Jobs Reports Affect Personal Job Loss Expectations

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Abstract

Using data from the New York Federal Reserve's Survey of Consumer Expectations, we study how the United States Bureau of Labor Statistics' Employment Situation Reports (Jobs Reports) affect individuals' expectations about the likelihood of losing their own job. We do this in two steps. First, we estimate the information shocks of the Jobs Reports on expectations about the development of the national unemployment rate in the next twelve months. We do this by comparing survey responses shortly before and after publication of the reports. Second, we estimate how these shocks affect individuals' expectations about losing their own job in the same time frame. The results show that when a report is estimated to increase beliefs about the likelihood of the unemployment rate increasing by 1 percentage point, beliefs about the likelihood of personal job loss during that time increase by up to 0.22 percentage points. We further find that the information shock negatively affects individuals' beliefs about the likelihood of finding a new job if they were to lose their current one, but (surprisingly) positively affects individuals' beliefs about the likelihood of voluntarily leaving their job. Our results are robust to the use of different bandwidths around the reports' publication dates and placebo treatments provide reassurance that the information shock is indeed the mechanism driving the result.

Keywords: Job loss, expectations, unemployment rate
JEL codes: D83, D84, E24, J20, J64

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1 Introduction

Providing individuals with information about the macroeconomy affects their personal economic expectations and behavior (Roth & Wohlfart, 2020). This evidence is based on an experimental study, however; it is unclear to what degree this is true for information that people acquire in their day-to-day lives. In this paper, we study the effect of the publication of the United States Bureau of Labor Statistics' Employment Situation Reports on individuals' expectations about the likelihood of losing their own job.

Every month, the United States Bureau of Labor Statistics publishes its Employment Situation Report, often referred to as the 'Jobs Report'. The report contains, among other things, information about the unemployment rate in the United States. As the Jobs Reports receive considerable attention in the media, it is likely that these reports play an important role in shaping individuals' expectations about the employment situation at the national level. The question we ask is whether it affects expectations about their own job security as well.

Understanding how information about the development of the unemployment rate affects individuals' expectations about the likelihood of losing their job is important, as these expectations have a wide range of implications. At the individual level, an increase in the expected likelihood of job loss is related to a decrease in expected earnings (Stephens Jr, 2004; Campbell, Carruth, Dickerson, & Green, 2007) as well as (and perhaps therefore) consumption (Pettinicchi & Vellekoop, 2019; Hendren, 2017; Brown & Taylor, 2006), saving and borrowing (Kłopocka, 2017). Fears of unemployment tend to be warranted, as they are indeed related to actual job loss (Dickerson & Green, 2012) and lower wage growth (Campbell et al., 2007). Economic expectations affect health outcomes too. The more likely individuals think it is that they will lose their job, the higher they score on depression scales (Mandal,

We make use of the Survey of Consumer Expectations. Source: Survey of Consumer Expectations, © 2013-2020 Federal Reserve Bank of New York (FRBNY). The SCE data are available without charge at http://www.newyorkfed.org/microeconomics/sce and may be used subject to license terms posted there. FRBNY disclaims any responsibility for this analysis and interpretation of Survey of Consumer Expectations data.

Ayyagari, & Gallo, 2011) and the more likely they are to develop a range of health issues (Caroli & Godard, 2016). At the macroeconomic level, the increase in precautionary savings because of unemployment fears may lead to a deflationary spiral under incomplete financial markets (Den Haan, Rendahl, & Riegler, 2018; Ravn & Sterk, 2017).

We employ an event study approach using data from the New York Federal Reserve's Survey of Consumer Expectations to study the extent to which the Jobs Reports affect individuals' expectations. Event study approaches have been commonly used in research on the effects of monetary policy announcements on macroeconomic expectations of various types of agents (see e.g., Bulligan, 2018; Bottone and Rosolia, 2019; De Fiore, Lombardi, and Schuffels, 2021; Lamla and Vinogradov, 2019; Mertens, Lewis, and Makridis, 2020). We restrict our sample to include working individuals only.

The two most relevant questions in the Survey of Consumer Expectations for our analyses are about (a) individuals' beliefs about the likelihood that the unemployment rate will increase in the twelve months following their response and (b) their beliefs about the likelihood that they will lose their own job in the same time frame. For every published Jobs Report, we first estimate its impact on individuals' beliefs about the development of the national unemployment rate by comparing respondents who answered the survey shortly before the report's publication to those who answered the survey shortly after the report's publication. Second, we estimate how the change in the expectations about the national unemployment rate is related to individuals' expectations about losing their own job.

We cannot use the full sample for both steps, however. If there is a correlation between individuals' expectations about the aggregate unemployment and their expectations about personal job loss caused by their personal circumstances, this would bias the results. Especially as the number of observations surrounding each Jobs Report is limited. It seems likely that the two outcomes are indeed correlated as described. Earlier literature has shown that individuals who experience unemployment, become more pessimistic about aggregate unemployment as well (Kuchler & Zafar, 2019). There is further evidence that the way in which individuals perceive macroeconomic conditions depends on their lived experiences. For instance, individuals give disproportional weight to inflation experienced during their lifetime when forming inflation expectations (Malmendier & Nagel, 2016). This also impacts behavior. Having experienced low stock market returns decreases the willingness to take financial risks and own stocks (Malmendier & Nagel, 2011), and growing up in a recession increases the relative importance individuals assign to income compared to meaning in their jobs (Cotofan, Cassar, Dur, & Meier, 2020). We tackle the above mentioned issue by employing two ways of splitting the sample between the first and second step.

In the first strategy, we split the sample in two mutually exclusive groups. We use the first group to estimate the impact of the Jobs Report on the expectations about the national unemployment rate. We use this estimate as the treatment intensity variable when we estimate the impact of the Jobs Report on personal job loss expectations in the second group. The advantage of this methodology is that we avoid the bias caused by individual-level correlations between expectations about the national unemployment rate and personal job loss expectations. The downside of this methodology is that our number of observations is effectively cut in half, significantly decreasing statistical power.

Our second strategy tackles the latter issue. It involves using a jackknife procedure. For each individual, we estimate the information shock of the Jobs Report on expectations about the national unemployment rate among all other participants in the survey. We then use this leave-out estimate as the treatment intensity variable in the second step. While this strategy does not negatively impact our effective sample size, it does have a different downside. While the national unemployment rate expectations of the individual do not affect the estimate assigned to them, they do affect the estimate assigned to every other individual. This means that those with the most extreme opinions about the national unemployment rate, get assigned the most conservative coefficients. This may lead to a downward bias. We show, however, that the variance in interpretation predominantly comes from between-Jobs Report differences. This means the bias is unlikely to be large.

We find that a Jobs Report we estimate to increase expectations about the likelihood that the unemployment rate will increase by 1 percentage point, leads to an increase of up to 0.22 percentage points in the expected likelihood of personal job loss during the same period. While the exact size of the estimate varies by bandwidth and approach used, the qualitative impact is consistent across these dimensions. Using the jackknife procedure, so as to conserve power, we find some evidence that expectations about personal job loss are more strongly affected for individuals below 40, and above 60 years of age, than for those between 40 and 60 years of age. We further show that Jobs Reports that lead to an increase in expectations about the likelihood of the unemployment rate increasing also negatively affect individuals' expected likelihood of finding a new job if they were to lose their current one. Somewhat surprisingly, the information shock positively affects individuals' expectations about leaving their jobs voluntarily. We argue that the most likely reason for this is increased search effort as a response to larger perceived job uncertainty. We find no evidence of an effect on expected earnings and expected spending. To ensure our result is not driven by idiosyncratic shocks affecting both unemployment expectations and personal job loss expectations, we conduct a placebo treatment analysis: we move the 'treatment' date forward by two weeks and show that the effects of the Jobs Reports disappear when we do so.

The rest of this paper is structured as follows. Section 2 provides more context on the Jobs Reports. Section 3 describes the data and methodology in more detail. Section 4 presents our main results, as well as robustness checks of our estimates, our analyses of heterogeneous treatment effects and of alternative outcomes. Section 5 concludes.

2 The Jobs Reports

The Jobs Reports, formally known as the Employment Situation Summaries, are monthly-published reports by the United States Bureau of Labor Statistics. The reports contain information on the change in nonfarm payroll employment as well as the unemployment rate in the United States. The report about a certain month is generally published in the first week of the subsequent month.

The reports garner considerable attention – both on financial markets and among the wider public. A number of event studies found significant movements in prices and trading activity after publications of Jobs Reports on exchange rate markets (e.g., Harris and Zabka, 1995), bond markets (e.g., Fleming and Remolona, 1997; Green, 2004) and stock markets (e.g., Graham, Nikkinen, and Sahlström, 2003; Rangel, 2011; Chan and Gray, 2018). This attention on financial markets is mirrored in economic journalism, the channel through which large parts of the general public receive information about the Jobs Reports. The New York Times referred to the monthly report as "the government's most watched economic indicator" (2018). Indeed, Google shows that approximately 10,900 news articles have been published referencing the Jobs Reports between June of 2013 and October of 2019. At the time of writing this paper, ahrefs.com's backlink checker shows that the main employment situation summary page has 310,550 backlinks[1], which are links from other websites referring to the Jobs Report. The PDF version of the document[2] has 143,720.

Individuals also look for the Jobs Reports themselves. Panel (a) of Figure 1 shows the average relative search interest for the Jobs Reports from June 2013 to October 2019 in the days surrounding the report's publication. The Panel clearly shows that interest in the reports peaks on the day of publication. There is some anticipation visible in the days leading up to the report's publication, as well as some persisting interest afterwards. However, search volume is barely higher than 20% of the publication day peak on the days right before and after, declining to below 10% on the other days.

[Figure 1 about here.]

Unfortunately, Google Trends do not provide any insight into the actual search volume. However, Panel (b) shows how the search interest for the Jobs Reports compares to search

[1]https://ahrefs.com/backlink-checker; Backlinks for URL https://www.bls.gov/news.release/empsit.nr0.htm; Retrieved 31 January, 2021.

[2]https://www.bls.gov/news.release/pdf/empsit.pdf

interest for the Federal Open Market Committee (FOMC) meetings. These FOMC meetings provide a nice comparison as they are also one-day events that provide information about the state of the macroeconomy. Similar to the search interest for the Jobs Reports, there are clear search interest peaks in the periods where FOMC meetings took place. However, the search interest for the Jobs Reports are consistently higher than that for the FOMC meetings. Given the findings of earlier literature that the FOMC meetings have an impact on peoples' expectations (see e.g., De Fiore et al., 2021; Mertens et al., 2020), it is likely that individuals are sufficiently aware of the Jobs Reports.

3 Data & Methodology

3.1 Data

The Survey of Consumer Expectations conducted by the Federal Reserve Bank of New York is a monthly survey with a rotating panel (see Armantier, Topa, Van der Klaauw, and Zafar (2017) for a detailed overview of the survey). We use data from the main module of the survey collected between June of 2013 and October of 2019 and restrict our sample to working individuals.

In the survey, respondents are asked about their expectations of a wide range of macroeconomic variables, such as the inflation rate, interest rate, stock prices, house prices and, of course, unemployment. In addition, people are asked about expectations related to their personal life, such as the likelihood that they will be financially better off in twelve months. Two questions are of particular importance to us. The first relates to the expectations about the development of unemployment in the United States as a whole. The question reads: *"What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?"*. Individuals can answer on a scale from 0 to 100. Unfortunately, the survey does not include a question in which respondents are asked about their estimates of the national unemployment rate. This makes it impossible for us to control for their level expectations, or compare their prior to the contents of the Jobs Reports. The second question is about their expectations regarding their own job and reads as follows: *"What do you think is the percent chance that you will lose your main/current job during the next 12 months?"*. The scale of this question is the same.

[Figure 2 about here.]

Panels (a) and (b) of Figure 2 respectively show the levels and indexed value of the answers to these questions and the actual unemployment rate over time. On average, individuals think that the likelihood that unemployment in the United States will increase in the next 12 months is slightly below 40%. This value hardly changed between 2013 and 2019. This is somewhat surprising, given the steady decrease of unemployment from 7.5 to 3.5% during this period. Individuals estimate that the likelihood that they will lose their job in the next 12 months is approximately 15%. Likewise, we do not find a strong indication that this figure is trending in any direction.

In addition to the questions mentioned above, the survey also contains questions about individuals' expectations of leaving their jobs voluntarily, the likelihood of finding a new job if they were to be displaced, expected changes in earnings conditional on remaining in their jobs and expected changes in spending. Appendix A provides an overview of the relevant questions. Lastly, the data contain broad information on peoples' age, numeracy skills, education level and household income.

Apart from the survey data, we have information on the exact date on which the Jobs Reports are published and their contents. We retrieve this information from the Bureau of Labor Statistics' website[3]. In total, 77 reports are included in our analyses.

3.2 Methodology

As the Jobs Reports provide individuals with information on the current unemployment rate, whereas the question in the Survey of Consumer Expectations is about the likelihood

[3] https://www.bls.gov/bls/news-release/empsit.htm

of it increasing in the next twelve months, it is not clear how individuals should interpret an individual Jobs Report. Analogous to monetary policy shocks identified using high-frequency data, we compare responses shortly before and after report publications to estimate the surprise component of Jobs Reports. We interpret the difference as the effect of the report's publication.

Figure 3 provides a visual representation of the treatment assignment if we were to choose a bandwidth of three days around the report. We exclude individuals who respond on the day of the report from the sample, as we do not have information on the exact time of day at which they responded. This means they could have responded either before or after the publication of the Jobs Report. Individuals who responded in the three days before the publication of the report are assigned to the control group. Individuals who responded in the three days after the publication of the report are assigned to the treatment group. Those who responded outside of this three-day bandwidth are excluded from the sample. In our estimations, we use bandwidths that vary from one to seven days. We refer to the group of individuals who responded within the bandwidth as a 'cohort'.

[Figure 3 about here.]

We analyze the impact of the Jobs Reports by estimating Jobs Report-specific coefficients of the impact on the national unemployment rate expectations. Using the full sample, it would amount to estimating the following Equation.

$$u_{i,\ t} = \alpha_t + \beta_t \times T_{i,\ t} + \zeta_i + \varepsilon_{i,\ t}. \tag{1}$$

Here, $u_{i,\ t}$ denotes individual i's expectations about the likelihood of the national unemployment rate increasing surrounding the Jobs Report published at time t. α_t is a period-specific constant (i.e., Jobs Report fixed effect). $T_{i,\ t}$ is the treatment indicator, which means β_t denotes the coefficient of the impact the Jobs Report published at time t had on the unemployment rate expectations. ζ_i denote the individual fixed effects and $\varepsilon_{i,\ t}$ the idiosyncratic error term.

The next step would be to include $\hat{\beta}_t$ in a similar Equation, with personal job loss expectations as the outcome variable:

$$J_{i,\ t} = \delta_t + \gamma \times \hat{\beta}_t \times T_{i,\ t} + \upsilon + \xi_i + \eta_{i,\ t}. \tag{2}$$

Here, $J_{i,\ t}$ denotes individual i's belief at time t about the likelihood of losing their job in the next twelve months. δ_t is a period-specific constant. γ is the coefficient of interest. It indicates the impact of a Jobs Report that changed unemployment rate expectations by $\hat{\beta}_t$ on personal job loss expectations. υ denotes the Jobs Report fixed effects, ξ_i denotes the individual fixed effects and $\eta_{i,\ t}$ the idiosyncratic error term.

Note that we do not use an instrumental variable strategy, but rather use $\hat{\beta}_t$ from Equation 1 as a proxy for the way in which the Jobs Report is interpreted. Using an instrumental variable approach would implicitly assume that the mechanism through which the Jobs Reports affect personal job loss expectations only goes through the expectations about the national unemployment rate. While it is likely that this mechanism plays a major role, it may not be the only factor. Specific information about, e.g., sectoral nonfarm payroll employment may also affect personal job loss expectations.

There is a problem with this methodology, however. Because we have 77 reports, the number of individuals in each cohort is limited and individuals thus have a large impact on $\hat{\beta}_t$. If there is a within-individual correlation between expectations about the development of the national unemployment rate and the likelihood of losing their own job caused by something other than the information shock, this would lead to biased results. This seems likely, given the results of prior research on the relationship between individuals' experiences and expectations (see e.g., Cotofan et al., 2020; Geishecker, Riedl, and Frijters 2012; Kuchler and Zafar, 2019 and Malmendier and Nagel, 2011, 2016). The reason that this leads to biased estimates is that any cohort where the treatment group is more optimistic (pessimistic) about the development of the national unemployment rate than the control group will have a negative (positive) value for $\hat{\beta}_t$. Because of the individual-level correlation between unemployment rate expectations and personal job loss expectations, it is likely that the treatment group in such a cohort will also be more optimistic (pessimistic) about the likelihood of personal job loss, creating an artificial positive correlation between our estimates of γ and β_t.

To solve this, we have to break the individual-level correlation. We propose two ways of doing this, each with its distinct advantages and disadvantages. The first strategy involves splitting the sample in two equally sized groups: the '50/50 sample split'. We use the first group to estimate Equation 1, and the other to estimate Equation 2. We repeat this process 500 times, to obtain estimates and standard errors for all of the variables in the model. The advantage of this methodology is that by using mutually exclusive samples to estimate the Equations, we avoid any bias caused by within-individual correlation between the two outcomes. The core identifying assumption is that the way in which the first group interprets the Jobs Report is correlated with the way in which the second group does. We expand on this in Section 3.3. The downside of this methodology is that our number of observations is effectively cut in half, significantly decreasing statistical power.

The second strategy follows the same intuition: we use others' interpretation of the Jobs Reports as an explanatory variable when we estimate a Jobs Report's impact on personal job loss expectations. In this case, however, we use a 'Jackknife procedure'. For each individual, we estimate the information shock of the Jobs Report on expectations about the national unemployment rate among all other participants in the survey. We then use this 'leave-out estimate' as the treatment intensity variable in the second step. More specifically, we estimate the following two Equations.

$$\mathbf{u}_{-i,\ t} = \alpha + \beta_{i,\ t} \times \mathbf{T}_{-i,\ t} + \zeta_{-i} + \varepsilon_{-i,\ t}. \tag{3}$$

Reusing the notation from Equation 1, $\mathbf{u}_{-i,t}$ is a vector denoting the expected likelihood that the national unemployment rate will increase in the next twelve months according to all individuals except for i at time t. α is a constant. We do not use Jobs Report fixed effects. Vector $\mathbf{T}_{-i,\ t}$ indicates whether an individual was in the treatment group at time t. $\beta_{i,\ t}$ can be viewed as the Jackknife equivalent of β_t in Equation 1. It denotes the impact of the Jobs Report published at time t on unemployment expectations of every individuals except for i. ζ_{-i} denotes the individual fixed effects and $\varepsilon_{-i,\ t}$ is an idiosyncratic error term.

Taking $\hat{\beta}_{i,\ t}$ from Equation 3, we then estimate the following Equation.

$$J_{i,\ t} = \delta + \gamma \times \hat{\beta}_{i,\ t} \times T_{i,\ t} + \xi_i + \eta_{i,\ t}. \tag{4}$$

Again reusing notation, $J_{i,\ t}$ denotes individual i's belief about the likelihood of losing their job in the next twelve months. δ is the constant. $T_{i,\ t}$ indicates whether individual i was in the treatment group at time t. γ is again the coefficient of interest. It indicates the impact of a Jobs Report that changed unemployment rate expectations by $\hat{\beta}_{i,\ t}$ on personal job loss expectations. ξ_i denotes the individual fixed effects, and $\eta_{i,\ t}$ is an idiosyncratic error term.

This strategy does not negatively impact our effective sample size, but it does have a different downside. While the national unemployment rate expectations of the individual do not affect the estimate assigned to them, they do affect the estimate assigned to every other individual. This means that those with the most extreme opinions about the national unemployment rate, get assigned the most conservative coefficients within the cohort. This may lead to a negative bias, especially if within cohort variance is large. Table B1 in the Appendix provides reassuring evidence that most of the variance is between cohorts, however. The second column of the first row shows that the overall variance of $\hat{\beta}_{i,t}$ is equal to $3.688^2 \approx 13.60$. The second row shows that the average within cohort variance is equal to 0.160; even for the cohort in which the variance is largest, it is only 1.40. This is reassuring, and means the bias is likely small. This potential bias is also the reason we do not use Jobs Report fixed effects in Equations 3 and 4.

3.3 Justification of identifying assumptions

The analysis we conduct relies on three main identifying assumptions:

1. The Jobs Reports actually move expectations.

2. Individuals' interpretations of the Jobs Reports are correlated with each other.

3. Expectations are not moved by anything other than the Jobs Reports.

In this Section, we provide support for the validity of these assumptions. We do this based on the 50/50 sample split, as it is most cleanly identified; it does not suffer from the (small) downward bias that the Jackknife procedure does. The subsections below each describe an identifying assumption and provide supporting evidence.

To do so, we need a benchmark. For this, we use placebo treatment analyses. This entails moving the 'treatment' date forward by 14 days and re-estimating our Equations. Given that no reports were published on the days of the placebo treatments, there should not be any effect of the placebo treatment. Figure 4 provides a visual representation for the placebo treatment if we were to choose a three-day window around the placebo publication.

[Figure 4 about here.]

3.3.1 The Jobs Reports actually move expectations

The first identifying assumption is that Jobs Reports actually move expectations. If this is indeed true, we would expect higher variance in expectations on the days surrounding the Jobs Reports than on other days. We analyze this by studying the variance of the estimated coefficient $\hat{\beta}_t$ from Equation 1 for both the true publication of the Jobs Reports and the placebo treatment. Figure 5 shows the distribution of the variance of $\hat{\beta}_t$ from 500 replications for both the actual Jobs Report as well as the placebo reports. The Figure shows what we would expect if Jobs Reports indeed affect expectations: the variance of $\hat{\beta}_t$ looks to be much higher for the real treatment than for the placebo treatment. Intuitively, this means that expectations shift more strongly on report dates than on placebo dates. A Kolmogorov-Smirnov test confirms that the distributions are not the same. We thus conclude that the Jobs Reports actually move expectations about the unemployment rate.

[Figure 5 about here.]

3.3.2 Individuals' interpretations of the Jobs Reports are correlated with each other

Our method further relies on the expectations of other individuals to get a measure of the way in which the Jobs Reports are interpreted. For this to make sense, it requires that peoples' expectations around the Jobs Report actually correlate with each other. To test this, we again employ the 50/50 sample split. We first estimate Equation 1, using the first subsample. Next, we estimate Equation 2 using the second subsample, but take the unemployment rate expectations as the outcome variable for both Equations instead. If the interpretations are indeed correlated, we would expect to see a positive value for $\hat{\beta}_t$. Table 1 shows the results from this exercise, using bandwidths of one to seven days around the publication dates of the Jobs Reports.

[Table 1 about here.]

The estimates are positive for all bandwidths, although insignificant (or only marginally significant) for bandwidths of one and two days around the report. For a bandwidth of three and more days around the reports, the point estimate is between 0.267 and 0.424, and significant at the 1% level in all cases. It shows that interpretation of Jobs Reports are indeed consistent across individuals.

3.3.3 Expectations should not be moved by anything other than the Jobs Reports

The last identifying assumption is that the Jobs Reports are the only source of variation in expectations. If this is indeed true, the exercise from Section 3.3.2 should show mostly null results for the placebo treatment.

With the exception of Column (6), which is marginally significant, Table 2 indeed shows no significant correlation between the expectations surrounding the Jobs Report of the first and the second subsample. The point estimates are also much smaller, for all but the tightest bandwidths. We thus conclude that it is unlikely that any other systematic event close to the publication of the Jobs Reports has a major impact on expectations in the days surrounding it.

[Table 2 about here.]

4 Results

4.1 An intuitive first look

Before we turn to our main results, we first conduct an intuitive exercise. Instead of estimating Equation 1 for just national unemployment rate expectations, we also do this for personal job loss expectations. This gives us two estimates for each Jobs Report: the impact on national unemployment rate expectations and the impact on personal job loss expectations. Figure 6 shows how these impacts correlate with each other. The x-axis shows the estimated impact of each Jobs Report on expectations about the development of the national unemployment rate on. The y-axis shows the estimated impact of each Jobs Report on the likelihood of losing one's own job. The Figure shows what we would expect. The higher the impact on national unemployment rate expectations, the higher the impact on personal job loss expectations. In the next Section, we formalize this result.

[Figure 6 about here.]

4.2 Main results

Turning to our main results, Tables 3 and 4 show our estimates from Equation 2 (50/50 split) and 4 (Jackknife procedure), respectively. The value of Treated $\times \hat{\beta}_{.}$ can be interpreted as the percentage point change in personal job loss expectations if we estimate the impact of the Jobs Report on national unemployment rate expectations to be 1 percentage point. We display the results for bandwidths of one to seven days around the publication of the Jobs Reports. Estimates differ slightly between the two methods, but tell the same story: a Jobs Report that increases individuals' expectations about the likelihood of the national unemployment rate increasing also increases their personal job loss expectations. Looking at the Tables into more detail, Table 3 shows no significant results for bandwidths of up to three days. For bandwidths of four days and more around the report, the effects are statistically significant and vary between 0.14 to 0.223 percentage points. For the Jackknife procedure, the results are apparent for all bandwidths, but not significant for the largest bandwidths. Estimates hover between 0.11 and 0.192 percentage points. The fact that for small bandwidths, the results are more convincing using the Jackknife procedure is unsurprising. As stated before, the 50/50 split causes the sample to be effectively halved.

[Tables 3 and 4 about here.]

It is worthwhile to confirm that placebo treatment analyses show no results with personal job loss expectations as the outcome as well. Tables 5 and 6 show the results of our placebo treatment analyses, again using the 50/50 split and Jackknife procedure, respectively. In contrast to the analysis conducted around publication days of Jobs Reports, the placebo treatment has no effects on personal job loss expectations that are significantly different from zero. This holds for both the 50/50 split and the Jackknife procedure. Additionally, all estimated coefficients are very close to zero.

[Tables 5 and 6 about here.]

If idiosyncratic shocks that affect both national unemployment rate expectations and personal job loss expectations would frequently occur, the placebo analysis would likely reveal significant effects and the results presented in Tables 3 and 4 could not be causally linked to the publication of Jobs Reports. The absence of such effects therefore supports the causal interpretation of the results presented in this subsection.

4.3 Heterogeneous treatment effects

The Jobs Reports may not have an equal impact on everyone. Differences in the attention individuals pay to macroeconomic news, their ability to interpret news and perceived business cycle sensitivity of job security may all affect the size of the impact. In this Section, we analyze how the impact of the Jobs Reports on personal job loss expectations differs between groups of individuals. For this analysis, we exclusively turn to the Jackknife procedure, as it provides more power and results look to be comparable.

Table 7 shows how the treatment effect differs for different groups of individuals.[4] We check for heterogeneous effects by age cohort, numeracy skills, education level and categories of household income. We find some evidence that the treatment effect is smaller for individuals aged between 40 and 60 years, and that it is higher for respondents with a college education and a household income of over $50,000 if we include the characteristics separately. However, if we include all personal characteristics in a single regression, only the effect of age remains (marginally) significant. This analysis only tells us that for a given interpretation of the Jobs Report, individuals aged between 40 and 60 react less strongly than younger and older respondents. A possible mechanism for this result is that individuals in these age categories feel that their job security is less dependent on the general state of the economy than those younger and older. However, the Table does not allow us to explore this, as $\hat{\beta}_{i,\ t}$ is not age-cohort specific. We therefore do not know if the heterogeneity is driven by differing interpretations of the Jobs Reports or by differences in the translations of these shocks into

[4] We do not re-estimate the first Equation, so that we can study how the impact of the information shock differs by group.

personal job loss expectations.

[Table 7 about here.]

4.4 Alternative outcomes

Apart from different impacts across individuals, shocks to expectations about the national unemployment rate may not only affect individuals' expectations about losing their own job, but could impact a number of other expectations about their personal life as well. We study how it impacts individuals' expectations about how easy it will be to find a new job if they were to lose their current one, how likely they think it is they will voluntarily leave their job and how their earnings and spending will change. We again use the Jackknife procedure for this analysis.

The Column (1) of Table 8 shows the impact on individuals' expected likelihood of finding a new job within three months if they were to lose theirs now. In line with our prior finding, it decreases. Somewhat surprisingly, we find a positive effect on people's expectation about leaving their own jobs voluntarily in Column (2). One potential explanation is that individuals start spending more time looking for other jobs when they expect it to be more likely that they will lose their own job, potentially leading to a voluntary exit. Table B2 in the Appendix provides some support for this hypothesis. The more worried an individual is about losing their job, the more likely they are to spend time searching for different jobs.

Columns (3) and (4) of Table 8 show the effect on expected earnings. An expected increase in the unemployment rate should worsen individuals' bargaining position, potentially driving their wages down. We find no evidence that people expect their earnings in their current job to decrease, however. We also do not find any evidence of changes in planned spending either, as shown in columns (5) and (6).

[Table 8 about here.]

5 Conclusion

The results from this paper show that individuals indeed acquire information about macroeconomic conditions in their day-to-day lives and relate this to their personal situation. It not only affects individuals' expected likelihood of losing their own jobs, but their expectations about the likelihood of being able to find a new job conditional on losing theirs as well. News that people interpret as increasing the likelihood of the unemployment rate increasing thus makes individuals more pessimistic about their employment prospects through multiple channels: an increase in the expected likelihood of job loss, and a decrease in the expected likelihood of being able to find employment.

Our finding that individuals between 40 and 60 years of age are somewhat more sensitive to the information shocks requires further research. One explanation is that these individuals feel their jobs are secure, even if the economy takes a turn for the worse. However, the analyses in this paper do not allow us to answer this question.

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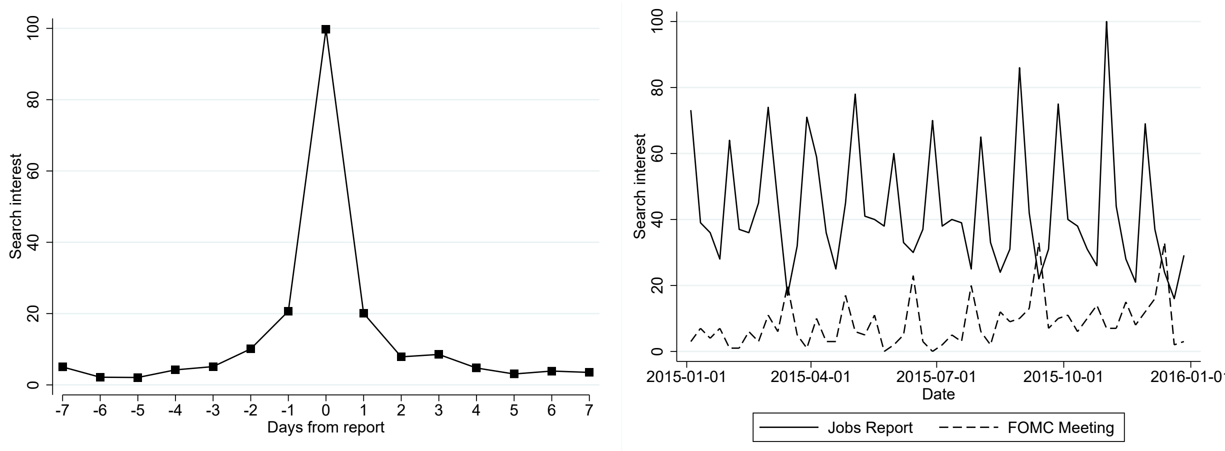
Figures

Figure 1: Search interest

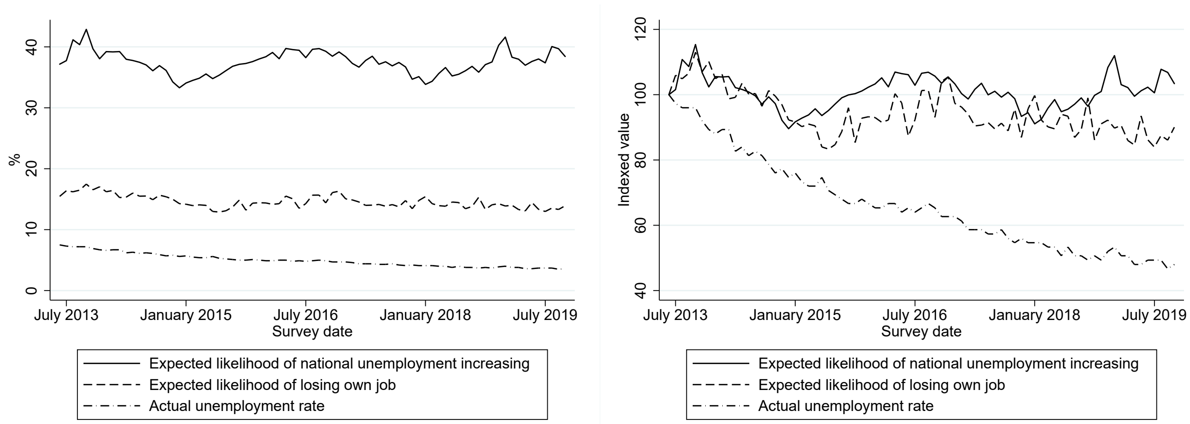


(a) Interest surrounding publication

(b) Interest compared to FOMC meeting

Note: Panel (a) shows the average search interest over all reports. Panel (b) shows the interest in each report over time.

Figure 2: Development of expectations and unemployment rate over time



(a) Real values

(b) Indexed values

Note: Panel (a) shows the average values for each variable per survey month. In Panel (b), values are indexed by their value in July 2013.

Figure 3: Visual representation of treatment allocation

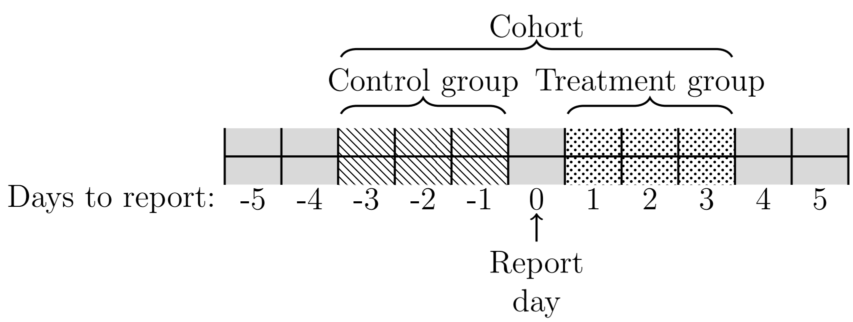


Figure 4: Visual representation of placebo treatment allocation

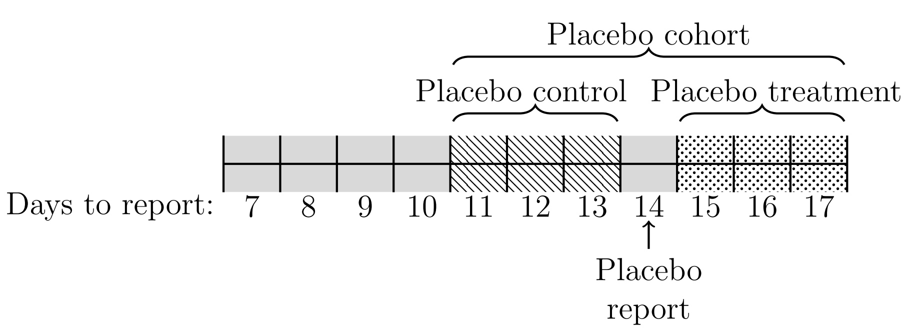
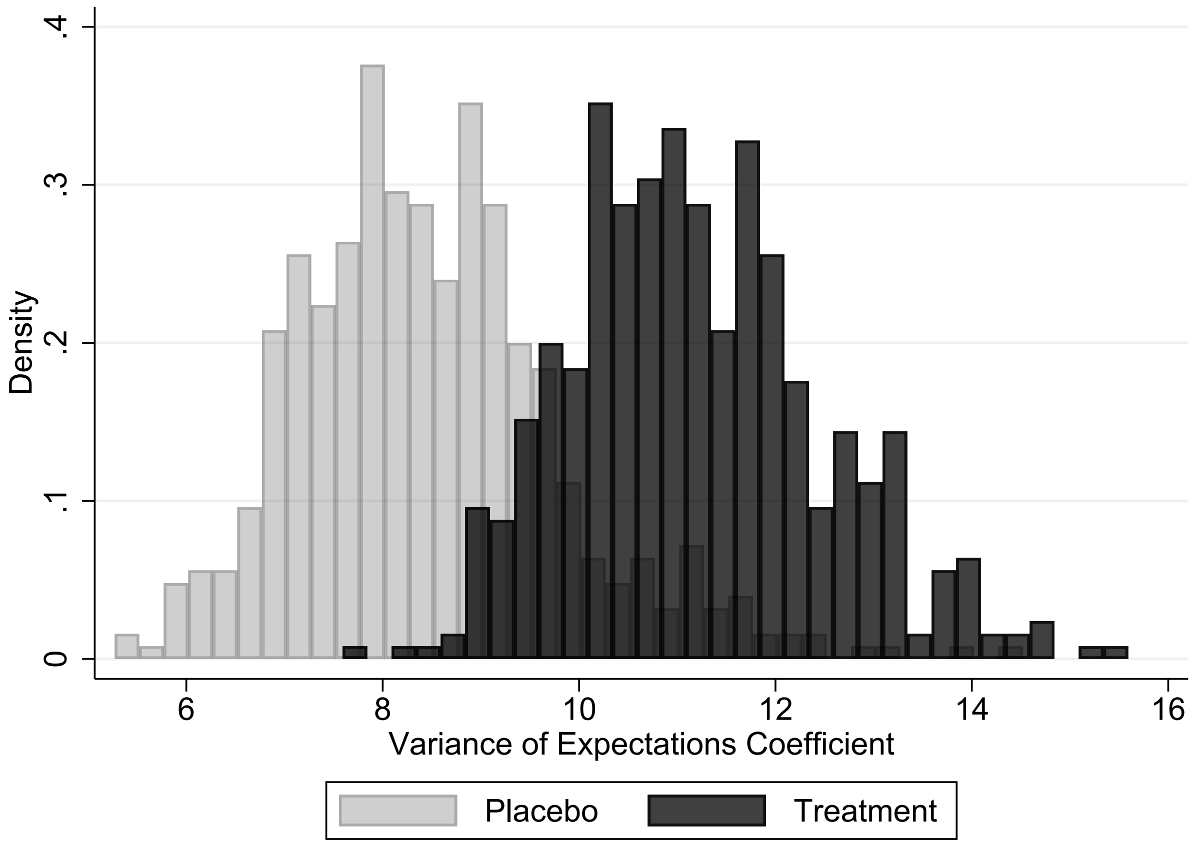
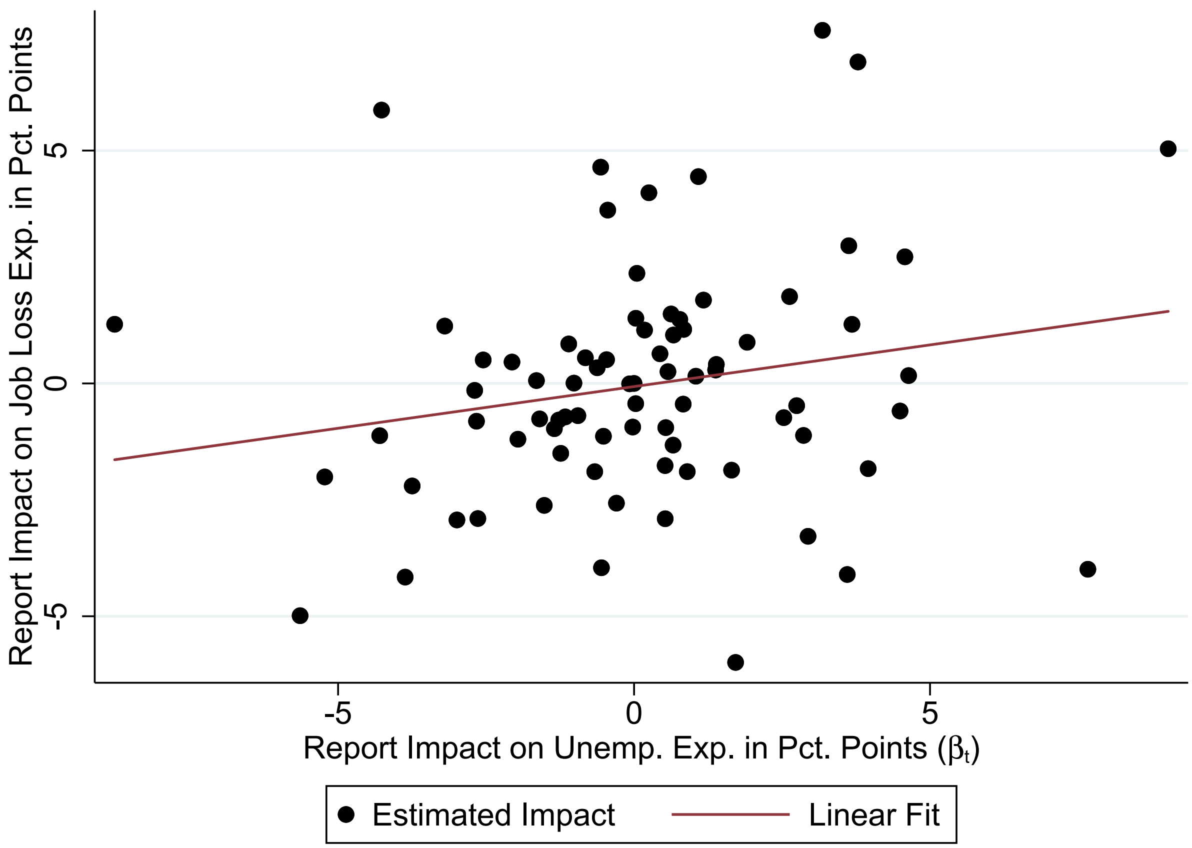


Figure 5: Variance of $\hat{\beta}_t$ for real Jobs Report and placebo Jobs Reports



Note: light gray bars show density of estimated variance in expectations coefficient for the treatment impact of the placebo Jobs Reports. Dark gray bars show the same for the treatment impact of the actual Jobs Reports.

Figure 6: Correlation between report impacts on expectations about national unemployment rate and personal job loss



Note: Figure shows how the estimated impact for both the national unemployment rate expectations and personal job loss expectations of each Jobs Report correlate with each other. Bandwidth is equal to 3.

Tables

Table 1: Correlation of news shocks between groups

	$B=1$	$B=2$	$B=3$	$B=4$	$B=5$	$B=6$	$B=7$
Treated	0.502	0.324	0.444	0.098	0.079	0.072	0.085
	(0.671)	(0.372)	(0.28)	(0.236)	(0.211)	(0.203)	(0.177)
Treated × $\hat{\beta}_t$	0.176*	0.14	0.267***	0.34***	0.371***	0.424***	0.418***
	(0.095)	(0.086)	(0.09)	(0.08)	(0.085)	(0.087)	(0.08)
Observations	1730	4819	8958	13208	16660	19929	22951
Average obs. per Group	865	2409	4479	6604	8330	9964	11475

Note: *Treated* is a dummy indicating whether the individual answered before (0) or after (1) the Jobs Report. $\hat{\beta}_t$ denotes the coefficient of the impact of the Jobs Report published at time t on national unemployment rate expectations. We include Jobs Report fixed effects in the regression, which means $\hat{\beta}_t$ drops out of the Equation. Results are based on 500 resamplings into the two groups. B indicates the bandwidth in days around the reports' publication dates. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 2: Correlation of news shocks between groups - Placebo treatment

	$B=1$	$B=2$	$B=3$	$B=4$	$B=5$	$B=6$	$B=7$
Placebo Treated	1.452	0.765	0.699	0.406	0.286	0.229	0.198
	(0.787)	(0.564)	(0.52)	(0.21)	(0.153)	(0.171)	(0.169)
Placebo Treated × $\hat{\beta}_t$	0.141	0.062	0.066	0.102	0.065	0.147*	0.062
	(0.117)	(0.099)	(0.097)	(0.093)	(0.092)	(0.081)	(0.083)
Observations	1984	5890	11225	16218	19685	22724	25776
Average obs. per Group	992	2945	5612	8109	9842	11362	12888

Note: *Placebo Treated* is a dummy indicating whether the individual answered before (0) or after (1) the placebo Jobs Report.$\hat{\beta}_t$ denotes the coefficient of the impact of the placebo Jobs Report on national unemployment rate expectations. We include placebo Jobs Report fixed effects in the regression, which means $\hat{\beta}_t$ drops out of the Equation. Results are based on 500 resamplings into the two groups. B indicates the bandwidth in days around the reports' publication dates. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 3: Effect of cohort-specific news shock on personal job loss expectations - 50/50 split

	$B=1$	$B=2$	$B=3$	$B=4$	$B=5$	$B=6$	$B=7$
Treated	-0.424	-0.193	0.137	-0.488	-0.04	0.017	0.052
	(0.466)	(0.272)	(0.193)	(0.152)	(0.137)	(0.111)	(0.109)
Treated × $\hat{\beta}_t$	0.02	0.085	0.131	0.169**	0.223***	0.165**	0.14**
	(0.086)	(0.086)	(0.083)	(0.076)	(0.083)	(0.068)	(0.07)
Observations	1730	4819	8958	13208	16660	19929	22951
Average obs. per Group	865	2409	4479	6604	8330	9964	11475

Note: *Treated* is a dummy indicating whether the individual answered before (0) or after (1) the Jobs Report. $\hat{\beta}_t$ denotes the coefficient of the impact of the Jobs Report published at time t on national unemployment rate expectations. We include Jobs Report fixed effects in the regression, which means $\hat{\beta}_t$ drops out of the Equation. Results are based on 500 resamplings into the two groups. B indicates the bandwidth in days around the reports' publication dates. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4: Effect of cohort-specific news shock on personal job loss expectations - Jackknife

	$B=1$	$B=2$	$B=3$	$B=4$	$B=5$	$B=6$	$B=7$
Treated	-1.157	-0.265	-0.167	-0.382	-0.191	-0.105	-0.148
	(0.793)	(0.483)	(0.314)	(0.278)	(0.241)	(0.213)	(0.209)
$\hat{\beta}_{i,t}$	-0.0321	-0.150**	-0.0382	-0.0295	-0.0413	-0.0529	-0.0614
	(0.0478)	(0.0623)	(0.0652)	(0.0599)	(0.0585)	(0.0634)	(0.0617)
Treated × $\hat{\beta}_{i,t}$	0.142**	0.192**	0.147*	0.178**	0.163**	0.110	0.127
	(0.0693)	(0.0828)	(0.0818)	(0.0887)	(0.0816)	(0.0838)	(0.0814)
Observations	1730	4819	8958	13208	16660	19929	22951

Note: *Treated* is a dummy indicating whether the individual answered before (0) or after (1) the Jobs Report. $\hat{\beta}_{i,t}$ denotes the coefficient of the impact of the Jobs Report published at time t on national unemployment rate expectations, when individual i is excluded from the regression. $\hat{\beta}_{i,t}$ is demeaned. B indicates the bandwidth in days around the reports' publication dates. Bootstrapped standard errors (500 replications) clustered at individual level between parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 5: Effect of Placebo news shock on personal job loss expectations - 50/50 split

	$B=1$	$B=2$	$B=3$	$B=4$	$B=5$	$B=6$	$B=7$
Placebo Treated	0.563	0.169	0.454	0.244	0.27	0.317	0.347
	(0.716)	(0.541)	(0.499)	(0.158)	(0.123)	(0.127)	(0.155)
Placebo Treated × $\hat{\beta}_t$	0.033	-0.067	0.028	0.064	-0.046	0.043	0.007
	(0.116)	(0.102)	(0.1)	(0.094)	(0.089)	(0.082)	(0.086)
Observations	1984	5890	11225	16218	19685	22724	25776
Average obs. per Group	865	2409	4479	6604	8330	9964	11475

Note: *Placebo Treated* is a dummy indicating whether the individual answered before (0) or after (1) the placebo Jobs Report. $\hat{\beta}_t$ denotes the coefficient of the impact of the placebo Jobs Report on national unemployment rate expectations. Includes placebo Jobs Report fixed effects. Results are based on 500 resamplings into the two groups. B indicates the bandwidth in days around the reports' publication dates. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 6: Effect of Placebo news shock on personal job loss expectations - Jackknife

	$B=1$	$B=2$	$B=3$	$B=4$	$B=5$	$B=6$	$B=7$
Placebo Treated	0.759	0.778	0.589*	0.529**	0.543**	0.541**	0.508**
	(0.923)	(0.477)	(0.327)	(0.270)	(0.227)	(0.224)	(0.210)
$\hat{\beta}_{i,t}$	-0.0308	-0.0301	-0.0713	-0.0291	-0.0582	-0.0535	-0.0248
	(0.0507)	(0.0611)	(0.0639)	(0.0645)	(0.0688)	(0.0636)	(0.0664)
Placebo Treated × $\hat{\beta}_{i,t}$	0.0753	0.0173	0.0198	-0.0184	0.0155	0.0561	-0.0132
	(0.0723)	(0.0861)	(0.0832)	(0.0861)	(0.0959)	(0.0918)	(0.0875)
Observations	1984	5890	11225	16218	19685	22724	25776

Note: *Placebo Treated* is a dummy indicating whether the individual answered before (0) or after (1) the placebo Jobs Report. $\hat{\beta}_{i,t}$ denotes the coefficient of the impact of the placebo Jobs Report on national unemployment rate expectations, when individual i is excluded from the regression. $\hat{\beta}_{i,t}$ is demeaned. Bootstrapped standard errors (500 replications) clustered at individual level between parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 7: Heterogeneous treatment effects - Jackknife

	Age	Numeracy	Education	Household Inc.	All
Treated	-0.289	-0.418	0.246	-0.103	-0.0527
	(0.487)	(0.732)	(0.874)	(0.624)	(1.076)
$\hat{\beta}_{i,t}$	-0.183*	0.0688	0.140	0.185	0.0670
	(0.110)	(0.133)	(0.145)	(0.118)	(0.222)
Treated × $\hat{\beta}_{i,t}$	0.311**	-0.0384	-0.0481	-0.160	-0.0239
	(0.143)	(0.165)	(0.182)	(0.164)	(0.268)
40 to 60 × $\hat{\beta}_{i,t}$	0.331**				0.355**
	(0.141)				(0.143)
Over 60 × $\hat{\beta}_{i,t}$	-0.0362				-0.0485
	(0.239)				(0.244)
Treated × 40 to 60 × $\hat{\beta}_{i,t}$	-0.365**				-0.342*
	(0.183)				(0.190)
Treated × Over 60 × $\hat{\beta}_{i,t}$	0.0278				0.102
	(0.283)				(0.300)
High numeracy × $\hat{\beta}_{i,t}$		-0.144			-0.0290
		(0.148)			(0.162)
Treated × High numeracy × $\hat{\beta}_{i,t}$		0.252			0.0788
		(0.195)			(0.218)
College × $\hat{\beta}_{i,t}$			-0.239		0.00119
			(0.171)		(0.198)
Some College × $\hat{\beta}_{i,t}$			-0.113		-0.0187
			(0.178)		(0.195)
Treated × College × $\hat{\beta}_{i,t}$			0.362*		0.105
			(0.218)		(0.258)
Treated × Some College × $\hat{\beta}_{i,t}$			-0.0787		-0.182
			(0.241)		(0.244)
50k to 100k × $\hat{\beta}_{i,t}$				-0.254*	-0.264
				(0.148)	(0.173)
Over 100k × $\hat{\beta}_{i,t}$				-0.382**	-0.404**
				(0.173)	(0.202)
Treated × 50k to 100k × $\hat{\beta}_{i,t}$				0.356*	0.298
				(0.197)	(0.228)
Treated × Over 100k × $\hat{\beta}_{i,t}$				0.545**	0.432
				(0.240)	(0.305)
Observations	8956	8954	8956	8886	8880
χ^2 Age	4.878				4.758
P-value χ^2 Age	0.087				0.093
χ^2 Edu			6.378		1.799
P-value χ^2 Edu			0.041		0.407
χ^2 HHI				5.585	2.267
P-value χ^2 HHI				0.061	0.322

Note: *Treated* is a dummy indicating whether the individual answered before (0) or after (1) the Jobs Report. Bandwidth is equal to 3. $\hat{\beta}_{i,t}$ denotes the coefficient of the impact of the Jobs Report published at time t on national unemployment rate expectations, when individual i is excluded from the regression. $\hat{\beta}_{i,t}$ is demeaned. Bootstrapped standard errors (500 replications) clustered at individual level between parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. χ^2 tests and P-values are for tests of joint significance for triple interactions of age, education and household income with 'Treated' and $\hat{\beta}_{i,t}$.

Table 8: Alternative outcomes - Jackknife

	Find new job	Leave voluntarily	Earnings increase (dummy)	Pct. earnings increase	Spending increase (dummy)	Pct. spending increase
Treated	-0.183	-0.208	0.00870*	0.231	0.00322	-0.103
	(0.441)	(0.400)	(0.00464)	(0.177)	(0.00658)	(0.245)
$\hat{\beta}_{i,t}$	0.139	-0.0597	-0.000560	0.0314	-0.000285	-0.0596
	(0.0918)	(0.0871)	(0.000901)	(0.0367)	(0.00140)	(0.0474)
Treated × $\hat{\beta}_{i,t}$	-0.214*	0.219*	-0.000795	-0.0327	-0.000927	0.0685
	(0.123)	(0.114)	(0.00123)	(0.0557)	(0.00190)	(0.0600)
Observations	8954	8956	8956	8950	8955	8953

Note: *Treated* is a dummy indicating whether the individual answered before (0) or after (1) the Jobs Report. Bandwidth is equal to 3. $\hat{\beta}_{i,t}$ denotes the coefficient of the impact of the Jobs Report published at time t on national unemployment rate expectations, when individual i is excluded from the regression. Columns indicate outcome variable. $\hat{\beta}_{i,t}$ is demeaned. Bootstrapped standard errors (500 replications) clustered at individual level between parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. χ^2 tests and P-values are for tests of joint significance for triple interactions of age, education and household income with 'Treated' and $\hat{\beta}_{i,t}$.

Appendix A: Additional survey questions

Leave job voluntarily: *What do you think is the percent chance that you will leave your main/current job voluntarily during the next 12 months?*

Find new job: *Suppose you were to lose your (main) job this month. What do you think is the percent chance that within the following 3 months, you will find a job that you will accept,considering the pay and type of work?*

Earnings increase (dummy): *Please think ahead to 12 months from now. Suppose that you are working in the exact same job at the same place you currently work, and working the exact same number of hours. What do you expect to have happened to your earnings on this job, before taxes and deductions?*

Twelve months from now, I expect my earnings to have...

- *increased by 0% or more*
- *decreased by 0% or more*

Pct. earnings increase: *By about what percent do you expect your earnings to have [increased/decreased as in previous question]? Please give your best guess.*

Twelve months from now, I expect my earnings to have [increased/decreased] by __ %

Spending increase (dummy): *Now think about your total household spending, including groceries, clothing, personal care, housing (such as rent, mortgage payments, utilities, maintenance, home improvements), medical expenses (including health insurance), transportation, recreation and entertainment, education, and any large items (such as home appliances, electronics, furniture, or car payments). Over the next 12 months, what do you expect will happen to the total spending of all members ofyour household (including you)?*

Over the next 12 months, I expect my total household spending to...

- *increase by 0% or more*
- *decrease by 0% or more*

Pct. spending increase: *By about what percent do you expect your total household spending to [increase/decrease as in previous question]? Please give your best guess.*

Over the next 12 months, I expect my total household spending to [increase/decrease] by __%

Appendix B: Additional Tables

Table B1: Summary statistics of $\hat{\beta}_{i,t}$

	Mean	Std. Dev.	Median	Min	Max
$\hat{\beta}_{i,t}$	-.1780225	3.687733	-.0962545	-18.19821	17.56856
Within cohort variance of $\hat{\beta}_{i,t}$	.160359	.1738912	.1020288	0	1.403147
Maximum value within cohort of $\hat{\beta}_{i,t}$	1.182855	3.687081	1.229935	-7.227622	17.56856
Minimum value within cohort of $\hat{\beta}_{i,t}$	-1.534244	3.663398	-1.421255	-18.19821	13.87807
Difference between maximum and minimum value of $\hat{\beta}_{i,t}$ w/i cohort	2.717099	1.496279	2.365716	0	13.39423
Observations	8958				

Note: first row displays general descriptive statistics of $\hat{\beta}_{i,t}$. The rows below show how $\hat{\beta}_{i,t}$ is distributed between cohorts.

Table B2: Expectations and Search

	Searched for Work	Hours Spent Searching
Expected Likelihood Losing Job	0.00360***	0.0197***
	(0.000462)	(0.00392)
Constant	0.182***	0.625***
	(0.00636)	(0.0540)
Observations	7614	7616

Note: results from a Fixed Effects regression. Standard errors clustered at individual level between parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.