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# Labor Market News and Expectations about Jobs & Earnings

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Working Paper No. 2314
October 2023

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# Labor Market News and Expectations about Jobs & Earnings

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October 16, 2023

**Abstract**

Little is known about how workers update expectations about job search and earnings when exposed to labor market news. To identify the impact of news on expectations, I exploit Foxconn's unexpected announcement to build a manufacturing plant in Racine County. Exposure to positive news leads to an increase in expected salary growth at the current firm. Individuals also revise their expectations about outside offers upward, anchoring their beliefs to Foxconn's announced wages. They act on their updated beliefs with a small increase in current consumption. Negative news from a scaled-down plan leads to a revision of expectations back toward baseline.

*JEL Codes:* C33, D84, E24, J31, J63
*Key words:* beliefs formation, wage expectations, outside options, consumption

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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. Delavande and Zafar, 2019; Wiswall and Zafar, 2021; Azmat and Kaufmann, 2022). In labor market models, expectations about labor market outcomes affect an individual's job search decision and search effort (e.g. Conlon et al., 2018; Mueller et al., 2021; Jäger et al., 2023). These expectations are likely not constant but individuals update them dynamically as new information and news about the labor market arrive. Still, little is known about how individuals use news about the labor market to adjust their expectations about jobs and wages, and whether they act on their updated beliefs (Mueller and Spinnewijn, 2023).[1] Gaining insights into these adjustment processes, however, is central to our understanding of how individuals perceive their opportunities in the labor market, the determination of wages, and ultimately inequality and effective policies (e.g. Hvidberg et al., 2023).

In this paper, I shed light on how individuals use public labor market news to adjust expectations about salary growth at the current firm and job offers, combining local labor market information with the New York Fed's Survey of Consumer Expectations (SCE). Concentrating on these outcomes allows me, on the one hand, to investigate how information affect workers' perception about outside options, in the spirit of Jäger et al. (2023), in a real world setting. On the other hand, they also allow me to explore the role of beliefs and public information on wages and the wage setting process. Linking expectation updating back to actual behavior, I also explore whether individuals act on their updated beliefs and adjust their current consumption, as proxied by household spending. Establishing empirically the relationship between exposure to news and belief updating is challenging, however.[2]

To identify the impact of news on individuals' labor market expectations, I exploit a largely unexpected news shock: Foxconn's announcement in October 2017 to build a LCD manufacturing plant in Racine County, Wisconsin. Foxconn, one of the largest contract manufacturers in the world, had considered to invest in the US since January 2017, but had not disclosed detailed plans prior to October 2017. At the announcement in October, Foxconn stated that it planned to create up to 13,000 jobs paying on average

[1]A few works explore dynamic expectations updating in different settings, for example, considering house prices (Armona et al., 2019) and inflation (D'Acunto et al., 2021).

[2]In general, empirically identifying outside options and wage setting processes is very difficult. See, for example, Lachowska (2017), Caldwell and Harmon (2019), Caldwell and Danieli (2022), Di Addario et al. (2022) for works on outside options and Hall and Krueger (2012), Lachowska et al. (2022), and Schmidpeter and Tô (2023) for evidence on wage setting processes.

$54,000 over the next 15 years.[3] In comparison, at the time of the announcement, total employment in Racine County was around 77,000 individuals earning an average annual wage of $43,000 (Bureau of Labor Statistics, 2017).

At the time of the announcement, Foxconn not only provided a detailed investment plan, but also actively advertised the associated job opportunities and planned hiring (Handelman, 2017; Kirchen, 2017). For example, Foxconn posted "want ads" for a wide range of jobs in Racine, such as in engineering, management, and health & safety, on their own web page and at Indeed.com, one of the most popular employment websites. It also distributed fliers with "sample positions" at local job fairs. Using information from Google Trends, I show that internet searches for jobs at Foxconn spiked at the announcement date in October 2017 in Wisconsin compared to the rest of the US. There was little difference in interest across regions before that date. I see this as evidence that there was no anticipation prior to Foxconn's actual announcement, while individuals became fully aware of the investment plan after being exposed to the news.[4]

Foxconn's unexpected announcement suggests comparing within a difference-in-difference (DiD) approach changes in expectations of individuals who resided close to Racine County at the time of the labor market news to those who did not. Under the so-called parallel trends assumption, one could then identify the impact of exposure to labor market news on individuals' expectations and behavior. In general, assessing whether the parallel trends assumption is satisfied is difficult in practice (see, e.g., Roth, 2022, for a discussion). It is particularly challenging in settings with relatively small sample sizes, such as mine, given that Foxconn's investment plan was concentrated very locally.

To overcome these difficulties, I employ the synthetic difference-in-difference (SC-DiD) approach proposed by Arkhangelsky et al. (2021). The SC-DiD approach combines synthetic control methods (Abadie et al., 2010) with a difference-in-difference approach. Intuitively, the SC-DiD compares only exposed individuals who are very similar to non-exposed individuals in their outcomes prior to Foxconn's announcement. By comparing only individuals with similar pre-exposure outcomes, the SC-DiD approach weakens the reliance on the parallel trends assumption for identification.[5] It is therefore robust in settings where it is difficult to assess pre-treatment trends and when only a few individuals receive treatment.[6] Importantly, within this estimation framework, I am able

[3] Besides its direct impact, Foxconn's investment was forecasted to create substantial spill-over effects of up to 26,000 additional jobs in various sectors such as financial & business services, health care, and education. (Williams 2017; EY, 2017).

[4] I provide additional evidence of no-anticipation in the Appendix.

[5] In fact, similar as with synthetic control methods, the SC-DiD approach makes any pre-announcement trends in the non-exposed group parallel to those in the exposed group giving each individual in the control group appropriate weights. I provide further evidence and robustness checks in the Appendix.

[6] Related to the SC-DiD of Arkhangelsky et al. (2021) is the bias-correction approach of Ben-Michael et al. (2021) as well as the "re-centering" methods of Doudchenko and Imbens (2017) and Ferman and Pinto (2021). The SC-DiD performs well in policy-evaluation type of settings, like mine, where usually one would use a difference-in-difference approach. I will show later that DiD and SC-DiD deliver virtually

to distinguish the systematic component of the expectation updating process related to news from other time-fixed unobserved heterogeneity. 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). Accounting for time-invariant idiosyncratic differences is particularity important when considering beliefs (Manski, 2004).

Being exposed to Foxconn's labor market news increased the expected yearly salary growth rate at the current employer significantly by around 3 percentage points, or roughly 22% of a standard deviation. This effect is quite sizable. Notice, however, that Foxconn's announced wages also were substantially higher than the local average wage rate in Racine County. One explanation for the upward adjustment of salary expectations is that some individuals may adjust the perceived value of their outside options upward. Being exposed to Foxconn's initial job postings and expecting the opening of many and high paying jobs, workers' anticipate improved opportunities when negotiating. Exploring the role of labor market news in determining wage settings further, I do not find evidence that the impact of news on expected salary growth in the current firm is driven by expectations about an actual outside offer. Workers who are more optimistic about receiving an outside job offer in the near future adjust their expectation similarly as workers who are more pessimistic. Likewise, I do not find any differential adjustments in wage growth expectations between workers who are optimistic about salary matching by the current employer and those who are more pessimistic.[7]

Rather, my results imply that exposure to Foxconn's labor market news leads to a more optimistic view about one's own prospect at the current firm. Individuals tend to hold misspecified beliefs about their labor market opportunities in general. Once public information about new job opportunities becomes available, individuals use it as the basis for their wage negotiations. This is also in line with results from the experimental information treatment of Jäger et al. (2023), where workers who received (private) information about outside options also state greater intention to re-negotiate their wages. It is worth pointing out that I account for individual time-invariant unobserved heterogeneity in my estimation, which is an important factor behind differences in individuals' earnings growth expectations (Koşar and van der Klaauw, 2023). Therefore, my effects here are unlikely driven by idiosyncratic differences in beliefs.

identical estimates in my setting, but that the SC-DiD is more efficient, something also pointed out by Arkhangelsky et al. (2021).

[7] I consider these effects as providing interesting insights into the wage setting process, but also want to highlight that they can only be interpreted as causal under very strong assumptions. Therefore, they should be interpreted with the necessary care. As I will show later, the news shock left the expected offer distribution largely unchanged. Therefore it seems unlikely that the results are solely driven by a shift in the expected offer distribution.

The results also point toward interesting implications for firm-worker wage bargaining, expected outside offers, and offer matching. For example, the results imply that firms do not only and exclusively engage in bargaining once the worker has received an outside offer (Postel-Vinay and Robin, 2002; Dey and Flinn, 2005; Cahuc et al., 2006). They also suggest that firms and workers bargain more frequently over wages (Gottfries, 2021). One possible explanation why firms engage in bargaining over wages, even if workers do not have an actual outside job offer at hand, is that they are not able to fully respond to potential outside offers. This suggests that not only workers are not well-informed about firms' pay policy (e.g. Cullen and Perez-Truglia, 2023), but also that firms do not have complete information about workers' outside options (Lavie and Robin, 2012). While I cannot directly test this explanation with my data at hand, it is in line with findings of Cullen et al. (2022), who provide survey evidence that HR managers have only limited or no information about potential outside offers of their employees.

Looking at expectations about outside job offers, I do not find evidence that individuals update their expectations about receiving any offer as response to the labor market news. My estimates for this outcome are close to zero and not statistically significant at any conventional level. Conditional on expecting an offer, however, individuals update their expectations about the offered salary considerably upward. My estimates show that Foxconn's announcement to create new jobs in Racine County led to an increase in expected average salary offered by around 20%. Using the mean annual wage of $43,000 in Racine County in 2017 as baseline, my results imply that workers expect to receive an offered salary close to Foxconn's announced average wage of $54,000. The results here complement those of Jäger et al. (2023). They show that workers tend to anchor their beliefs about outside options wrongly to their current wage and these beliefs are very persistent. They are also in line with Hall and Krueger (2012) who find that a large share of job applicants have no precise idea about the possible wage offered for a position prior to the first interview. I show that workers dynamically adjust their beliefs about outside options in public news, when available.

Interpreting these results through the lens of theoretical job search models, they are consistent with predictions from (partially) directed search (Menzio, 2007; Banfi and Villena-Roldán, 2019; Wright et al., 2021). Individuals anticipate that the creation of new, high-paying vacancies will attract many more applicants. The anticipated longer queue length for the new jobs then in turn leaves the expected job offer arrival rate unaffected. When expecting a job offer, however, individuals anchor their wage expectations to the public available information about Foxconn's announced wages for the vacancies.[8]

[8] An alternative explanation is that individuals expect incumbent firms to increase wages but, to stay competitive, also to reduce employment substantially as a response to Foxconn's announcement. Such an adjustment process would create the same empirical results and be consistent with predictions from random search models (Rogerson et al., 2005). The evidence in my data is not consistent with such an explanation. The scenario would imply that individuals held strong and negative beliefs about the

I conduct various checks to assess the robustness of my results. For example, I apply the SC-DiD approach to labor market expectations measured well before Foxconn's first announcement. The results from these placebo regressions are all small and not statistically significant at any conventional level. I also show that my results are unlikely driven by adjustments of beliefs unrelated to labor market news. For example, individuals residing in other parts of Wisconsin not selected by Foxconn may have been disappointed by the decision and disproportionately downward shifted their beliefs. My results are robust to excluding these individuals from my analysis. One may also be concerned that the effects I estimate are driven by political sentiments and different trends in the general expectations about the future state of the economy rather than exposure to labor market news.[9] Using information from Autor et al. (2020), I only consider individuals in Republican-leaning commuting zones, as defined by their vote share in the 2016 presidential election, for robustness. Applying this restriction gives virtually identical results as my baseline estimates.[10]

I provide further evidence on the robustness of my estimates in the Appendix. My results do not crucially depend on the specific weightings and my conclusions remain valid even when employing a standard difference-in-difference approach. Furthermore, following Manski and Pepper (2018) and Rambachan and Roth (2022), I show that any other local shock associated with individuals' expectations but unrelated to Foxconn's announcement, such as changes in productivity and local labor demand, would need to be unrealistically large. For example, relating my results to the relationship between vacancy rates and wage growth (Domash and Summers, 2022), I show that an unrelated local labor demand shock would need to double the local vacancy rate to invalidate my estimated impacts of labor market news on salary expectations.

Exploring whether individuals act on their updated beliefs and change their behavior, I find small positive effects on current consumption, as proxied by household expenditures. I provide evidence that the consumption increase is driven by households spending relatively more on smaller items, such as clothes and personal care. I do not find evidence that individuals make larger spending adjustments. Overall, the results suggests that individuals adjust their current consumption according to their expect future economic resources, in line with a consumption Euler equations (see also, for example, Roth and Wohlfart, 2020; Dräger and Nghiem, 2021). Furthermore, they imply that individ-

employment externalities of Foxconn's investment plan. Foxconn's investment plan was predicted to create up to 26,000 additional jobs through spillover effects in many different sectors, such as transportation, business service, health care and education, however. These employment projections were also distributed and discussed widely in the local press.

[9] For example, then President Trump played a role in facilitating the meetings between Foxconn and the Wisconsin Governor. This might have created a general sense of optimism in Republican-leaning areas.

[10] In fact, the estimates are almost symmetric when including only individuals residing in Democratic- or Republican-leaning commuting zones in my control group.

uals increase consumption as they are more optimistic about their future, mirroring the results in Coibion et al. (2021).

Finally, I also explore Foxconn's announcement of a scaled down version in January 2019 to investigate the persistence of individual beliefs. As this new announcement revealed significant uncertainty about the project and number of created jobs, one would expect individuals to reverse their expectations toward baseline if they used labor market news to form their beliefs.[11] Indeed, I find that the announcement about labor market uncertainty leads to a reversal in the expected salary growth rate for exposed workers, although the effects are largely imprecisely estimated. Moreover, I find that, in case of an outside offer, workers adjust their expectations about offered wages substantially downward. Taken together, my findings show that individuals update expectations and beliefs dynamically to the arrival of new public information and news.

With my work I make several contributions to different strands of the literature. I contribute to the mostly experimental literature exploring how individuals use new information to form expectations, specifically about the labor market (Conlon et al., 2018; Haaland and Roth, 2020; Roth et al., 2022). The closest related to my work is the study by Jäger et al. (2023). They show that workers have misspecified beliefs about their outside options, specifically those in low-paying firms, wrongly anchoring their beliefs to the current wage. Using an experimental information treatment and providing workers with wage statistics of similar workers, they show that individuals adjust their expectations about their outside options. Individuals receiving the information treatment also showed an increased willingness to search for a new job and to negotiate for higher pay with the current employer.

Relative to the existing works, my contributions are twofold. First, using a real-world setting and the occurrence of an arguably exogenous shock , I find that providing new information leads to a systematic updating of individuals' expectations about jobs and wages, adding additional external validity to the experimental part of the literature. But, my results also show that individuals reverse their expectations when labor market news suggest future uncertainty, highlighting that expectation updating happens very dynamically in real life.[12] Second, I also show that positive labor market news change workers' beliefs about their wage growth at the current firm, even when they do not expect any outside offers. This implies that workers become optimistic about their future career prospect when exposed to good news about the labor market, and likely use the new information as basis to bargain with their employer. The results also suggest the existence of information asymmetries about wages and pay structure for both firms and

[11] Using information from Google Trends, I show that interest in Foxconn increased again following the announcement, suggesting that individuals became aware of the uncertainty about future job prospects after exposure to the news.

[12] Manski (2018) also highlights the importance of analyzing the revisions of expectations to unanticipated shocks to better understand expectations formation.

workers. In that sense, my results also speak empirically to the mostly theoretical labor market search literature incorporating firm-worker bargaining (Postel-Vinay and Robin, 2002; Dey and Flinn, 2005; Cahuc et al., 2006; Gottfries, 2021).

Lastly, I also contributes to the literature on expectations and consumption behavior. The majority of the existing works has focused on the role of expectations about macroeconomic conditions (Roth and Wohlfart, 2020; Dräger and Nghiem, 2021; Coibion et al., 2021; Crump et al., 2022). They show, for example, that consumption spending depends on the perceived or (exogenously) received information about future inflation and recession probabilities. My findings presented here give strong indication that individuals also act on their expectations about their future labor market outcomes and adjust their current consumption accordingly.[13]

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 main results. I provide evidence that individuals act on their updated expectations in Section 5. In Section 6, I show that individuals' expectations reverse toward baseline when exposed to uncertainty about future job postings. Finally, Section 7 concludes.

# 2 Background & Data

## 2.1 Foxconn in Wisconsin

In January 2017, Foxconn first considered publicly to invest more than $7 billion in a panel display plant in the United States, which could create up to 50,000 jobs (Wu, 2017). In April of 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).

On 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 at this time 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 affecting many different industries, such as transporta-

[13] Related, Koşar and van der Klaauw (2023) show that expected consumption depends on expected earnings growth.

tion, business services, health care and education (Williams 2017, EY, 2017).[14] At the time of the announcement, the exact location of the proposed plant within Wisconsin was still unknown.

At the beginning of October 2017, Foxconn publicly announced that the LCD manufacturing plant would be built in Mount Pleasent, Racine County. Around the time of the publication, Foxconn also started to actively promote possible future hiring. It posted "want ads" for a wide range of jobs in Wisconsin, such as in engineering, IT, health and safety, quality control, and management on their own web page and on Indeed.com, one of the most popular employment websites. Foxconn also 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. The hiring intentions of Foxconn were also widely distributed and discussed in the local news and media (Handelman, 2017; Kirchen, 2017).

In line with substantial public interest, there was a spike in Google searches for "Foxconn Jobs" in Wisconsin and specifically the metropolitan area of Milwaukee–Racine–Waukesha at this time, see Panel a of Figure 1. In contrast, interest in jobs at Foxconn from other areas of the US was rather low. I consider this as evidence, that individuals residing in the exposed areas became fully aware of Foxconn's plans after the announcement. The flat and almost parallel trends between the metropolitan area of Milwaukee–Racine–Waukesha and the rest of the USA prior to the announcement also indicate that there was little anticipation of the event prior to the actual announcement.

In November 2017, four months after Foxconn published its initial investment plan, the Foxconn-Wisconsin partnership was also officially formalized. 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 would cost Wisconsin an additional $800 million (Deza, 2020).

Foxconn agreed to invest up to $10 billion in a new display manufacturing plant resulting in the creation of up to 13,000 new jobs over a 15 years time period. 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 average annual wages were around $42,300 in Racine County (Bureau of Labor Statistics, 2017).

[14]The estimated indirect and induced employment effects for sectors outside of construction were substantial. For example, it was estimated that almost three times as many jobs in health care and education will be created than in construction and utilities (EY, 2017).

Some time after signing the agreement, uncertainty about the final numbers of jobs created rose, as Foxconn had yet to start to build the plant. 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 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). Panel b of Figure 1 shows that this announcement created again a spike in the general interest in Foxconn, implying that individuals became aware of the new scaled down version of the initial investment plan. I considered this announcement in my work to investigate how persistent expectations are and whether individuals reverse their beliefs when exposed to uncertain labor market news.

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

My analysis is based on 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. The panel structure of the SCE Labor Market Survey allows me to identify the impact of news on expectations formation for the same individual over time. This is crucial to determine the impact of news on expectations as other unobserved factors, such as over-optimism or risk aversion, likely play a crucial role in the updating process. The importance of using panel data when measuring expectations is also highlighted in Mueller and Spinnewijn (2023); see also Manski (2004).

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 *initial announcement* while individuals in the second group constitute the *reversal* 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 initial announcement sample and November 2018 for the reversal 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, 2021). As Milwaukee-Waukesha-West Allis is the commuting zone adjacent to Racine County, workers there may also be affected by the labor market news.[15] Table 2 summarizes the sample of individuals exposed to the initial announcement, on which the main part of my analysis is based, and the reversal sample.

The initial announcement sample consists of 498 observations, while the reversal sample comprises 516 observations. In both samples, over 90% of individuals are employed, mostly in full-time positions. They also 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. By exploiting the panel dimension of the data, this should play only a minor role in my estimation, however.

To analyze the impact of labor market news on the expected increase in earnings in the current job I use the following survey question from th SCE:

- Expected earnings growth: *Please think ahead to 12 months from now. Suppose that you are working in the exact same ('main') job at the same place you currently work, and working the exact same number of hours. By about what percent do you expect your earnings to have increased/decreased? Please give your best guess.*

[15] 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 4.2.

Notice that the question is framed in such a way that the respondent should consider the status quo. Therefore, it captures individuals' expected wage growth in their current firms and is not influenced by other margins of adjustments, such as changes in hours worked or changes in employer.

I use three different measures to analyze the impact of news on individuals' expectations about labor market search:

- Expected number of job offers[16]: *Over the next 4 months, how many job offers do you expect to receive? Remember that a job offer is not necessarily a job you will accept.*

- Expected average salary offer: *Think about the job offers that you may receive within the coming four months. Roughly speaking, what do you think the average annual salary for these offers will be for the first year?*

- Maximum salary offer: *Think about the job offers that you may receive within the coming four months. Roughly speaking, what do you think the annual salary for the best offer will be for the first year?*

Following Conlon et al. (2018), I convert the expected salary offers 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. When considering expectations about job search, I disregard individuals with unusually low or high hourly expected salaries. I set the lower bound to \$3.13, corresponding to half the federal minimum wage, and the upper bound is set to \$200, corresponding to ten times the national median hourly wage rate.

## 3 Empirical Approach

To estimate the impact of labor market news on individuals' expectations, I adopt a modified version of the standard difference-in-difference (DiD) approach proposed by Arkhangelsky et al. (2021) which is particularly suitable for my setting. The standard DiD approach relies on the *parallel trends assumption*. It requires that the outcome for treated individuals evolves the same way as the outcome for control individuals in the absence of treatment. In general, assessing the parallel trends assumption is difficult in practice. In case of relatively small sample sizes, as in my case, trying to evaluate the parallel trends assumption might be uninformative (see, for example Roth, 2022, for a discussion).[17]

[16]The SCE also asks respondents about the perceived probability of receiving an offer. My results are virtually identical using this outcome instead.

[17]In addition, I need to assume that individuals did not adjust their expectations prior to Foxconn's actual announcement, the no-anticipation assumption. As discussed in Section 2, there is little evidence

The modified DiD estimator of Arkhangelsky et al. (2021) combines synthetic control (SC) methods (e.g. Abadie et al., 2010) with a difference-in-difference approach. By combining both methods, this estimator becomes more robust in settings where assessing pre-treatment trends is challenging or where pre-treatment fits are not perfect. As a result, it weakens the reliance on the parallel trends assumption necessary for identification in DiD models.

Intuitively, within the SC-DiD framework only individuals not exposed to the news and who are very similar in their pre-exposure outcomes are compared to individuals who are exposed. This comparison is done by up (down) weighting non-exposed individuals who are the most (least) similar to an exposed individual. Comparing only similar individuals with respect to their pre-exposure outcomes ensures that there are no systematic differences between exposed and unexposed individuals in my estimation. The importance to account for pre-exposure outcomes to obtain unbiased effects is also highlighted by Doudchenko and Imbens (2017).

The estimation then follows in two steps. In a first step, time- and individual weights are estimated by making the outcome in the group of non-exposed individuals parallel to the outcomes of exposed individuals. In the second step, these weights are used in a "standard" two-way fixed effects regression. Below, I describe the SC-DiD approach in more detail and contrast it with the standard DiD estimator.

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

$$y_{it} = \alpha + S_{it}\Delta^{DiD} + \gamma_t + \nu_i + \epsilon_{it} \tag{1}$$

where $S_{it}$ is the time-varying treatment indicator and $\gamma_t$ and $\nu_i$ reflect time- and individual fixed effects. The effect of exposures to news on expectations in the difference-in-difference framework is reflected by the coefficient $\Delta^{DiD}$.

Let $S$ be now the news indicator which takes a value of one if an individual is exposed to 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 news (treatment) and $N_{co}$ are not (control). Denote by $T$ the time periods observed in the data and by $T_{pre}$ the pre-treatment periods. Finally, let $\mathbb{1}_A$ be the indicator function which takes a value of one if the argument $A$ is true and zero otherwise.

individuals anticipated that the plant should be build in Mount Pleasant. I provide further evidence that the no-anticipation assumption holds in the robustness section.

Using the introduced notation, one can express $\Delta^{DiD}$ in Equation (1) explicitly as differences in the outcomes before and after the exposure

$$\Delta^{DiD} = \sum_{i=1}^{N} \mathbb{1}_{S_i=1} N_{tr}^{-1} \left( \frac{1}{T - T_{pre}} \sum_{t=T_{pre}+1}^{T} Y_{it} - \frac{1}{T_{pre}} \sum_{t=1}^{T_{pre}} Y_{it} \right) - \sum_{i=1}^{N} \mathbb{1}_{S_i=0} N_{co}^{-1} \left( \frac{1}{T - T_{pre}} \sum_{t=T_{pre}+1}^{T} Y_{it} - \frac{1}{T_{pre}} \sum_{t=1}^{T_{pre}} Y_{it} \right) \tag{2}$$

Equation (2) will be useful to highlight the difference between DiD and the SC-DiD approach.

As discussed above, to interpret the DiD estimates $\Delta^{DiD}$ in a causal way one needs to assume that the expectations of individuals who are exposed to labor market news (treated) would have evolved similarly to those of non-exposed control individuals in the absence of any news about Foxconn's investment plans. Assessing whether such an assumption hold is difficult in practice, specifically when only very few individuals are treated (e.g. Roth, 2022). Instead of directly estimating Equation (1), I estimate a re-weighted version of it, making use of the synthetic DiD (SC-DiD) of Arkhangelsky et al. (2021).

More formally, the SC-DiD can be expressed as the weighted difference-in-difference estimator where observations receive individual and time weights

$$\Delta^{SC-DiD} = \sum_{i=1}^{N} \mathbb{1}_{S_i=1} N_{tr}^{-1} \left( \frac{1}{T - T_{pre}} \sum_{t=T_{pre}+1}^{T} Y_{it} - \sum_{t=1}^{T_{pre}} \lambda_t Y_{it} \right) - \sum_{i=1}^{N} \mathbb{1}_{S_i=0} \omega_i \left( \frac{1}{T - T_{pre}} \sum_{t=T_{pre}+1}^{T} Y_{it} - \sum_{t=1}^{T_{pre}} \lambda_t Y_{it} \right) \tag{3}$$

where $\omega_i$ are individual weights and $\lambda_t$ are the time weights. Notice that Equation (3) differs from Equation (2) only by the weights assigned to pre-treatment periods and to control individuals.

The intuition behind using individual weights $\omega_i$ 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 time weights $\lambda_t$ 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. By using both individual and time-weights, only similar individuals in my treatment and control groups are compared.

As in a DiD framework and unlike in the standard SC approach the SC-DiD estimator allows for unobserved individual and time-invariant heterogeneity. Therefore, the weighting approach leads to more robust estimation results. For example, I can allow for situations where some individuals report lower job offer expectations because they exhibit in general lower job search effort. 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). Koşar and van der Klaauw (2023) show that difference in earnings expectations are likely driven by differences in time-invariant unobservable characteristics. 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. By re-weighting and matching pre-exposure trends, the reliance on the parallel trends assumption for identification is weakened, however.

I obtain the SC-DiD estimates of $\Delta^{SC-DiD}$ in two steps. First, both individual weights and time weights are estimated from the data. I provide details about the estimation procedure and summaries of the estimated weights in the Appendix. In the second step, I use the time and individual weights in a weighted two-way fixed effects regression, similar to the one in Equation (1). I base inference on the cluster bootstrap using 1,000 replications, as shown to have good properties by Arkhangelsky et al. (2021).

My estimates would still be biased, however, if there were any time-varying unobserved factors jointly related to Foxconn's investment decisions and individuals' adjustments of expectations. 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, after most of the pre-treatment period interviews were already conducted. 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 substantial uncertainty remained, such as the plant's exact location and the types of jobs created. This uncertainty lasted at least until the beginning of October 2017 when Foxconn revealed announced details of their project and posted their wanted ads. Google Trends data also suggests that before that date there was little differences in the interest in Foxconn between people residing in Racine County and those living outside; see Figure 1. Thus, there was likely little room for anticipation and adjustments of individuals' expectations prior to the news exposure. Lastly, any possible remaining bias from general time-varying unobserved factors, such as a general shifts in labor demand, is accounted for by the time weights in my estimation.

# 4 Labor Market News and Expectation Updating

## 4.1 The Impact of Foxconn's Initial Announcement

The results for the impact of Foxconn's initial announcement on individuals' expectations about their labor market outcomes are reported in Table 3. Each column represents estimates for a separate outcome or sample.

**Expectations about Wage Growth:** Column (1) of Table 3 reports the estimates for the impact of the news on the expected salary increase within the next twelve months at the current employer. Individuals exposed to positive labor market news expect an almost 3 percentage points higher salary increase, or around 22% of a standard deviation, over the next 12 months compared to individuals who were not exposed to the news. These estimates are not only quite large in magnitude but also highly statistically significant. Notice, however, that Foxconn announced that new positions will pay relatively high average wages of around $54,000 in comparison to the average wage rate of roughly $43,000 in Racine County at this time. Therefore, the results indicate that individuals exposed to positive labor market news become more optimistic about their future prospects at the current employer. The results also suggests that workers actually expect to engage in bargaining over salaries with their current employer in the near future

On explanation for the upward adjustment of salary expectations is that individuals also adjust their perceived outside option upward, based on the new information about Foxconn's investment plan. Being exposed to Foxconn's initial job postings and expecting the opening of many more high paying vacancies, workers' anticipate an improved bargaining situation when negotiating for higher wages.

To shed light on the implications of labor market news on bargaining, I investigate whether these adjustments reflect expectations about outside options and expected salary matching by the current employer. I consider an individual to be optimistic (pessimistic) about her outside options if her expectations to receives an outside offer lies above (below) the median of the observed job offer distribution. Similarly, an individual is optimistic (pessimistic) about salary matching if her expectations that the current employer matches an outside offer lies above (below) the median of the observed outside offer matching distribution.[18] The results are presented in Columns (2) and (3) for outside offers, and Columns (4) and (5) for offer matching.

Estimating the expected salary growth separately for optimistic and pessimistic workers, I do not find strong evidence that expectations about outside job offers can explain my results. The SC-DiD estimate for optimistic individuals is 2.94 and for the pessimistic sample it is 2.46. Due to the now smaller sample size, the estimates become

[18] In both cases, the median expected likelihood is 0.10. Applying a higher threshold, such as 0.5, leads to qualitatively similar results.

noisier, however. But still, they indicate a substantial impact of news on salary growth expectations. Given the small differences in my estimates, I also fail to reject the Null hypothesis that both estimates are equal. These results imply that the positive impact of news on expected salary growth in the current firm does not seem to be (entirely) driven by expectations about outside offers.

Considering expectations about salary matching, I derive a similar conclusion. The estimate for the sample of individuals who are optimistic about salary matching is 2.78 while for the pessimistic sample I find an effect of 2.76, indicating an even smaller difference between both groups. While each sample becomes considerably smaller when splitting by optimistic versus pessimistic workers and the estimates become therefore noisy, the very small difference between my estimates does not indicate any important differences in the adjustment process.

Taken together, my results imply that exposure to positive labor market news leads to a more optimistic view about one's own prospect at the current firm. Individuals tend to hold misspecified beliefs about their labor market opportunities in general. Once public information about new job opportunities becomes available, individuals use it as the basis for their wage negotiations. It is worth stressing again that these results are not driven by difference in individual time-invariant but unobserved characteristics and, therefore, by idiosyncratic differences in beliefs. They add real-world evidence to the findings in Jäger et al. (2023) who show that providing workers with (private) information about outside options increases the willingness to re-negotiate wages.

The results also suggest interesting implications for firm-worker wage bargaining, expected outside offers, and offer matching. While the effects by worker types can only be interpreted as causal under very strong assumption, they suggest that the adjustment process is not solely driven by expectations about outside options and offer matching. An implication of my results is that firms do not only and exclusively engage in bargaining once the worker has received an outside offer (Postel-Vinay and Robin, 2002; Dey and Flinn, 2005; Cahuc et al., 2006), but firms and workers bargain more frequently over wages, as in Gottfries (2021). A possible explanations why firms engage in bargaining over wages, even if workers do not have an actual outside job offer at hand, is that they are not able to fully respond to potential outside offers. This suggests that not only workers are not well-informed about firms' pay policy (e.g. Cullen and Perez-Truglia, 2023), but also that firms do not have complete information about workers' outside options (Lavie and Robin, 2012). While I cannot directly test such an explanation with my data at hand, it is in line with Cullen et al. (2022), who surveyed 1,350 HR managers and found that more than 80% have only limited or no information about potential outside offers of their employees.

**Expectations about New Jobs:** Next, I estimate the impact of positive labor market news on expected job offers. Column (6) shows the estimated impact of positive news on the expected number of job offers received within the next four months. I do not find evidence that positive labor markets news leads to any adjustments. My estimates are very small and not statistically significant at any conventional level.[19] Notice that I also include individuals who do not expect to receive any offer in my estimation sample. But, my results remain virtually unchanged if only individuals who expect at least one offer are included in the analysis.[20]

While individuals do not adjust their expectations about the job arrival rate, positive labor market news leads to a substantially upward revision of expected average salary offers among individuals who expect to receive at least one offer; see the results in Columns (7) and (8). The magnitude of this updating is quite large. The expected average salary offer is around 20% higher for individuals exposed to Foxconn's initial announcement compared to the expectations of individuals who were not exposed.[21] I find an effect of similar magnitude when concentrating on the expected maximum salary offered, shown in Column (8).

My results suggest that individuals anchor their expectations about outside offers to Foxconn's announcements. Using the average annual mean wage in Racine County of around $42,300 in 2017 as baseline and comparing this to Foxconn's announced average wage of around $54,000, my estimates imply that individuals adjust their wage offer expectations to align closely to the publicly announced wages. The results here complement the findings in Jäger et al. (2023), who show that individuals have wrong and persistent beliefs about their outside options, anchoring their expectations to the current wage. In my setting, individuals adjust their expectations dynamically to information provided in the news, thereby using the content as anchor for their updated beliefs. Notice that Foxconn's investment plan was widely discussed and information about it was easily accessible. This is different to the private measures of outside options and information in Jäger et al. (2023). Also notice, that in my difference-in-difference setting the updating process is not driven by unobserved individual heterogeneity, such as overconfidence or overoptimism. Therefore, the results can be interpreted as a general way of how individuals update their expectations to labor market news. In that sense, my estimates also complement and extend the experimental literature on the role of information on expectations about labor market outcomes (Haaland and Roth, 2020; Roth et al., 2022) to a real-world setting.

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

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

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

One can also interpret my results through the lens of theoretical job search models. My estimates here are consistent with predictions of (partially) directed search models (Menzio, 2007; Banfi and Villena-Roldán, 2019; Wright et al., 2021).[22] Workers anticipate that Foxconn's investment will lead to the creation of higher paying jobs, thereby also increasing 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 jobs. Therefore, workers do not adjust their expected probability of receiving a job offer, anticipating the longer queue length. But if they are expecting an offer, then they anchor their beliefs to the new information.

### 4.2 Robustness of Results

I assess the robustness of my results in various ways. To assess the plausibility of my identification assumptions, I first estimate a set of placebo regressions, 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 first announcements of Foxconn's investment plans in the United States. These two years were also marked by stable economic conditions. I include two years to increase statistical power to detect any possible pre-announcement effects in my data.

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. 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, despite the larger sample size. 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, such as household income, employment status and type, which may affect the expectation formation process. If my results were not the results of exposure to labor market news but caused, for example, by individuals' labor market dynamics, this would be captured by the included time-varying

[22] Belot et al. (2020) also find evidence in favor of directed search models studying how unemployed workers react to wage announcements in an experimental setting.

covariates. If this was the case, one would expect to see my news effects to change substantially.[23] The results are reported in Panel B of the table.

In general, including covariates in my estimation does not alter any of my conclusions. My estimates are virtually unchanged compared to my baseline. 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.

I also exclude all individuals who resided in other parts of Wisconsin from my control group. This is to see whether potentially dynamic adjustments and anticipation of Foxconns' initial project 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, leading to a disproportional downward adjustment of expectations there. 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.

Excluding control individuals from Wisconsin from my analysis does not significantly affect my results. The estimates for the positive news sample are virtually identical to my baseline results and are even more precisely estimated, in the case of maximum log salary offer.

Lastly, I only include Republican-leaning commuting zones in my control group. Since the first meetings between Scott Walker and Terry Gou were arranged by the Trump administration, one may wonder whether the effects I find represent political sentiments and general economic expectations rather than adjustments to labor market news. To distinguish between Democratic- and Republican-leaning commuting zones, I use the vote share for the Republican presidential candidate in the 2016 election as in Autor et al. (2020).[24] As one can see in Panel D, only including control individuals residing in Republican-leaning commuting zones does not alter my conclusions. The effects are very similar to my baseline estimates, both in magnitude and statistical significance.[25]

I provide further robustness checks in the Appendix. For example, I show that a "standard" difference-in-difference approach gives similar results, although the estimates are slightly less precise. Therefore, my conclusions do not crucially depend on the weights used. I also do not find any evidence that pre-trends differ between individuals exposed to

[23] Assessing the robustness of the results when including covariates may also alleviate some concerns regarding pre-treatment fit; see, for example, the discussions in Ferman and Pinto (2021) and Pickett et al. (2022).

[24] I map the voting share on the county level provided in Autor et al. (2020) to commuting zones using the county-commuting zone crosswalk provided by USDA (`https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/`).

[25] Only including Democratic-leaning commuting zone gives virtually identical results as the ones reported here.

the labor market news or not. Further investigating the role of pre-trends in my analysis, I show that any violation of the parallel trends assumption, such as local labor demand shocks unrelated to Foxconn's investment plans, would need to be unrealistically large to overturn my results. For example, using results about vacancy rates and wage growth from Domash and Summers (2022), a local shock to labor demand would need to double the local vacancy rate to have a true effects of news exposure on expected average salary of zero.

# 5 Expectation Updating and Current Consumption

Given that exposure to labor market news affects expectations about future earnings growth, an important question is: Do individuals act on the updated expectations about their future labor market outcomes? To answer this question, I use information on changes in total consumption expenditures, as proxied by total household spending. As part of the SCE, the SCE Household Expenditure Survey is fielded every four months in April, August, and December.[26] In the Expenditure Survey, I use the answer to the questions:

- Change in consumption expenditures: *In percentage terms, by how much has your current monthly household spending [increased/decreased] compared to 12 months ago?*

I estimate the impact of exposure to news using the same empirical approach as for my main results in Section 4, concentrating on balanced panel of individuals with valid answer to the consumption question.[27] The results are presented in Table 5.

Changes in expected future income have a small but significantly positive effect on consumption. The results presented in Column (1) show that exposure to positive labor market news increases consumption expenditures by around 2.3 percentage points. This finding is in line with consumption adjustments based on a standard Euler equation. Individuals, expecting higher future income, adjust their current consumption.

It is interesting to investigate whether the increase in consumption is driven by small items or relatively large investments. The SCE asks individuals about the relative expenditure share for different categories, such as housing, food, personal items, and others. The effects of labor market news on *relative* consumption by these subcategories are shown in Columns (2) to (5).[28] Looking at the table, one can see that most effects

[26] The SCE Household Expenditure Survey is therefore fielded one month after the SCE Labor Market Survey.

[27] I drop individuals reporting an unusually large decrease or increase in consumption corresponding to the 5st and 95th percentile in the data, which is equivalent to -10% and 20%. Applying a less strict threshold delivers qualitatively similar results.

[28] The expenditure share has to sum to one among these categories. Therefore, the estimates only indicate whether individuals spent on one category relatively more compared to another one. It is, however, possible, that individuals increased spending in all four categories.

are noisily estimates. There is evidence, however, that individuals increase their relative spending on smaller items, such as clothes and personal care. Connecting this to my previous findings, this implies that individuals increase current consumption, but this increase is likely concentrated among smaller items, not requiring long-term financing commitments.

My results here complement the findings in the literature on inflation expectations and consumption spending (Dräger and Nghiem, 2021; Coibion et al., 2021; Crump et al., 2022). In general, these works show that consumption spending depends on the perceived or (exogenously) received news about elevated inflation. Using a survey of Dutch households, Coibion et al. (2021) provide evidence that consumer lower the purchase of durable good as they become pessimistic about their real income. My work complements and extends their findings. My estimates indicate a related but opposite effect. When exposed to positive labor market news individuals adjust their consumption upward. This upward adjustment occurs because they are more optimistic about their future income.

# 6 Project Uncertainty and Revision of Expectations

My results indicate strong upward adjustment of expectations about labor market outcomes when exposed to positive labor market news. It is interesting to see how persistent those updated beliefs are and how they react to news about increasing labor market uncertainty. To explore this further, I use Foxconn's revision of the initial project announcement in January 2019; see Section 2 for details. The results are show in Table 6.

Being exposed to the reversal of the initial announcement leads to a downward revision of the expected salary growth rate by around 1.96 percentage points in the current firm, see Column (1). The coefficient is, however, quite noisily estimated. While not statistically significant, the results imply that individuals tend to revise their expectations roughly back to baseline; the estimates of Foxconn's initial announcement are with 2.71 relatively close to the current one.

Evaluating how negative news affect expectations about job search, I find that the expected number of job offers is largely unaffected, see Column (2). This mirrors my previous findings. In contrast, the reversal in the labor market news leads individuals to revise their expectations about expected average and maximum salaries offered significantly downward; see Columns (3) and (4). The downward revision in offered salary expectations is slightly smaller in magnitude compared to Foxconn's initial announcement.

Overall, the estimates show that individuals reverse their expectations back to baseline when confronted with uncertain labor market news. This implies a general dynamic in the updating process when new information and news about the labor market arrive.

# 7 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 on this topic is still scant, specifically about the labor market and in real-world settings. Understanding the formation process is important, however, to better understand how individuals perceive their outside option, wage determination, and ultimately inequality. It is also vital for the design of effective policies.

Using the New York Fed's Survey of the Consumer Expectations, I investigate how individuals adjust their expectations about wage growth and jobs when exposed to news about the labor market. To identify the impact of positive labor market news on individuals' expectations, I exploit Foxconn's laregely unexpected announcement in October 2017 to build a manufacturing plant in Racine County, Wisconsin, and create up to 13,000 high paying jobs in various occupations.

Exposure to positive labor market news leads to significant upward revision of expectations about future salary growth at the current employer. This implies that workers become more optimistic about their career prospects when exposed to the news. They also suggest that workers expect to enter wage negotiations with their current employer in the near future. I also provide evidence that the upward adjustments of salary expectations cannot be attributed to perceived improvements in outside job opportunities or potential offer matching. Workers who expect to receive an outside offer in the future update their beliefs in the same way as workers who do not expect any offer. These results imply that firms do not only engage in bargaining once the worker has received an outside offer. They also lent support to a theory of more frequent bargaining over wages between firms and workers, suggesting that firms may not be fully informed about workers' potential outside options.

Looking at the impact of news on expectations about future jobs, I find that positive labor market news has no effect on the expected job offer arrival rate. But, conditional on expecting an outside offer, positive news leads to a significant increase in the expected salary offered. Workers anchor hereby their expected offered wages to Foxconn's publicly announced wage rate.

Exploring the impact of adjustment of labor market expectations on current behavior, I find that individuals increase their current consumption spending. This increase is mainly driven by relatively larger spending on smaller items and personal care. My estimates are in line with predictions from standard Euler equations, suggesting that higher future economic resources lead to an increase in consumption today.

Finally, I also show that the updating process reacts dynamically to new information and news about the labor market. Using Foxconn's later announced scaled down version of their initial project, I find that individuals tend to revise their labor market expectations back toward baseline.

An important implication of my results is that providing workers with public information about their labor market prospect, such as possible pay at jobs, could be one viable approach to increase wages and reduce inequality. As individuals act on their updated beliefs, such policy could also have broader macroeconomic effects. At the same time, as adjustments to new information are dynamic, firms have incentives to understate the possible pay offered and therefore lowering workers' wage expectations, specifically in less competitive labor markets. Exploring further the (equilibrium) effects of providing public labor market information on firms and workers is an important and exciting topic for future research (see, for example, Cullen, 2023).

## References


Abadie, A., Diamond, A. and Heinmueller, J. (2010), 'Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program', *Journal of the American Statistical Association* **105**(490), 493–505.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W. and Wager, S. (2021), 'Synthetic Difference in Difference', *American Economic Review* **111**(12), 4088–4118.

Armantier, O., Topa, G., van der Klaauw, W. and Zafar, B. (2017), 'An Overview of the Survey of Consumer Expectations', *FRBNY Economic Policy Review* **23**(2), 51–72.

Armona, L., Fuster, A. and Zafar, B. (2019), 'Home Price Expectations and Behavior: Evidence from a Randomized Information Experiment', *Review of Economic Studies* **86**(4), 1371–1410.

Autor, D., Dorn, D., Hanson, G. and Majlesi, K. (2020), 'Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure', *American Economic Review* **110**(10), 3139–3183.

Azmat, G. and Kaufmann, K. M. (2022), 'Formation of college plans: Expected returns, preferences and adjustment process', *mimeo* .

Banfi, S. and Villena-Roldán, B. (2019), 'Do High-Wage Jobs Attract more Applicants?Directed Search Evidencefrom the Online Labor Market', *Journal of Labor Economics* **37**(3), 715–746.

Belot, M., Kircher, P. and Muller, P. (2020), 'How Wage Announcements Affect Job Search - A Field Experiment', *American Economic Journal: Macroeconomcs* **14**(4), 1–67.

Ben-Michael, E., Feller, A. and Rothstein, J. (2021), 'The Augmented Synthetic Control Method', *Journal of the American Statistical Association* **116**(536), 1789–1803.

Bureau of Labor Statistics (2017), 'May 2017 Metropolitan and Nonmetropolitan Area Occupational Employment and Wage Estimates - Racine, WI', https://www.bls.gov/oes/2017/may/oes_39540.htm.

Cahuc, P., Postel-Vinay, F. and Robin, J. (2006), 'Wage Bargaining with On-the-Job-Search: Theory and Evidence', *Econometrica* **74**(2), 323–364.

Caldwell, S. and Danieli, O. (2022), 'Outside Options in the Labor Market', *forthcoming Review of Economic Studies* .

Caldwell, S. and Harmon, N. (2019), 'Outside Options, Bargaining, and Wages: Evidence from Coworker Networks', *mimeo* .

Coibion, O., Georgarakos, D., Gorodnichenko, Y. and van Rooij, M. (2021), 'How Does Consumption Respond to News about Inflation? Field Evidence from a Randomized Control Trial', *forthcoming American Economic Journal: Macroeconomics* .

Coibion, O., Gorodnichenko, Y. and Ropele, T. (2020), 'Inflation Expectations and Firm Decisions: New Causal Evidence', *Quarterly Journal of Ecnomics* **135**(1), 165–219.

Conlon, J. J., Pilossoph, L., Wiswall, M. and Zafar, B. (2018), 'Labor Market Search With Imperfect Information and Learning', *mimeo* .

Crump, R. K., Eusepi, S., Tambalotti, A. and Topa, G. (2022), 'Subjective Intertemporal Substitution', *Journal of Monetary Economics* **126**, 118–133.

Cullen, Z. (2023), 'Is Pay Transparency Good', *NBER Working Paper No. 31060* .

Cullen, Z. B., Li, S. and Perez-Truglia, R. (2022), 'What is my Employee Worth? The Effects of Salary Benchmarking', *NBER Working Paper 30570* .

Cullen, Z. and Perez-Truglia, R. (2023), 'The Salary Taboo: Privacy Norms and the Diffuision of Information', *Journal of Public Ecoonomics* **222**, 104890.

D'Acunto, F., Malmendier, U., Ospina, J. and Weber, M. (2021), 'Exposure to Grocery Prices and Inflation Expectations', *Journal of Political Economy* **129**(5), 1615–1639.

Delavande, A. and Zafar, B. (2019), 'University Choice: The Role of Expected Earnings, Nonpecuniary Outcomes, and Financial Constraints', *Journal of Political Economy* **127**(5), 2343–2393.

Dey, M. S. and Flinn, C. J. (2005), 'An Equilibrium Model of Health Insurance Provision and Wage Determination', *Econometrica* **73**(2), 571–627.

Deza, J. (2020), 'The 8th Wonder of the World', https://www.theverge.com/21507966/foxconn-empty-factories-wisconsin-jobs-loophole-trump. [online; accessed 27-July-2021].

Di Addario, S., Kline, P., Saggio, R. and Sølvsten, M. (2022), 'It ain't where you're from, it's where you're at: Hiring origins, firm heterogeneity, and wages', *Journal of Econometrics* **233**(2), 340–374.

Domash, A. and Summers, L. H. (2022), 'How Tight Are U.S. Labor Markets', *NBER Working Paper 29739* .

Doudchenko, N. and Imbens, G. W. (2017), 'Balancing, Regression,Difference-In-Differences and Synthetic ControlMethods: A Synthesis', *mimeo* .

Dräger, L. and Nghiem, G. (2021), 'Are Consumers' Spending Decisions in Line with a Euler Equation?', *Review of Economics and Statistics* **130**(3), 580–596.

EY Quantitative Economics and Statistics (QUEST) (2017), 'Quantifying Project Flying Eagle's potential economic impacts in Wisconsin', *report* .

Ferman, B. and Pinto, C. (2021), 'Synthetic controls with imperfect pretreatment fit', *Quantitative Economics* **12**(4), 1197–1221.

Gottfries, A. (2021), 'Bargaining with Renegotiation in Models with On-the-Job-Search', *mimeo* .

Haaland, I. and Roth, C. (2020), 'Labor Market Concerns and Support for Immigration', *Journal of Public Economics* **191**, 104256.

Hall, R. E. and Krueger, A. B. (2012), 'Evidence on the Incidence of Wage Posting, Wage Bargaining, and On-the-Job Searc', *American Economic Journal: Macroeconomics* **4**(4), 56–67.

Handelman, B. (2017), 'Job postings appear online as Foxconn announces plant location: "Growing work environment"', https://www.fox6now.com/news/job-postings-appear-online-as-foxconn-announces-plant-location-growing-work-environment. [online; accessed 27-July-2021].

Hoffman, M. and Burks, S. V. (2020), 'Worker Overconfidence: Field Evidence and Implications for Employee Turnover and Firm Profit', *Quantitative Economics* **11**(1), 315–348.

Hvidberg, K. B., Steiner, C. T. and Stantcheva, S. (2023), 'Social Position and Fairness: Views on Inequality', *forthcoming Review of Economic Studies* .

Jäger, S., Rothe, C., Rousille, N. and Schoefer, B. (2023), 'Worker Beliefs About Outside Options', *NBER Working Paper 29263* .

Kirchen, R. (2017), 'See the jobs Foxconn is looking to fill in Wisconsin', https://www.bizjournals.com/milwaukee/news/2017/10/11/see-the-jobs-foxconn-is-looking-to-fill-in.html. [online; accessed 27-July-2021].

Koşar, G. and van der Klaauw, W. (2023), 'Workers' Perception of Earnings Growth and Employment Risk', *mimeo* .

Lachowska, M. (2017), 'Outside Options and Wages: What Can We Learn from Subjective Assessements', *Empirical Economics* **52**, 79–121.

Lachowska, M., Mas, A., Saggio, R. and Woodbury, S. A. (2022), 'Wage Posting or Wage Bargaining? A Test Using Dual Jobholders', *Journal of Labor Economics* **40**(S1), S469–S492.

Lavie, M. and Robin, J. (2012), 'Match me if you can: Wage secrecy and matching in a search model', *mimeo* .

Macy, J. and Plume, K. (2019), 'Exclusive: Foxconn reconsidering plans to make LCD panels at Wisconsin plant', %https://www.reuters.com/article/us-foxconn-wisconsin-exclusive/exclusive-foxconn-reconsidering-plans-to-make-lcd-panels-at-wisconsin-plant-idUSKCN1PO0FV. [online; accessed 27-July-2021].

Manning, A. and Petrongolo, B. (2017), 'How Local Are Labor Markets? Evidence from a Spatial Job Search Model', *American Economic Review* **107**(10), 2877–2907.

Manski, C. (2018), 'Survey Measurement of Probablistic Macroeconomic Expectations: Progress and Promises', *NBER Marcroecnomics Annual* **32**(1), 411–471.

Manski, C. F. (2004), 'Measuring Expectations', *Econometrica* **72**(5), 1329–1376.

Manski, C. F. and Pepper, J. V. (2018), 'How Do Right-to-Carry Laws Affect Crime Rates? Coping with Ambiguity Using Bounded-Variation Assumptions', *Review of Economics and Statistics* **100**(2), 232–244.

Menzio, G. (2007), 'A Theory of Partial Directed Search', *Journal of Political Economy* **115**(5), 748–769.

Mueller, A. I. and Spinnewijn, J. (2023), *Expectations Data, Labor Market and Job Search*, Academic Press, pp. 677–713.

Mueller, A. I., Spinnewijn, J. and Topa, G. (2021), 'Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence, and Bias', *American Economic Review* **111**(1), 324–363.

Paquette, D., Frankel, T. C. and Shaban, H. (2017), 'Foxconn announces new factory in Wisconsin in much-needed win for Trump and Scott Walker', https://www.washingtonpost.com/news/wonk/wp/2017/07/26/foxconn-to-announce-new-factory-in-wisconsin-in-much-needed-win-for-trump-and-scott-walker/. [online; accessed 27-July-2021].

Pickett, R. E., Hill, J. and Conwan, S. K. (2022), 'The Mythos of Synthetic Control: Recommendation in Practice', *mimeo* .

Postel-Vinay, F. and Robin, J. (2002), 'Equilibrium Wage Dispersion with Worker and Employer Heterogeneity', *Econometrica* **70**(6), 2295–2350.

Rambachan, A. and Roth, J. (2022), 'A More Credible Approach to Parallel Trends', *forthcoming Review of Economics Studies* .

Rogerson, R., Shimer, R. and Wright, R. (2005), 'Search-Theoretic Models of the Labor Market: A Survey', *Journal of Economic Literature* **43**(4), 959–988.

Roth, C., Settele, S. and Wohlfart, J. (2022), 'Risk of Exposure and Acuqisition of Macroenomic Information', *American Economic Review: Insights* **4**(1), 34–53.

Roth, C. and Wohlfart, J. (2020), 'How Do Expectations about the Macroeconomy Affect Personal Expectations and Behavior?', *Review of Economics and Statistics* **102**(4), 731–748.

Roth, J. (2022), 'Pre-test with Caution: Event-study Estimates After Testing for Parallel Trends.', *American Economic Review: Insight* **4**(3), 305–322.

Schmidpeter, B. and Tô, L. (2023), 'Negotiable wage postings', *mimeo* .

Shepardson, D. and Pierog, K. (2021), 'Foxconn mostly abandons $10 billion Wisconsin project touted by Trump', https://www.reuters.com/business/foxconn-sharply-scales-back-wisconsin-investment-2021-04-20/. [online; accessed 27-July-2021].

Williams, N. (2017), 'An Evaluation of the Economic Impact of the Foxconn Proposal', *Center for Research On the Wisconsin Economy Report* .

Wilson, R. (2021), 'Moving to Jobs: The Role of Information in Migration Decisions', *Journal of Labor Economics* **39**(4), 1083–1128.

Wisconsin Economic Development Corporation (2017), 'Governor Walker, Foxconn Chairman Gou Sign historic agreement to bring $10 billion manufacturing campus to Wisconsin', https://wedc.org/blog/governor-walker-foxconn-chairman-gou-sign-historic-agreement-bring-10-billion-manufacturing-campus-wisconsin/. [online; accessed 27-July-2021].

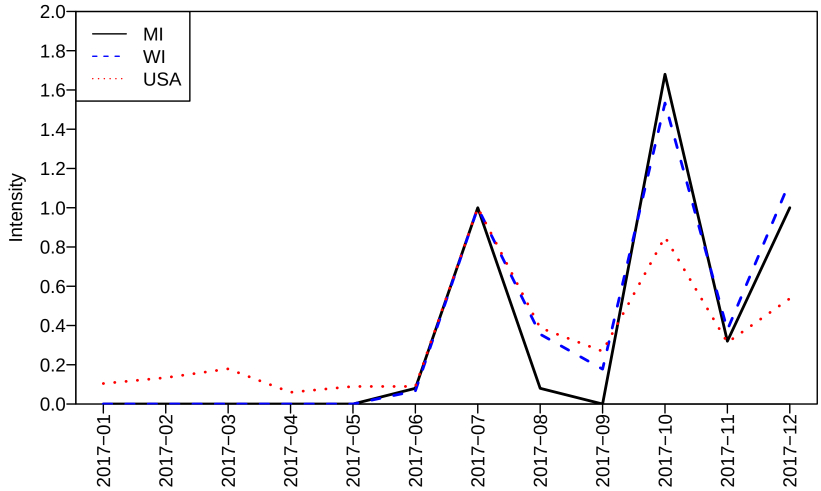
Wiswall, M. and Zafar, B. (2021), 'Human Capital Investments and Expectations about Career and Family', *Journal of Political Economy* **129**(5), 1361–1424.

Wright, R., Kircher, P., Julien, B. and Guerrieri, V. (2021), 'Directed Search and Competitive Search Equilibrium: A Guided Tour', *Journal of Economic Literature* **59**(1), 90–148.

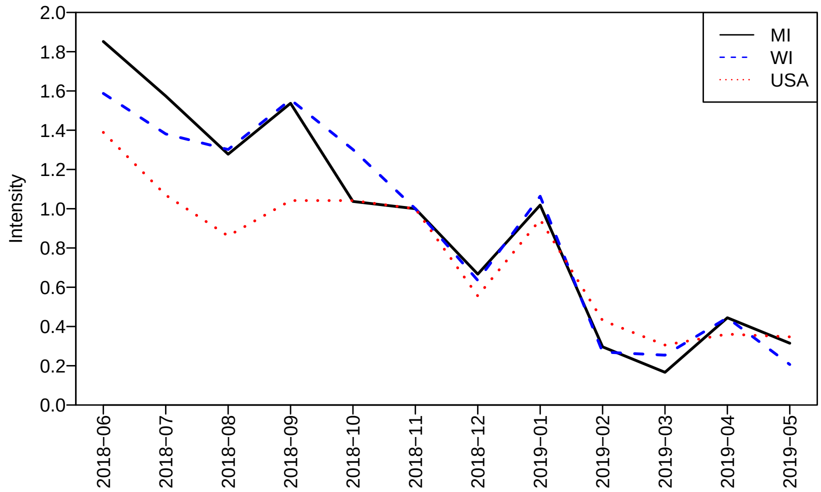
Wu, J. (2017), 'Foxconn CEO says investment for display plant in U.S. would exceed $7 billion', https://www.reuters.com/article/us-taiwan-foxconn-idUSKBN1560JP. [online; accessed 27-July2021].

# Figures

Figure 1: Interest in Foxconn Jobs




a. Initial Announcement




b. Reversal

The figure shows the search intensity for "Foxconn Jobs" in the metropolitan are of Milwaukee–Racine–Waukesha (MI), in Wisconsin (WI), and U.S.-wide using information from Google Trends. Search intensity at the survey data directly preceding the announcements, July 2017 for the initial announcement of Foxconn's project and November 2011 for the reversal, are normalized to one.

# Tables

Table 1: Timeline of 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 | |
| October 2017 | Foxconn announces that the plant will be built Mount Pleasant, Racine County. Foxconn started to post "want ads" for a wide range of jobs on their own webpage and at Indeed.com. It also distributed 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. | ***Initial Announcement*** |
| 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. | |
| 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. | ***Reversal*** |
| 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

| | Initial Announcement | Reversal |
|---|---|---|
| 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 samples. The *Initial Announcement* sample consists of all individuals interviewed in March, July, and November 2017. The *Reversal* 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 Labor Market Expectations

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Salary Increase in Current Job | Salary Increase in Current Job by Type | | | | Number of Job Offers | Average Log Salary Offer | Maximum Log Salary Offer |
| | | Outside Offer | | Offer Matching | | | | |
| | | Optimistic | Pessimistic | Optimistic | Pessimistic | | | |
| $\Delta^{SC-DiD}$ | 2.71 | 2.94 | 2.46 | 2.78 | 2.76 | 0.14 | 19.25 | 19.19 |
| | (1.21) | (1.46) | (1.57) | (1.57) | (1.72) | (0.24) | (6.66) | (7.73) |
| Observations | 459 | 204 | 255 | 237 | 216 | 498 | 279 | 291 |
| P-value: Equality of Effect | | (2) vs. (3) | | (4) vs. (5) | | | | |
| | | 0.88 | | 0.96 | | | | |

This table summarizes the SC-DiD estimates of the effect of labor market news on individuals' expectations about job search and earnings. All individuals exposed to Foxconn's initial announcement of opening a plant in Racine County, Wisconsin, in November 2017 are considered as treated; see also Section 2. The estimation approach is described in Section 3. The dependent variable used in Column (1) is the expected percentage increase in the salary in the current job over the next year. In Columns (2) and (3), the sample is split by individuals who are optimistic or pessimistic about receiving an outside offer, using the median of the expected outside offer distribution. Similarly, in Columns (4) and (5), the sample is divided whether an individuals expects the current employee to match any outside offer or not, using the median of the offer matching distribution. In Column (6) the expected number of job offers over the next four months is used as outcome. The dependent variable in Columns (7) and (8) is the expected log average salary and the expected log maximum salary offered when receiving at lease one offer, multiplied by 100. Standard errors are obtained using the cluster bootstrap with 1,000 replications.

Table 4: Effect of News on Labor Market Expectations - Placebo and Robustness

| | (1) Salary Increase Current Job | (2) Number of Job Offers | (3) Average Log Salary Offer | (4) Maximum Log Salary Offer |
|---|---|---|---|---|
| **Panel A: Placebo Treatment** | | | | |
| $\Delta^{SC-DiD}$ | 1.36 | 0.18 | 7.32 | 5.27 |
| | (1.39) | (0.30) | (9.34) | (10.07) |
| Observations | 840 | 951 | 504 | 513 |
| **Panel B: Including Covariates** | | | | |
| $\Delta^{SC-DiD}$ | 3.04 | 0.26 | 19.63 | 19.07 |
| | (1.19) | (0.24) | (6.69) | (7.71) |
| Observations | 459 | 498 | 279 | 291 |
| **Panel C: Excluding Rest of Wisconsin** | | | | |
| $\Delta^{SC-DiD}$ | 2.75 | 0.15 | 19.81 | 19.54 |
| | (1.27) | (0.23) | (6.67) | (7.59) |
| Observations | 450 | 489 | 273 | 285 |
| **Panel D: Only Including Republican-leaning Commuting Zones** | | | | |
| $\Delta^{SC-DiD}$ | 2.76 | 0.11 | 17.97 | 16.27 |
| | (1.34) | (0.18) | (8.18) | (10.05) |
| Observations | 231 | 279 | 135 | 144 |

This table summarizes the robustness and placebo results as described in Section 4. The dependent variable used in Column (1) is the expected percentage increase in the salary in the current job over the next year. In Column (2), the expected number of job offers over the next four months is used as outcome. The dependent variable in Columns (3) and (4) is the expected log average salary and the expected log maximum salary offered when receiving an offer, multiplied by 100. Panel A uses a placebo announcement of Foxconn's plant opening in Racine County, using November for the years 2015 and 2016 as the relevant date. Panel B includes covariates in the estimation. Panel C excludes individuals residing in Wisconsin from the control group. In Panel D, only MSAs where the share of Republican votes in the 2016 presidential election was above 50% are included in the control group, using the election data from Autor et al. (2020). Standard errors are obtained using the cluster bootstrap with 1,000 replications.

Table 5: Effect of News on Current Consumption Behavior

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Change in Current Expenditures | Relative Change by Categories | | | |
| | | Housing | Food | Personal Items | Others |
| $\Delta^{SC-DiD}$ | 2.31 | 2.40 | $-0.17$ | 2.09 | $-5.77$ |
| | (1.14) | (4.72) | (2.72) | (1.18) | (4.21) |
| Observations | 567 | 561 | 561 | 561 | 561 |

This table summarizes the SC-DiD estimates of the effect of labor market news on individuals' percentage change in annual consumption expenditures; see also Section 5. Due to small sample sizes, all individuals with valid responses to the consumption question are considered. The estimation approach is described in Section 3. In Column (1) the change in *total* household expenditures over the past 12 months is used, and the estimated coefficient reflects percentage point changes in consumption. In Column (2), the *relative* share of household expenditure is used as outcome. The coefficient can therefore be interpreted as relative growth rate. Housing includes all expenditures related to housing (rent, mortgage, and maintenance) as well as utilities. Food includes direct expenditure for food and beverages, as well as eating out. Personal items comprises of clothes, footwear, and personal care. Other expenditures include transportation, recreation, education, medical care, and other miscellaneous. Standard errors are obtained using the cluster bootstrap with 1,000 replications.

Table 6: Effect of News on Labor Market Expectations - Reversal

| | (1)<br>Salary Increase<br>Current Job | (2)<br>Number of<br>Job Offers | (3)<br>Average Log<br>Salary Offer | (4)<br>Maximum Log<br>Salary Offer |
|---|---|---|---|---|
| $\Delta^{SC-DiD}$ | $-1.96$ | $-0.74$ | $-7.57$ | $-12.15$ |
| | (1.82) | (0.45) | (4.51) | (5.41) |
| Observations | 438 | 516 | 249 | 261 |

This table summarizes the SC-DiD estimates of the effect of labor market news on individuals' expectations about job search and earnings. All individuals exposed to Foxconn's reversed announcement in January 2019 of a downscaled project are considered as treated; see also Section 2. The estimation approach is described in Section 3. The dependent variable used in Column (1) is the expected percentage increase in the salary in the current job over the next year. In Column (2), the expected number of job offers over the next four months is used as outcome. The dependent variable in Columns (3) and (4) is the expected log average salary and the expected log maximum salary offered when receiving an offer, multiplied by 100. Standard errors are obtained using the cluster bootstrap with 1,000 replications.

**Online Appendix for "Labor Market News and Expectations about Jobs & Earnings"**

Bernhard Schmidpeter

October 13, 2023

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

# A Time and Individual Weights

## A.1 Estimation of the Weights

The individual weights $\omega_i$ in the SC-DiD approach of Arkhangelsky et al. (2021) can be obtained by solving the following quadratic program subject to linear constraints on the weights

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

where $P$ is a regularization penalty.[1] 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.

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

[1]In my setting, $P$ is given by $N_{Tr}^{1/2} \widehat{\sigma}^2 \|\omega\|_2^2$, where $\widehat{\sigma}$ 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).

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

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

I present summaries of the estimates for $\omega_i$ and $\lambda_t$ in the next section.

As described in Section 3, the weights can then be used in a two-way fixed effects regression. In particular, the SC-DiD can be obtained by solving

$$(\widehat{\Delta}^{SC-DiD}, \widehat{\alpha}, \widehat{\gamma}, \widehat{\nu}) = \arg \min_{\Delta^{SC-DiD}, \alpha, \gamma, \nu} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left( \alpha + S_{i,t} \Delta^{SC-DiD} + \gamma_t + \nu_i + \epsilon_{it} \right)^2 \widehat{\omega}_i \widehat{\lambda}_t \right\} \tag{A.3}$$

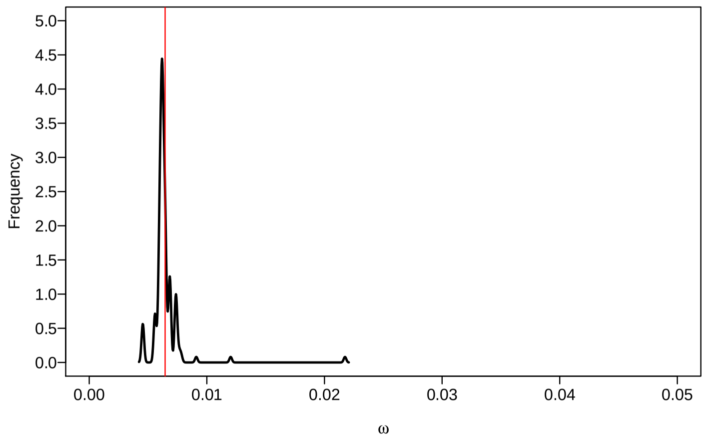
where $\widehat{\Delta}^{SC-DiD}$ reflects the SC-DiD estimate of exposure to labor market news.

## A.2 Estimated Time and Individual Weights

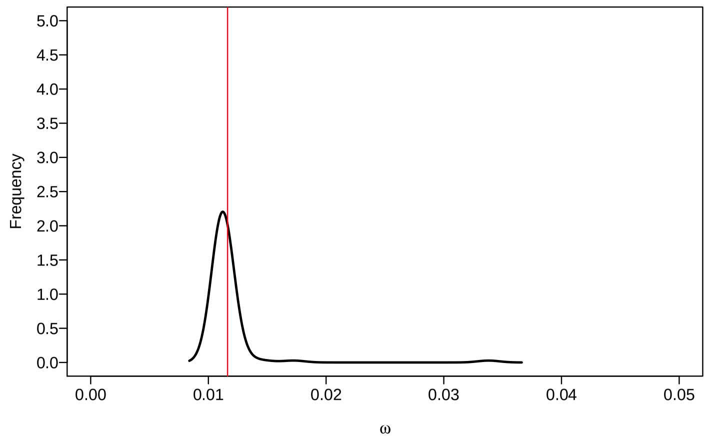
Figures A.1 and A.2 show the distribution of estimates for the individual weights $\omega_i$ obtained from Equation (A.1) for Foxconn's initial announcement and later reversal respectively. In each panel, the distribution for the four considered outcomes are shown.

Looking at the figure 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 initial announcement sample when considering the expected average salary offered and 0.045 in the reversal 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 and without weighting. I provide further evidence on this point below, showing that results from a standard difference-in-difference estimation are very similar to my estimates from the weighted version.

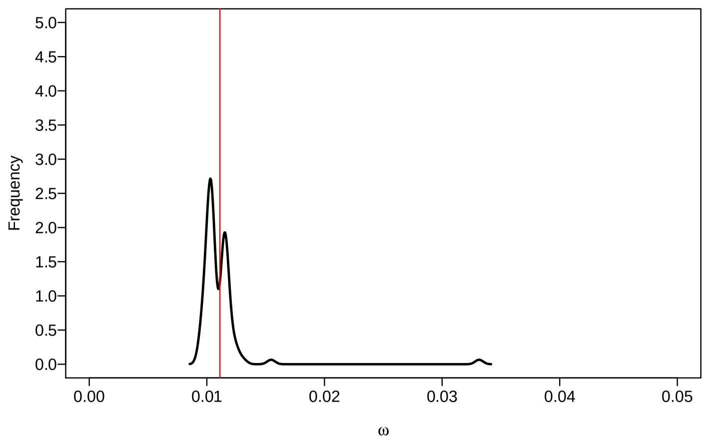
Figure A.1: Distribution of Estimated Individual Weights - Initial Announcement



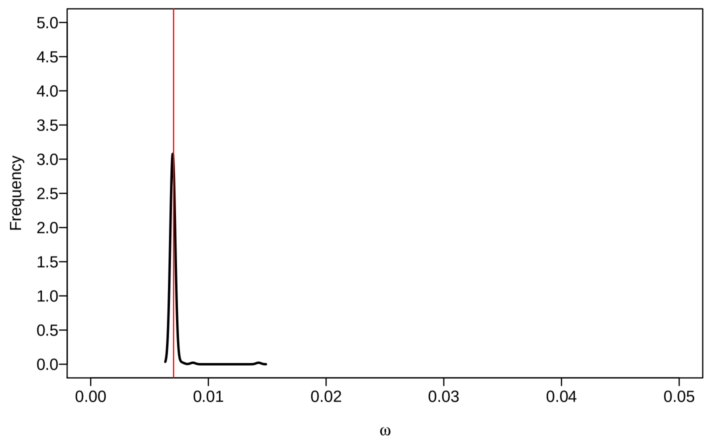

a. Number of Offers




b. Average Salary Offered



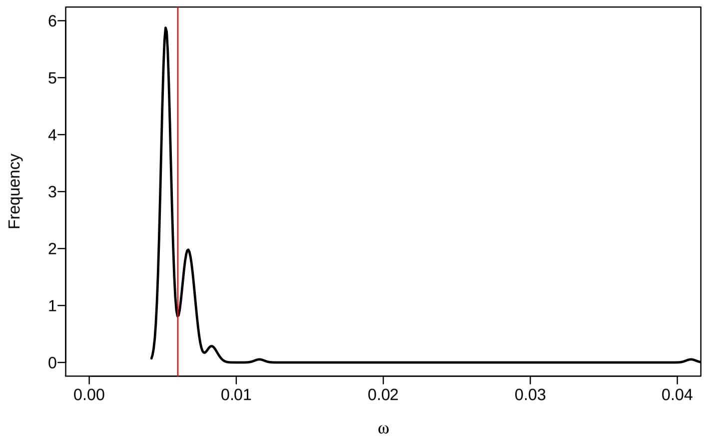

c. Maximum Salary Offered



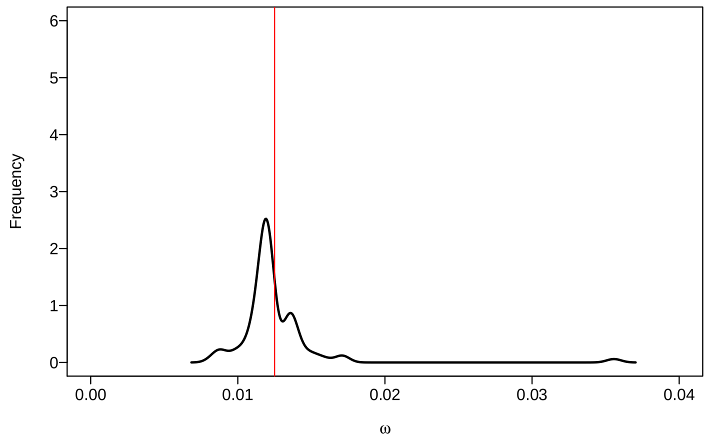

d. Salary Current Job

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

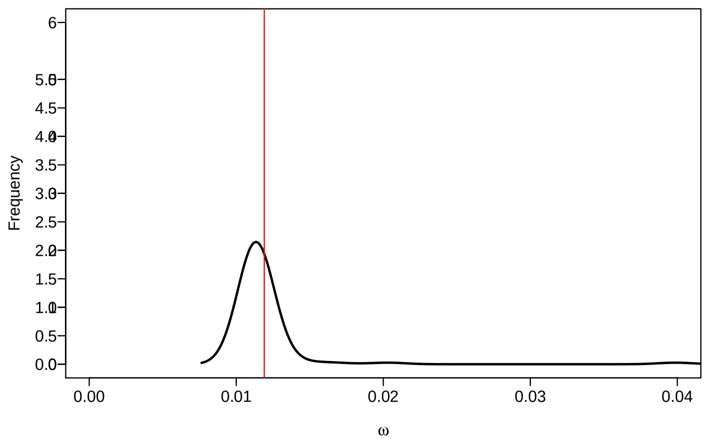
Figure A.2: Distribution of Estimated Individual Weights - Reversal



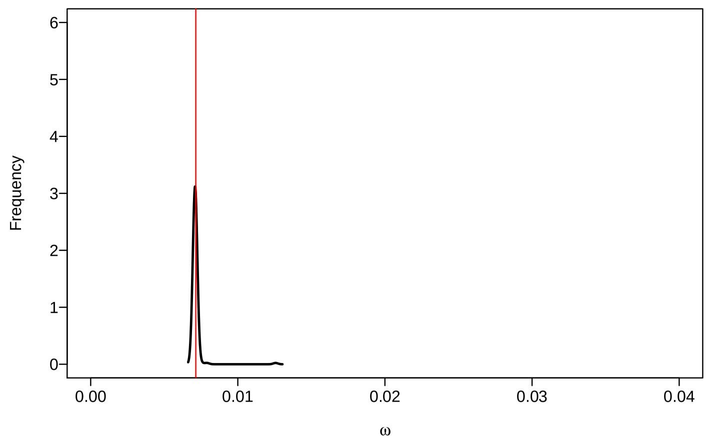

a. Number of Offers




b. Average Salary Offered




c. Maximum Salary Offered




d. Salary Current Job

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

The estimates for the time weights $\lambda_t$ obtained from Equation (A.2) are shown in Table A.1. In the initial announcement sample, presented in Panel A of the table, more weight is assigned to the period farther away from the treatment date for most of my outcomes. The differences in the weights between the two period are, however, small. Moreover, the estimates for $\lambda$ are also very close to the standard DiD time weights of $\frac{1}{2}$.

Considering the reversal 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)<br>Number of Job Offers | (2)<br>Average Log Salary Offer | (3)<br>Maximum Log Salary Offer | (4)<br>Salary Increase Current Job |
|---|---|---|---|---|
| **Panel A: Initial Announcement** | | | | |
| $\lambda_{-1}$ | 0.40 | 0.46 | 0.49 | 0.44 |
| $\lambda_{-2}$ | 0.60 | 0.54 | 0.51 | 0.56 |
| **Panel B: Reversal** | | | | |
| $\lambda_{-1}$ | 1.00 | 0.68 | 0.72 | 0.75 |
| $\lambda_{-2}$ | 0.00 | 0.32 | 0.28 | 0.25 |

This table summarizes the estimates of the pre-treatment time weights $\lambda_t$ for the different outcomes obtained from Equation (A.2). Panel A refers to Foxconn's initial announcement sample and Panel B to the reversal sample.

# B Robustness & Placebo using Foxconn's Reversal

The results of the robustness checks using individuals in the reversal sample are reported in Table B.1. The Table follows a similar structure as Table 4 in the main text.

Table B.1: Effect of News on Labor Market Expectations - Placebo and Robustness using the Reversal Sample

| | (1)<br>Salary Increase<br>Current Job | (2)<br>Number of<br>Job Offers | (3)<br>Average Log<br>Salary Offer | (4)<br>Maximum Log<br>Salary Offer |
|---|---|---|---|---|
| **Panel A: Including Covariates** | | | | |
| $\Delta^{SC-DiD}$ | −1.95 | −0.72 | −8.42 | −13.15 |
| | (1.86) | (0.43) | (6.21) | (7.83) |
| Observations | 438 | 516 | 249 | 261 |
| **Panel B: Excluding Rest of Wisconsin** | | | | |
| $\Delta^{SC-DiD}$ | −1.96 | −0.72 | −6.43 | −13.03 |
| | (1.88) | (0.47) | (4.10) | (5.34) |
| Observations | 423 | 501 | 237 | 246 |
| **Panel C: Only Including Republican-leaning Commuting Zones** | | | | |
| $\Delta^{SC-DiD}$ | −3.79 | −0.57 | −6.82 | −12.05 |
| | (3.04) | (0.33) | (5.26) | (6.09) |
| Observations | 231 | 279 | 135 | 144 |

This table summarizes the robustness and placebo results as described in Section B, using the reversal sample; see also Section 2. The dependent variable used in Column (1) is the expected percentage increase in the salary in the current job over the next year. In Column (2), the expected number of job offers over the next four months is used as outcome. The dependent variable in Columns (3) and (4) is the expected log average salary and the expected log maximum salary offered when receiving an offer, multiplied by 100. Panel A includes covariates in the estimation. Panel B excludes individuals residing in Wisconsin from the control group. In Panel C, only MSAs where the share of Republican votes in the 2016 presidential election was above 50% are included in the control group, using the election data from Autor et al. (2020). Standard errors are obtained using the cluster bootstrap with 1,000 replications.

I do not find evidence that my results are driven by other factors than exposure to labor market news. Including time-varying characteristics slightly increases my estimates in magnitude in some cases, although I also observe an increase in the estimated standard errors too; see Panel A. Similarly, excluding the rest of Wisconsin from my sample has a minor impact on the results (Panel B). Furthermore, I do not find any evidence that political sentiments play any role. As shown in Panel C, only including control individuals residing in Republican-leaning commuting zones does not alter my conclusions. There is some noisy evidence, however, that individuals in these areas are slightly more pessimistic about their future wage growth when exposed to Foxconn's reversal.

# C Difference-in-Difference Results

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

$$y_{it} = \alpha^{DiD} + S_{i,t}\Delta^{DiD} + \gamma_t^{DiD} + \nu_i^{DiD} + \epsilon_{it}^{DiD} \tag{C.1}$$

and is given by the coefficient $\Delta^{DiD}$.[2] The results of the DiD estimation are reported in Table C.1.

Looking at the results in the Table, one can see that the DiD estimates and the results obtained from the synthetic difference-in-difference approach, as reported in Table 3, are very similar. This is not surprising given that my estimated weights in the SC-DiD estimation are close to the standard DiD weights, as discussed in Section A. The estimates using the SC-DiD are, however, slightly more precise in some cases. This feature also has been pointed out in Arkhangelsky et al. (2021). The results in this section show that my results do not crucially depend on the weighting approached used in the estimation. All my conclusions remain valid when using a normal DiD approach.

# D Event-Study Estimates & Balancing Properties

## D.1 Event-Study Estimates

I also estimate a weighted event-study. Although, I have only two pre-treatment period, it is still informative to investigate whether the outcomes in these pre-treatment period differ substantially between my treatment and control groups. Such estimates are also interesting in that they allow to assess whether individuals anticipated Foxconn's invest-

[2] Alternatively, it can also be obtained by setting the weights $\omega_i$ for control observations to constant weights $N_{co}^{-1}$ and $\lambda_t$ to constant weights $1/T$ in Equation (3) in the main part of the paper

Table C.1: Effect of News on Labor Market Expectations - Difference-in-Difference Estimates

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

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 initial announcement of opening the Foxconn plant in Racine County, Wisconsin, in November 2017 as treatment. Panel B uses the announced reversal in January 2019 that Foxconn's expansion plans are smaller than previously announced; see also Section 2. The dependent variable used in Column (1) is the expected percentage increase in the salary in the current job over the next year. In Column (2), the expected number of job offers over the next four months is used as outcome. The dependent variable in Columns (3) and (4) is the expected log average salary and the expected log maximum salary offered when receiving an offer, multiplied by 100. Standard errors are obtained using the cluster bootstrap with 1,000 replications.

ments and its announcements. If they did, one would expect large effects even prior to the actual news.

I estimate the event-study in two steps. In a first step, I obtain the individual and time weights, as described in Section A. In a second step, I estimate a event-study and applying the first-step SC-DiD weights

$$Y_{i,t} = \alpha^{ES} + \sum_{\substack{\ell=-2 \\ \ell \neq -1}}^{0} \mathbb{1}[t - E = \ell]\delta_\ell + \gamma_t^{ES} + \nu_i^{ES} + \epsilon_{it}^{ES} \tag{D.1}$$

where $E$ is the event time, October 2017 for the initial announcement and January 2019 for the reversal. The estimates for the event-studies are shown in Table D.1.

As one can see from the estimates, there is no evidence that individuals ultimately exposed to the positive news about Foxconn's investment plan had different expectations about their labor market outcomes before the actual announcement than individuals who were not exposed to the news. All of my pre-treatment estimates are not statistically significant on any conventional level. They are also small and I can rule out large effects for most of my outcomes. For example, I estimate a difference of 0.01 percentage points in the pre-treatment expectations when considering expected salary increases; see Column (1). The results in the table also highlight the large and significant jump in expectations after the announcement of the investment plan.

I come to a similar conclusion when considering the exposure to Foxconn's reversal, see Panel B Table D.1. All my pre-trends are small and do not indicate that, prior to the announcement, individuals ultimately exposed to the news adjust their expectations differently than individuals who were not. Notice, that the event-study estimates when considering the expected number of job offers as outcomes are not well defined. This is as the entire time weight is put on the period directly preceding the announcement date; see also Table A.1 in Section A.

## D.2 Robustness to Violation of Parallel Trends

I also investigate how large any other local shock unrelated to Foxconn's announcement but possibly affecting individuals' expectations, such as changes in productivity, improvement in the business climate or hiring, would need to be in order to invalidate my estimates. Put differently, such a shock would violate the parallel trends assumption but would lead me to wrongly conclude that individuals updated their expectations because of the labor market news. I assess the robustness of my results following Manski and Pepper (2018) and Rambachan and Roth (2022).

Assuming that possible local shocks after the announcement of Foxconn are not too different to local shocks prior to the announcement and using my event-study estimates

Table D.1: Effect of News on Labor Market Expectations - Event-Study Type Estimates

| | (1) Salary Increase Current Job | (2) Number of Job Offers | (3) Average Log Salary Offer | (4) Maximum Log Salary Offer |
|---|---|---|---|---|
| **Panel A: Initial Announcement** | | | | |
| $\delta_{-2}^{Positive}$ | 0.01 | 0.06 | 0.02 | 0.07 |
| | (0.42) | (0.07) | (1.34) | (1.57) |
| $\delta_{-1}^{Positive}$ | | *omitted* | | |
| $\delta_{0}^{Positive}$ | 2.71 | 0.18 | 19.26 | 19.22 |
| | (1.43) | (0.21) | (7.09) | (8.25) |
| Observations | 459 | 498 | 279 | 291 |
| **Panel B: Reversal** | | | | |
| $\delta_{-2}^{Negative}$ | $-0.01$ | $ND$ | $-0.17$ | 0.03 |
| | (0.42) | | (0.90) | (0.65) |
| $\delta_{-1}^{Negative}$ | | *omitted* | | |
| $\delta_{0}^{Negative}$ | $-1.96$ | $ND$ | $-7.62$ | $-12.14$ |
| | (1.43) | | (4.38) | (5.63) |
| Observations | 438 | | 249 | 261 |

This table summarizes the weighted event-study estimates of the effect of labor market new on individuals' expectations about job search and earnings. The dependent variable used in Column (1) is the expected percentage increase in the salary in the current job over the next year. In Column (2), the expected number of job offers over the next four months is used as outcome. Notice that the event-study estimates for the expected number of job offers is not defined for the negative news sample as the assigned time weight for $t = -2$ is zero. The dependent variable in Columns (3) and (4) is the expected log average salary and the expected log maximum salary offered when receiving an offer, multiplied by 100. Panel A uses the initial announcement of opening the Foxconn plant in Racine County, Wisconsin, in November 2017 as treatment. Panel B uses the announced reversal in January 2019 that Foxconn's expansion plans are smaller than previously announced; see also Section 2. Standard errors are obtained using the cluster bootstrap with 1,000 replications.

from the previous section, the results in Manski and Pepper (2018) and Rambachan and Roth (2022) imply that I can bound the true impact of labor market exposure $\delta_0^{true}$ in a straightforward manner.[3] The bounds are given by

$$\widehat{\delta}_0 - M \cdot \widehat{\delta}_{t-2} \leq \delta_0^{true} \leq \widehat{\delta}_0 + M \cdot \widehat{\delta}_{t-2} \tag{D.2}$$

where the constant $M$ corresponds to the allowed maximum departure of post-exposure trends from the pre-exposure trends. For example, setting $M = 1$ implies that post-treatment trends are allowed to diverge at most as much as the worst observed pre-treatment trends. By varying the magnitude of $M$, I can then evaluate when these bounds cover zero, the breakdown value, and whether the magnitude is sensible in my setting. The results are shown in Table D.2.

As one can see, the obtained breakdown values are extremely high in my setting. For example, considering expected wage growth in the positive news sample, the shock would need to have an impact of 271 times the pre-exposure trend to render my conclusions invalid. Similarly, in the negative news sample, I obtain a breakdown point of 196. These breakpoints seem unrealistically high, further supporting the robustness of my findings. They highlight that after re-weighting any remaining local shock in my setting has to be unrealistically high to draw different conclusions.

One might still be concerned that my robustness analysis here is based on only two pre-treatment periods. If there are more than two pre-treatment periods, one can replace $M \cdot \widehat{\delta}_{t-2}$ in Equation (D.2) by $M \cdot \max_{s<-1} |\delta_{s+1} - \delta_s|$, where $\delta_s$ are estimates from an event study. While it is not possible to obtain estimates for $s > 2$, I can fixed a value for $M$ and then investigate how large any maximum prior trend violation needs to be to invalidate my results.

Imposing the sensible restriction that post-exposure trends cannot diverge more than the worst pre-treatment trends ($M = 1$), the bounds still imply that any trend violations in my setting prior to my first observation period would need to be unusually large to render my conclusions invalid. For example, for the average expected salary offer such a shock would need to translate into 19.26 percent to push my effect to zero.[4] To put the magnitude into perspective, the results in Domash and Summers (2022) suggest that a 1% increase in the 4-quarter moving average vacancy rate increase year-to-year wage growth by 0.20%. While only roughly comparable and actual wages are not necessarily equal expected ones, this implies that a local shock would need to double the vacancy

[3] Rambachan and Roth (2022) also show how to incorporate statistical uncertainty when constructing the bounds. But it is not obvious how one would do so in my setting and account for the first-step estimation of the weights. I therefore only report bounds without statistical uncertainty but noting that the implied breakpoints are extremely high in my empirical setting.

[4] Notice that even if I allow post-treatment trends to diverge twice or three times as much, the maximum allowed divergence in trends still needs to be extremely large, with 9.81 percent and 6.32 percent respectively.

rate to have a true exposure effect of zero on individuals' wage offer expectations. One can use similar reasoning to investigate the magnitude of a local shock necessary to drive the estimates for salary growth expectations at the current firm down to zero. Assuming an average year-to-year vacancy growth rate of 5% for the rest of the US, a local shock would need to more than triple the vacancy growth rate in my treatment region to nullify my results.[5]

## D.3 Balancing Properties

I also assess pre-treatment differences in covariates in my SC-DiD setting, similar to what is done when using SC methods (e.g. Abadie et al., 2010). A difference to the standard SCM approach is that the weighting approach when using the SC-DiD method does not impose a perfect pre-treatment fit. All remaining differences are captured by the individual fixed effect; see also Section A. This implies that one can apply an event-study similar as in Equation (D.1), using individual background characteristics as outcome instead. When assessing the balancing properties of my SC-DiD estimator, I do *not* include any covariates in the first step estimation of the weights or in the outcome model.[6] No or small differences between my two groups would give reassurance in my identification strategy.

The results from this exercises are shown in D.3 for different covariates.[7] Notice that some of the variables I use to assess the balancing properties of my estimator may be themselves considered as outcomes and therefore affected by the treatment, such as employment status of the partner.

[5] The vacancy rate grew by around 5% between October 2016 and 2017; see `https://www.bls.gov/jlt/`. Using the estimates of Domash and Summers (2022), this implies a wage increase of roughly 1%. As my estimates indicate an increase of wage expectations by around 2.7 percentage points, to obtain a true effect of zero, the vacancy rate in my treatment regions would need to increase by 18.5%, implying a wage increase of around 3.7%.

[6] This is similar to what is often done in matching studies to assess the balancing properties of a certain estimator.

[7] All weights are based on the SC-DiD approach using expected wage growth as outcome, with exception of the binary employment status indicator, which is not defined in this sample. When assessing the balancing property using employment status I use the SC-DiD weights obtained using expected maximum wage offered as outcome. In general, the balancing properties are very similar regardless of the outcome used to calculate the weights.

Table D.2: Breakdown Values for SC-DiD Event Study

| | (1) Salary Increase Current Job | (2) Number of Job Offers | (3) Average Log Salary Offer | (4) Maximum Log Salary Offer |
|---|---|---|---|---|
| **Panel A: Initial Announcement** | | | | |
| $\overline{M}^{Positive}$ | 271 | 3 | 963 | 274.57 |
| **Panel B: Reversal** | | | | |
| $\overline{M}^{Negative}$ | 196 | $ND$ | 44.82 | 404.67 |

This table summarizes the minimum allowed violation of post-exposure trends in relation to estimated pre-treatment trends such that the acutal treatment effect is possibly zero, following Manski and Pepper (2018) and Rambachan and Roth (2022). The breakdown points $\overline{M}$ are based on the event-study estimates reported in Table D.1 and Equation D.2. The variable used in Column (1) is the expected percentage increase in the salary in the current job over the next year. In Column (2), the expected number of job offers over the next four months is used as outcome. Notice that the event-study estimates for the expected number of job offers is not defined for the negative news sample as the assigned time weight for $t = -2$ is zero. Therefore $\bar{M}$ is undefined here. The dependent variable in Columns (3) and (4) is the expected log average salary and the expected log maximum salary offered when receiving an offer, multiplied by 100. Panel A uses the initial announcement of opening the Foxconn plant in Racine County, Wisconsin, in November 2017 as treatment. Panel B uses the announced reversal in January 2019 that Foxconn's expansion plans are smaller than previously announced; see also Section 2.

Table D.3: Balancing Properties of SC-DiD Estimator

| | (1) Employed | (2) Full Time Job | (3) Tenure in Job | (4) Has Partner | (5) Partner Employed | (6) Low Income |
|---|---|---|---|---|---|---|
| **Panel A: Initial Announcement** | | | | | | |
| $\delta_{-2}^{Positive}$ | 0.02 | 0.06 | −0.69 | 0.00 | −0.08 | −0.01 |
| | (0.02) | (0.09) | (0.41) | (0.15) | (0.10) | (0.03) |
| $\delta_{-1}^{Positive}$ | | | *omitted* | | | |
| $\delta_{0}^{Positive}$ | 0.02 | −0.02 | −0.11 | −0.01 | 0.08 | −0.09 |
| | (0.02) | (0.03) | (0.19) | (0.01) | (0.10) | (0.10) |
| **Panel B: Reversal** | | | | | | |
| $\delta_{-2}^{Negative}$ | 0.02 | 0.02 | 2.20 | 0.15 | 0.19 | −0.02 |
| | (0.03) | (0.02) | (1.87) | (0.17) | (0.17) | (0.02) |
| $\delta_{-1}^{Negative}$ | | | *omitted* | | | |
| $\delta_{0}^{Negative}$ | −0.00 | −0.00 | −0.69 | −0.01 | 0.01 | −0.00 |
| | (0.03) | (0.01) | (0.85) | (0.01) | (0.02) | (0.03) |

This table summarizes the weighted event-study estimates of the effect of labor market new on individuals' expectations using individual background characteristics as outcomes. The dependent variable used in Column (1) is a binary variable whether the indiviual is currently employed. Notice as this variable is not defined in the wage growth expectation sample, SC-DiD weights using the expected maximum wage offered as outcome are used. In Column (2), a binary variable whether the current job is a full-time job is used. The dependent variable in Columns (3) is the tenure in years in the current job. Columns (4) and (5) use a binary indicator whether the individual currently has a partner and whether the partner workers, respectively. The last column uses a binary indicator whether the household income was below $61,000, corresponding to the median household income in the US. Panel A uses the initial announcement of opening the Foxconn plant in Racine County, Wisconsin, in November 2017 as treatment. Panel B uses the announced reversal in January 2019 that Foxconn's expansion plans are smaller than previously announced; see also Section 2. Standard errors are obtained using the cluster bootstrap with 1,000 replications.

As one can see from the table, all the covariates are balanced (in differences), even though they are not used in the estimation. The difference in background characteristics between individuals exposed to labor market news and those who are not is not only statistically insignificant on any conventional level but also relatively small. This is true for both, my initial announcement sample (Panel A) and the reversal sample (Panel B). More reassuring, even after exposure to labor market news there are no changes in observable background characteristics. The good balancing properties of my approach also suggest that possible unobserved dynamic adjustments of individuals likely do not play an important role in explaining my results.

# References


Abadie, A., Diamond, A. and Heinmueller, J. (2010), 'Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program', *Journal of the American Statistical Association* **105**(490), 493–505.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W. and Wager, S. (2021), 'Synthetic Difference in Difference', *American Economic Review* **111**(12), 4088–4118.

Autor, D., Dorn, D., Hanson, G. and Majlesi, K. (2020), 'Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure', *American Economic Review* **110**(10), 3139–3183.

Domash, A. and Summers, L. H. (2022), 'How Tight Are U.S. Labor Markets', *NBER Working Paper 29739* .

Manski, C. F. and Pepper, J. V. (2018), 'How Do Right-to-Carry Laws Affect Crime Rates? Coping with Ambiguity Using Bounded-Variation Assumptions', *Review of Economics and Statistics* **100**(2), 232–244.

Rambachan, A. and Roth, J. (2022), 'A More Credible Approach to Parallel Trends', *forthcoming Review of Economics Studies* .

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