the search information present in the CPS Basic. For that, I construct a measure of search effort in the CPS Basic by adding up the number of search methods used by each individual as in Shimer (2004). The results are depicted in Figure A4. The picture now is much more noisy and estimates are not statistically significant, with a pattern consistent with my main results where effort increases after the reform but where there is a decline afterwards. This highlights the value of the methodology used for the main analysis.

Additionally, even though precision is limited, I also explore how each of the different methods reacts individually to the minimum wage as shown in Figure A5. After the reform, individuals tend to read more about job openings and send applications, and they seem to contact friends and relatives less often in order to find jobs.

5 Economic Implications

5.1 Employment Effect of the Minimum Wage

Given the main results obtained in the previous section—minimum wage increases effort but does not increase job finding—, here I proceed to interpret the estimates within the framework of a standard random search model. In particular, I focus on a DMP model with unemployed's search effort (Pissarides, 2000; Acemoglu, 2001; Lalive et al., 2015; Landais et al., 2018) . Firms post vacancies v, and unemployed individuals u exert search effort s. The total number of matches is given by a constant returns to scale matching function (Petrongolo and Pissarides, 2001). Market tightness is $\theta = \frac{v}{su}$. Endogenous job finding rate is $h = sf(\theta)$ and exogenous job destruction rate is δ. Steady state employment probability is $e = \dfrac{sf(\theta)}{\delta + sf(\theta)}$.

Individual's problem. Value functions for an individual whose potential wage is the minimum wage are:

$$V^u = \max_s b - \psi(s) + sf(\theta)[V^e - V^u] \tag{2}$$

$$V^e = MW + \delta[V^u - V^e] \tag{3}$$

where V^u and V^e denote the value of being unemployed and employed respectively, $\psi(\cdot)$ is and increasing and convex search cost, b refers to income while unemployed, and MW refers to the income earned upon employment, which corresponds to the minimum wage.
This problem leads to an optimal search effort that is given by:

$$\underbrace{s^*(MW)}_{\textbf{search effort}} = \psi^{'-1}(\underbrace{f(\theta)}_{\substack{\textbf{return to search} \\ (+)}} \underbrace{[V^e(MW) - V^u]}_{\substack{\textbf{value of employment} \\ (+)}}) \tag{4}$$

That is, the model predicts that search effort should be higher when $f(\theta)$—the return to effort in terms of job finding per unit of effort— is higher, and when $V^e(MW) - V^u$—the gap between the value of employment and unemployment— is larger.

Mechanisms of Equilibrium Employment. Here I analyze the mechanisms highlighted by this framework to explain the employment effect of the minimum wage. The objective is to fix ideas and to quantify the different forces at play behind the null impact in equilibrium. Given that job destruction is exogenous, I focus on how the job finding rate responds to the change in the minimum wage[2]. For simplicity in the exposition, I assume that effort does not react to tightness (i.e., $\frac{\partial s}{\partial \theta} = 0$), but it is relaxed in the empirical design where the effort response also captures this effect. The impact of the minimum wage on job finding can be decomposed as follows:

$$\frac{dh}{dMW} = \frac{d(s \cdot f(\theta))}{dMW} = \underbrace{\left.\frac{\partial s}{\partial MW}\right|_{\theta} \cdot f(\theta)}_{\textbf{effort response}} + \underbrace{\left. s \cdot \frac{\partial f(\theta)}{\partial MW}\right|_{s}}_{\textbf{market-level adjustment}} \tag{5}$$

The first term captures the change in search effort induced by the change in the minimum wage while market tightness is held fixed. The second term is the market-level adjustment, which captures the impact on job finding that comes from changes in market tightness, keeping effort fixed. In equilibrium, the minimum wage may cause equilibrium vacancies to decrease and equilibrium effort to increase, which unambiguously decrease tightness. That is, for a given level of effort, the returns in terms of job finding are lower when tightness is lower, so that job finding may decrease via labor market adjustment.

In order to quantify the importance of each mechanism, I leverage the estimates of the main analysis on the job finding and the effort responses, and back up the implied market-level response. In the main analysis, I estimated the impact on job finding ($\frac{dh}{dMW}$) and effort ($\left.\frac{\partial s}{\partial MW}\right|_{\theta}$). However, we also need to estimate $f(\theta)$ in the effort response term, in order to know how effort affects job finding. I estimate it in Appendix B , where I provide a full explanation of the empirical design and show the estimates obtained. The key idea of the approach is an instrumental variables strategy where I use Unemployment Insurance extensions as a shifter of search effort, and compare the search behavior of UI eligible individuals relative to ineligible individuals within the same labor market. In that way, I identify the parameter of interest, being able to net out market level effects (Lalive et al., 2015). The results are shown in Table 3 where I find that a 1% increase in search effort leads to a 0.014 increase in the 2-month job finding.

Impact of the Minimum Wage on Equilibrium Employment. To recap, I found that a 12% increase in the minimum wage increases effort by 6.1%. I also find that a 1% increase in search effort leads to a 0.014 increase in job finding. In addition, I find that a 12% increase in the minimum wage has zero impact on equilibrium employment. Given the data, I also have

[2]Given the findings in the literature that job destruction may decrease in response to the minimum wage (e.g. Dube et al., 2016), my findings here are a lower bound, implying that the quantified forces could be larger if job destruction is allowed to adjust.

that employment probability is $e = 0.8$, and job destruction rate is $\delta = 0.065$.
Putting all together, this implies that the effort response term in equation 5 equals 4 p.p. In other words, given the observed effort increase, the model predicts a sizable increase in job finding. Since, in equilibrium, job finding does not change, then it must be the case that the market-level adjustment term goes in opposite direction with a similar magnitude. Specifically, this means that market tightness goes down (since effort goes up and vacancies may go down), bringing job finding back to the pre-reform level.

5.2 Welfare Effect of the Minimum Wage

Given the results and framework above, I now proceed to study the welfare impact of the minimum wage. The effort response obtained in this setup allows me to investigate whether the policy increased welfare for minimum wage individuals. The key idea is that the change in search effort by the unemployed after the minimum wage is increased reveals information about the welfare impact of the policy. For simplicity of exposition, I consider a two period model. Before the policy, unemployed's indirect utility is given by:

$$V^u_{preMW} = b - \psi(s^*_{preMW}) + s^*_{preMW} f(\theta) preMW + (1 - s^*_{preMW} f(\theta))b \tag{6}$$

After the minimum wage is increased, the individual can choose between keeping search effort fixed at the previous level:

$$V^u_{postMW} = b - \psi(s^*_{preMW}) + s^*_{preMW} f(\theta) postMW + (1 - s^*_{preMW} f(\theta))b \tag{7}$$

or changing it after the policy:

$$V^u_{postMW} = b - \psi(s^*_{postMW}) + s^*_{postMW} f(\theta) postMW + (1 - s^*_{postMW} f(\theta))b \tag{8}$$

As documented before, the change in the policy led to an increase in search effort ($s^*_{postMW} > s^*_{preMW}$), which implies that the latter individual's utility is higher (i.e., (8) $\geq$ (7)). Using this inequality and the numbers from the results section, I obtain an upper bound for the welfare cost incurred due to increased search effort:

$$0.04(11.2 - b) \geq \psi(s^*_{postMW}) - \psi(s^*_{preMW}) \tag{9}$$

This allows me to finally assess the overall welfare impact:

$$
\begin{aligned}
\Delta W &= V^u_{postMW} - V^u_{preMW} \\
&= b - \psi(s^*_{postMW}) + 0.8 \cdot 11.2 + 0.2b - (b - \psi(s^*_{preMW}) + 0.8 \cdot 10 + 0.2b) \\
&= -(\psi(s^*_{postMW}) - \psi(s^*_{preMW})) + 0.8 \cdot 1.2 \qquad (10) \\
&= -0.04(11.2 - b) + 0.8 \cdot 1.2 \\
&> 0.
\end{aligned}
$$

where the third equality uses the upper bound argument from (9), and the final expression holds for any plausible value of unemployed's income b. As a lower bound, for the case of $b = 0$, I find that a $\$1$ increase in the minimum wage increases welfare by $\$0.43$.

In summary, the increase in the minimum wage led to a positive welfare impact on individuals exposed to the policy.

6 Conclusion

Supply side responses by the unemployed through search effort may offer an alternative explanation for the observed equilibrium impacts of minimum wage policies. Yet, existing evidence is limited. Using a combination of datasets, machine learning methods, and an event-study approach exploiting 49 minimum wage events over 20 years in the United States, I find that the search effort channel has empirical relevance. Seen through the lens of a simple search model, the minimum wage may reduce market tightness, but the increased search effort by the unemployed acts as a counteracting force leading to a null employment effect in equilibrium. Moreover, the policy increases welfare.

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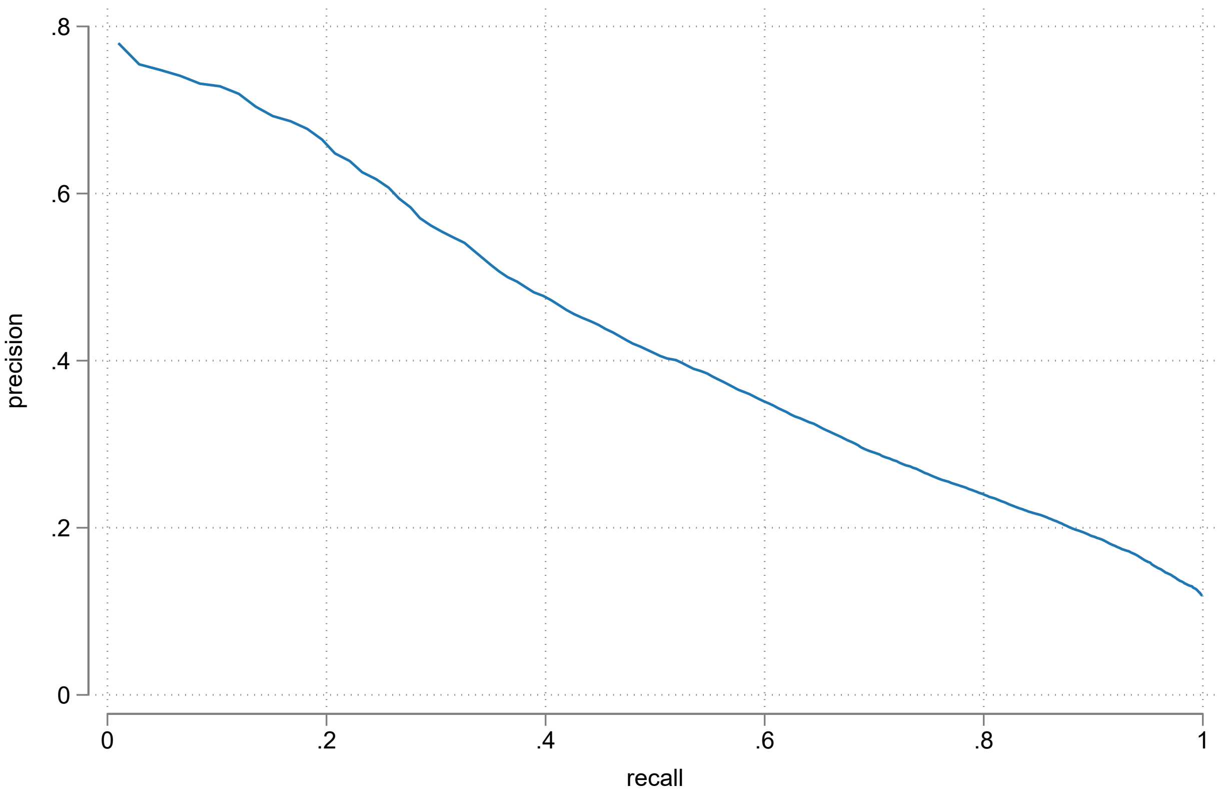
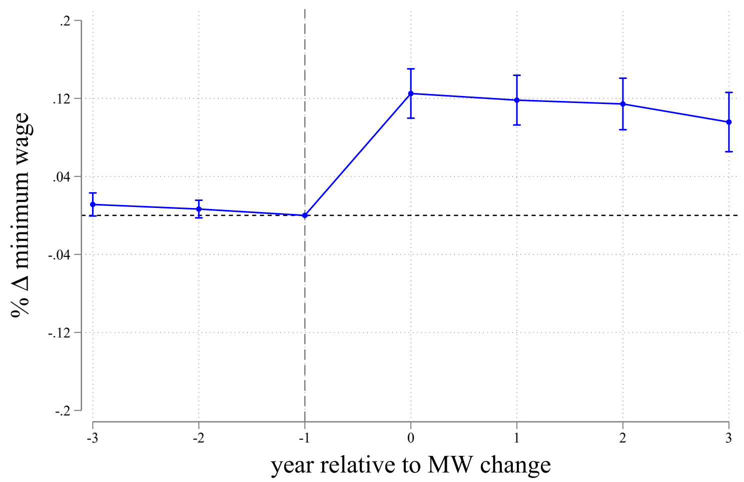
Figure 1: Precision-Recall Curve



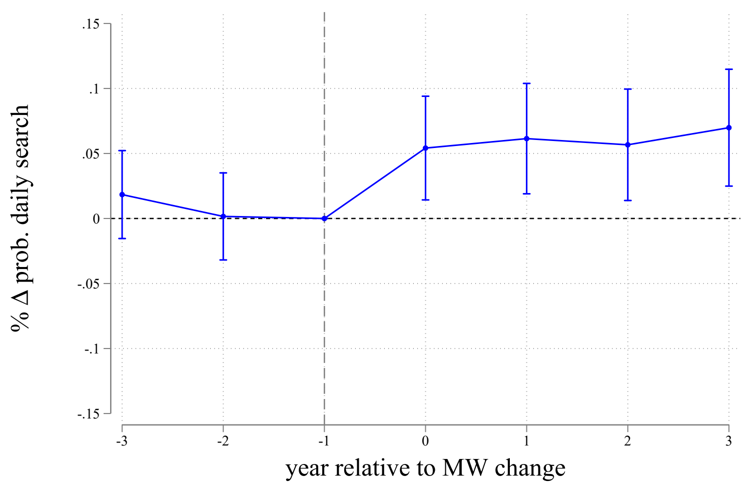
Note: This graph depicts the precision-recall curve as explained in Section 3.1. The precision rate is the number of minimum wage individuals as a proportion of the number of individuals in a given sample. The recall rate is the number of minimum wage individuals as a proportion of the total number of minimum wage individuals in the population. The graph highlights the key trade off faced when choosing a sample in order to study the impact of the minimum wage: a higher recall will yield a larger sample size but it will be composed of a lower share of true minimum wage individuals.

Figure 2: Minimum Wage and Labor Market Outcomes - Exposed Individuals

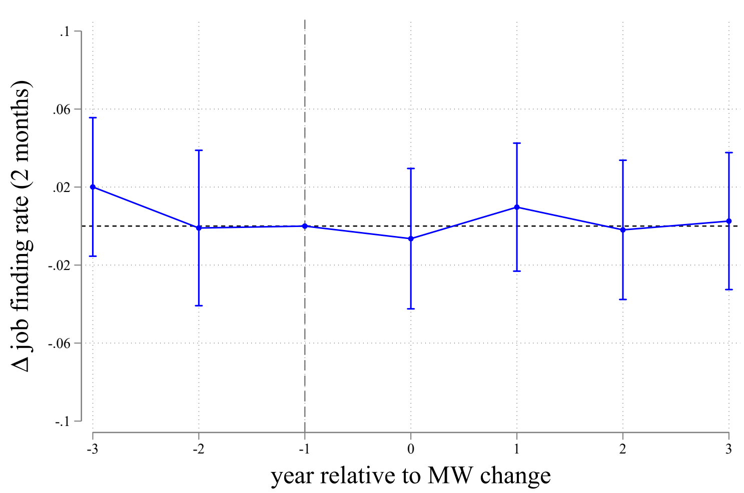
(a) Minimum Wage



(b) Search Effort



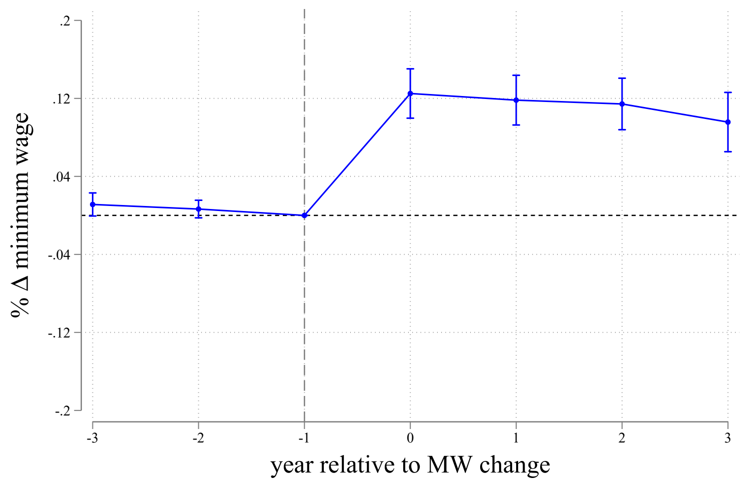
(c) Job Finding



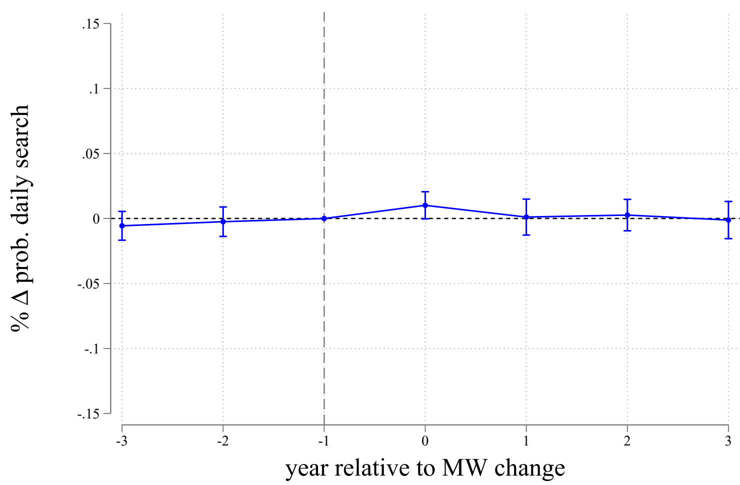
Note: This figure shows the impact of the minimum wage on several labor market outcomes, following the stacked-event study specification explained in Section 3.3. Panel (a) shows the increase in the statutory minimum wage, Panel (b) shows the impact on the probability of daily search, and Panel (c) shows the impact on the 2-month job finding rate. The sample comprises the group of highly exposed individuals, defined as being above the 90^{th} percentile in the distribution of predicted probability of being a minimum wage individual. Point estimates are shown along with 95% confidence intervals.

Figure 3: Minimum Wage and Labor Market Outcomes - Non-Exposed Individuals

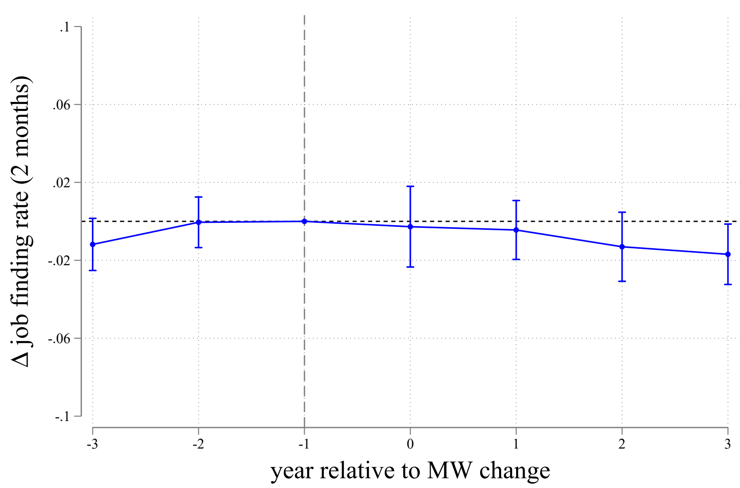
(a) Minimum Wage



(b) Search Effort

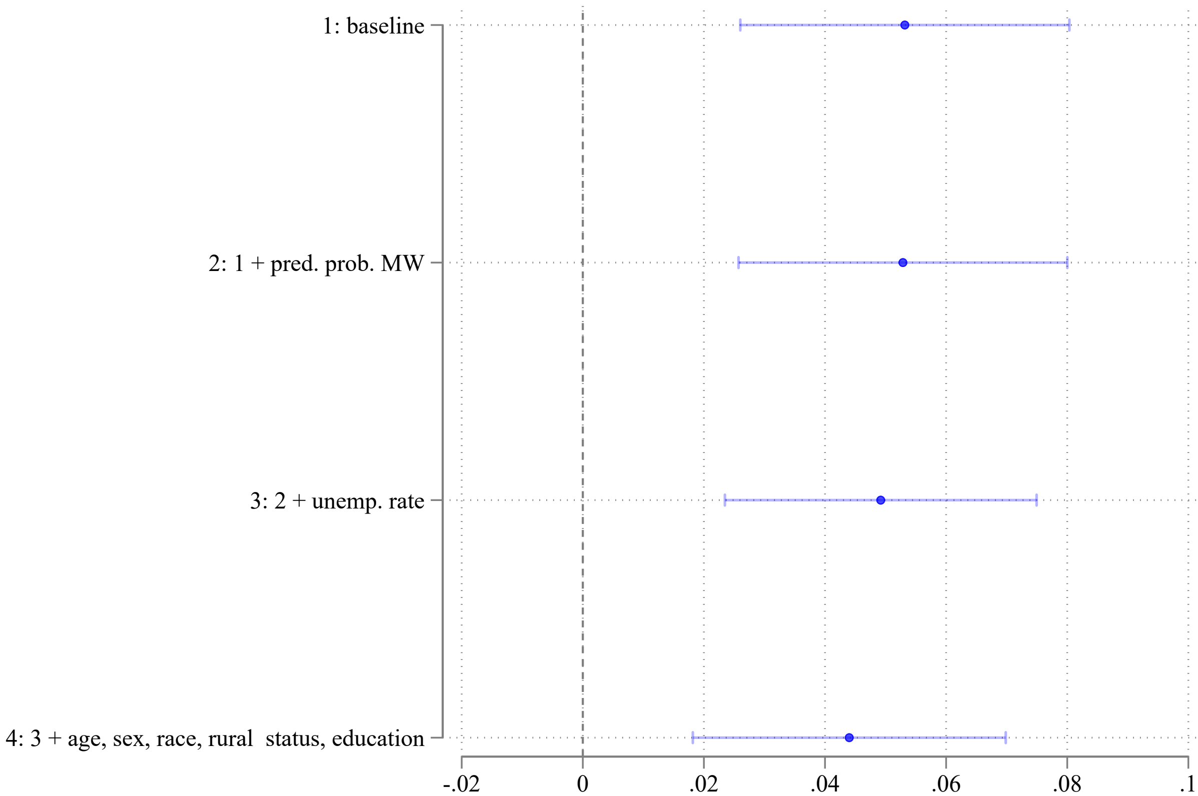


(c) Job Finding



Note: This figure shows the impact of the minimum wage on several labor market outcomes, following the stacked-event study specification explained in Section 3.3. Panel (a) shows the increase in the statutory minimum wage, Panel (b) shows the impact on the probability of daily search, and Panel (c) shows the impact on the 2-month job finding rate. The sample comprises the group of least exposed individuals, defined as being below the 90^{th} percentile in the distribution of predicted probability of being a minimum wage individual. Point estimates are shown along with 95% confidence intervals.

Figure 4: Effect on Search Effort - Robustness with Controls



Note: This graph shows whether the main (post-reform averaged) estimate from the stacked-event study specification described in Section 3.3 is robust to iteratively including different controls. First row shows the baseline specification. Second row adds the predicted probability of being a minimum wage individual. Third row adds the state-level unemployment rate. Fourth row adds several demographic characteristics (age, sex, race, rural status and education).

Table 1: Demographics

	MW individuals	Non-MW individuals
Precision rate	0.69	0.10
Age	17.33	36.49
High school	1.00	0.53
College	0.00	0.18
Male	0.54	0.54
Rural residency	0.82	0.86
Black	0.20	0.21
Hispanic	0.19	0.18
Married	0.01	0.34
Veteran	0.01	0.06
N	245,713	1,745,085

Note: The table shows average demographics for the two groups of unemployed individuals: exposed and non-exposed to the minimum wage, defined as being above or below the 90^{th} percentile in the distribution of the predicted probability of being a minimum wage individual. The groups are defined after applying the prediction model explained in Section 3.1.

Table 2: Questions on Search Methods

Questions on search methods in CPS Basic and ATUS
Contacting an employer directly or having a job interview
Contacting a public employment agency
Contacting a private employment agency
Contacting friends or relatives
Contacting a school or university employment center
Checking union or professional registers
Sending out resumes or filling out applications
Placing or answering advertisements
Other means of active job search
Reading about job openings that are posted in newspapers or on the internet
Attending job training program or course
Other means of passive job search

Note: The table shows the different job search methods present in the questions of both the ATUS and CPS Basic. These are the questions exploited to construct the main search effort variable as explained in Section 3.2.

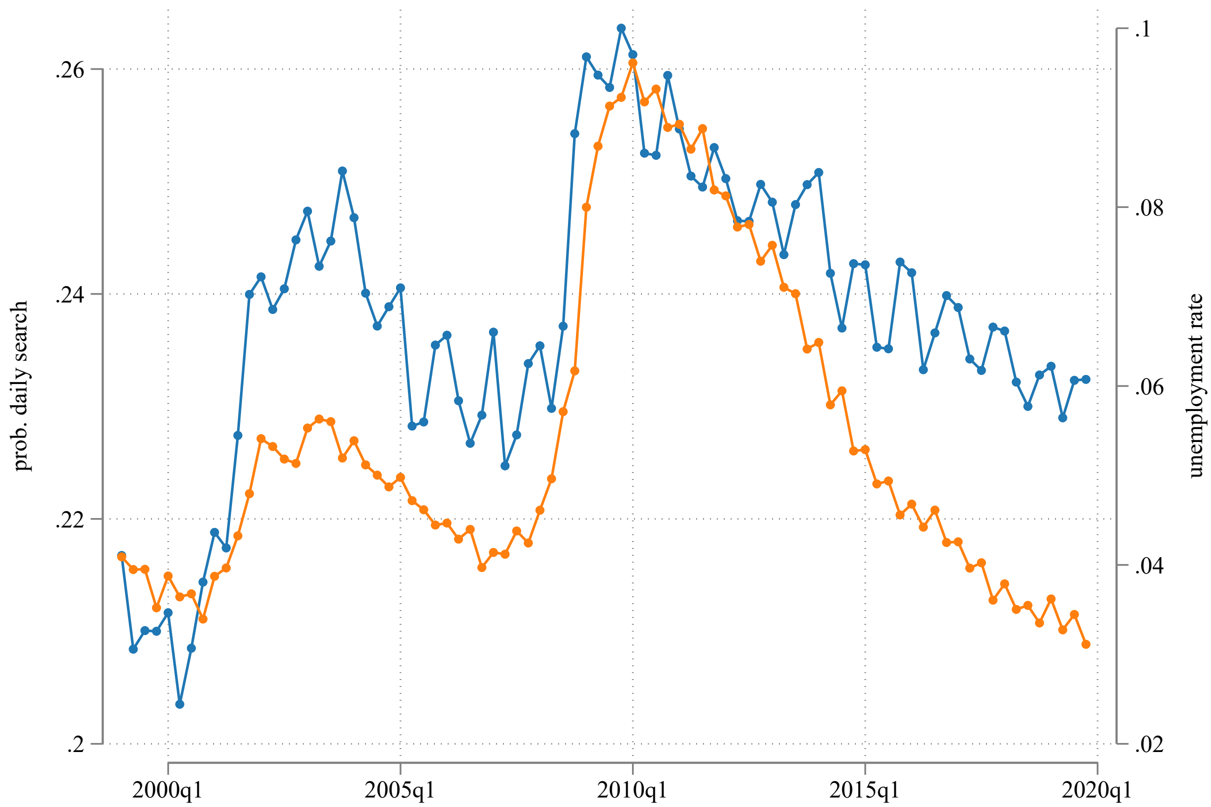
Table 3: IV - Probability of Daily Search

	Job finding (2 months)		Job finding (12 months)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Log(Prob. daily search)	-0.007*	1.386***	0.009**	1.327***
	(0.004)	(0.385)	(0.004)	(0.534)
State x month FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	185808	185808	182045	182045
First-stage F		23.22		11.76

Note: This Table shows the results on the estimated relationship between probability of daily search and job finding. It is obtained by employing an instrumental variables strategy as described in Appendix B. The OLS columns estimate equation 11, while the IV columns instrument search effort with the interaction between UI eligibility and UI duration. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix A Figures and Tables

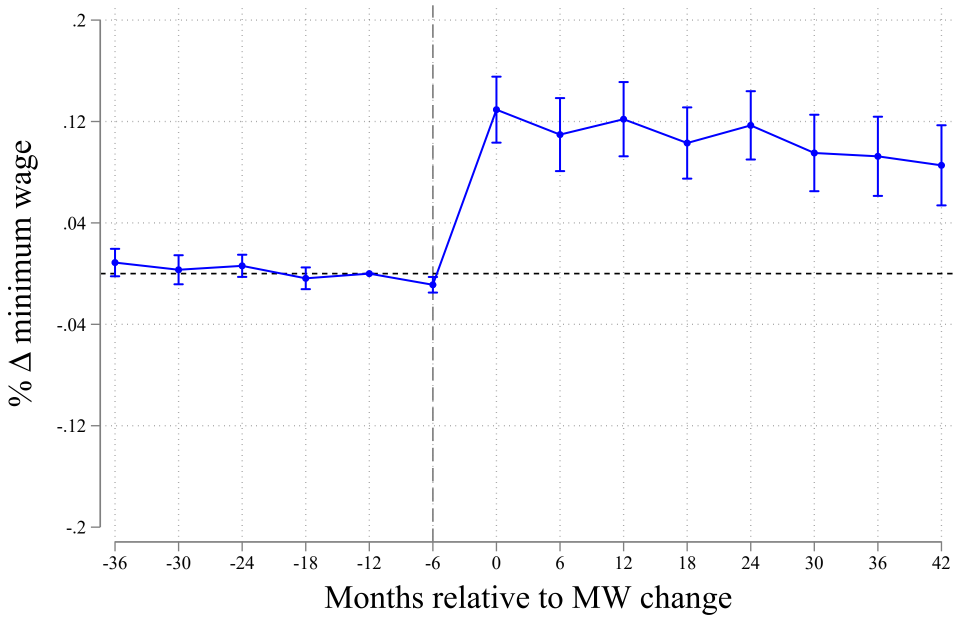
Figure A1: Search Effort over the Cycle



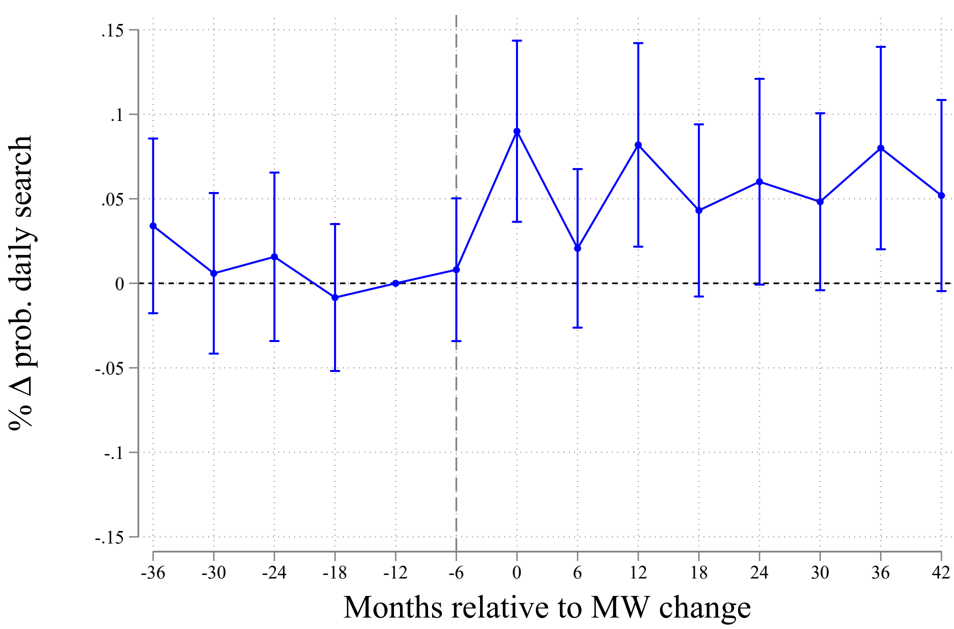
Note: This plot depicts the behavior of the main search effort measure—the probability of daily search—along with the national unemployment rate over the years 1999-2019. Search effort is depicted in blue, while unemployment rate is depicted in orange.

Figure A2: Minimum Wage and Search Effort - Exposed Individuals, High Frequency

(a) Minimum Wage

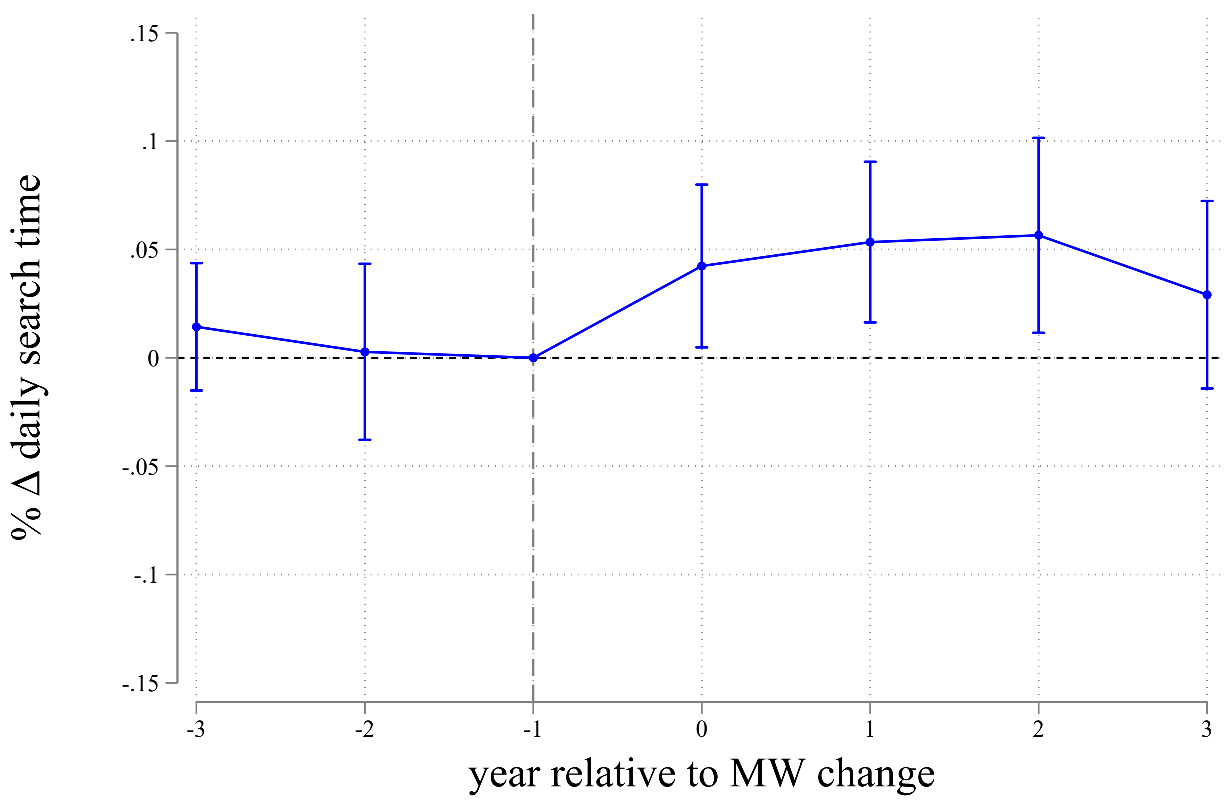


(b) Search Effort



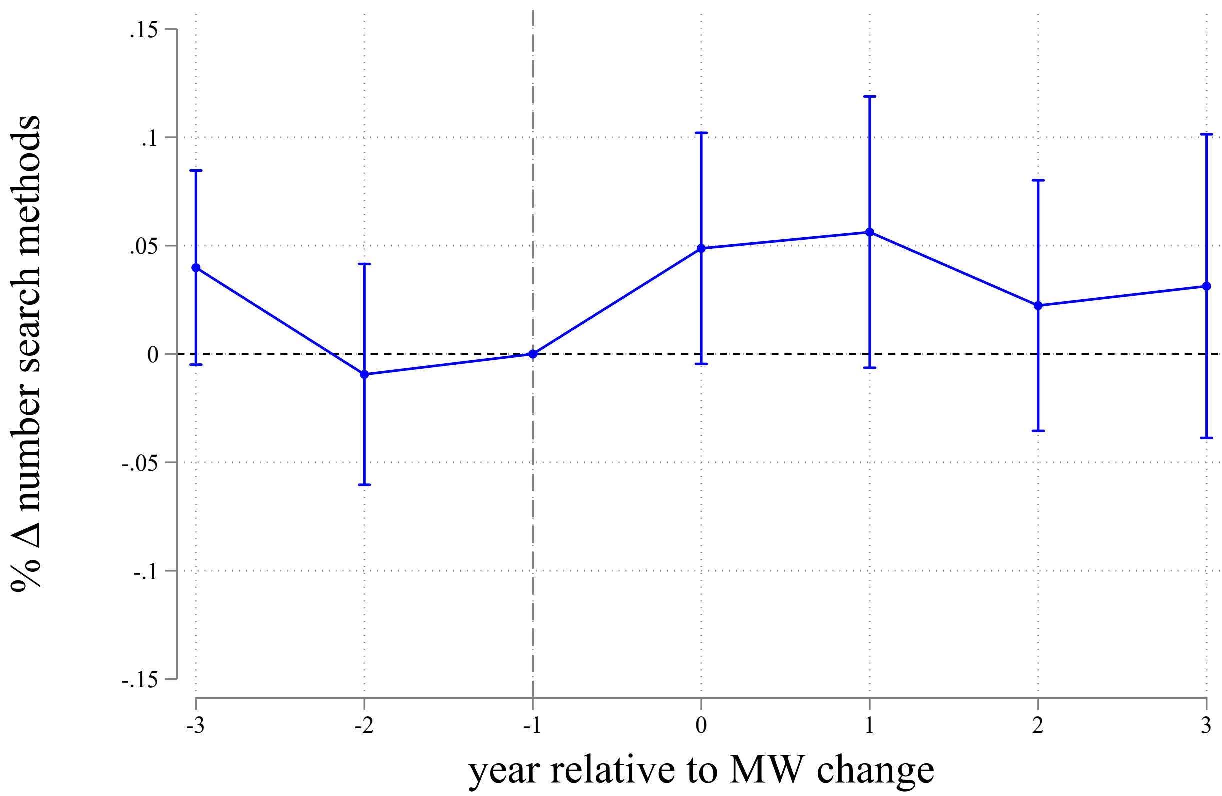
Note: This figure shows the impact of the minimum wage on several labor market outcomes, following the stacked-event study specification explained in Section 3.3. Panel (a) shows the increase in the statutory minimum wage, and Panel (b) shows the impact on the probability of daily search. The sample comprises the group of highly exposed individuals, defined as being above the 90^{th} percentile in the distribution of predicted probability of being a minimum wage individual. The period length here is 6 months, as opposed to 1 year in the main specification. Point estimates are shown along with 95% confidence intervals.

Figure A3: Search Effort - Daily Search Time



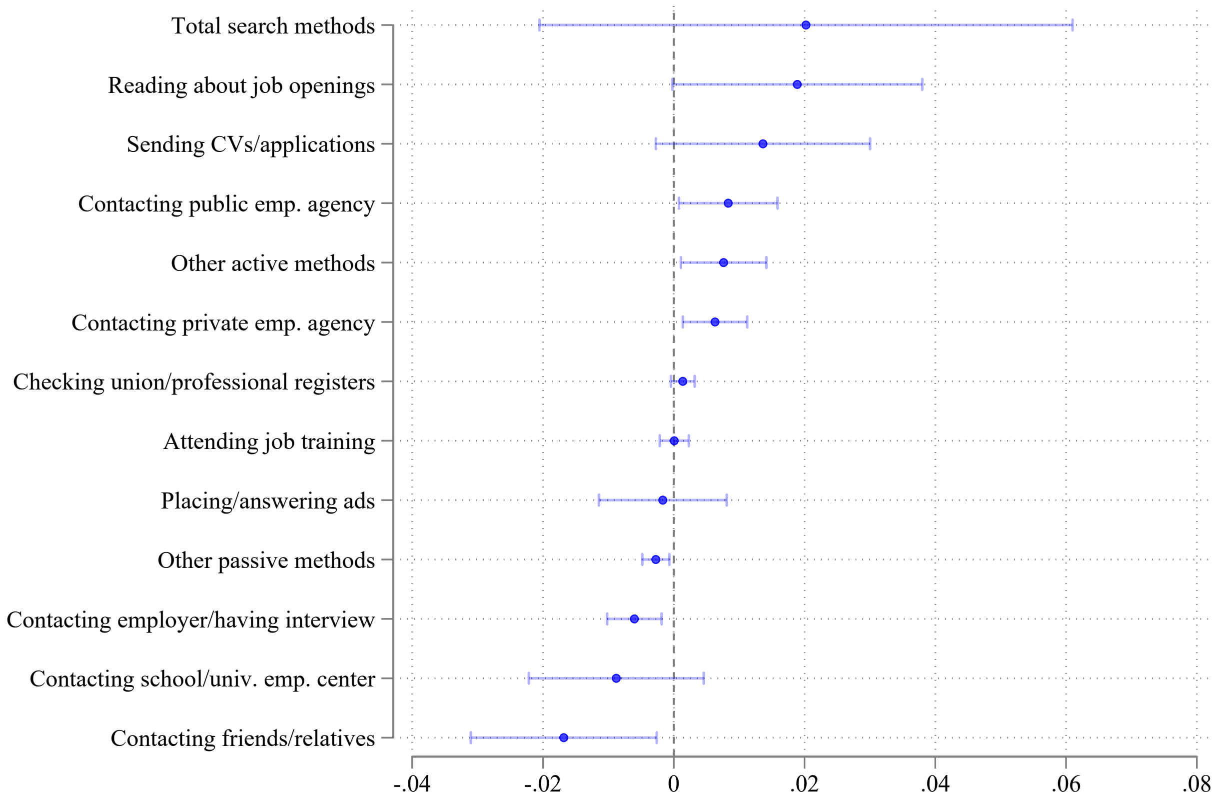
Note: This figure shows the impact of the minimum wage on time spent on job search activities, following the stacked-event study specification explained in Section 3.3. This search effort model is obtained using a Poisson model for prediction. The sample comprises the group of highly exposed individuals, defined as being above the 90^{th} percentile in the distribution of predicted probability of being a minimum wage individual. Point estimates are shown along with 95% confidence intervals.

Figure A4: Search Effort - Number of Search Methods



Note: This figure shows the impact of the minimum wage on search effort, following the stacked-event study specification explained in Section 3.3. This search effort measure corresponds to the total number of methods used by an individual as in Shimer (2004), which only uses CPS Basic information. The sample comprises the group of highly exposed individuals, defined as being above the 90^{th} percentile in the distribution of predicted probability of being a minimum wage individual. Point estimates are shown along with 95% confidence intervals.

Figure A5: Search Effort - Effect by Search Method



Note: This figure shows the impact of the minimum wage on different search methods. Each row is a post-reform average of the effect of the minimum wage on the probability of using each job search method. The sample comprises the group of highly exposed individuals, defined as being above the 90^{th} percentile in the distribution of predicted probability of being a minimum wage individual. Point estimates are shown along with 95% confidence intervals.

Table A1: IV - Daily Search Time

	Job finding (2 months)		Job finding (12 months)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Log(Daily search time)	0.008***	0.913***	0.017***	0.688***
	(0.003)	(0.232)	(0.003)	(0.213)
State x month FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	185808	185808	182045	182045
First-stage F		25.41		30.32

Note: This Table shows the results on the estimated relationship between time spent on job search activities and job finding. It is obtained by employing an instrumental variables strategy as described in Appendix B. The OLS columns estimate equation 11, while the IV columns instrument search effort with the interaction between UI eligibility and UI duration. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix B Estimating Returns to Search Effort

In order to quantify the effort response term in equation 5, we need an estimate of the relationship between search effort and job finding (i.e., $f(\theta) = \frac{\partial h}{\partial s}\big|_{\theta}$). In particular, we would like to estimate the following model:

$$h_{ist} = \alpha + log(s_{ist}) + \beta UIeligible_{ist} + \lambda X_{ist} + \mu_{st} + u_{ist} \tag{11}$$

However, there are multiple endogeneity issues such as measurement error (since my variable is predicted) and omitted variable bias (there can be heterogeneity where high/low job finding individuals search more/less, producing an upward/downward bias). I approach this challenge by using an instrumental variables strategy where the instrument is the interaction between Unemployment Insurance (UI) duration and UI eligibility. The idea is to use Unemployment Insurance duration extensions as a shifter of search effort, and compare individuals within the same labor market to net out market level effects (Lalive et al., 2015). I exploit the fact that within a labor market, some individuals are eligible and some ineligible for UI, so that an UI extension should differentially affect these groups of individuals (i.e., eligible reducing effort relative to eligible as documented by the literature). Importantly, the model includes μ_{st}, which refers to month-state fixed effects so that we effectively compare individuals within the same labor market with different UI eligibility status. The first-stage relationship is:

$$log(s_{ist}) = \pi + \eta UIeligible \times UIduration_{ist} + \tau UIeligible_{ist} + \gamma X_{ist} + \mu_{st} + v_{ist} \tag{12}$$

I use data on UI extensions during the Great Recession from Boone et al. (2021). This strategy requires to have individuals that are eligible and ineligible, so I use all the unemployed individuals, except unemployed on temporary layoffs and job quitters. The results are shown in Table 3. I find that a 1% increase in search effort leads to a 0.014 increase in the 2-month job finding. The magnitude for the 12-month job finding is very similar. Alternatively, I also estimate this relationship using daily search time predicted by the Poisson model instead of the main effort outcome, the probability of daily search from the machine learning model. These results are qualitatively similar and are shown in Table A1.