The Minimum Wage and Search Effort

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February 1, 2021

Abstract

Labor market search-and-matching models posit supply-side responses to minimum wage increases that may lead to improved matches and lessen or even reverse negative employment effects. Yet there is sparse empirical evidence on this crucial assumption. Using event study analysis of recent minimum wage increases, we find that these changes do not affect the likelihood of searching, but do lead to large yet very transitory spikes in search effort by individuals already looking for work. These results are not driven by changes in the composition of searchers.

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Acknowledgements: We are grateful for useful comments from Adam Bestenbostel, Jeffrey Clemens, Jennifer Doleac, Mark Duggan, Mark Hoekstra, Lisa Kahn, Jason Lindo, Abigail Peralta, Juan Carlos Suarez Serrato, Meradee Tangvatcharapong and Jeremy West.

1 Introduction

Do minimum wage increases affect search effort by job seekers? Predictions of the impact of the minimum wage in search-and-matching models of the labor market depend heavily on endogenous search effort responses (Acemoglu, 2001; Flinn, 2006; Ahn et al., 2011). In these models, the increased cost of hiring can be offset by the supply side: workers enter the labor force and search more intensely, leading to better job matches.[1] Indeed, this is one of the primary reasons posited for the lack of employment response to the minimum wage sometimes seen in the empirical literature (e.g. Allegretto et al., 2011).

We investigate the effect of minimum wage increases on job search effort utilizing data from the Current Population Survey (CPS), the Survey of Income and Program Participation (SIPP), and the American Time Use Survey (ATUS) (U.S. Bureau of Labor Statistics, 2016). We exploit the staggered nature of CPS, SIPP, and ATUS interviews and use an event-study approach, leveraging within-state variation in the adoption of minimum wage changes. We account for shocks affecting a particular state in a given year as well as month effects to control for seasonality. We also control for individual demographic characteristics. Intuitively, we compare the outcomes in each month near the treatment date to the outcomes for otherwise-identical individuals in the same state and year whose survey period was not near a treatment date.

We find no evidence that the minimum wage has persistent effects on search effort; the likelihood of searching does not increase in the aftermath of minimum wage increases. These

[1] Burdett and Mortensen (1998) suggest that search frictions can generate monopsonistic competition, leading to employment increases as a result of minimum wage increases. Recent work by Liu (2019) suggests that the minimum wage increases occupational mismatch by reducing job mobility.

results are sufficiently precise that we can reject fairly small increases in the likelihood of searching. However, there is a large yet transitory increase in the intensive margin of search effort, concentrated in the month of the minimum wage increase, that fades almost immediately. There is no short-run increase in the employment rate nor changes in observable characteristics of searchers, suggesting that our results are not driven by changes in the composition of job seekers. These findings are robust to the inclusion of demographic controls in the CPS and ATUS, individual fixed effects in the SIPP, the duration of unemployment benefits, and month-by-year fixed effects that account for any idiosyncratic national-level variation in a given month. We find no evidence that changes in the composition of searchers are driving the results, neither through differential employment probabilities nor differential entry into the labor force. We also conduct a permutation test for our search duration results in which we randomly assign minimum wage increases across time periods and show that these results do not appear to be due to chance.

Our results call into question the assumption underpinning search-and-matching models as applied to analysis of the minimum wage – namely, that more workers will enter the labor market and workers will search harder, increasing the returns to firm vacancy postings. Importantly, we find minimum wage increases do not induce individuals to begin searching. While we find that minimum wage increases yield significant increases in worker search effort on the intensive margin, they are short-lived. We are only able to speculate as to the cause of this pattern of results. But increases in the minimum wage during the time period we study may not have been large enough to induce entry into the labor force, while the labor demand response may have led those already searching to discover that finding a job was more difficult. A reduction in the returns to search might therefore reduce search effort. This type of quick response to a policy change that affects the returns to searching can be seen in other contexts, such as extensions to unemployment insurance benefits (see, for example, (Krueger and Mueller, 2010; DellaVigna et al., 2020)).

Our results contribute to the existing literature in several ways. To the best of our knowledge, we provide the first direct evidence of an important input into search-and-matching models as applied to the minimum wage. We also add to the empirical literature on job search behavior. These studies consider the role of macroeconomics conditions (e.g. Aguiar et al., 2013; Mukoyama et al., 2018), safety net programs including but not limited to unemployment benefits (e.g. Clemens et al., 2015; Krueger and Mueller, 2010; Krueger and Meyer, 2002), and the impact of wage dispersion (Mueller, 2010). Our paper is also related to recent work on online job search (Brown and Matsa, 2016; Kroft and Pope, 2014; Faberman and Kudlyak, 2019), although we consider all types of search effort. Finally, we add to a small but growing literature that investigates the effect of minimum wage on the supply side of the labor market, which primarily focuses on commuting and relocation patterns. The results in this nascent literature thus far have similar findings: Cadena (2014), McKinnish (2017), and Pérez (2018) find evidence suggesting that workers are less likely to locate in, more likely to commute out of, and less likely to commute into areas that increase their local minimum wages, respectively.

The paper proceeds as follows: in Section 2, we discuss our primary data sources. Section 3 describes our econometric approach, and Section 4 presents our results. We conclude in Section 5.

2 Data

2.1 Current Population Survey

We use the 2003-2016 basic monthly survey of the CPS for data on employment, demographics and searching status, consisting of 2.2 million respondents. We use only a household's first interview to avoid selection problems; the CPS does not prioritize locating respondents who move after their first interview (Dixon, 2002; U.S. Bureau of Labor Statistics, 2006).[2] Every year, the CPS basic monthly survey includes about 160,000 first-time respondents.

We define job search using the CPS's question about looking for work over the previous four weeks. Searching is recorded for all those not in the labor force and those who are unemployed but not on temporary layoff (851,731 respondents).[3] Employment is evaluated according to the respondent's reported employment status based on her activities in the week that includes the 12th of the month. Panel A of Table 1 provides summary statistics on respondents, job searchers and the unemployed. Among those in our potential-searcher sample, 11 percent report searching in the previous month.

[2] A natural approach is to a within-individual specification. However, selection issues may arise due to household attrition. Those with lower income and education, and thus more likely to be affected by a minimum wage change, are less likely to be observed multiple times. Nevertheless, we examine the estimates using panel version of the CPS and including individual fixed effects (Flood et al., 2016). The pattern of results is not meaningfully different from those using the full repeated cross-section, nor from those using the Survey of Income and Program Participation, which is more suited for this purpose.

[3] Employed individuals and those unemployed but on layoff are not asked about job search, since "working or having a job takes precedence over looking for work" in the CPS's classification scheme (U.S. Bureau of Labor Statistics, 2015). Some of those classified as not in the labor force are not asked this question, while others are. We define all those classified as not in the labor force who are not asked the question as non-searchers, since not being in the labor force is, at least in part, defined by lack of search effort. Dropping those individuals from the sample entirely does not impact our results in a meaningful way. There are also a small number of what appear to be coding errors for employed respondents; about 200 are coded as searchers in the entire 2.2-million-observation data set. We drop them from the universe of potential searchers; including them does not alter our results.

2.2 Survey of Income and Program Participation

We supplement our analysis of the extensive margin of searching with the Survey of Income and Program Participation. Using the 2004 and 2008 waves of the SIPP, covering 2003-2013, we construct a multi-year panel of about 7.2 million observations and over 200,000 individual respondents. The SIPP's strength is its panel structure, allowing for the inclusion of fixed effects to control for time-invariant individual-level characteristics; further, a panel reduces concerns about differential response rates driving our results.

We define an individual as a searcher if they report searching for work in the previous four weeks. Participants who did not work during the previous four weeks who are not retired, disabled, or who worked some, but not all, of the last four weeks are asked about their searching status, including the number of weeks during that time that they searched. We also assume that those who are not asked about their searching status are not searching.[4] Table 1 Panel B provides summary statistics on respondents, job searchers, and the unemployed. About 6 percent of the entire sample is defined as searching, with 95 percent of those who are unemployed engaging in search behavior. Twenty-two percent (45,554) of respondents report variation in searching status over their survey period.

2.3 American Time Use Survey

The CPS and the SIPP do not ask about the intensive margin of daily search effort and they do not ask all respondents about their searching status. We therefore turn to the 2003-2016 waves of the American Time Use Survey. Individuals are sampled for the ATUS from the

[4]We obtain similar results when using only the individuals who were directly asked about searching behavior and when limiting the sample to those who have ever reported searching.

CPS, and are surveyed approximately three months after their final CPS survey. The ATUS includes a one-time twenty-four hour diary detailing daily activities of respondents in 400 categories. Each year, the ATUS records a time-use diary for about 13,000 respondents.[5]

We consider an individual to be searching for work if they report non-zero time searching for work on the day of their time diary. As such, an individual can be considered searching even if they are categorized as not being in the labor force by the Bureau of Labor Statistics definition, which is reported according to the activities in the seven days preceding the ATUS interview. We define time spent on job search broadly, including all time spent searching and interviewing, as well as activities that are categorized as related to job search. This sample includes all 181,335 ATUS respondents filing a time-use diary between 2003 and 2016. Table 2 provides summary statistics on respondents, job searchers, and the unemployed; note that the ATUS oversamples weekend dates. About one percent of the entire sample reports engaging in search-related activities, with about 15 percent of the unemployed doing so. The unconditional mean time spent searching by all individuals in the sample search is 1.5 minutes a day; the unemployed and those who report non-zero search (including those concurrently employed and searching) do so for 21 and 133 minutes, respectively.[6]

[5]The primary disadvantage of these data is that the ATUS lacks the sample size to examine effects by subgroups of interest when conditioning on positive search effort. This is a major limitation, as effects are expected to be larger for more-affected groups (like those without high school degrees), and more-educated groups can be used as a comparison. On average, there are only about 110 individuals without a high school degree per minimum wage event (about 10 per event-month); even fewer report searching. Regardless, the ATUS is the only data source in the United States that collects information on time use in this manner at all.

[6]Faberman et al. (2020) note that the ATUS likely understates job search effort, as individuals only record their primary activity; for instance, those searching for new employment while on the job would therefore most likely be coded as working rather than searching.

2.4 Minimum Wage

Our minimum wage data is compiled from the Bureau of Labor Statistics website, supplemented with corrections and additions from Meer and West (2016) and Clemens et al. (2018). There are 259 state-level minimum wage changes across 2003-2016, taking the most expansive definition of such changes, including those induced by increases in the federal minimum wages and those linked to inflation indexing. States experienced an average of six minimum wage changes. The average nominal minimum wage over the time period was \$6.88 (median \$7.25), and the average nominal change was 53 cents (median 50 cents). We define the minimum wage in a given month as its value on the first of that month.

3 Specification

Our specification captures the short-run dynamic effects of a minimum wage change on the extensive and intensive margins of search effort. We estimate the following equation:

$$\begin{aligned} Y_{i,s,t,m,p} = \sum_{p=-5}^{5} \beta_p I(MonthOfTreatment)_p + \beta_c I(AllOtherMonths)_c + \alpha_1 StateYear_{s,t} \\ + \alpha_2 Month_m + \tau IndividualControls_{i,s,t,m} + \gamma X_{s,t} + \epsilon_{i,s,t,m,p} \end{aligned} \tag{1}$$

β_p represents a different coefficient for each of the eleven months, five months before through five months after, centered on the month of minimum wage change. We selected this time frame as the longest one for which there was no overlap between before- and after-periods. All observations that do not fall in this eleven-month window around a treatment are grouped into the excluded category.

We account for state-specific shocks in a particular year that may be correlated with minimum wage increases with state-by-year fixed effects and for seasonal differences with month fixed effects. We also include age and its quadratic, gender, race, a series of indicators for education level, and whether the respondent was interviewed on the weekend.[7] The duration of unemployment benefits available to respondents in state s for year t in month m, measured in weeks, are included in $X_{m,s,t}$.[8] Finally, using the SIPP data only, we are able to include individual fixed effects in place of time-invariant demographic characteristics. Standard errors are multi-way clustered at the state and year-by-quarter level.[9]

We use our model with all three datasets to explore three main outcome variables: (1) the likelihood of searching (2) weeks searching for work (SIPP only) (3) daily time spent searching (ATUS only). We check for pre-trends within a state-year by examining the pattern of coefficients for the months leading up to the minimum wage change. Such trends could reflect potentially biasing spurious correlation or anticipatory effects by prospective workers; regardless, we find no evidence of them.[10]

Another potential concern is that composition of respondents varies systematically in a

[7]The weekend status of an interview is only observed in the ATUS.

[8]These data were compiled by Rothstein and Valletta (2017) and supplemented with additional data that we gathered.

[9]After accounting for individual characteristics, length of unemployment benefits, seasonality, and within-state-year effects, it is difficult to imagine a shock to search effort that is uncorrelated with those controls, and coincidental solely with the month of a state-specific minimum wage change. Nevertheless, we also add month-by-year (that is, time) effects that account for national-level idiosyncratic shocks in a particular month. The results, in Figures A.7, A.8, and A.9, are similar to our main specifications.

[10]As suggested by Borusyak and Jaravel (2016), we perform an F-test on the pre-period coefficients and can reject the existence of pre-trends in outcomes for both datasets. It is also possible that trends in unobservables correlated with treatment and searching behavior could be driving our results. We implement the instrumental variable approach suggested in Freyaldenhoven et al. (2018) and re-estimate our dynamic results. Although this approach yields noisier estimates, our results remain similar for both the ATUS and the CPS.

manner that is correlated with the minimum wage changes we examine, despite the random sampling of respondents by the Bureau of Labor Statistics. Figures A.10 and A.11 plot the relationship between the monthly treatment-time indicators and demographic variables like age, race, education and gender for the CPS and SIPP.[11] There is some variation from month to month – for example, sampled respondents tended to be a few months older in the month of minimum wage changes and less educated in the month before an increase relative to the comparison group – but these are unlikely to affect our results, which control for these demographic variables.

To further address this concern, we exploit the panel nature of the SIPP by adding individual fixed effects to Equation (1). Suppose that individuals with a greater propensity to search are more likely to be searching prior to a minimum wage change but stop doing so afterwards, merely by happenstance. In that case, there may be spurious negative correlation between search behavior and the minimum wage. Individual fixed effects would account for such issues.

4 Results

4.1 Current Population Survey

Figure 1 shows that there are no changes in searching status after a minimum wage increase when examining the entire sample. The coefficients are small and precisely estimated, and show that minimum wage increases do not induce prospective workers to begin searching.

[11] Sample sizes in the ATUS conditional on demographic characteristics are too small for meaningful inference; there are no unusual patterns or statistically significant effects, but the estimates are quite noisy.

No coefficient on the likelihood of searching in the period after a minimum wage change is larger than 0.2 percentage points, or a 2 percent increase relative to the baseline.[12] There are no meaningful trends in search status in the five months prior to a minimum wage change. Further, there are no impacts on the probability of not being in the workforce or on the likelihood of employment in the months before and after a minimum wage change. The lack of impact on entry into the labor force provides further evidence that individuals are not more likely to seek a job in the wake of a minimum wage increase. The results on employment suggests that there is no negative selection in the composition of searchers caused by the entry of higher-value searchers into employment; we return to the question of changes in the composition of searchers in Section 4.4, including estimates of results by subgroups.[13]

These results provide precisely-estimated zero results on the extensive margin of search, indicating that minimum wage changes do not increase the number of individuals searching for work. However, we are not able to estimate a within-individual specification because of potential selection due to household attrition. To do so, we turn to the SIPP.

4.2 Survey of Income and Program Participation

Similar to the results from the CPS, Figure 2b shows no changes in searching status preceding or following treatment of minimum wage increase. The largest coefficient following the

[12] For the largest coefficient in the post-period, we are able to rule out increases in searching of about 7%.

[13] We also consider results by age group for the probability of searching. There are no meaningful patterns by age; even among the youngest potential workers (under 20 years old), there is no increase in searching behavior after a minimum wage change. We also investigate results by method of search (active and passive). The CPS defines active search methods as methods that have the potential of resulting in a job offer without any further action by the job seeker. Passive methods are those that could not result in a job offer unless additional steps were taken. For example, contacting an employer directly would be considered an active search method, while taking a training course would be a passive search method. There is no meaningful increase in active or passive searching after a minimum wage change. There is also no impact on the number of search methods utilized. Mukoyama et al. (2018) impute search time by method in the CPS and find that search effort increased more in states with more severe recessions.

minimum wage increase shows a .04 percentage point (0.7 percent) increase relative to the baseline.[14] In addition, Figures 2a and 2d show no change in probability of employment, or weeks searching following treatment of minimum wage change, respectively. There is a statistically significant decrease in the probability of not being in the labor force after the treatment month, but the estimate is extremely small, about 0.25 percentage points, or 0.7 percent of the baseline. For each outcome, the coefficients are small and the standard errors rule out positive effects of economically meaningful size.[15]

Therefore, the inclusion of individual fixed effects yields results similar to those in the CPS.[16] Namely, there is no entry into searching as a response to minimum wage increases. This helps reduce concerns about differences in composition of those sampled. However, the CPS and the SIPP do not record the daily intensity of job search and do not directly ask all respondents about searching behavior. We next use the ATUS to examine impacts the intensive margin.

4.3 American Time Use Survey

We begin by replicating the extensive-margin results from the CPS and SIPP using the smaller ATUS sample. In Figure 3, we show that there are no statistically significant changes in the likelihood of searching for work after a minimum wage increase. The results are small and and fairly precise, with no positive coefficient larger than 0.08 percentage points, or 7% of the baseline value. Again, there is no impact on the probability of not being in the

[14] For the largest coefficient in the post-period, we are able to rule out increases in searching of about 5%.

[15] As with the CPS, there are no meaningful differences in probability of searching probability or weeks searched by age group.

[16] Results using demographic characteristics rather than individual fixed effects do not show a different pattern of results; that is, there is no increase in searching after minimum wage increases relative to the time period before.

workforce and the probability of employment, and there are no trends. There is therefore no evidence of increased likelihood of searching.

We turn to the intensive margin of search effort – the number of minutes spent engaged in job-search-related activity. Figure 4 shows the dynamic effects of minimum wage changes on search duration using the entire sample, including those not in the labor force and those not searching. There is a positive and statistically significant effect of 0.8 minutes, or about 50 percent of the baseline level, but only in the month of the minimum wage increase. The effect in the following months are small and arrayed around zero.

Next, we focus on the unemployed. Figure 5 shows that the likelihood of searching by the unemployed does not change around the treatment periods. As with the whole-sample results in Figure 4, time spent searching only increases in the month of the minimum wage change. Figure 5 shows an increase of 16 minutes per day, or 8 hours extrapolated for the month of the minimum wage change; this amount is about 75 percent of the baseline value. Again, the effect is transitory, with coefficients in the following five months being close to zero.

Finally, we show results for those reporting positive search minutes only. Once again, the effects are entirely concentrated in the month of the minimum wage change. Figure 6 shows an increase of 75 minutes a day, about 55 percent of the baseline value, and the effect is short-lived. None of the following five months have an effect that is even one-third the size of the effect in the month of the change, and most are much smaller.[17] These results are consonant with the lack of impact on the likelihood of searching: multiplying the effect on

[17] We replicate these results using an inverse hyperbolic sine transformation, Poisson, and negative binomial model in Figure A.12 There are no meaningful changes in the pattern of results.

non-zero searchers by the prevalence of searchers in the sample yields a value nearly identical to the coefficient estimated using the whole sample.

4.4 Changes in the Composition of Searchers

Taken together, our results indicate that there is little or no entry into search activity as a result of minimum wage increases, and increases in search effort among searchers are short-lived. It is difficult to pin down the cause of this pattern, though we can reject the possibility that employment increases around the time of the minimum wage change. If that were the case, it could lead to negative selection of those continuing to search; that is, those still searching are less attractive to employers and thus need to put forth more effort to find employment. This type of selection would not be likely to lead to the one-month increase in search effort.

However, it is possible that the composition of searchers does change in some other way, though the results using the SIPP alleviate some of these concerns. For example, if employer preferences for workers change in response to minimum wage increases, there may be offsetting shifts in the likelihood of search by education level (Clemens et al., 2018). Figures A.13 and A.14 show these results for the likelihood of searching in the CPS and the SIPP by education level; as noted above, the ATUS sample is too small to yield meaningful inference for subgroups. There is little evidence that more-educated workers are meaningfully more likely to search while less-educated workers exit the labor force entirely.[18]

We next investigate whether any observable characteristics of job-seekers changes around minimum wage increases. Again using the CPS, we estimate Equation (1) using respon-

[18] There is no evidence of an increase in searching probability when dividing the sample by age.

dent characteristics as the outcome variables, restricting the sample to searchers only. The results, in Figure A.15, show little evidence that suggests such changes. There may be a slight increase in the prevalence of high school dropouts among searchers in the month of the minimum wage increase, but the estimate is not statistically significant. Several other coefficients are statistically significant (for example, searchers in the third month after a minimum wage increase are about 1 year older than the comparison group), but as there are dozens of estimates shown in these graphs and no discernible pattern, we do not emphasize these findings.

When considering the results of CPS and ATUS, it is still possible that the composition of job-seekers changes dramatically in response to the minimum wage in a manner that leaves the overall search rate unaffected, but leads to low-activity searchers exiting and high-activity searchers entering the labor market. That is, a minimum wage increase causes those who are searching for a small number of hours to shift to zero search, while inducing entry by individuals who were previously not searching but now search for substantial amounts of time. In that case, our results would reflect unobserved heterogeneity in the monthly cross sections of the data, though would remain an interesting response to minimum wage increases. To the extent that those who begin searching provide more productive matches for employers, this mechanism would be consonant with the search-and-matching literature. However, this type of sorting would have to be uncorrelated with the demographic characteristics examined above and for which we control; given the size of the response in Figure 6, this seems unlikely. Moreover, it is difficult to reconcile with the short-lived spike in search effort. On balance, there is very limited evidence for the notion that search activity increases in response to the minimum wage in a manner consistent with theoretical search-and-matching models. Similarly, with the use of within-individual specification in the SIPP, there is no observed entry into searching following minimum wage change. Therefore, we can further rule out the concern of a changing composition of individuals driving our results.

4.5 Placebo Tests

To evaluate the possibility that our search duration results arise from random chance rather than a causal relationship, we estimate Equation (1) on a series of placebo treatments in a method similar to Bertrand et al. (2004). For each permutation, we draw with replacement from a distribution of potential treatment time periods, an eleven month window centered on a minimum wage change based on the true distribution of monthly changes we observe in the actual data. For example, we place greater weight on January and August, when most of the minimum wage changes occur in the data. Unlike the month of change, we place equal weight on year and state probabilities. We then assign each state multiple placebo treatment dates. With draws of simulated changes, we estimate Equation (1) one thousand times.

Figure A.16 compares the actual results from Figure 4 to those estimated from the placebo exercise. Each coefficient in this latter estimate, including the in the month of the minimum wage change, is about zero. Figure A.17 plots the actual coefficient on the distribution of the placebo estimates. For the baseline model including the entire sample, our estimate of the impact in the month of the minimum wage change is greater than 91 percent than the simulated coefficients.

Figure A.18 makes the same comparison for the sample conditioned on unemployment.

Again, the placebo estimates are close to zero. Figure A.19 compares our estimates to the placebo distribution. Effects in months other than the month of the change, are not unusual relative to the simulated coefficients. In the month of the change, though, the estimated coefficient is greater than 96 percent of the placebo estimates. Finally, a similar pattern is seen in Figure A.19, comparing results for non-zero searchers, and Figure A.21, which shows that the estimate during the month of the change is also greater than 96 percent of the simulated coefficients.

We conclude that our findings in the dynamic event-study specifications are highly unlikely to have occurred by chance and that they reflect a transitory increase in search effort on the intensive margin.

5 Conclusion

This paper explores the relationship between minimum wage increases and search effort. We estimate the dynamic response of search behavior to increases in the minimum wage using three separate datasets. Our findings provide robust evidence that minimum wage changes increase search effort on the intensive margin but only during the month of the minimum wage change. Perhaps most significantly given its importance to search-and-matching models of the labor market, we show that increasing the minimum wage does not induce individuals not already searching to begin doing so.

This transitory effect, although not predicted by standard labor theory, has been documented in a similar setting. Krueger and Mueller (2010) find that job search responses to unemployment benefit exhaustion are transitory. Specifically, they document that individuals increase their search effort just before unemployment benefits expire, but that effort declines back to previous levels soon after UI benefits are exhausted. Our findings similarly suggest that the search responses to the increased value of obtaining a job may be short-lived.[19]

Understanding the impact of the minimum wage on different aspects of the labor market, rather than simply equilibrium employment outcomes, is of significant importance given its increasing prevalence as a policy instrument. Our findings suggest the need for greater analysis of not only job search behavior after a minimum wage change, but also of other supply side responses.

[19]DellaVigna et al. (2020) also find that "search effort exhibits an increase up to UI exhaustion and a decrease thereafter." Faberman and Kudlyak (2019) use high-frequency data from an online job-finding platform to document that the number of applications sent by job seekers drops significantly after the first week of search, providing further evidence of rapidly fading search effort.

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Tables and Figures

Table 1: CPS and SIPP Summary Statistics

	(1) Entire Sample	(2) Searchers	(3) Non-Searchers	(4) Unemployed	(5) Employed	(6) NILF
Panel A: CPS						
Probability of employment	0.607	0	0	0	1	0
	(0.488)	(0)	(0)	(0)	(0)	(0)
Probability of Searching	0.110	1	0	1	0	0.0125
	(0.312)	(0)	(0)	(0)	(0)	(0.111)
Age of respondent	45.47	35.48	52.67	36.18	42.13	52.44
	(18.51)	(14.98)	(22.94)	(14.91)	(14.14)	(22.95)
High school dropouts	0.172	0.230	0.296	0.229	0.0975	0.295
	(0.378)	(0.421)	(0.456)	(0.420)	(0.297)	(0.456)
Male respondent	0.478	0.523	0.394	0.546	0.520	0.395
	(0.499)	(0.499)	(0.489)	(0.498)	(0.500)	(0.489)
White respondent	0.827	0.728	0.819	0.738	0.840	0.818
	(0.378)	(0.445)	(0.385)	(0.440)	(0.367)	(0.386)
Weeks unemployment insurance	45.10	51.29	45.26	51.42	44.54	45.28
	(25.86)	(28.16)	(26.12)	(28.14)	(25.48)	(26.13)
Observations	2199503	93323	758408	95480	1335978	768045
Panel B: SIPP						
Probability of employment	0.593	0.275	0.612	0	1	0
	(0.491)	(0.447)	(0.487)	(0)	(0)	(0)
Probability of searching	0.0568	1	0	0.953	0.0263	0.0152
	(0.231)	(0)	(0)	(0.211)	(0.160)	(0.122)
Weeks searching	0.801	2.813	0.152	4.084	0.732	0
	(1.631)	(1.966)	(0.739)	(0.930)	(1.385)	(0)
Age of respondent	45.51	34.22	46.19	35.96	41.93	52.22
	(18.85)	(14.09)	(18.88)	(14.37)	(13.98)	(23.49)
High school dropouts	0.174	0.219	0.171	0.213	0.0959	0.295
	(0.379)	(0.413)	(0.376)	(0.409)	(0.294)	(0.456)
Male respondent	0.471	0.521	0.468	0.522	0.518	0.392
	(0.499)	(0.500)	(0.499)	(0.500)	(0.500)	(0.488)
White respondent	0.804	0.723	0.809	0.708	0.819	0.790
	(0.397)	(0.447)	(0.393)	(0.454)	(0.385)	(0.407)
Weeks unemployment insurance	54.77	59.47	54.49	62.92	53.58	55.88
	(28.51)	(28.83)	(28.47)	(28.59)	(28.30)	(28.67)
Observations	7224651	410298	6814353	269432	4284938	2670281

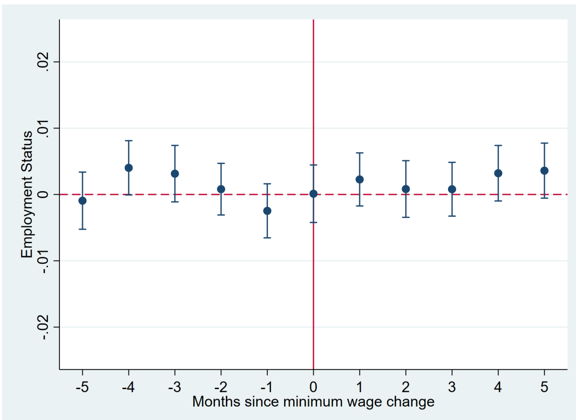
This table reports the mean and standard deviation for key variables by searching and unemployment status. Data are from the Current Population Survey (Panel A) and the Survey of Income and Program Participation (Panel B). Column (1) includes the entire sample for each dataset. Columns (2) and (3) include summary statistics for those who report non-zero search in the last month (Searchers) and those who do not report searching (Non-Searchers), respectively. Columns (4), (5) and (6) report summary statistics for the unemployed, employed and not in the labor force. Employment is measured for the entire population (including those not in the work force). For the SIPP and the CPS, we define an individual as a searcher if they report searching for work in the last four weeks. In the CPS, the sample for searching status is only measured for 851,731 respondents (all unemployed but not on layoff, and not in the labor force) and we define all those classified as not in the labor force who are not asked the question as non-searchers even if they are not directly asked about search behavior. Respondents are considered not in the labor force if they are not employed or unemployed. Not in the labor force includes retired persons, students, those taking care of children or other family members, and others who are neither working nor seeking work in the CPS. In the SIPP only participants in the survey who did not work during the last four weeks who are not retired, disabled, or who worked some, but not all of the last four weeks are directly asked about their searching status (99,429 individuals and 1,599,905 observations). We assume those who are not asked about their searching status are not searching (probability of searching is zero and weeks searching is zero). Not in the labor force for the SIPP includes respondents with no job all month, no time on layoff, and no time looking for work. There are 210,942 individual respondents in the SIPP.

Table 2: ATUS Summary Statistics

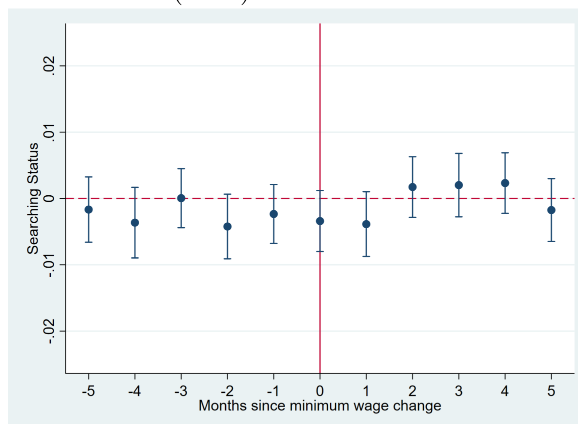
	(1) Entire Sample	(2) Searchers	(3) Non-Searchers	(4) Unemployed	(5) Employed	(6) NILF
Panel A: ATUS						
Probability of employment	0.623	0.271	0.627	0	1	0
	(0.485)	(0.444)	(0.484)	(0)	(0)	(0)
Probability of searching for work	0.0113	1	0	0.150	0.00491	0.00319
	(0.106)	(0)	(0)	(0.357)	(0.0699)	(0.0564)
Daily minutes searching for work	1.498	132.5	0	21.42	0.532	0.416
	(19.48)	(127.3)	(0)	(72.91)	(10.68)	(9.981)
Daily minutes searching (non-zero)	132.5	132.5	0	143.0	108.3	130.5
	(127.3)	(127.3)	(0)	(134.6)	(107.5)	(119.8)
Age of respondent	47.04	39.58	47.13	36.22	42.70	56.84
	(17.74)	(13.36)	(17.76)	(15.96)	(13.36)	(20.79)
Percent high school dropouts	0.158	0.121	0.158	0.305	0.0940	0.257
	(0.365)	(0.327)	(0.365)	(0.460)	(0.292)	(0.437)
Male respondent	0.438	0.535	0.436	0.461	0.489	0.337
	(0.496)	(0.499)	(0.496)	(0.498)	(0.500)	(0.473)
White respondent	0.808	0.710	0.809	0.712	0.822	0.797
	(0.394)	(0.454)	(0.393)	(0.453)	(0.383)	(0.402)
Surveyed on weekend	0.502	0.290	0.504	0.499	0.502	0.502
	(0.500)	(0.454)	(0.500)	(0.500)	(0.500)	(0.500)
Weeks unemployment insurance	45.91	51.84	45.84	51.77	45.39	46.03
	(26.28)	(28.39)	(26.25)	(28.37)	(25.93)	(26.52)
Observations	181335	2051	179284	8720	112996	59619

This table reports the mean and standard deviation for key variables by searching and unemployment status. Data are from the American Time Use Survey. Column (1) includes the entire sample for each dataset. Columns (2) and (3) include summary statistics for those who report non-zero daily search (Searchers) and those who do not report searching (Non-Searchers), respectively. Columns (4), (5) and (6) report summary statistics for the unemployed, employed and not in the labor force. Employment is measured for the entire population (including those not in the work force). As in the CPS, respondents are considered not in the labor force if they are not employed or unemployed. Not in the labor force includes retired persons, students, those taking care of children or other family members, and others who are neither working nor seeking work in the ATUS. Not in the labor force includes retired persons, students, those taking care of children or other family members, and others who are neither working nor seeking work in the ATUS (the same as in the CPS).

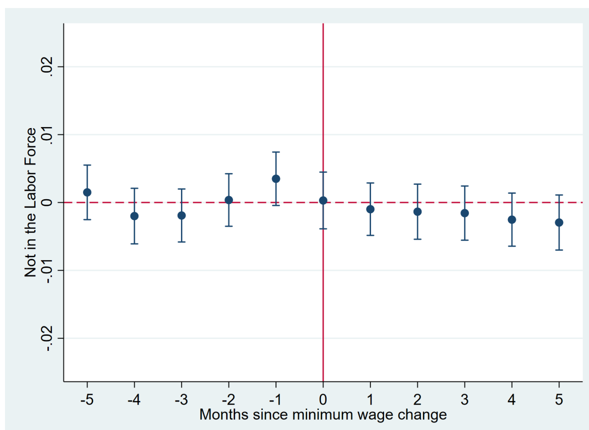
Figure 1: Employment and Search (CPS)



(a) Employment Status



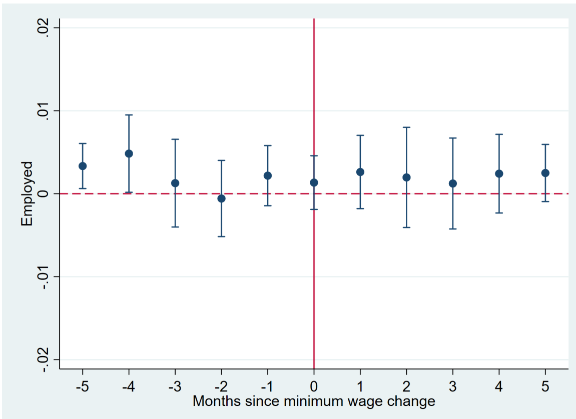
(b) Searching Status



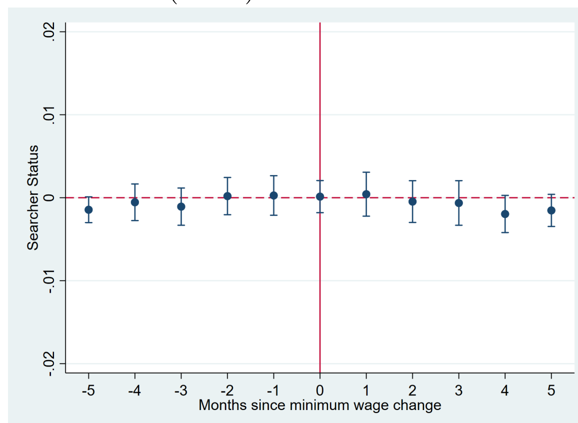
(c) Not in the Labor Force

This figure plots coefficients from the regression of employment, searching probability or not in the labor force on months before/after treatment, accounting for state-by-year and month fixed effects. Controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Ninety-five percent confidence intervals are presented. Employment status equals one if the respondent is employed and zero if they are unemployed or not in the workforce. Probability of searching is one if the individual reports searching in the last four weeks, regardless of labor force status, and zero if they do not. Not in the work force is equal to one if an individuals is not employed or unemployed. Panels (a) and (c) use 2,199,503 observations and Panel (b) uses 851,731. Data are from the Current Population Survey.

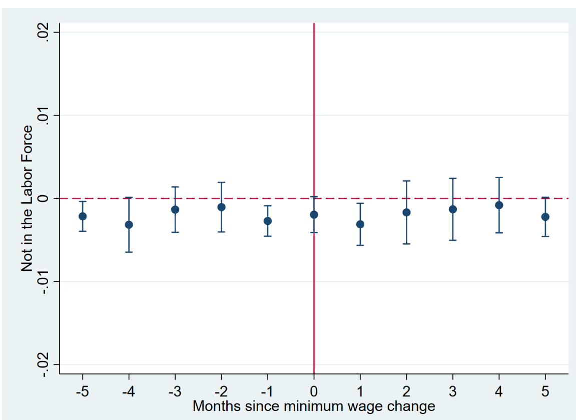
Figure 2: Employment and Search (SIPP)



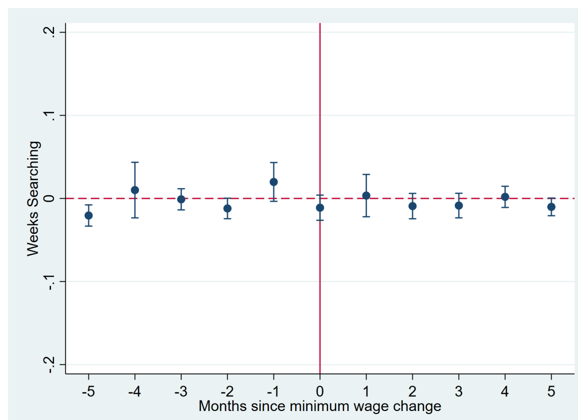
(a) Employment Status



(b) Searching Status



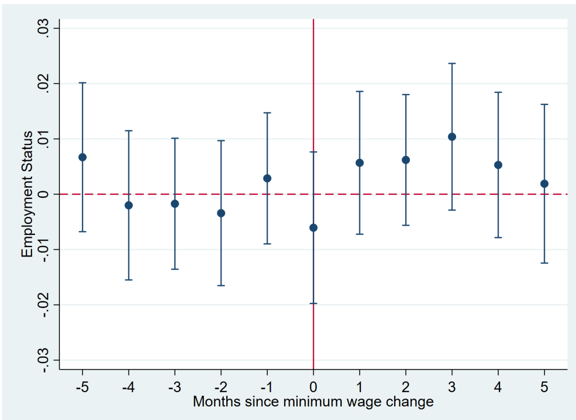
(c) Not in the Labor Force



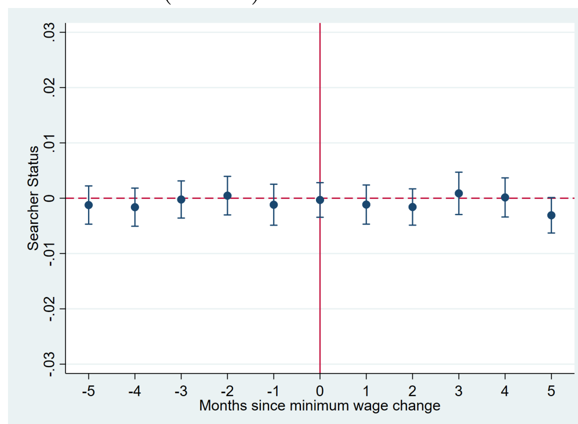
(d) Weeks Searching for Work

This figure plots coefficients from the regression of employment, searching probability, not in the labor force and weeks searching on months before/after treatment, accounting for state-by-year and month fixed effects. Individual fixed effects are included. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Ninety-five percent confidence intervals are presented. Employment status equals one if the respondent is employed and zero if they are unemployed or not in the workforce. Probability of searching is one if the individual reports searching in the last four weeks, regardless of labor force status, and zero if they do not. Not in the work force is equal to one if an individual is not employed or unemployed. Each panel uses all 7,224,651 observations from the Survey of Income Participation Program.

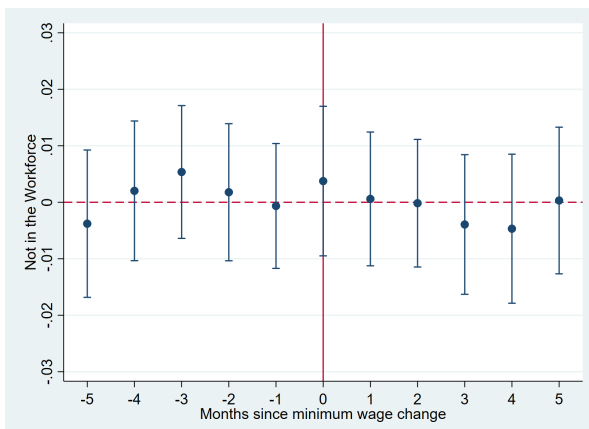
Figure 3: Employment and Search (ATUS)



(a) Employment Status



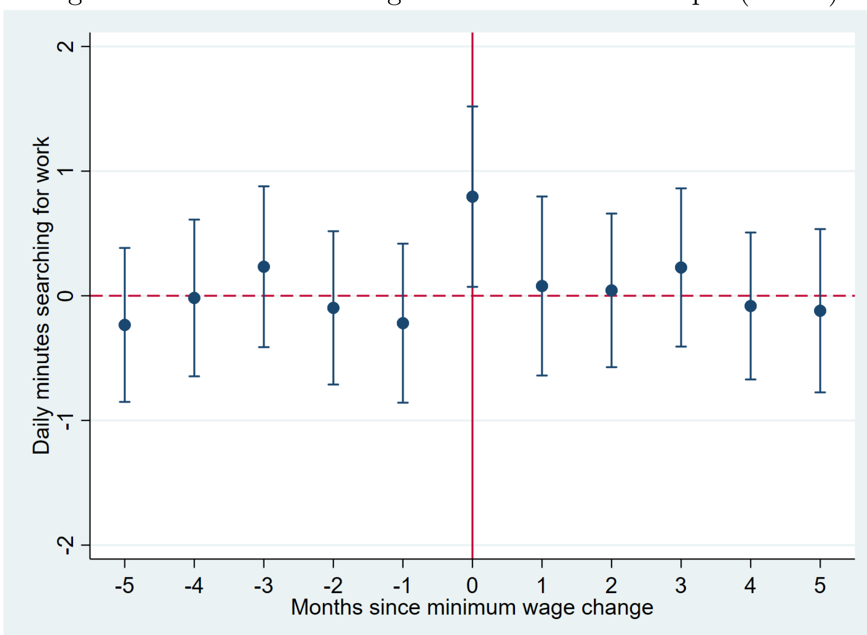
(b) Searching Status



(c) Not in the Workforce

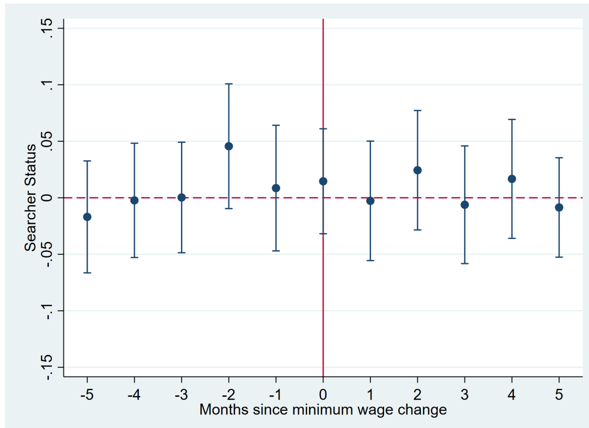
This figure plots coefficients from the regression of employment or searching probability on months before/after treatment, accounting for state-by-year and month fixed effects. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Ninety-five percent confidence intervals are presented. Employment status equals one if the respondent is employed and zero if they are unemployed or not in the workforce. Probability of searching is one if the individual reports searching, regardless of employment status, and zero if they do not. Not if the work force is equal to one if an individuals is not employed or unemployed. All panels use 181,335 observations from the American Time Survey.

Figure 4: Minutes Searching for Work: Whole Sample (ATUS)

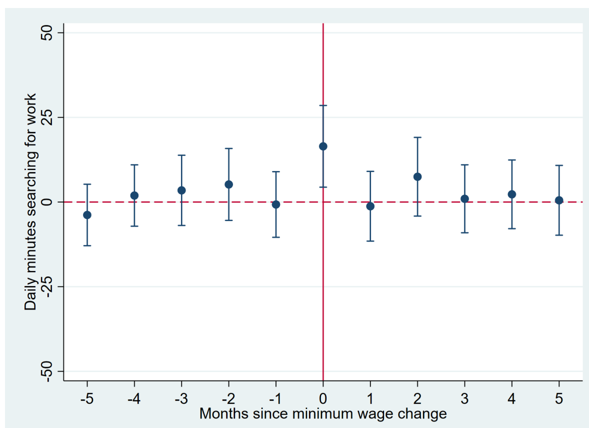


This figure plots coefficients from the regression of minutes searching for work on months before/after treatment dummies, controlling for state-by-year and month fixed effects. The omitted group is all observations not in the 5 months before/after treatment. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. Standard errors are multi-way clustered for state and year/quarter. Ninety-five percent confidence intervals are presented. Results are estimated using 181,335 observations from the American Time Use Survey.

Figure 5: Searching and Minutes Searching: Unemployed (ATUS)



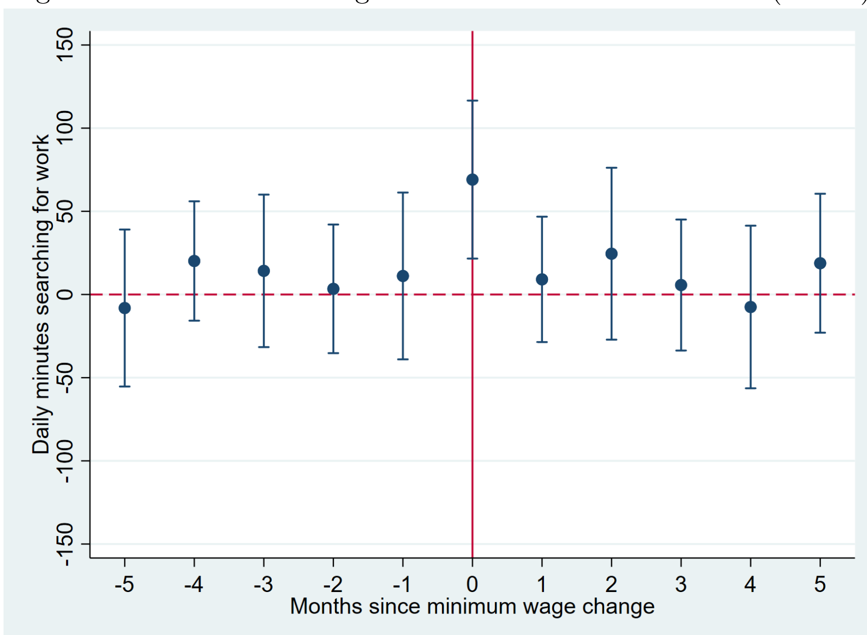
(a) Searching Status



(b) Minutes Searching for Work

This figure plots coefficients from the regression of searching status or minutes searching for work on months before/after treatment dummies, controlling for state-by-year, and month fixed effects. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Unemployment is only measured for those who report being in the workforce. Ninety-five percent confidence intervals are presented. Both results are estimated using 8,720 observations from the American Time Use Survey.

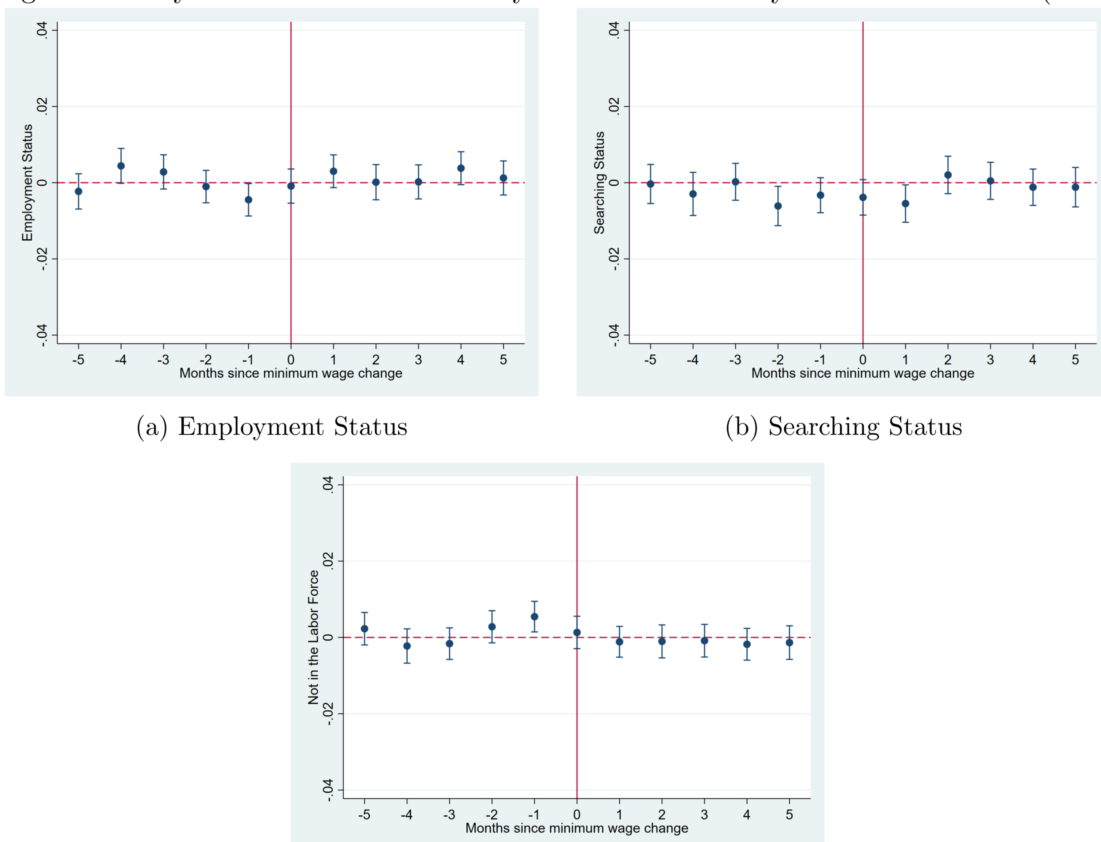
Figure 6: Minutes Searching for Work: Non-Zero Searchers (ATUS)



This figure plots coefficients from the regression of minutes searching for work on months before/after treatment dummies, controlling for state-by-year and month fixed effects. The omitted group is all observations not in the 5 months before/after treatment. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. Standard errors are multi-way clustered for state and year/quarter. Individuals are non-zero searchers if they report any time spent searching (regardless of participation in the workforce). Ninety-five percent confidence intervals are presented. Results are estimated using 2,051 observations from the American Time Use Survey.

A Appendix

Figure A.7: Dynamic Results for State-by-Year and Month-by-Year Fixed Effects (CPS)



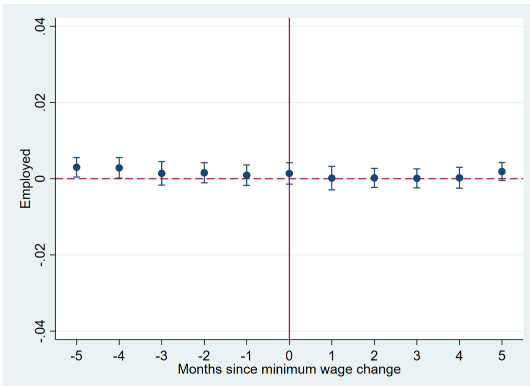
(a) Employment Status

(b) Searching Status

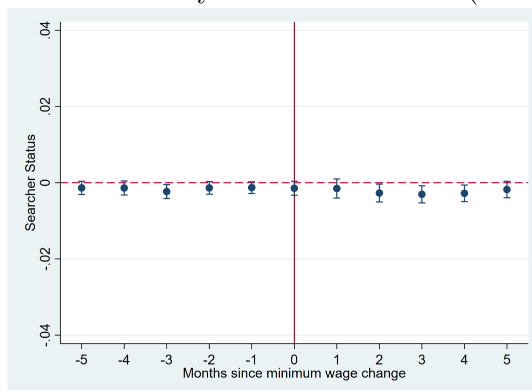
(c) Not in the Labor Force

This figure plots coefficients from regression of probability of employment, searching, or daily minutes searching for work on months before/after treatment dummies, controlling for state and month by year fixed effects. Controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Panel (a) reports results for the probability of employment for the entire sample. Panel (b) presents results for the entire sample and the probability of searching. Panel (c) shows results for the probability of not being in the labor force. Data are from the Current Population Survey.

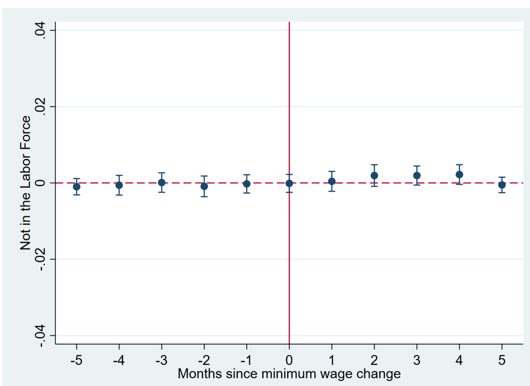
Figure A.8: Dynamic Results for State-by-Year and Month-by-Year Fixed Effects (SIPP)



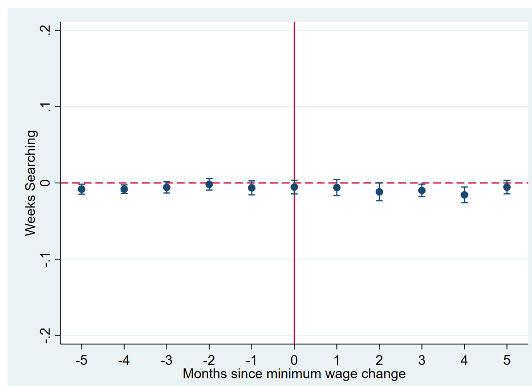
(a) Employment Status



(b) Searching Status



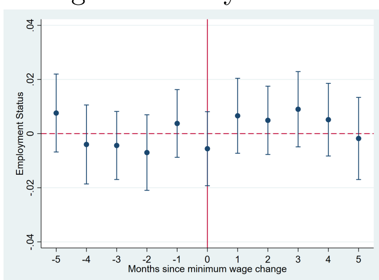
(c) Not in the Labor Force



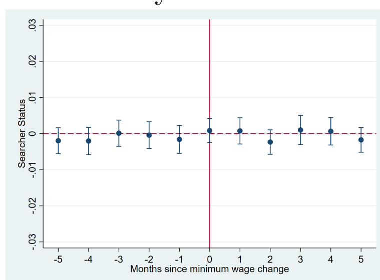
(d) Weeks Searching for Work

This figure plots coefficients from regression of probability of employment, searching, or daily minutes searching for work on months before/after treatment dummies, controlling for state and month by year fixed effects. Controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Panel (a) reports results for the probability of employment for the entire sample. Panel (b) presents results for the entire sample and the probability of searching. Panel (c) shows results for the probability of not being in the labor force and Panel (d) show weeks searching for work in the previous month. Each panel uses all 7,224,651 observations from the Survey of Income Participation Program.

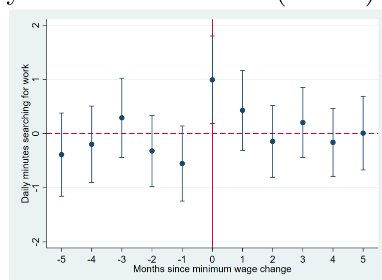
Figure A.9: Dynamic Results for State-by-Year and Month-by-Year Fixed Effects (ATUS)



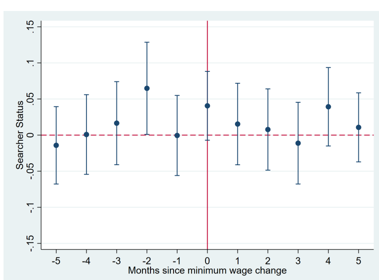
(a) Employment



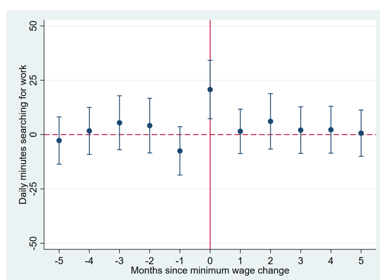
(b) Searching



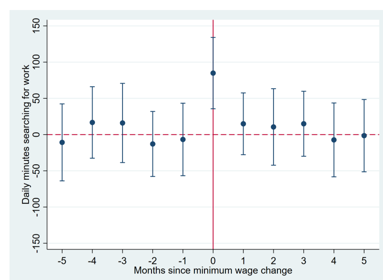
(c) Minutes Searching



(d) Unemployed Searching Status



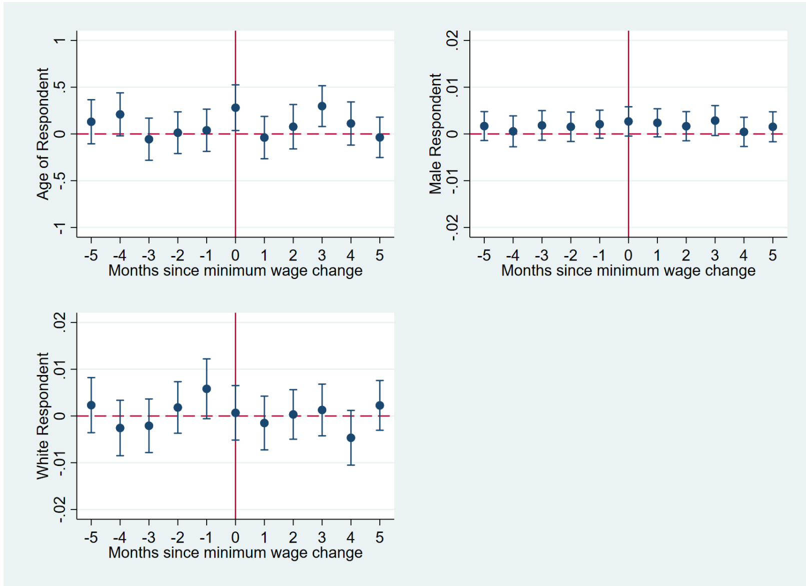
(e) Unemployed Minutes Searching



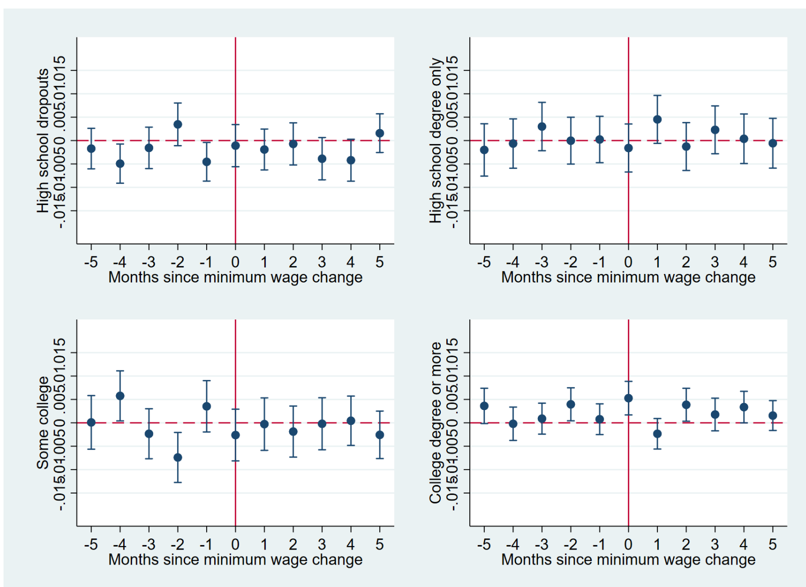
(f) Non-Zero Searchers Minutes Searching

This figure plots coefficients from regression of probability of employment, searching, or daily minutes searching for work on months before/after treatment dummies, controlling for state and month by year fixed effects. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Panel (a) reports results for the probability of employment for the entire sample. Panel (b) presents results for the entire sample and the probability of searching. Panel (c) presents results for the entire sample and daily minutes searching for work. Panel (d) and (e) present results for the unemployed for probability of searching and minutes searching respectively. Finally, Panel (f) presents results for those who report non-zero search for minutes searching for work. Data are from the American Time Use Survey.

Figure A.10: Respondent Characteristics (CPS)



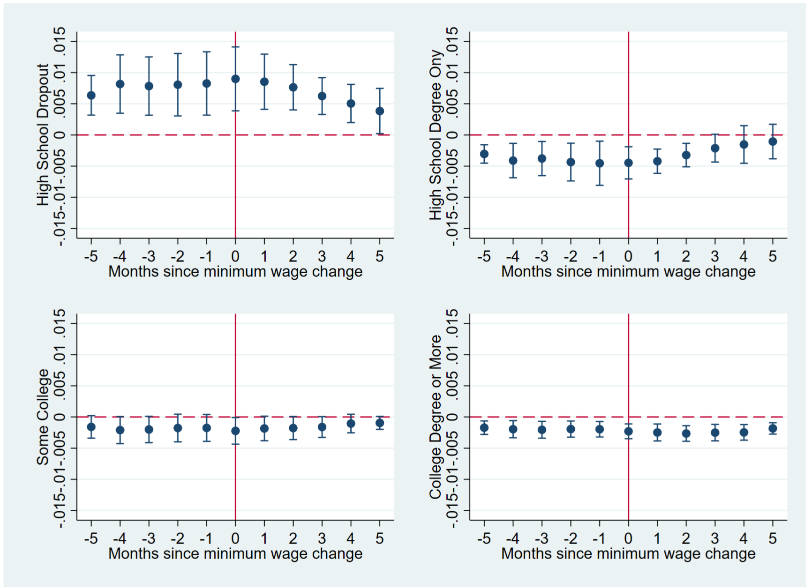
(a) Age, Gender, Race



(b) Education

This figure plots coefficients from the regression of level of education indicator variables on months before/after treatment dummies, controlling for state-by-year and month fixed effects. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Each graph uses the entire sample of 2,199,503 observations. Figure (a) shows results for respondent age, gender and race. Figure (b) shows results for respondent education level. For figure (b) the outcome variable for the upper left graph is a one for all individuals who complete less than a high school degree and zero for all others. For the upper right graph, the outcome variable is one for those with only a high school degree and zero for everyone else. The outcome variable for the lower left graph is one for those who complete more than a high school degree, but less than a four year college degree, and zero for all others. Finally, the outcome variable for the bottom right graph takes on a value of one for those with a college degree or more and zero for anyone with less than a four year college degree. Data are from the Current Population Survey.

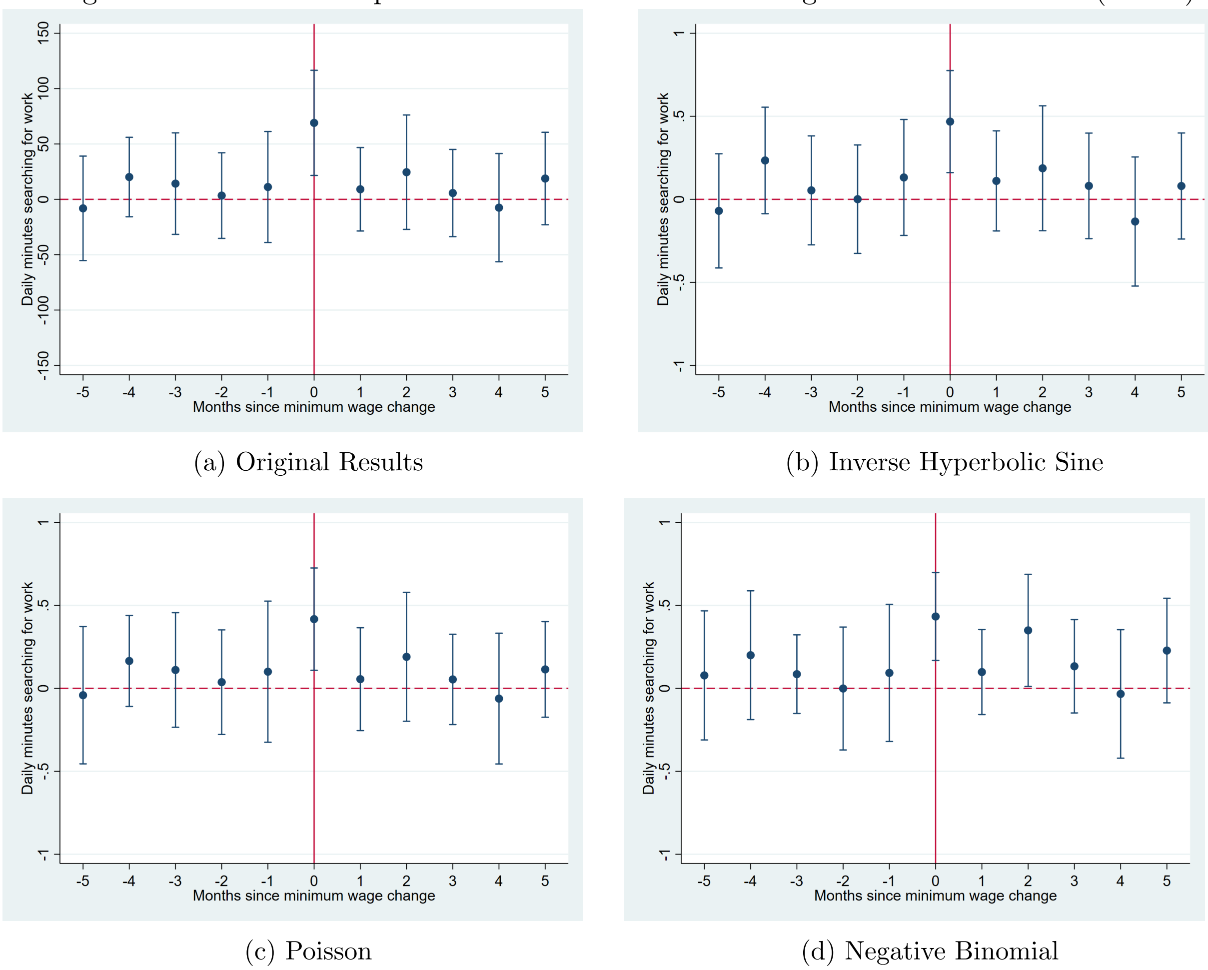
Figure A.11: Respondent Characteristics (SIPP)



(a) Education

This figure plots coefficients from the regression of level of education indicator variables on months before/after treatment dummies, controlling for state-by-year and month fixed effects. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Each graph uses the entire sample of 7,224,651 observations. Figure (a) shows results for respondent education level. For figure (a) the outcome variable for the upper left graph is a one for all individuals who complete less than a high school degree and zero for all others. For the upper right graph, the outcome variable is one for those with only a high school degree and zero for everyone else. The outcome variable for the lower left graph is one for those who complete more than a high school degree, but less than a four year college degree, and zero for all others. Finally, the outcome variable for the bottom right graph takes on a value of one for those with a college degree or more and zero for anyone with less than a four year college degree. Each panel uses all 7,224,651 observations from the Survey of Income Participation Program.

Figure A.12: Alternate Specifications for Minutes Searching: Non-Zero Searchers (ATUS)



(a) Original Results

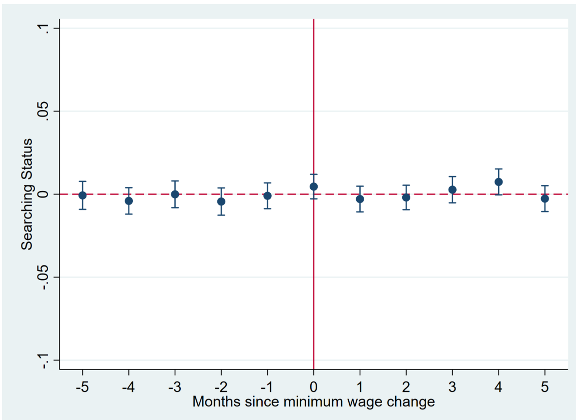
(b) Inverse Hyperbolic Sine

(c) Poisson

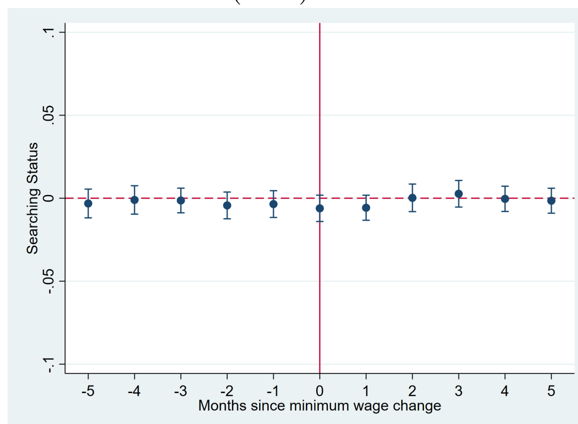
(d) Negative Binomial

This figure plots coefficients from the regression of minutes searching for work on months before/after treatment dummies, controlling for state-by-year and month fixed effects. The omitted group is all observations not in the 5 months before/after treatment. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. Standard errors are multi-way clustered for state and year/quarter. Individuals are non-zero searchers if they report any time spent searching (regardless of participation in the workforce). Ninety-five percent confidence intervals are presented. Panel (a) is a replication of Figure 4. Panel (b) transforms minutes searching for work using inverse hyperbolic sine. Panel(c) presents results for the Poisson specification and Panel (d) shows results for the negative binomial specification. Data are from the American Time Use Survey.

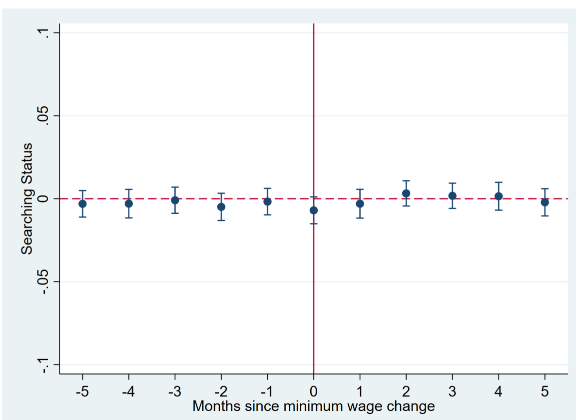
Figure A.13: Search by Education Level (CPS)



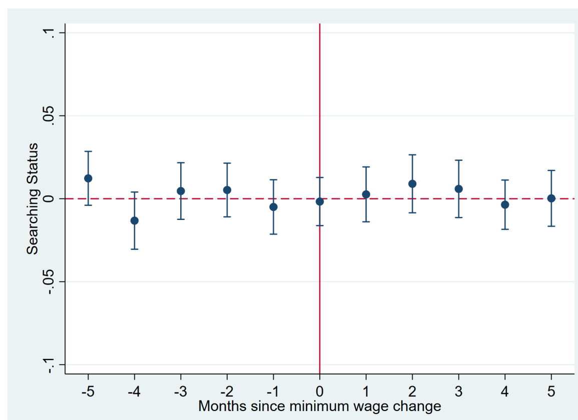
(a) High School Dropouts



(b) High School Degree Only



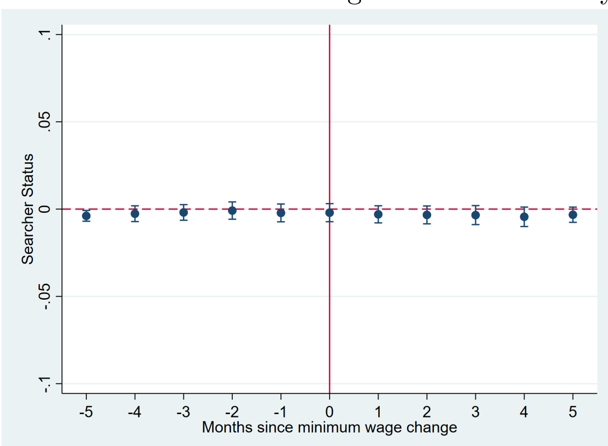
(c) Some College



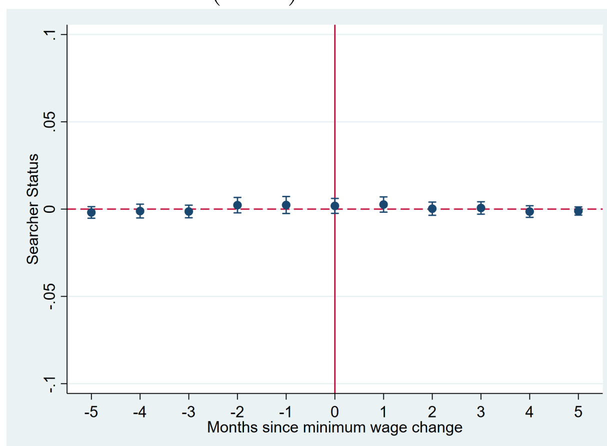
(d) College Degree or More

This figure plots coefficients from the regression of searching probability on months before/after treatment, accounting for state-by-year and month fixed effects. Controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Ninety-five percent confidence intervals are presented. Probability of searching is only recorded for the unemployed and some not in the labor force. Data are from from the Current Population Survey.

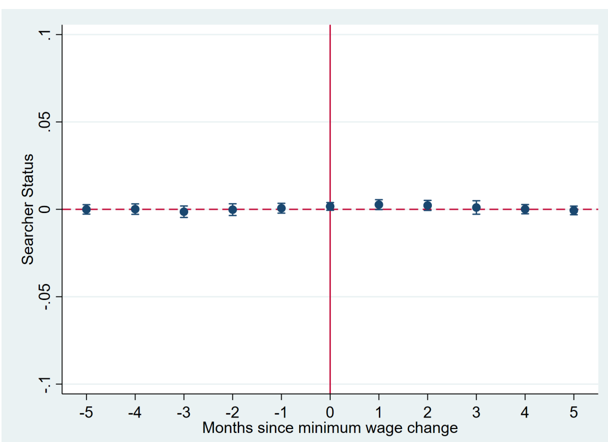
Figure A.14: Search by Education Level (SIPP)



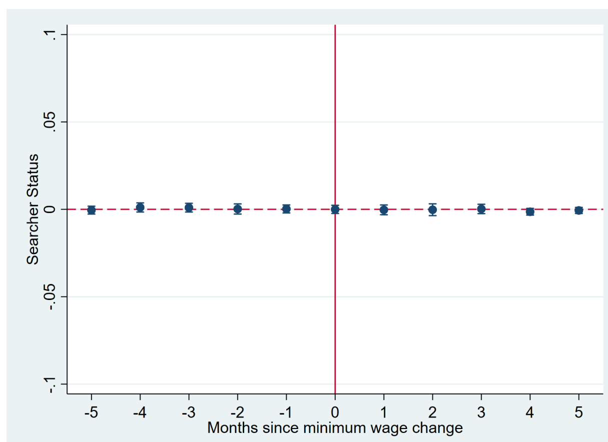
(a) Less than High School Degree



(b) High School Degree Only



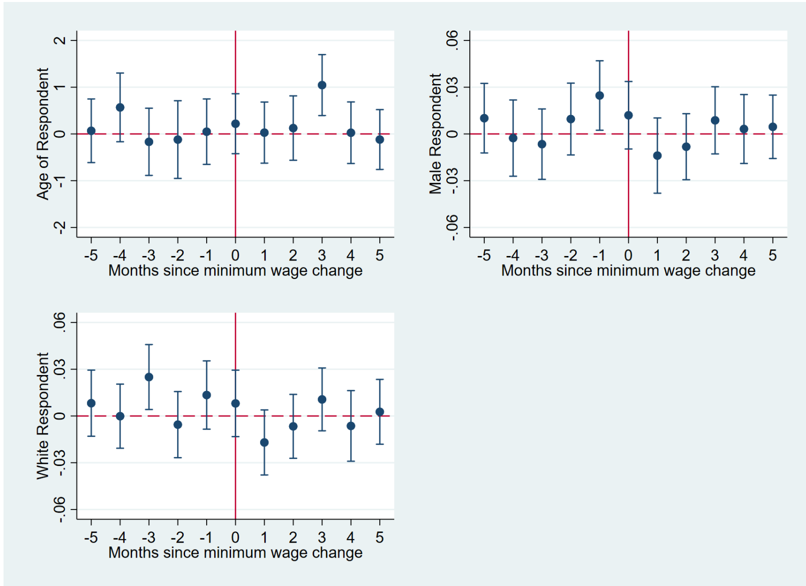
(c) Some College



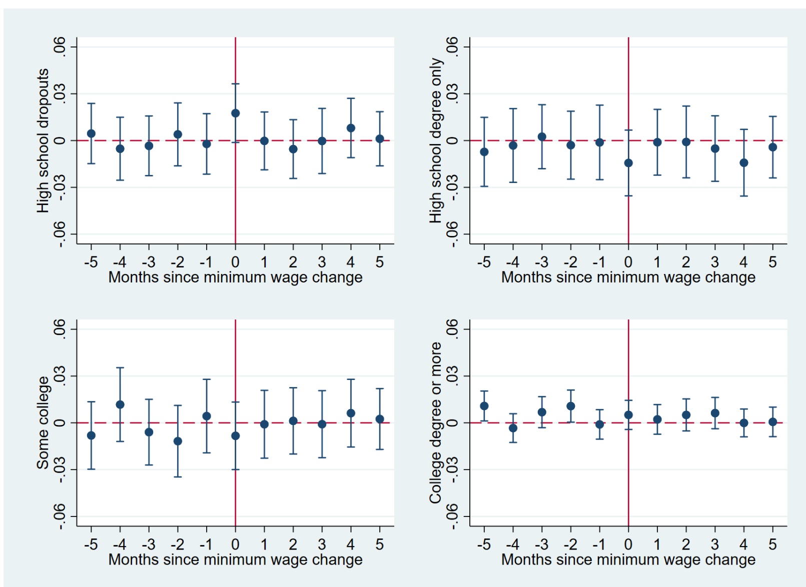
(d) College Degree or More

This figure plots coefficients from the regression of searching probability on months before/after treatment, accounting for state-by-year and month fixed effects. Individual level fixed effects are included. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Ninety-five percent confidence intervals are presented. Data are from the Survey of Income and Program Participation.

Figure A.15: Characteristics of Searchers (CPS)



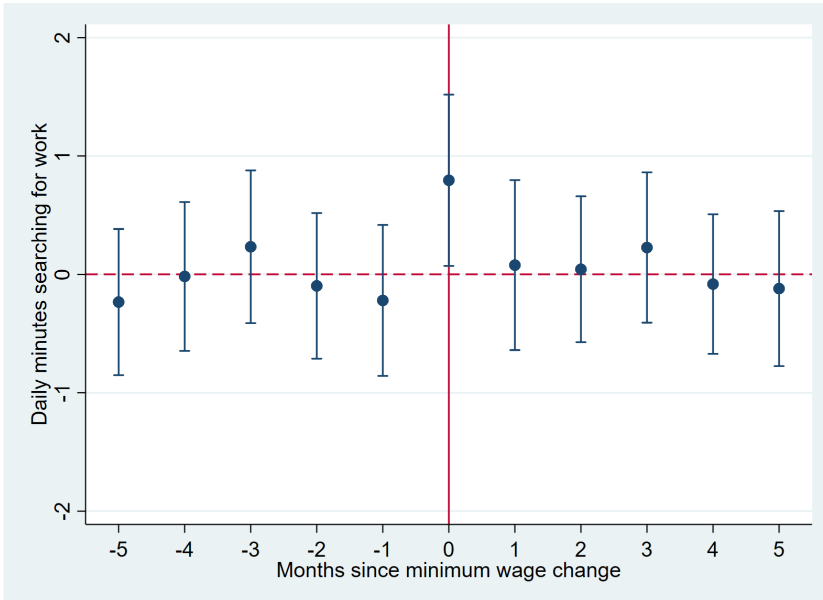
(a) Age, Gender, Race



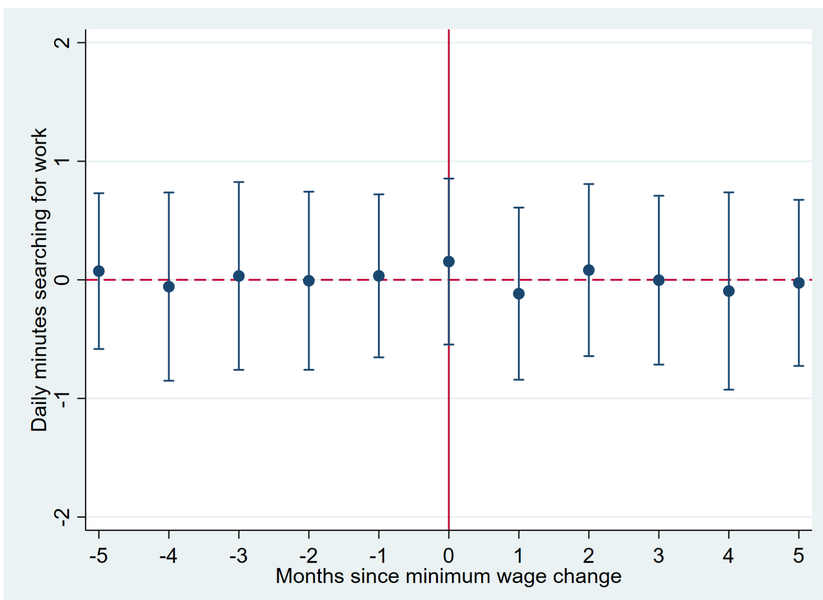
(b) Education

This figure plots coefficients from the regression of level of education indicator variables on months before/after treatment dummies, controlling for state-by-year and month fixed effects. The omitted group is all observations not in the 5 months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Each graph uses the sample of searchers (123,289 observataions). Figure (a) shows results for respondent age, gender and race. Figure (b) shows results for respondent education level. For figure (b) the outcome variable for the upper left graph is a one for all individuals who complete less than a high school degree and zero for all others. For the upper right graph, the outcome variable is one for those with only a high school degree and zero for everyone else. The outcome variable for the lower left graph is one for those who complete more than a high school degree, but less than a four year college degree, and zero for all others. Finally, the outcome variable for the bottom right graph takes on a value of one for those with a college degree or more and zero for anyone with less than a four year college degree. Data are from the Current Population Survey.

Figure A.16: Placebo Results: Entire Sample (ATUS)



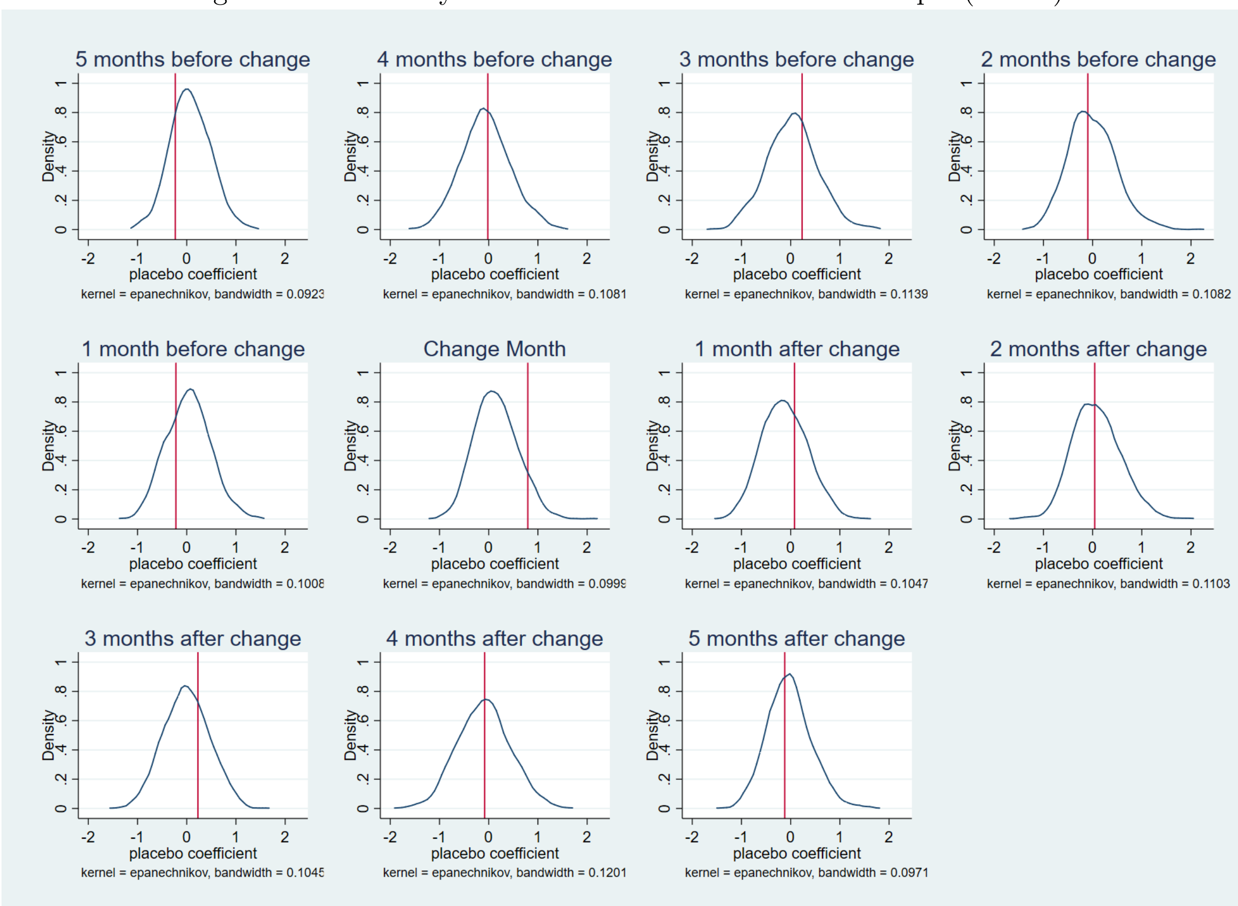
(a) Minutes Searching for Work Results



(b) Placebo Results

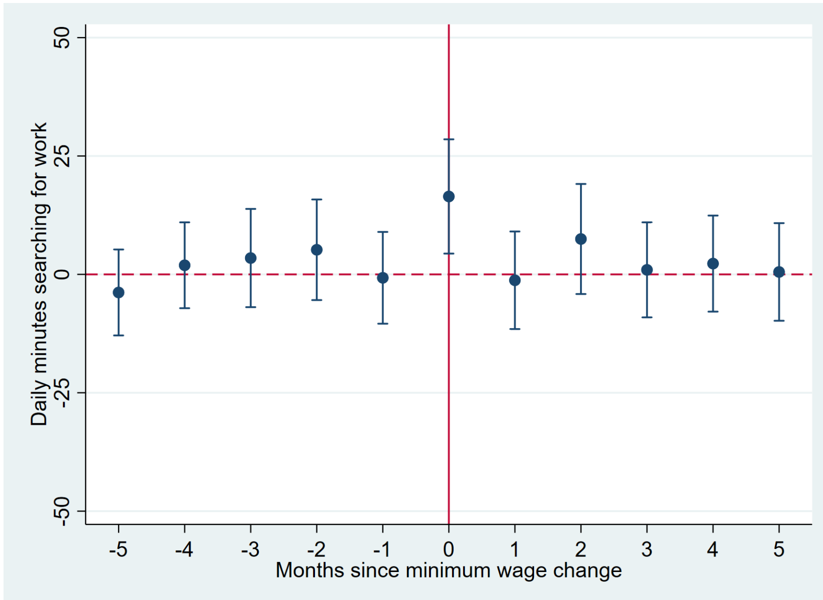
This figure plots coefficients from regression of daily minutes searching for work on months before/after treatment dummies, controlling for state-by-year and month fixed effects. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in months before/after treatment. Standard errors are multi-way clustered for state and year/quarter. Panel (a) is a replication of Figure 2. Panel (b) presents placebo results from 1000 replications. The mean placebo coefficients and mean 95 percent confidence intervals are plotted for Panel (b).

Figure A.17: Density of Placebo Coefficients: Entire Sample (ATUS)

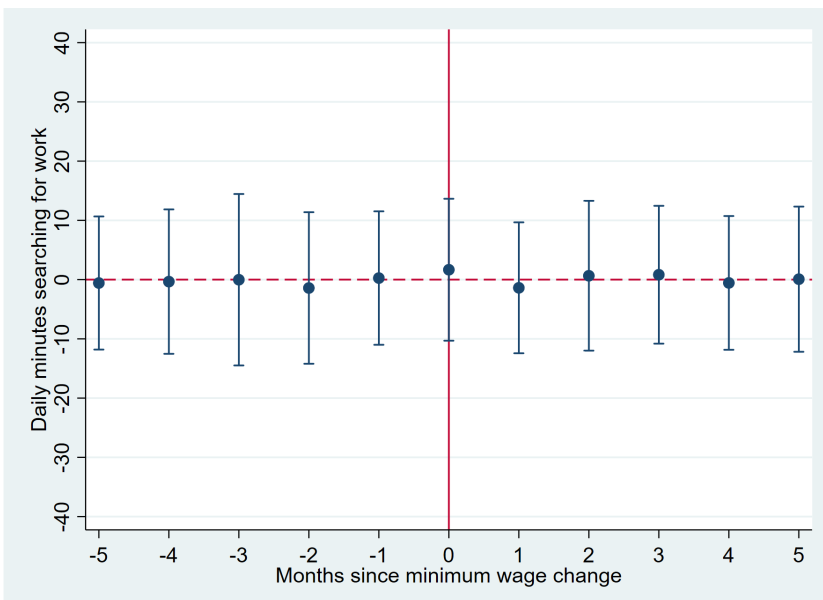


Above are the resulting distributions of 1,000 placebo coefficient estimates of Equation (1) for minutes searching for work. The lines represent the coefficients estimated in our true data for daily minutes searching for each time period.

Figure A.18: Placebo Results: Unemployed (ATUS)



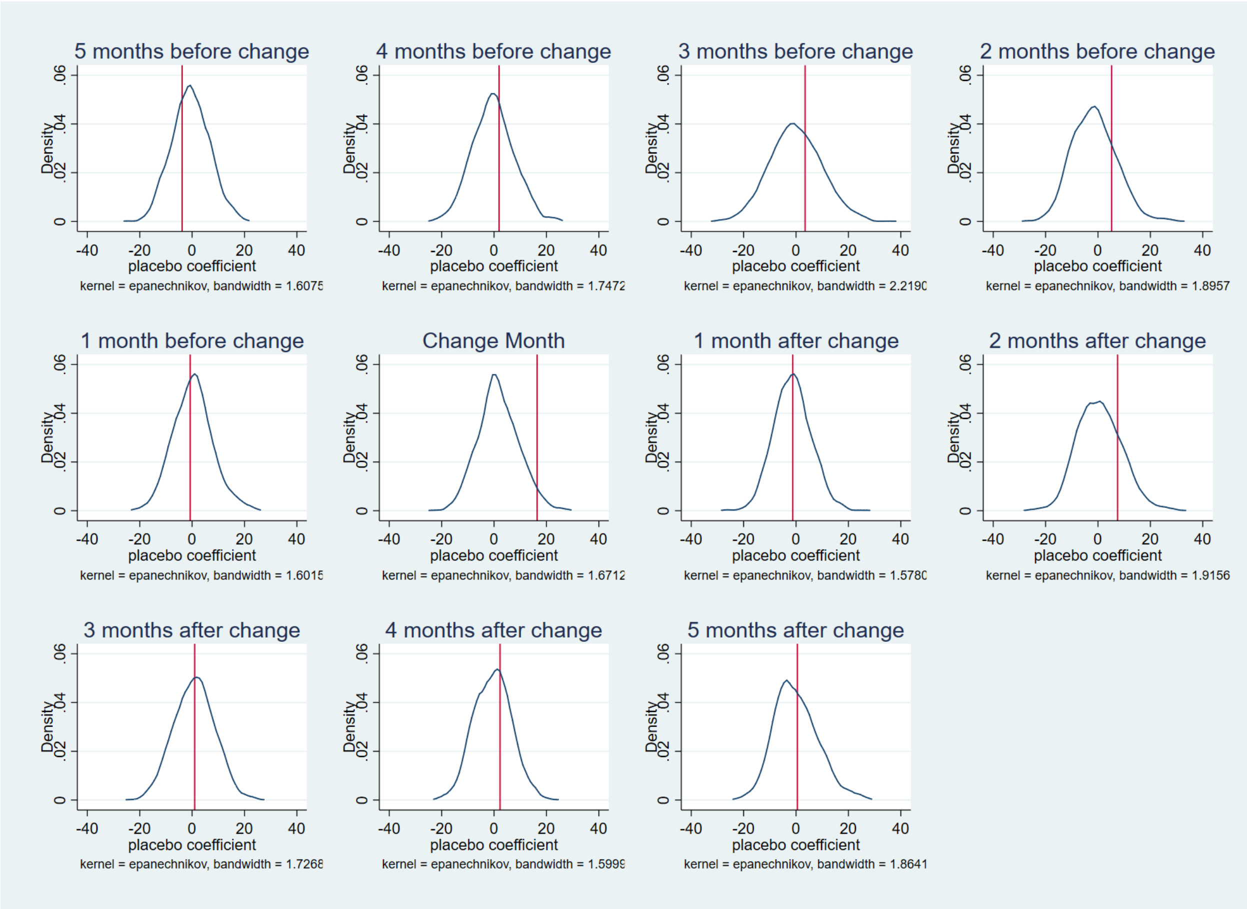
(a) Minutes Searching for Work Results



(b) Placebo Results

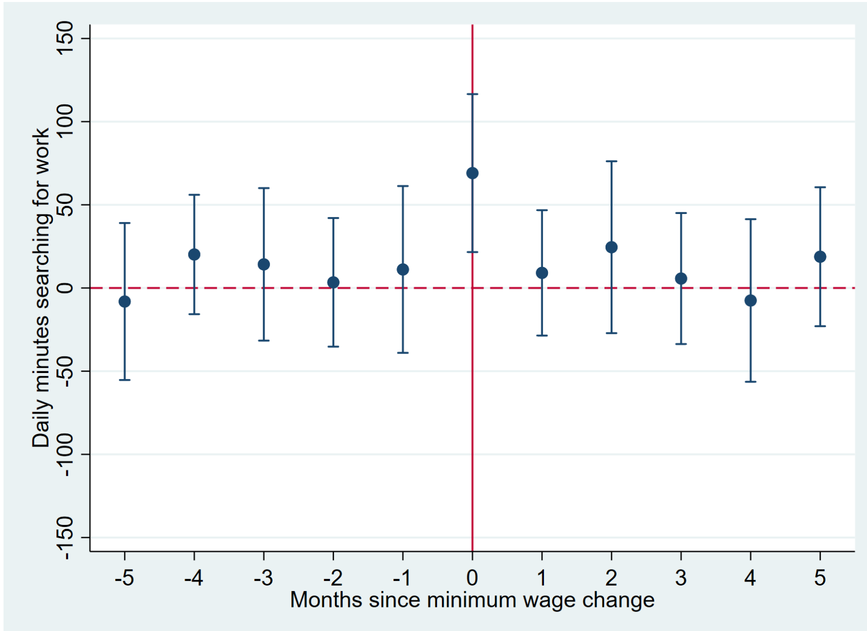
This figure plots coefficients from regression of probability of searching or minutes searching for work on months before/after treatment dummies, controlling for state by year and month fixed effects. Standard errors are multi-way clustered for state and year/quarter. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in months before/after treatment. Only those who report unemployment are included. Panel (a) is a replication of Figure 3 panel (a). Panel (b) shows placebo results from 1000 replications. The mean placebo coefficients and mean 95 percent confidence intervals are plotted for Panel (b).

Figure A.19: Density of Placebo Coefficients: Unemployed (ATUS)

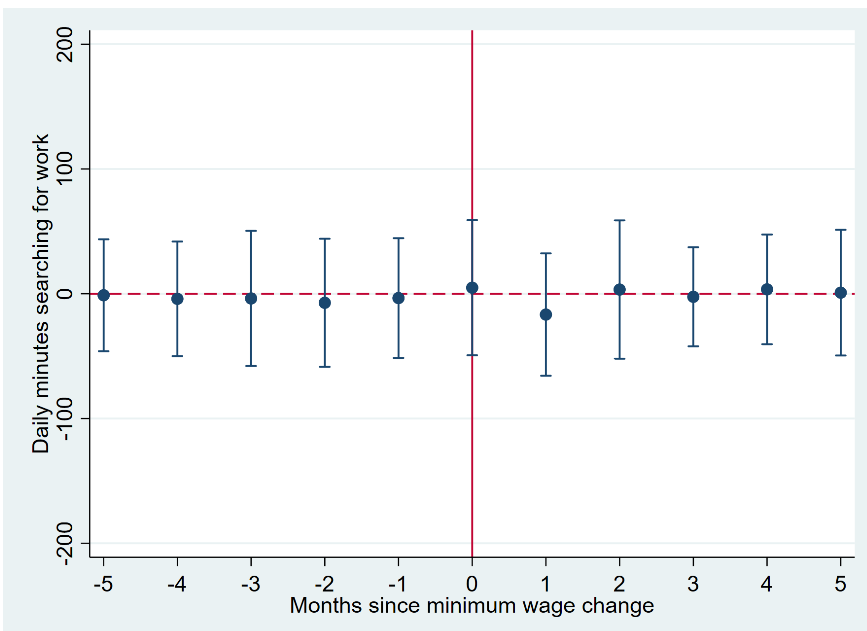


Above are the resulting distributions of 1,000 placebo coefficient estimates of Equation (1) for minutes searching for work. The lines represent the coefficients estimated in our true data for daily minutes searching for each time period. Only the unemployed are included.

Figure A.20: Placebo Results: Non-Zero Searchers (ATUS)



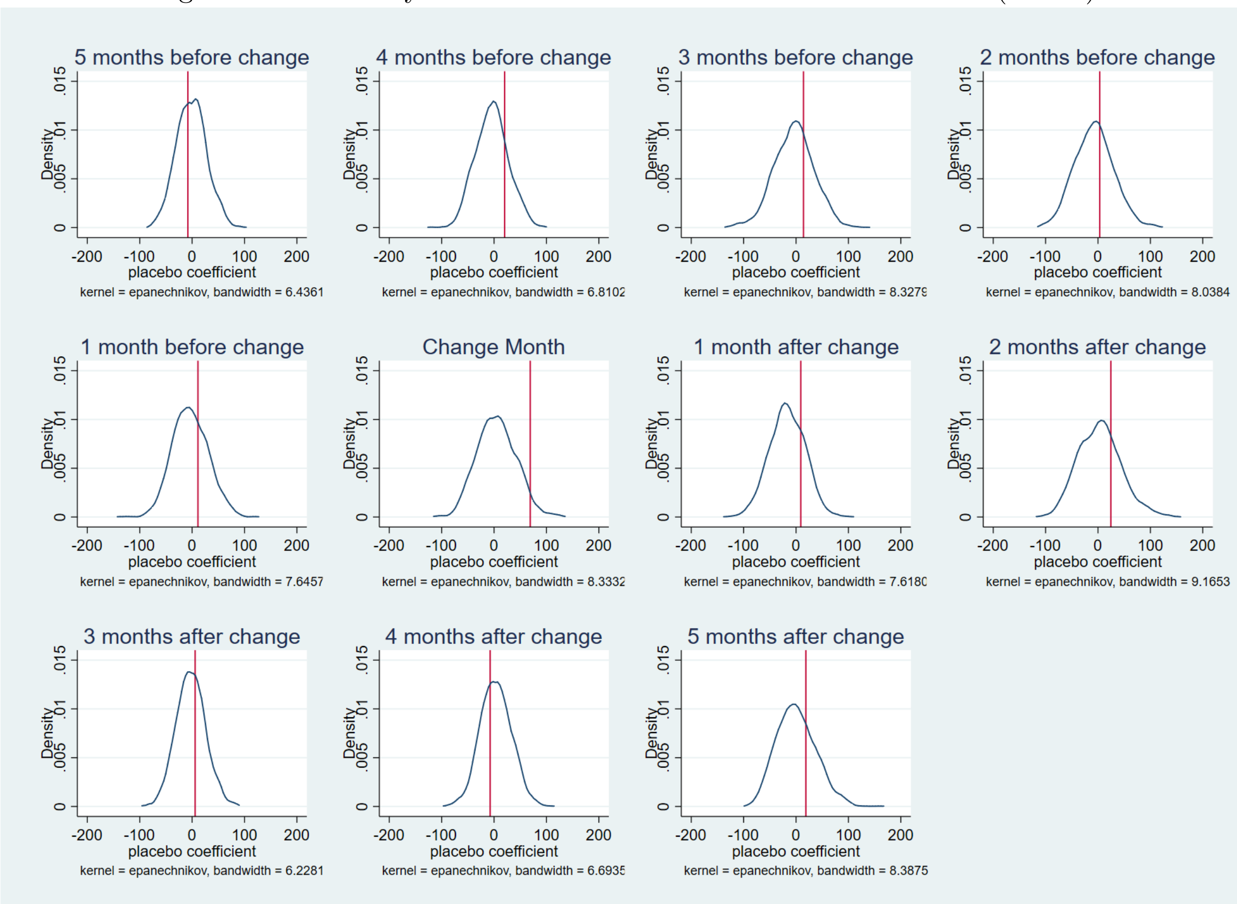
(a) Minutes Searching for Work Results



(b) Placebo Results

This figure plots coefficients from regression of probability of searching or minutes searching for work on months before/after treatment dummies, controlling for state by year and month fixed effects. Standard errors are multi-way clustered for state and year/quarter. An indicator for week or weekend interview and controls for age (age and age^2), education level (indicators for less than a high school degree, high school degree, some college and college graduate or more), race (indicator for white or not), gender (indicator for female or not), and unemployment benefits (week duration of benefits available) are included. The omitted group is all observations not in months before/after treatment. Only those who report non-zero search are included. Panel (a) is replication of Figure 4. Panel (b) shows placebo results from 1000 replications. The mean placebo coefficients and mean 95 percent confidence intervals are plotted for Panel (b).

Figure A.21: Density of Placebo Coefficients: Non-Zero Searchers (ATUS)



Above are the resulting distributions of 1,000 placebo coefficient estimates of Equation (1) for minutes searching for work. The lines represent the coefficients estimated in our true data for daily minutes searching for each time period. Only the those who report non-zero search are included.