Exposure to Labor Market News and Expectations about Job Search & Earnings*

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Abstract

I show that workers update expectations about job search and earnings when exposed to both positive and negative labor market news. To identify the impact of positive news, I exploit a unique setting, Foxconn's announcement to create thousands of high-paying jobs in Racine, Wisconsin. Consistent with predictions from directed search models, I find that individuals exposed to positive labor market news do not adjust their expectations about the job arrival rate. But, conditional on expecting an offer, they revise their expectations about potential salary offered considerably upward. Exposure to positive news also increases the expected salary growth at the current firm, even if an individual does not expect the employer to match any potential outside offer. This implies that positive news leads to an increase in workers' perceived bargaining power, but also that firms and workers frequently bargain over wages, even without explicit outside offers. Using Foxconn's later announcement of a downward revised new investment plan to identify the impact of bad news, I find strong asymmetries in the updating process.

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1 Introduction

Expectations play a key role in decision making processes and modern economic models. Inflation expectations affect individual consumption and firms' decision making (e.g. Coibion et al., 2020, 2021; Dräger and Nghiem, 2021). Expectations about one's own future career can affect the decision of how much to invest in human capital (e.g. Wiswall and Zafar, 2021). In labor market models, expectations about labor market outcomes affect an individual's job search decision and search effort (see, for example, the discussion in Mueller and Spinnewijn, 2021). These expectations are likely not static but individuals update them dynamically as new information and news arrive (e.g. Armona et al., 2019; D'Acunto et al., 2021), leading to important implications for theoretical models featuring beliefs. Empirical evidence on if and how individuals adjust their expectations to new information and news is still scant, however, specifically outside of the lab and when considering expectations about labor market outcomes.

In this work, I shed more light on how individuals update their expectations about job search and earnings when exposed to both positive and negative labor market news, using the U.S. Survey of Consumer Expectations (SEC). Estimating the relationship between news and expectation updating is challenging, however. To identify the impact of news on individuals' expectations, I exploiting Foxconn's announcement in 2017 to invest \$10 billion and to create up to 13,000 high paying jobs over the next 15 years in Racine County, Wisconsin (positive news). This initial proposed investment was substantial compared to overall employment of around 77,000 individuals in Racine at this time Bureau of Labor Statistics (2017). I also consider Foxconn's later considerably downward revised final plan to create only 1,000 jobs to identify the impact of negative news on individuals' expectations. The unique setting of Foxconn's investment plan also allows me to evaluate how consistent different types of labor market theories are with my results.

An additional challenge arises in my analysis as I only observe a few treated individuals in my data, given that Foxconn's investment plans were concentrated very locally. To overcome this problem, I employ the synthetic Difference-in-Difference (SC-DiD) approach of Arkhangelsky et al. (2021). The SC-DiD approach combines synthetic control methods (Abadie et al., 2010) with a difference-in-difference approach and is particularly suitable in settings with only a few treated observations. Importantly, within this estimation framework, I am still able to distinguish the impact of news on the expectation updating process from other unobserved heterogeneity; see also the discussion in Manski (2004). For example, I can allow for situations where some individuals have biased self-perceptions about their productivity or are in general over-optimistic about their labor market prospects (e.g. Hoffman and Burks, 2020; Mueller et al., 2021). In all these cases I am able to recover the impact of news on individuals' expectation formation process.

My empirical estimates are consistent with predictions from directed search models (e.g. Wright et al., 2021, for an overview). I do not find evidence that individuals update their expectations about receiving a job offer as response to the positive news of creating the vacancies. My estimates for this outcome are very close to zero and not statistically significant at any conventional level. Conditional on expecting an offer, individuals update their expectations about the value of the offer considerably upward, however. My estimates show that Foxconn's announcement to create new jobs in Racine County led to an increase in expected average and maximum salary offers received over the next four months by around 20%. As predicted by directed search models, individuals anticipate that the creation of new, high-paying vacancies will attract more applicants. The anticipated longer queue length for the new jobs in turn lowers the expected job offer arrival rate. At the same time, conditional on expecting an offer, they also expect to be offered higher salaries.

An alternative explanation for my results might be that individuals expecting incumbent firms to increase wages but, to stay competitive, also to reduce employment as response to Foxconn's announcement to create high paying vacancies. If individuals expect a sufficiently strong reduction in employment by incumbent firms, this could offset the impact of new vacancies and leave the expected job offer arrival rate unaffected, therefore explaining my results. This explanation would also be consistent with predictions from random search models.[1] Such a scenario would imply that individuals held strong and negative beliefs about the employment spillovers effects of Foxconn's investment plan. An early evaluation of Foxconn's investment plan predicted a positive impact on the local economy and employment, with the possibility of up to 26,000 additional jobs created through spillover effects (Williams, 2017). These employment predictions were also distributed and discussed widely in the local press (Romell and Stein, 2017).[2] Therefore, it is quite unlikely that Foxconn's initial announcement created strong pessimistic beliefs about employment growth in incumbent firms. In this light, I interpret my results more in line with predictions from labor market models where search is at least partially directed.

Being exposed to positive labor market news also increases the expected yearly salary growth rate at the current firm by around 3 percentage points. Interestingly, I do not find any differences in my estimates between workers who expect the current employer to match any potential outside offer and workers who do not expect offer matching. On the one side, these results show that individuals adjust their expectations about their bargaining power upward as response to positive labor market news. On the other

[1] For example, when considering a simple random search model as in Rogerson et al. (2005) with homogeneous firms but where workers' outside option increase after Foxconn's announcement, in equilibrium job filling rates (job arrival rates) have to increase (decrease) for incumbent firms to stay in the market.

[2] Both Williams (2017) and Romell and Stein (2017) highlight that there were uncertainties associated with the final number of jobs created.

side, they also point toward frequent bargaining between firms and workers over wages, even in cases without explicit outside offers. An explanation for these results is that firms cannot match outside offers perfectly, for example, because workers have private information about their outside options or negotiation is very costly, inducing firms to pay higher wages to retain workers; see Lavie and Robin (2012) and Gottfries (2021), as well as Burdett and Mortensen (1998) for an earlier work on how turnover depends on contracted wages.

Using Foxconn's later announcement of its downward revised investment plan to investigate the impact of bad labor market news on individuals' expectations, my results show clear asymmetries in the updating process. While bad labor market news lead to a general downward reversal in salary expectations, the magnitude of these adjustments are only half as large in size as my estimates for the impact of positive news. Notice that within my difference-in-difference framework, the estimates are not driven by individual unobserved heterogeneity. These results have important implications for the understanding of the effectiveness of labor market policies. For example, asymmetric and slow updating may be one reason about the lower job finding rate of long-term unemployed workers, which could be taken into account by case workers when giving job search advice.[3] I also find that bad labor market news lowers the expected salary growth rate at the current employer, supporting the theory of frequent wage bargaining in firms. These effects are rather noisily estimated, however.

With my work I make several contributions. First, I contribute to the literature on labor market search and the role of directed versus random search in the labor market (see, for example, Rogerson et al. 2005 and Wright et al. 2021 for a review). My results on the exposure of labor market news on individuals' expectations about job search are in line with predictions from directed search models, specifically in settings with noisy information about jobs (Banfi and Villena-Roldán, 2019) and even if workers are homogeneous (Delacroix and Shi, 2006). Workers anticipate that the creation of high paying jobs attracts more applicants which suppresses their perceived job offer probability. In turn, they do not adjust their job offer expectations.[4] At the same time and conditional on receiving an offer, they revise their expectations about salaries offered substantially upward, as response to the news about the creation of high paying vacancies.

My work also speaks to the part of the literature on labor market search which incorporates worker-firm bargaining. Most of these works assume that firms engage in offer matching once the worker receives an outside offer as, for example, in Postel-Vinay and Robin (2002), Dey and Flinn (2005), and Cahuc et al. (2006). My results imply that

[3] Mueller et al. (2021) find that the long-term unemployed tend to hold overoptimistic beliefs about their job finding probabilities. This is in line with my findings that individuals tend to update their expectations less strongly downward when receiving negative news, for example, application rejections.

[4] Using an experiment with variation in wage announcements, Belot et al. (2018) also find results in favor of directed search models.

bargaining over wages likely occurs more frequently between firms and workers, such as in Gottfries (2021). Interestingly, my results also suggest that such bargaining might take place even without an explicit outside offer or expected offer matching.

Second, my work contributes and complements the mostly experimental literature on how individuals update their beliefs (Eil and Rao, 2011; Möbius et al., 2014; Sarson, 2019). My results indicate clear asymmetries in the updating process of expectations when good news is received versus bad ones. Good news leads to an adjustment of roughly twice the size in magnitude compared to adjustments as a response to bad news. Since my estimation approach takes individual unobserved heterogeneity into account, this asymmetric updating is not driven by individual perceptions or other unobserved components. It rather reflects a general way of how individuals process and update to news and show that asymmetric updating happens also in non-lab settings and when receiving public, non-personalized news.

To a certain extend, my work also contributes to the literature on how providing labor market information affects the search behavior of workers (Altmann et al., 2018; Skandalis, 2018; Belot et al., 2018, 2019). Most of the existing studies use information interventions within an experimental settings. An exception is Skandalis (2018) who uses administrative data for France and news about actual job openings as a type of information treatment to investigate workers' job search behavior. In my work, I concentrate on the impact of exposure to both good and bad labor market news on expectations, a key component for individuals' decision making. How individuals form expectations about earnings and job search allows me to evaluate different theories of the labor market. In addition and in contrast to existing works, information in my setting can also be regarded as noisy. My results show that individuals form and update expectations about job search and earnings to labor market news, even if the information content is noisy and no actual vacancies has been posted.

The paper proceeds by first describing Foxconn's investment plans in Wisconsin and the data. In Section 3, I discuss my empirical approach. Section 4 presents and discusses the results. I provide evidence of robustness of my results in Section 5. Finally, Section 6 concludes.

2 Background & Data

2.1 Foxconn in Wisconsin

In January 2017, Foxconn first considered to invest more than $7 billion in a panel display plant in the United States, which could create as many as 50,000 jobs (Wu, 2017). In April the same year, the Trump administration arranged a meeting between Terry Gou, the chairman of Foxconn, and the then Governor of Wisconsin, Scott Walker, to discuss a potential investment of Foxconn in Wisconsin (Deza, 2020).

At July 27, 2017, Foxconn announced that it plans to invest $10 billion in Wisconsin to build a new manufacturing plant for LCD panels. The project was estimated to create 13,000 new jobs over the next 15 years according to Governor Walker. Walker also announced that Foxconn will be offered $ 3 billion in economic incentives. Foxconn's estimates for the project were more conservative, stating the creation of 3,000 jobs with the potential to generate up to 13,000 (Paquette et al., 2017). An early economic evaluation of the investment plan estimated that up to 26,000 additional jobs could be created through spillover effects (Williams, 2017).[5] At the time of the announcement, the exact location of the proposed plant within Wisconsin was still unknown. The planned project created widespread coverage in local and national media.

Four months after Foxconn published its initial investment plan, the Foxconn-Wisconsin partnership was officially announced and formalized at the beginning of November 2017. The Wisconsin Economic Development Corporation (WEDC), Walker, and Gou singed a contract under which Wisconsin agreed to provide up to $2.85 billion in state income tax credits to Foxconn to support a display manufacturing campus in Mount Pleasant, Racine County. In addition to providing state income tax credits, Wisconsin also promised to built infrastructure and to set-up employee training programs. It was estimated that these promises will cost Wisconsin an additional $800 million (Deza, 2020).

In return, Foxconn agreed to invest up to $10 billion to produce displays and to create up to 13,000 new jobs. Under the contract, it was also specified that these new jobs had to pay an average annual salary of $53,875 (Wisconsin Economic Development Corporation, 2017). The proposed investment was economically substantial. In 2017 total employment was around 77,000 and annual average wage was $42,300 in Racine County (Bureau of Labor Statistics, 2017). Around the time of the agreement no actual vacancies had been posted yet but Foxconn distributed fliers with "sample positions" at job fairs stating that it is soliciting applications of candidates who want to be considered for positions that will see hiring in the coming months (Kirchen, 2017).[6] I consider this official announcement and formalization of the investment plan of Foxconn as *positive* labor market news for workers residing in Racine County.

In January 2019, Louis Woo, then the special assistant to Terry Gou, said that Foxconn's plans in Wisconsin may be scaled back or even entirely dismissed, citing the high costs of producing advanced TV screens and the relatively high labor costs in the United States. Instead of a manufacturing plant, Foxconn proposed to create a technology hub in

[5] Williams (2017) highlighted that there was uncertainty associated with the final realization of employment gains.

[6] According to Google Trends, there was also a substantial spike in Google searches for "Foxconn Jobs" in Wisconsin at this time.

Wisconsin, consisting of a research facility along with packing and assembly operations. It also reduced its forecast of new jobs created until 2020 from 5,200 to 1,000 jobs (Macy and Plume, 2019). This announcement can be considered as *negative* labor market news for workers residing in Racine County.

Finally, in April 2021, Foxconn signed a new deal with Wisconsin, dramatically scaling back its planned investment from $ 10 billion to $642 million. It also cut the predicted number of new jobs created to around 1,500. Under the new deal between the WEDC and Foxconn, the company will receive $ 80 million in performance-based tax credits over six years, similar as other companies (Shepardson and Pierog, 2021). Table 1 summarizes the most important milestones of Foxconn in Wisconsin.

2.2 Data

I use the Survey of Consumer Expectations (SCE) Labor Market Survey (Armantier et al., 2017). Launched in 2013 and fielded by the Federal Reserve Bank of New York, the SCE is an internet-based monthly survey of a rotating panel of around 1,3000 household heads from across the U.S. The survey elicits expectations about a large range of economic variables, such as inflation, household finances, and labor market conditions. Respondents participate in the survey up to twelve months. Each month, a roughly equal number of participants rotate in and out of the panel.

The SCE Labor Market Survey is fielded every four months in March, July, and November, as part of the SCE. As respondents are up to twelve months in the SCE, they may end up taking the Labor Market Survey between one and three times. A nice feature of the SCE Labor Market Survey is its panel structure. This allows me to identify the impact of news on expectation updating of the same individual. The importance of using panel data when measuring expectations is also stressed in Mueller and Spinnewijn (2021).

From the data, I first select all individuals who were interviewed either in November 2017 or March 2019. Individuals in the first group are exposed to the *positive news* while individuals in the second group make up the *negative news* sample. From these two samples, I select all individuals who were interviewed three times out of which two interviews were conducted prior to the relevant news dates, either November 2017 or January 2019. As my focus is on expectations about labor market outcomes, I disregard all those individuals not in the labor force at the last interview prior to the (possible) news exposure.

To define my treatment and control group, I obtain the place of residence of an individual at the last survey prior to Foxconn's announcements; July 2017 for the positive news sample and November 2018 for the negative news sample. Individuals who resided within the commuting zones of Racine County and adjacent Milwaukee-Waukesha-West

Allis are considered as treated while all other individuals in the samples constitute the control group. I include individuals in Milwaukee-Waukesha-West Allis in my treatment group to take into account that job search happens locally in general but, at the same time, information about employment opportunities can affect workers' migration decisions (Manning and Petrongolo, 2017; Wilson, 2020).[7] My results are not sensitive to excluding individuals residing in Milwaukee-Waukesha-West Allis or any other commuting zone in Wisconsin from the analysis; see Section 5. Table 2 summarizes both my positive and negative news samples.

My positive news sample consists of 498 observations and my negative news comprises 516 observations. Individuals in my samples tend to be young and highly educated. Around 60% of individuals graduated from college. As discussed in Conlon et al. (2018), while the SCE is comparable with national-statistics in terms of labor market outcomes, participants tend to be higher educated compared to the U.S. average. Over 90% of individuals are employed and most of these employments are full-time.

I use three different measures to analyze the impact of news on individuals' expectations about labor market search. First, I look at how news affects the number of job offers an individual expects to receive within the next four months after the interview date. This expected number of offers also includes expected job offers which are not necessarily accepted by the individual.

Then, I also look at how news affects the expected average salary offer and the expected maximum salary offer received. Following Conlon et al. (2018), I convert these variables into expected hourly salaries, assuming that an individual works 52 weeks per year and 40 hours per week if full-time and 20 hours per week if part-time. I also disregard individuals with unusually low or high hourly expected salaries where I put the lower bound at \$3.13, corresponding to half the federal minimum wage, and the upper bound to \$200, corresponding to ten times the national median hourly wage rate.

Theses three outcomes reflect an individual's expectations about job search. The expected number of offers gives an indication of how the individual perceives the job arrival rate in the near future. The expected average and maximum salaries are good measures of an individual's beliefs about the value of a potential offer, that is the value of her outside option.

I also use the expected yearly increase in earnings in the current job among employed individuals. This variable proxies an individual's perceived bargaining power within her current firm. It also allows me to investigate the firm-worker bargaining process, such as frequent bargaining over wages and potential offer matching by the current employer.

[7] Milwaukee-Waukesha-West Allis is the commuting zone adjacent to Racine County and therefore may also be affected by the labor market news.

Overall,there variables provides a thorough picture of how news can affect individuals' labor market expectations.

3 Empirical Approach

To estimate the impact of labor market news on individuals' expectations, I combine synthetic control (SC) methods with a difference-in-difference (DiD) framework, as in Arkhangelsky et al. (2021). This approach is particularly suitable in settings where only a few treated observations are observed, such as in my setting. It also weakens the reliance on the so-called *parallel trend assumption*, the requirement that the outcome for treated individuals evolved the same way as the outcome for control individuals absent of treatment, necessary for identification in DiD models. Such a parallel trend assumption is in general difficult to assess in practice.

Let S be the news indicator which takes a value of one if an individual experienced positive (negative) news and zero otherwise. Let N be the total number of individuals in my sample, out of which N_{tr} are exposed to the treatment and N_{co} are controls. Denote by $t = -1$ and $t = -2$ the two pre-treatment periods and by $t = 0$ the post-treatment period. Finally, let $\mathbb{1}_A$ be the indicator function which takes a value of one if the argument A is true and zero otherwise.

The standard DiD estimate $\widehat{\Delta}^{DiD}$ can be obtained from a two-way fixed effects regression of the form

$$y_{it} = \alpha + D_{i,t}\Delta^{DiD} + \gamma_t + \nu_i + \epsilon_{it}$$

where D_{it} is the time-varying treatment indicator and γ_t and ν_i reflect time- and individual fixed effects. The effect of exposures to news in the difference-in-difference framework is then reflected by the coefficient Δ^{DiD}.

To facilitate the comparison between Δ^{DiD} and the synthetic DiD estimator I use in my work it is useful to express Δ^{DiD} explicitly as differences (see also Arkhangelsky et al., 2021)

$$\begin{aligned}\Delta^{DiD} = &\sum_{i=1}^{N} \mathbb{1}_{S_i=1} N_{tr}^{-1} \left(Y_{i0} - \frac{1}{2} \sum_{t=-2}^{-1} Y_{it} \right) - \\ &\sum_{i=1}^{N} \mathbb{1}_{S_i=0} N_{co}^{-1} \left(Y_{i0} - \frac{1}{2} \sum_{t=-2}^{-1} Y_{it} \right)\end{aligned} \tag{1}$$

To interpret estimates from Equation (1) causally one needs to assume that the expectations of individuals who received labor market news (treated) would have evolved similarly to those of non-treated individuals in the absence of any news about Foxconn's investment plans. This is the so-called *parallel trend assumption*. Assessing the validity of such a parallel trend assumption is difficult in practice, specifically in settings where the number of treated individuals is small, as in my setting (e.g. Roth, 2021).

Instead of Equation (1), I estimate a weighted version of the DiD estimator which is suitable with very few treated individuals and which weakens the parallel trend assumption, making use of the synthetic DiD (SC-DiD) of Arkhangelsky et al. (2021). The SC-DiD estimator combines synthetic control methods (e.g. Abadie et al., 2010) with a difference-in-difference approach and is robust in settings with imperfect pre-treatment trends and where only a few individuals receive treatment. Like the standard DiD in Equation (1), the SC-DiD estimates can be expressed as weighted differences

$$\begin{aligned}\Delta^{SC-DiD} = &\sum_{i=1}^{N} \mathbb{1}_{S_i=1} N_{tr}^{-1} \left(Y_{i0} - \sum_{t=-2}^{-1} \lambda_t Y_{it} \right) - \\ &\sum_{i=1}^{N} \mathbb{1}_{S_i=0} \omega_i \left(Y_{i0} - \sum_{t=-2}^{-1} \lambda_t Y_{it} \right)\end{aligned} \tag{2}$$

where ω_i are individual weights and λ_t are time weights; see further below for a discussion on how these weights are estimated. Notice that Equation (1) differs from Equation (2) by the weights assigned to pre-treatment periods and to control individuals.

The intuition behind using individual weights ω_i is to weight pre-treatment trends in the outcomes for untreated individuals to make them comparable to those of treated individuals. In other words, past outcomes are not only used to assess parallel trends but also to construct weights to make them parallel to the outcomes of treated individuals. The motivation to use time weights in the estimation is very similar. The λ_ts weight pre-treatment periods down (up) which are dissimilar (similar) to the treatment periods. Therefore, if there was a general adjustment of expectations in anticipation to Foxconn's announcement this would be reflected in these time weights. Therefore, parallel trends hold in my setting by construction, even if the number of observations is small or pre-trends in the raw data are imperfect.

By incorporating the SC approach in the DiD setting, I use re-weighting and matching pre-exposure trends to weaken the reliance on the so-called parallel trends assumption, as in standard SC settings (e.g. Abadie et al., 2010). As in a DiD framework and unlike in the standard SC approach, the SC-DiD estimator also allows for unobserved individual and time-invariant heterogeneity. Therefore, the weighting approach leads to more robust estimation results.

As my SC-DiD estimation incorporates unobserved but time-fixed individual heterogeneity I can allow for situations where some individuals report lower job offer expectations because they search little in general. Similarly, I can also allow for situations in which some individuals might expect a higher salary increase in the future based on biased self-perceived productivity and over-optimism (e.g. Hoffman and Burks, 2020; Mueller et al., 2021). In my setting, these types of unobserved heterogeneity are accounted for and thus my estimates reflect the impact of labor market news on the updating process of individuals' expectations.

My estimates would still be biased if there were any time-varying unobserved factors jointly related to Foxconn's investment decisions and individuals' adjustments of expectations, however. This is unlikely in my setting for several reasons. First, Foxconn revealed some vague plan to invest in Wisconsin only by the end of July 2017, a time where most of the pre-treatment period interviews were likely already conducted.[8] A similar argument holds when considering Foxconn's official announcement of a scaled-back version of the initial proposed project in January 2019. Second, even after the initial investment announcement in July there was a substantial amount of uncertainty about the exact investment process, such as the location of the plant and the types of jobs created. This uncertainty lasted at least until November 2017, my post-treatment period, when the final and formal agreement between Foxconn and Wisconsin was signed and details about the project were published. Thus, there was likely little room for anticipation and adjustments of individuals' expectations prior to the news exposure. Third, any possible remaining bias generated by general time-varying unobserved factors will be taken care of by using the time weights λ in my estimation.[9]

I obtain the SC-DiD estimate in Equation (2) in two steps. In a first step, I estimate both individual weights ω_i and time weights λ_t from the data.

The individual weights ω_i can be obtained by solving the following quadratic program subject to linear constraints on the weights. The constraints require that the weights for control individuals are positive and sum to one while the weights for treated individuals are equal to N_{tr}^{-1}, the usual DiD weights (Arkhangelsky et al., 2021):

$$\begin{aligned} &\min_{\omega_c \in \mathbb{R}, \omega \in \Omega} \quad \sum_{t=-2}^{-1} \left(\omega_c + \sum_{i=1}^{N} \mathbb{1}_{S_i=0} \omega_i Y_{it} - N_{tr}^{-1} \sum_{i=1}^{N} \mathbb{1}_{S_i=1} Y_{it} \right)^2 + P \\ &\text{s.t.} \quad \Omega = \left\{ \omega \in \mathbb{R}_+^N : \sum_{i=1}^{N} \mathbb{1}_{S_i=0} \omega_i = 1, w_i = N_{tr}^{-1} \text{ for all treated individuals} \right\} \end{aligned} \tag{3}$$

where P is a regularization penalty.[10]

[8] Unfortunately, the SCE Survey does not contain information about the exact day of the interview.

[9] As I show in the appendix, the estimates of my time weights do not indicate in general that a certain pre-treatment period receives an unusual large weight. Therefore, there is little indication that the pre-treatment periods are very different from the post-treatment period in my sample.

[10] In my setting, P is given by $N_{Tr}^{1/2} \hat{\sigma}^2 \|\omega\|_2^2$, where $\hat{\sigma}$ is an estimate of the the deviation of a typical one-period outcome change of control individuals in the pre-treatment period (see Arkhangelsky et al., 2021).

This is similar to the SC approach of Abadie et al. (2010) with two exceptions. First, a constant ω_c is included in the estimation which allows for greater flexibility.[11] Second, a regularization penalty P is used to increase dispersion and ensure uniqueness of the weights.

The time weights λ_t can be obtained in a similar fashion, but without imposing any regularization and using the sample of control individuals only

$$\begin{aligned} &\min_{\lambda_c \in \mathbb{R}, \lambda \in \Lambda} \quad \sum_{i=1}^{N} \mathbb{1}_{S_i=0} \left(\lambda_c + \sum_{t=-2}^{-1} \lambda_t Y_{it} - Y_{i0} \right)^2 \\ &\text{s.t.} \quad \Lambda = \left\{ \lambda \in \mathbb{R}_+^2 : \sum_{t=-2}^{-1} \lambda_t = 1, \lambda_0 = 1 \right\} \end{aligned} \tag{4}$$

In the Appendix, I present summaries of the estimates for ω_i and λ_t. While the SC-DiD accounts for imperfect pre-treatment trends, the estimates of my weights do not indicate that certain time-periods or individuals receive particularly large weights. Therefore, it is unlikely that a certain group or time-period is driving my results. I interpret this as a support for my identification strategy.

In a second step, I use the estimated weights $\widehat{\omega}_i$ and $\widehat{\lambda}_t$ in Equation (2) to obtain my SC-DiD estimator. By using weighted differences, my estimates of the impact of labor market news on individuals' expectation updating are likely more robust and less biased than the results obtained from a standard DiD. I base inference on the bootstrap using 1,000 replications. Arkhangelsky et al. (2021) show that the bootstrap performs well in small panels with only a few treated individuals.

4 Exposure to Labor Market News and Expectations

My SC-DiD estimates for the impact of labor market news on individuals' labor market expectations are reported in Table 3. In Panel A of the table, I present the impact of positive news on individuals' expectations about job search and earnings.

Looking at the impact of positive news on the expected number of job offers received within the next four months, reported in Column (1), I do not find evidence that positive labor markets news leads to any adjustments. My estimates are with 0.14 very small.[12] They are also not statistically significant at any conventional level. Notice that the sample

[11] This also means that the weighted pre-trends of untreated individuals do not need to exactly match those of treated ones. Any remaining (constant) differences will be absorbed by individual fixed effects.

[12] Using the expected probability of receiving a job offer as outcome leads to similar conclusions.

also includes individuals who do not expect to receive any offer. The results are, however, similar if only individuals are included in the analysis who expect at least one offer.[13]

In contrast, positive labor market news leads to a substantially upward revision of expected average log salary offers among individuals who expect to receive at least one offer; see the results in Column (2). The magnitude of individuals' expectation updating is also quite large. The expected average salary offer is around 20% higher for individuals exposed to the positive news about Foxconn's investment plan compared to the expectations of individuals in my control group.[14] The effects of a similar magnitude when looking at the impact of positive news on the expected maximum salary offered, as shown in Column (3).

Using the average annual mean wage in Racine County of around $42,300 in 2017 as baseline, my estimates imply that individuals affected by positive labor market news adjust their expectations in such a fashion upward that these are close to the $53,000 mean salary announced in the Foxconn-Wisconsin contract (see the discussion in Section 2).Therefore, individuals seem to anchor their expectations to the noisy information content in the news and update them as a response to uncertain labor market information. Notice that in my Difference-in-Difference setting the updating process is not driven by individual heterogeneity, such as overconfidence or overoptimism. Rather, the results can be interpreted as a general way of how individuals update their expectations to noisy news. In that sense, my estimates complement and extend the literature on the role of information on labor market outcomes (Altmann et al., 2018; Skandalis, 2018; Belot et al., 2019) to a real-world and noisy setting.

My results on the impact of news on the expected job arrival rate and salaries have direct implications for theoretical labor search models. They are consistent with predictions from directed search models (e.g. see Wright et al., 2021, for an overview) and in particular models with noisy information about jobs (Banfi and Villena-Roldán, 2019).[15] Workers anticipate that Foxconn's investment will create higher paying jobs which also increases their (expected) wages in a potential new job. At the same time, workers also expect that creating higher paying jobs will attract more applicants and increase competition for theses new jobs. Therefore, and despite Foxconn's plan to create up to 13,000 jobs over 15 years, workers do not adjust their expected probability of receiving a job offer, anticipating the longer queue length. These findings are in contrast to implications from random search models where more (expected) vacancy postings

[13] The SC-DiD estimate concentrating on a sample of individuals who expect to receive at least one offer is -0.05 (s.e. 0.22).

[14] I do not find evidence that individuals adjust their reservation wage to labor market news. My SC-DiD estimate using the log-reservation wage as outcome is 0.08 with a standard error of 0.07.

[15] Belot et al. (2018) also find evidence in favor of directed search models studying how unemployed workers react to wage announcements in an experimental setting.

should increase the (expected) job offer arrival rate (see, for example, Rogerson et al., 2005).

An alternative explanation for my results might be that individuals expect, as a response to Foxconn's announcement, incumbent firms also to increase wages. At the same time, individuals also expect incumbent firms to reduce employment to remain operative, offsetting the positive impact of Foxconn's investment plan. A simple random search model as in Rogerson et al. (2005) with homogeneous firms but where workers' outside option increase after Foxconn's announcement would create such a prediction. In order to stay active, in equilibrium job-filling rates (job arrival rates) have to increase (decrease) for incumbent firms to stay in the market.

To be consistent with my results, such an explanation would imply that individuals held strong and negative beliefs about the employment spillovers effects of Foxconn's investment plan. Such strong negative beliefs stand, however, in contrast to early predictions made about Foxconn's impact on local employment. An early evaluation of Foxconn's investment plan predicted a positive impact on the local economy, and stated that up to 26,000 additional jobs could be created through spillover effects (Williams, 2017). These projections were widely discussed in the local news (Romell and Stein, 2017). Given the rather optimistic forecasts of Foxconn's employment spillover effects, it is unlikely that individuals held very pessimistic beliefs. I therefore interpret my results as more in line with labor market models where search is at least partially directed.

In Column (4) of Table 3, I present the estimation results on the impact of positive labor market news on the expected salary increase at the current employer within the next twelve months. As one can see, positive news significantly increases the expected salary growth rate. Individuals exposed to positive labor market news expect an almost 3 percentage points higher salary increase compared to my control individuals. These estimates are not only quite large in magnitude but also highly statistical significant.

The estimates give interesting implications about firm-worker wage bargaining and offer matching. Labor market news leads to an update of the expected salary change at the current employer. On the one side, this suggests that individuals adjust their perceived bargaining power to negotiate with their current employer upward to the new information, even if this information is noisy. On the other side, the results also imply that individuals actually expect to engage in bargaining with their current employer in the near future, both as a response to positive labor markets news and, as I will show further below, to a lesser extent also to negative news.

To shed more light on the implications of labor market news on bargaining and perceived bargaining power, I also investigate if these adjustments are larger for workers who expect their current employer to match any outside offer. The difference in the SC-DiD estimates between workers who expect likely offer matching and those who do not is 0.04 and not statistically different from zero (not reported in the table). While such an estimated effect is arguably not causal, it shows that the adjustment process is not driven by expectations about offer matching. Taken together, the results do not imply that firms exclusively engage in bargaining once the worker has received an outside offer as, for example, in Postel-Vinay and Robin (2002), Dey and Flinn (2005), and Cahuc et al. (2006). They also lent support to a theory of more frequent bargaining over wages between firms and workers, such as in Gottfries (2021).

One explanation why firms engage in bargaining over wages, even if workers do not have an outside offer at hand, is that they are not able to fully respond to potential outside offers. For example, workers can have private information about their outside offer or costs to renegotiate contracts are high. Firms' inability to fully respond to outside offers induces them to pay higher wages to retain workers (Lavie and Robin, 2012; Gottfries, 2021).

Lastly, I also investigate the impact of negative news on individuals' expectations. The results are shown in Panel B of Table 3. Expectations about the job offer arrival rate are unaffected by negative news. As it was the case before, the impact of negative news on the expected number of offers is rather small and not statistically significant different from zero; see Column (1) in Panel B.

In contrast, negative labor market news leads individuals to revise their expectations about future average and maximum salaries offered significantly downward; see Columns (2) and (3). The downward revisions to negative news are substantially smaller in magnitude compared to updating in response to positive news. Negative news reduces the expected average salary offered by around 7% and the expected maximum salary offered by around 12%. These reductions are one-third to halve of the size compared to the impact of positive news.

Interestingly, I also find that negative labor market news leads to a downward revision of the expected salary growth rate in the current firm, although the coefficient is noisily estimated and not statistically significant from zero. As it was the case with my previous estimates, this downward adjustment is substantially smaller in magnitude compared to the upward adjustment as a response to positive news.

The results indicate clear asymmetries in the updating process of expectations. Positive news leads to a large and significant upward revision of both the expected value of job search and the expected salary increase at the current employer. While negative news leads in general to a more pessimistic view about future labor market outcomes, the downward revisions are substantially smaller in magnitude. These results imply that even when accounting for individual heterogeneity, individuals tend to put more weight on positive labor market news than negative ones. In that sense, my findings here complement the mostly experimental literature on how individuals update their beliefs (e.g.

Eil and Rao, 2011; Möbius et al., 2014; Sarson, 2019) and show that asymmetric updating happens in non-lab settings and to general, non-personalized news.

5 Robustness & Placebo

I assess the robustness of my estimation results in various ways. First, I estimate a placebo regression using a similar design as discussed above but concentrating on individuals who were surveyed between the beginning of 2015 and the end of 2016. These two years are sufficiently distant to the the first speculations surrounding Foxconn's investment plans in the United States. They were also marked by stable economic conditions. As before, I concentrate on a balanced samples of individuals being interviewed in March, July, and November. Those individuals residing within the commuting zones of Racine County and Milwaukee-Waukesha-West Allis are considered as treated while all other individuals in the samples constitute the control group. If my results were driven by some spurious, mechanical reasons then one would expect to see similar expectation updating using this sample. Notice that by choosing two survey years, I almost double the sample size compared to my baseline sample. The larger sample size makes it easier to detect effects and thus any possible violations of my identification assumptions. The results are reported in Panel A of Table 4.

As one can see in Panel A of Table 4, my placebo estimates are rather small. The estimated coefficients are only one-third to one-half in magnitude in comparison to my baseline results. None of my placebo estimates is also statistically significant at any conventional level, although the sample is now considerably larger. Thus, I interpret these results as support of my identification assumptions.

Second, I re-estimate the model from Section 3 including time-varying covariates. Specifically, I now include personal time varying characteristics which may affect expectation formation, such as household income and employment status in my estimation; see also the characteristics presented in Table 2. If my results were not the results of exposure to labor market news but caused by individuals' labor market dynamics, this would be (partially) captured by the included time-varying covariates. The results are reported in Panel B of the table.

Including covariates leaves my estimates virtually unchanged in the positive news sample. Considering the negative news sample, including individual time-varying characteristics even slightly increases my estimates in magnitude in some cases, although I also observe an increase in the estimated standard errors. In general, including covariates in my estimation does not alter any of my conclusions. The minor role of covariates has also been noted by Doudchenko and Imbens (2017) who emphasize that accounting for pre-treatment outcomes, as in my SC-DiD setting, is more important to obtain unbiased results.

Lastly, I also exclude all individuals who resided in Wisconsin from my control group. This is to see if potentially dynamic adjustments and anticipation to Foxconns' initial announcements play a role in explaining my results. For example, the announcement that the plant will finally be built in Racine County might have disappointed individuals residing in other parts of Wisconsin, in turn leading to a disproportional downward adjustment of expectations. In that case, my estimates would overstate the impact of positive labor market news. The results are reported in Panel C of the Table 4.

As one can see, excluding control individuals from Wisconsin from my analysis does not crucially affect my results. My estimates for the positive news sample are virtually identical to my baseline results and are now, in the case for maximum log salary offer, even more precisely estimated. I come to a similar conclusion when looking at the negative news sample, although excluding the rest of Wisconsin leads to slightly larger standard errors in some cases. Overall, the results here do not point toward dynamic adjustments and anticipation in expectations prior to exposure labor market news as an important driver of my results.

6 Conclusion

Expectations are key for individuals' decision making and are important ingredients in many modern economic models. Despite an increasing interest in how individuals form and adjust expectations empirical evidence is still scant. Understanding the dynamics of expectations is important, however, not only for the design of effective policies but also to inform theories, such as those of the labor market.

Using the Survey of the Consumer Expectations for the U.S. and applying a synthetic difference-in-difference approach I investigate how individuals adjust their expectations to receiving both good and bad labor market news. To do so, I exploiting a unique setting, Foxconn's plan to create up to 13,000 high paying jobs over 15 years in Racine County, Wisconsin in 2017 (positive news) and its later considerably downward revised forecast for the project (negative news).

My results are consistent with predictions from directed search models. I find that individuals strongly adjust their expectations to the exposure to news. I do not find evidence that positive labor market news affect an individual's expected job offer arrival rate. But, conditional on expecting an offer, positive labor market news leads to a significant increase of the expected salary offered. Workers anticipate that higher paying vacancies will also attract more applicants and therefore do not adjust their job finding probabilities. At the same time, conditional on expecting an offer, the expected value of the offer is adjusted considerably upwards. I provide additional evidence why other theories, such as a general equilibrium effects where individuals adjust expectations about hiring of incumbent firms downward as response to Foxconn's expansion plan, are unlikely to explain my results.

Positive labor market news also leads to an upward adjustment of the expected salary growth rate at the current employer. Interestingly, exposed individuals expect higher wage growth even if they do not expect the current employer to match any potential outside offer. These results imply that, on the one side, positive labor market news increases workers' perceived bargaining power. On the other side, the results also point toward a more frequent bargaining over wages between firms and workers, even in the absence of an outside offer for the worker. Such frequent bargaining may take places as firms cannot fully match potential outside offers, for example, as outside options are not fully verifiable or negotiation is very costly, leading firms to pay higher wages.

Looking at the impact of negative labor market news on individuals' expectations, my results reveal asymmetries in the updating process. Negative labor market news lead to smaller downward adjustments of expectations in magnitude when compared to the impact of positive news. Taken together, my results show an asymmetric updating of expectations even to non-personalized news and outside of the lab. Such findings have also important implications for policy makers. For example, asymmetric updating of expectations may be part of the explanation why long-term unemployed tend to overestimate their job finding probabilities as in Mueller et al. (2021).

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Tables

Table 1: Foxconn in Wisconsin

Date	Event	News Exposure
January 2017	Foxconn first considers to invest in the U.S.	
April 2017	First Meeting between Foxconn's chairman Gou and Governor Walker to discuss potential investments in Wisconsin	
July 2017	Memorandum of Understanding between Foxconn and Wisconsin	
November 2017	Formal agreement to build plant in Racine County, WI. Foxconn is offered $2.85 billion in state income tax credit. In addition, Wisconsin promises to invest additional $800 million in infrastructure and other training programs. Foxconn will invest $10 billion and create 13,000 jobs with an average annual pay of around $54,000 over the next 15 years. Distribution of fliers with "sample positions" at job fairs stating that Foxconn is soliciting applications of candidates who want to be considered for positions that will see hiring in the coming months.	***Positive News***
January 2019	Foxconn official expresses doubts about viability of the initial investment plans and states that final investments will likely be much smaller. The number of new jobs created by 2020 could be as low as 1,000 - downward revised from originally 5,200.	***Negative News***
April 2021	New agreement between Foxconn and Wisconsin. Foxconn will only invest $642 million and create only 1,500 jobs over the next four years. In return, the company will only receive $ 80 million in performance-based tax credits.	

Table 2: Summary of Samples

	Positive News Sample	Negative News Sample
Age below 40	43.37	35.47
	(49.61)	(47.89)
College Degree	64.46	65.12
	(47.91)	(47.71)
Employed	94.18	90.31
	(23.44)	(29.61)
Full-Time Job	77.31	75.58
	(41.93)	(43.00)
Living with Partner	70.48	62.40
	(45.66)	(48.48)
Partner Employed	58.84	50.19
	(49.26)	(50.05)
Low HH Income	36.95	41.47
	(48.31)	(49.32)
Individuals	166	172
Observations	498	516

This table summarizes the estimation xamples. The Positive News sample consists of all individuals interviewed in March, July, and November 2017. The Negative News sample consists of all individuals interviewed in July and November 2018 as well as in January 2019. Low HH Income refers to households with total household income of at most $ 61,000, the median household income in the U.S. Standard deviations are reported in parentheses.

Table 3: Effect of News on Expectations about Job Search and Earnings

	(1) Number of Job Offers	(2) Average Log Salary Offer x 100	(3) Maximum Log Salary Offer x 100	(4) Salary Increase Current Job x 100
Panel A: Positive News				
Δ^{SC-DiD}	0.14	19.25***	19.19**	2.71**
	(0.24)	(6.66)	(7.73)	(1.21)
Observations	498	279	291	459
Panel B: Negative News				
Δ^{SC-DiD}	−0.74	−7.57*	−12.15**	−1.96
	(0.45)	(4.51)	(5.41)	(1.82)
Observations	516	249	261	438

This table summarizes the SC-DiD estimates of the effect of labor market new on individuals' expectations about job search and earnings. Panel A uses the announcement of opening the Foxconn plant in Racine County, Wisconsin, in November 2017 as treatment (positive news). Panel B uses the news in January 2019 that Foxconn's expansion plans are smaller than previously announced (negative news); see also Section 2. The estimation approach is described in Section 3. In Column (1), the expected number of job offers over the next four months is used as outcome. The dependent variable in Columns (2) and (3) is the expected log average salary and the expected log maximum salary offered when receiving an offer. The dependent variable used in Column (4) is the expected percentage increase in the salary in the current job over the next year. Standard errors are obtained using the bootstrap with 1,000 replications. *, **, and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level,respectively.

Table 4: Placebo and Robustness

	(1) Number of Job Offers	(2) Average Log Salary Offer x 100	(3) Maximum Log Salary Offer x 100	(4) Salary Increase Current Job x 100
Panel A: Placebo Treatment				
Δ^{SC-DiD}	0.18	7.32	5.27	1.36
	(0.30)	(9.34)	(10.07)	(1.39)
Observations	951	504	513	840
Panel B: Including Covariates				
$\Delta^{SC-DiD}_{Positive}$	0.26	19.63***	19.07**	3.04***
	(0.24)	(6.69)	(7.71)	(1.19)
Observations	498	279	291	459
$\Delta^{SC-DiD}_{Negative}$	−0.72	−8.42	−13.15*	−1.95
	(0.43)	(6.21)	(7.83)	(1.86)
Observations	516	249	261	438
Panel C: Excluding Rest of Wisconsin				
$\Delta^{SC-DiD}_{Positive}$	0.15	19.81***	19.54***	2.75**
	(0.23)	(6.67)	(7.59)	(1.27)
Observations	489	273	285	450
$\Delta^{SC-DiD}_{Negative}$	−0.72	−6.43	−13.03**	−1.96
	(0.47)	(4.10)	(5.34)	(1.88)
Observations	501	237	246	423

This table summarizes the robustness and placebo results as described in Section 5. Panel A uses a placebo announcement of Foxconn's plant opening in Racine County using years 2015 and 2016. Panel B includes covariates in the estimation. Panel C excludes individuals residing in Wisconsin from the control group. In Column (1), the expected number of job offers over the next four months is used as outcome. The dependent variable in Columns (2) and (3) is the expected log average salary and the expected log maximum salary offered when receiving an offer. The dependent variable used in Column (4) is the expected percentage increase in the salary in the current job over the next year. Standard errors are obtained using the bootstrap with 1,000 replications. *, **, and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level,respectively.

Online Appendix for "The Impact of Labor Market News on Individuals' Expectations"

Bernhard Schmidpeter

January 13, 2022

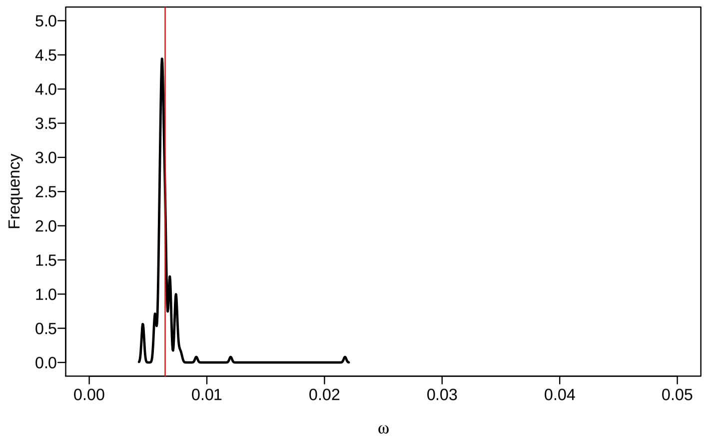
This Web Appendix provides additional details and results not discussed in the manuscript.

A Summary of Estimated Time and Individual Weights

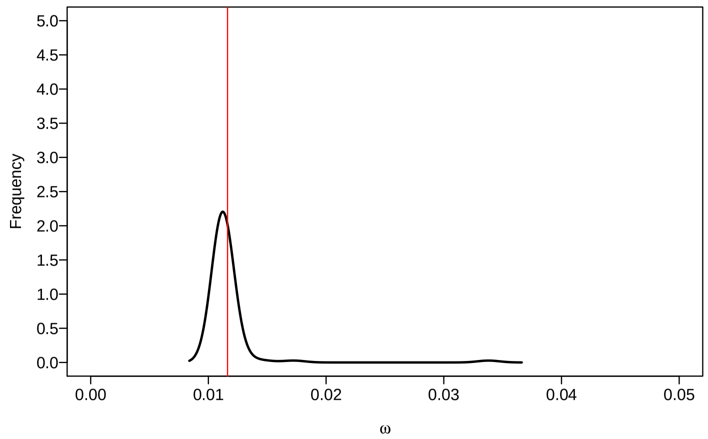
Figures A.1 and A.2 present the estimation results for the individual weights ω_i obtained from Equation (3) for my four outcomes and for the positive and negative news sample respectively. Looking at the density estimates in the figures two features become apparent.

First, there is no evidence that a particular individual receives an unusually large or small weight in my estimation. The maximum weight assigned to a single individual is around 0.035 in the positive news sample when considering the expected average salary offered and 0.045 in the negative news sample using expected number of job offers as outcome. Second, in both my samples and all outcomes considered there is a large mass around the standard DiD weight of N_{co}^{-1}. This suggests that many of my untreated observations are comparable with respect to pre-treatment outcomes, even in the raw data. Overall, the evidence presented here shows that it is unlikely that very few individuals alone are driving my results.

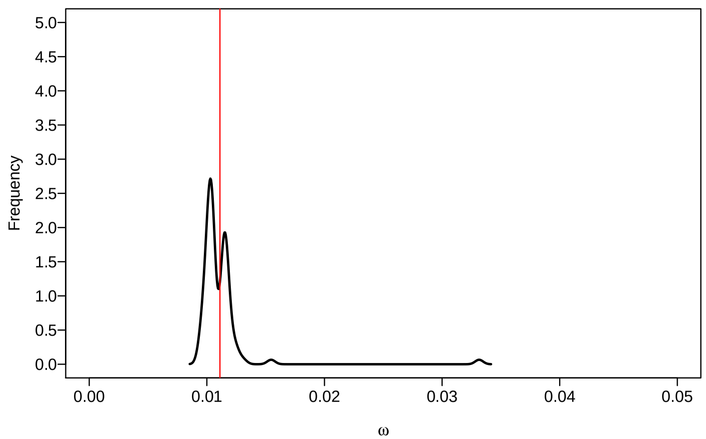
Figure A.1: Distribution of Estimated Individual Weights - Positive News Sample



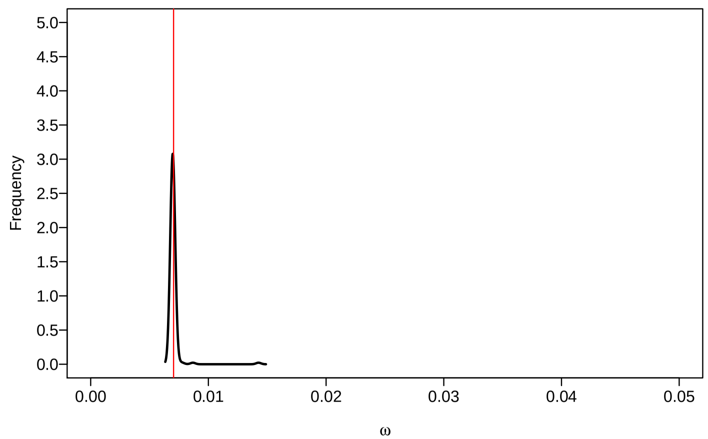
a. Number of Offers



b. Average Salary Offered



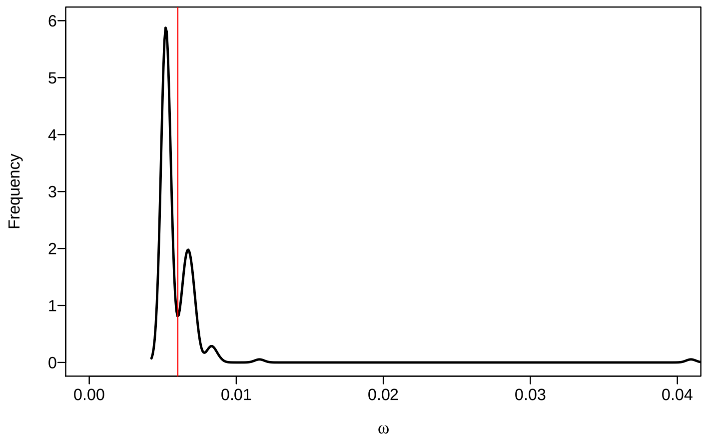
c. Maximum Salary Offered



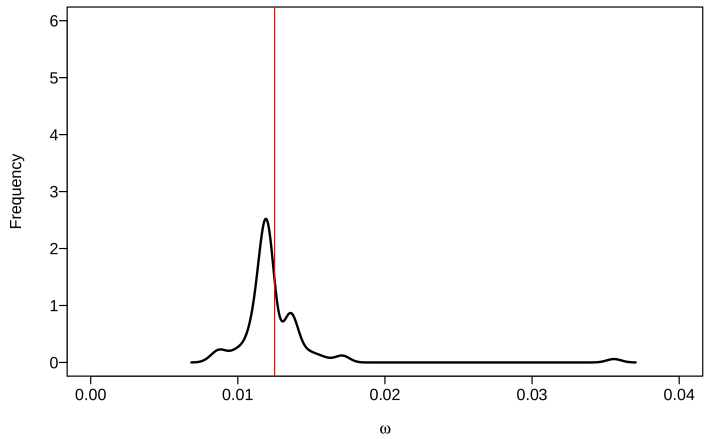
d. Salary Current Job

The figure shows kernel density estimates of the estimated individual weights ω_i for control individuals and the positive news sample using a Gaussian Kernel and Silverman's Rule-of-Thumb (Silverman, 1998). The weights were obtained from Equation (3). The vertical line depicts the standard DiD weights corresponding to N_{co}^{-1}

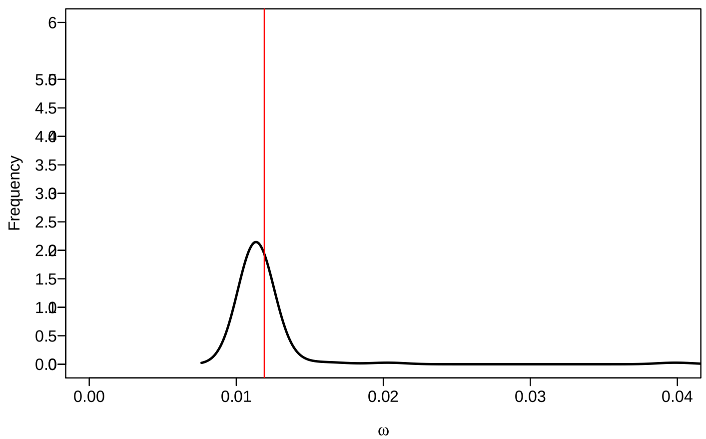
Figure A.2: Distribution of Estimated Individual Weights - Negative News Sample



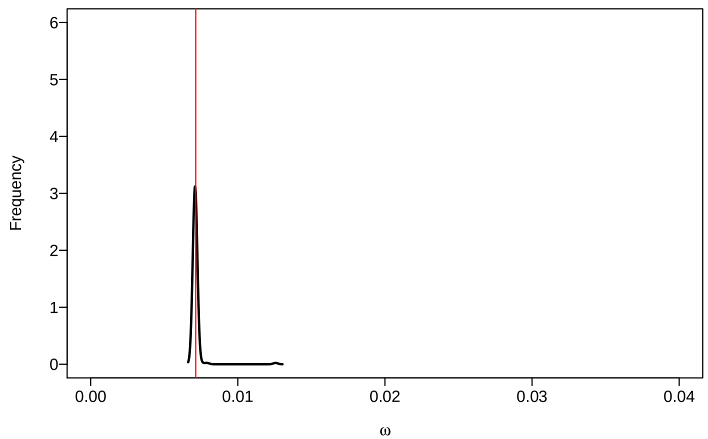
a. Number of Offers



b. Average Salary Offered



c. Maximum Salary Offered



d. Salary Current Job

The figure shows kernel density estimates of the estimated individual weights ω_i for control individuals and the negative news sample using a Gaussian Kernel and Silverman's Rule-of-Thumb (Silverman, 1998). The weights were obtained from Equation (3). The vertical line depicts the standard DiD weights, corresponding to N_{co}^{-1}

The estimates for the time weights λ_t obtained from Equation (4) are shown in Table A.1. For the positive news sample presented in Panel A of the table, more weight is in general assigned to the period farther away from the treatment date for most of my outcomes. The differences in the weights across my two period are, however, small. The estimates for λ are also very close to the standard DiD time weights of $\frac{1}{2}$.

Considering the negative news sample, more weight is put on the period directly preceding the treatment; in the case of the expected number of job offers even the entire weight. There is also a larger difference in the weights between pre-treatment period compared to the positive news sample and the weights tend to deviate stronger from the standard DiD time weights.

Table A.1: Estimated Time Weights

	(1) Number of Job Offers	(2) Average Log Salary Offer	(3) Maximum Log Salary Offer	(4) Salary Increase Current Job
Panel A: Positive News				
λ_{-1}	0.40	0.46	0.49	0.44
λ_{-2}	0.60	0.54	0.51	0.56
Panel B: Negative News				
λ_{-1}	1.00	0.68	0.72	0.75
λ_{-2}	0.00	0.32	0.28	0.25

This table summarizes the estimates of the pre-treatment time weights λ_t for the different outcomes obtained from Equation (4). Panel A refers to the positive news sample and Panel B to the negative sample.

B Difference-in-Difference Results

In this section, I present results from a "standard" Difference-in-Difference (DiD) estimation. The estimators can be obtained from a two-way fixed effects regression

$$y_{it} = \alpha + D_{i,t}\Delta^{DiD} + \gamma_t + \nu_i + \epsilon_{it}$$

and is given by the coefficient Δ^{DiD}.[1] The results of the DiD estimation are reported in Table B.2.

Looking at the results in the Table, one can see that my DiD estimates are slightly smaller compared to the results obtained from the synthetic difference-in-difference ap-

[1]Alternatively, it can also be obtained by setting the weights ω_i for control observations to constant weights N_{co}^{-1} and λ_t to constant weights 1/2 in Equation (2). in the main part of the paper

Table B.2: Effect of News on Expectations about Job Search and Earnings - Difference-in-Difference Estimates

	(1) Number of Job Offers	(2) Average Log Salary Offer x 100	(3) Maximum Log Salary Offer x 100	(4) Salary Increase Current Job x 100
Panel A: Positive News				
$\Delta^{DiD}_{Positive}$	0.10	18.53***	18.49**	2.36**
	(0.27)	(6.84)	(7.48)	(1.01)
Observations	498	279	291	459
Panel B: Negative News				
$\Delta^{DiD}_{Negative}$	0.03	−6.04	−16.74**	−1.99
	(0.28)	(3.87)	(7.35)	(1.70)
Observations	516	249	261	438

This table summarizes the DiD estimates of the effect of labor market new on individuals' expectations about job search and earnings. The estimates were obtained from a two-way fixed effects regression. Panel A uses the announcement of opening the Foxconn plant in Racine County, Wisconsin, in November 2017 as treatment (positive news). Panel B uses the news in January 2019 that Foxconn's expansion plans are smaller than previously announced (negative news); see also Section 2. In Column (1), the expected number of job offers over the next four months is used as outcome. The dependent variable in Columns (2) and (3) is the expected log average salary and the expected log maximum salary offered when receiving an offer. The dependent variable used in Column (4) is the expected percentage increase in the salary in the current job over the next year. Standard errors are obtained using the bootstrap with 1,000 replications. Standard errors are obtained using the bootstrap with 1,000 replications. *, **, and *** indicate statistical significance at the 10 percent level, 5 percent level and 1 percent level,respectively.

proach, reported in Table 3 in the main part of the paper. Using a DiD approach does not affect my conclusions made in the main part of the paper, however. The differences in the estimated effects between the two methods are also small. This is not surprising given that my estimated weights in the SC-DiD estimation are close to the standard DiD weights; see Section A. Overall, the results in this section show that my results are robust to the weighting approached used in the estimation.

References

Silverman, B. W. (1998), *Density Estimation for Statistics and Data Analysis*, London: Chapmann & Hall / CRC.