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In Hot Water? The Macroeconomic Impacts of El Niño*

Brigitte Roth Tran[†]

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Abstract

Despite their potentially major impacts, little is known about how El Niños impact the U.S. economy. El Niños are distinct from other commonly studied weather shocks because they are a global phenomenon, unfold over a period of months, can be forecast months in advance, are relatively infrequent, and have very different effects on weather outcomes depending on the time of year and region. These features make traditional analytical methods ill-suited to studying the economic impacts of El Niño events. In this paper I use a new approach to estimating the impulse response functions of El Niños. I find that El Niños pose material upside risk for PCE prices and employment. The longer-run price effects are driven by core services and food prices and depend on whether La Niñas follow El Niños, a very common occurrence. After modest offsetting initial effects, employment increases are widespread in terms of both sectors and states in the year following the El Niño. These results indicate El Niños can have material impacts on the US economy even though it is neither tropical nor agriculturally focused.

JEL classification: Q54, E31, E24

Keywords: El Niño, prices, employment, estimating weather effects

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1 Introduction

El Niños are a part of the global El Niño Southern Oscillation (ENSO) phenomenon in which the trade winds over the Pacific Ocean that blow warm water from the east to the west weaken, causing complex and significant shifts in global weather patterns. Although the impacts of El Niños on GDP growth of countries has been studied in a variety of ways, relatively little is known about the dynamic impacts on macroeconomic outcomes like inflation and employment, which are closely monitored by central banks like the Federal Reserve in the United States. This is not due to lack of interest in the economic impacts of weather events. A large literature has shown that a wide range of weather shocks can impact a broad set of economic outcomes. However, El Niños are distinct from the weather shocks like daily temperature anomalies and hurricanes that are more commonly studied. El Niños shock the entire globe at once, are infrequent, can be forecast months in advance, unfold over months, vary in length, and have very heterogeneous effects on weather outcomes depending on the time of year and region. These features preclude the simple application of existing empirical methods from the weather effects literature.

In this paper, I present a new approach to examine macroeconomic impacts of El Niños and apply it to U.S. inflation and employment, examining both the dynamics and the categories driving aggregate effects. My method is a modified stacked local projections that has the following three key features. First, I use a continuous annual treatment measure based on the Relative Oceanic Niño Index (RONI), which the National Oceanic and Atmospheric Administration (NOAA) uses to classify El Niño effects (see Figure 1). This distinguishes between stronger and weaker El Niños. Second, I focus on what I call “ENSO years,” the 12-month periods starting in May of each year, in order to center the year around the typical peaks of El Niños. Third, I estimate responses for each calendar month to reflect the strong seasonal heterogeneity of El Niños. I validate this model by confirming that it produces the following key weather patterns characteristic of El Niño episodes: a contemporaneous reduction in Atlantic Hurricanes, an increase in winter precipitation across the southern swath of the United States (including California), and a decrease in winter heating degree days in the northeastern and northwestern parts of the United States.

Focusing on PCE prices and employment outcomes in the United States, I find the following. First, El Niños tend to be inflationary. Relative to April prices, El Niños temporarily boost PCE

price levels from May through July. This temporary boost to PCE prices is driven by energy, food, and core service prices. PCE then starts to rise again the following March, with the typical very strong El Niño event adding about 1 percent to headline PCE prices level by the end of the following November. This large second year increase in prices is driven by food and core services.

Second, I find that the large increase in prices in the year following El Niño owes to the fact that La Niñas often follow El Niños. When I add to the specification a control for the following year’s El Niño (or La Niña) realization, these price increases go away. It turns out that La Niñas often follow El Niños.¹ Thus, this second year inflationary effect is highly uncertain and actually owes to the La Niña that follows. Because these La Niñas follow El Niños so frequently, I consider them to be part of the expectation of price effects when a strong El Niño occurs unless or until there are meteorological forecasts indicating that a La Niña is unlikely to follow.

Third, I find that El Niños result in significant increases in employment. In the early stages of the El Niño, there are modest offsetting employment responses. Starting in the April at the end of the ENSO year, employment sees increases. Unlike the second year rise in prices, these employment increases are not conditional on La Niña occurring the second year. Furthermore, the positive effect on employment is widespread in terms of both sectors and geographies.

This paper contributes to two literatures. First is the literature examining the impacts of El Niños on various financial and economic outcomes. This literature has examined a wide-ranging set of outcomes, including fisheries, construction, and civil conflict (e.g., Hsiang et al. (2011), Downey et al. (2023), and Shrader (2023)). Quite a few papers have examined impacts on agricultural output, stock, and commodity prices (see for example, Brunner (2002), Hsiang and Meng (2015), Ubilava (2018), Atems and Sardar (2021), and Gallegati et al. (2026).) The most relevant literature is that examining macroeconomic outcomes like growth and inflation. Using VARs with quarterly data, Brunner (2002) finds that G-7 countries’ inflation and GDP growth are affected by ENSO shocks with lags and with some ups and downs. Cashin et al. (2017) estimates impulse response functions for inflation and GDP for 21 countries using both country-specific local projections and a global VAR. The paper finds El Niño shocks have very heterogeneous impacts and that in the U.S. they increase real GDP growth and temporarily boost inflation. Callahan and Mankin (2023)

¹See NOAA, “El Niño and La Niña: Frequently asked questions” at <https://www.climate.gov/news-features/understanding-climate/el-nino-and-la-nina-frequently-asked-questions>.

interacts ENSO treatment measures with country-specific teleconnection measures and finds that El Niños reduce economic growth. Liu et al. (2023) uses quadratic functions to estimate non-linear effects of ENSO on global per capita GDP growth and finds that El Niños decrease GDP growth for several years, with effects being more pronounced in teleconnected, agriculture-dependent, and lower-income countries. The effects of la Niñas are less clearly negative. Generoso et al. (2020) find that El Niños decrease GDP and TFP growth particularly for dry countries in the tropical sphere. I complement this work with a novel modeling approach that allows for responses to El Niño shocks to vary by season and with a focus on inflation and employment in the United States, examine employment and explore the different subcategories driving overall PCE prices. My approach can be applied to other countries for those seeking to dig deeper into the dynamics and drivers of El Niño effects. Furthermore, my analysis brings to this literature new insights on the importance of La Niñas that tend to follow El Niños.

Second, this paper contributes to the broader literature examining the macroeconomic impacts of various weather phenomena. Within this large and growing literature, some papers have focused specifically on natural disasters and extreme weather events (see, for example, Hsiang and Jina (2014), Roth Tran and Wilson (2025), and Kim et al. (2025)), while others have considered responses to shocks in terms of temperature, precipitation, and other dimensions of weather (see for example, Starr (2000), Natoli (2023), and Wilson (2019).) These papers are generally relevant to the analysis herein because El Niños cause temperature, precipitation, and extreme weather shocks. However, El Niño is a much slower-moving phenomenon than heatwaves or hurricanes that generally last a matter of days and have very distinct start and end points. Although one might look to droughts for methodology as they also have longer time frames, they are not global (though they can be caused by El Niños), can last much longer than El Niños, and have not been studied as much in terms of their impacts on macroeconomic outcomes other than agriculture (for examples, see Russ (2020) and Zaveri et al. (2023).) Because El Niños have such distinct features from the types of weather events that have been studied most, the methods used in this broader literature do not work well for El Niños. This paper brings to that literature an intuitive and broadly-applicable methodology for studying the impacts of El Niño on macroeconomic outcomes that could be applied to other settings.

The findings in this paper indicate that El Niños can have very significant macroeconomic

impacts on the United States, even though it is not an agriculturally-focused or tropical economy. Given the ability to forecast El Niños months ahead, it is not only important but also of great value for policymakers to understand the implications of these major global meteorological events.

This paper proceeds as follows, in section 2 I explain some basic background on El Niños. I follow this in section 3 with a brief overview of the data used and a description of the empirical strategy in section 4. I present results in sections 5 and 6. Finally, I discuss some caveats in section 7 and then conclude in section 8.

2 Background

El Niño describes the part of the El Niño-Southern Oscillation (ENSO) pattern in which the trade winds over the Pacific Ocean that blow warm water from the east to the west weaken. This causes a complex shift in global weather patterns, as the eastern Pacific Ocean becomes warmer than usual and the Pacific jet stream shifts south, resulting in altered weather patterns. For example, in the United States, there are typically fewer Atlantic hurricanes and more Pacific hurricanes during El Niños. During winters, precipitation tends to increase in the southern swath of the lower 48 states (including California) and temperatures are warmer in the northeast and northwest.²

NOAA uses RONI to classify El Niños. An El Niño (La Niña) occurs when RONI is above 0.5 (below -0.5) for at least 5 consecutive months. RONI measures the anomalies of the sea surface temperature (SST) in the Niño 3.4 region relative to the mean tropical anomaly. As such, the RONI is stripped of trends and anomalies that occur across the entire tropical latitudes.³ El Niños range in strength from “weak” to “very strong” (when RONI exceeds 2.0 for at least three consecutive months.) There were 25 El Niño episodes between 1950 and 2025. As can be seen in Figure 2, these episodes have lasted anywhere from 5 to 18 months, with peak RONI values ranging from 0.6 to 2.4. Only four of those El Niños were very strong.

Figure 1 shows the historical RONI series produced by NOAA. This series is a three-month moving average. The orange shaded regions are El Niños, when this RONI measure is at least 0.5 for at least five consecutive months. The blue shaded regions are the La Niña episodes, when RONI

²See NOAA “Weather Impacts of ENSO” available at https://www.noaa.gov/jetstream/enso_impacts.

³This yields lower values when the entire tropical latitude is warmer than usual and could make the estimates in this paper conservative.

is below -0.5 for at least five consecutive months. Note that the strong El Niños are often followed by La Niñas, in which the Pacific trade winds strengthen, shifting the jet stream north and cooling the eastern Pacific Ocean waters.

3 Data

For the treatment of interest, I use RONI data which are produced by NOAA and available back to 1950. I use the version 6 data available at https://cpc.ncep.noaa.gov/products/analysis_monitoring/enso/roni/. These come in the form of three-month moving averages. When merging with monthly data, I assign each RONI observation based on the first month of the three-month moving average period. The sample used in this paper spans January/February/March 1959 - May/June/July 2026. I describe how I use these data in section 4. In addition to the ENSO data, I use hurricane, precipitation, and temperature data from NOAA to validate my model. I use region-month level data produced by NOAA to examine regional impacts on precipitation and temperature. I model precipitation in terms of cumulative inches and temperature as cumulative heating degree days. I consider the count of hurricanes that made landfall along the Atlantic or Gulf coasts.

I use the following economic data and sources, which I have accessed through Haver. For inflation, I focus on the monthly Personal Consumption Expenditures (PCE) price series produced by the Bureau of Economic Analysis (BEA), which are available starting in 1950. For employment, I focus on Total Nonfarm Payrolls, which start in 1950 and come from the Bureau of Labor Statistics (BLS). I also use unemployment and sector- and state-specific employment data that also come from the BLS and go back to 1950. Industrial output data come from the Federal Reserve and go back to 1950, while single family housing starts come from the Census Bureau and go back to 1959. I also use WTI oil price data. Because these only go back to 1985, I use a version that supplements earlier periods with offer prices.

4 Empirical Strategy

As I described above, the impacts of El Niño are tricky to model because El Niños are global, infrequent, predictable, relatively slow-moving, and variable in length. Monthly observations are

highly correlated, with El Niños displaying strong seasonality. Figure 3 shows this correlation and the fact that El Niños tend to peak between October and December. Furthermore, the impacts of El Niño vary by the time of year and region. For example, El Niños tend to increase precipitation along the southern swath of the United States in the winter but not in the summer. In winters, El Niños tend to make the northeast warmer but the southeast cooler. As a result of these features, standard approaches for studying the impacts of weather shocks that rely on spatial variation or the element of surprise are not appropriate.

I use modified stacked local projections to examine the impacts of El Niños on the U.S. economy. I consider a series of 12-month periods that span from May to the following April each year, which I call “ENSO years.” For the El Niño treatment measure, I sum the monthly RONI values exceeding 0.5 over each ENSO year, which yields a continuous treatment measure for each ENSO year that I call $RONI_EN_{yr}$. More formally,

$$RONI_EN_{yr} = \sum_{m \in yr} \max[0, RONI_m - 0.5] \cdot \mathbf{1}[m \in \text{El Niño episode}], \quad (1)$$

where m indexes the three-month moving average observations. This is similar to the approach taken in Hsiang and Meng (2015), who use the average Nino3.4 index over May-December each year, and Liu et al. (2023) who use the Niño 3.4 SST anomaly averaged over December, January, and February. The key differences are that I (a) use observations from May - April, (b) use the RONI (which removes anomalies common across the full tropics and thus may actually be conservative), (c) subtract off 0.5 from each monthly observation (which puts greater emphasis on stronger El Niños), and (d) interact the values with an indicator for whether the event is an El Niño to allow for asymmetric effects. Looking at Figure 1, $RONI_EN_{yr}$ basically corresponds to the integrals of the orange shaded regions. By subtracting off 0.5, this measure intentionally introduces some non-linearity to distinguish more between weak El Niños, which could easily have $RONI_EN_{yr}$ values below 1 and very strong El Niños.

I then adapt the typical local projection approach in Jordà (2005) of considering outcomes in period $t + h$ relative to horizon $t - 1$. As with the traditional local projection approach, I consider the change in an outcome at a horizon relative to a baseline period. However, I fix the baseline period for each ENSO year to be the April at the end of the previous ENSO year. The horizons I

consider start with May for horizon 0, June for horizon 1, and so on up to 18 months after the start of the ENSO year. This means for each horizon, I have one observation per year. For example, I consider how the PCE price index in August 1997 has changed relative to April 1997 in response to the sum of RONI values above 0.5 from May 1997-April 1998.

Although much of the treatment has not yet occurred in the early months of the ENSO year, there may be anticipation effects due to high serial correlation and predictability of RONI. Forecasts have improved dramatically since the start of the RONI data. El Niños can now be predicted months in advance (though forecasts made in spring for winter are better than forecasts made in fall for summer). Research has shown some commodity prices can be predicted well out of sample using ENSO anomalies and that economic agents appear to use El Niño forecasts in their decision-making. For example, Ubilava (2018) shows that ENSO has predictive power out-of-sample for commodity prices. Downey et al. (2023) find that construction employment responds to precipitation effects based on ENSO forecasts up to six months ahead. Shrader (2023) finds that fisheries respond to three-month-ahead ENSO forecasts.

With these concerns in mind, in this paper, I estimate the following equation. Here the β^h values are the coefficients of interest. Each horizon h corresponds to a calendar month of the year. The month of May that starts the ENSO year is horizon 0.

$$\begin{aligned}
y_{MAY+h,yr} - y_{APR,yr} = & \beta^h RONI_EN_{yr} + \theta^h RONI_LN_{yr} \\
& + \gamma_1 RONI_{NOV,yr-1} + \gamma_2 RONI_{AUG,yr-1} \\
& + \phi \mathbf{X}_{L(MAY,yr)} + \psi \cdot yr + \alpha + \varepsilon_{MAY,yr,h}
\end{aligned} \tag{2}$$

The independent variable $RONI_LN_{yr}$ is the La Niña version of the $RONI_EN_{yr}$ variable and corresponds to the blue shaded regions in Figure 1. I measure El Niño effects distinctly from La Niña effects due to concerns about asymmetries.⁴

I include two lags (6- and 9-month lags relative to horizon 0, which occur in November and August of $yr - 1$, respectively) of the raw RONI measure. These terms control for potential lagged effects from the previous year and the serial correlation in RONI. I include a time trend (yr) and a vector of lagged controls, $\mathbf{X}_{L(MAY,yr)}$. This vector includes lagged differences in logs of PCE

⁴Atems and Sardar (2021) document asymmetric responses to El Niños and La Niñas.

core prices, PCE food prices, and WTI oil prices, as well as the raw unemployment rate. I have chosen these controls to capture pretrends in the main outcomes of interest, food prices as a central potential channel for El Niño effects, and oil prices to reflect energy impacts and to capture potential anticipation effects. The $L(MAY, yr)$ subscript represents the 3- and 12-month log differences for the baseline period of April, where the 3-month log difference is from January to April. I use Newey-West standard errors.

This baseline specification is set up to control for potentially important pretrends in a parsimonious fashion. This is important given that the annual nature of the specification limits how many degrees of freedom are available and thus the number of covariates one can include without overfitting the data. The lags of differences in $X_{L(MAY, yr)}$ capture any potential effects due to anticipation up through the April right before each ENSO year. The distinct implications of El Niños at different times of year make it important to separately estimate responses in different calendar months.

I examine a wide range of economic outcomes, focusing on PCE prices and real outcomes including employment, industrial production, and construction. The key exceptions are the unemployment rate, which I model as the difference in levels, and the weather outcomes, which I model as the cumulative count.

When I present the results, I rescale the coefficients by the mean $RONI_EN_{yr}$ value observed for ENSO years with very strong El Niño episodes in the sample. These are episodes where RONI is at least 2.0 for at least three consecutive observations.⁵

I validate the model by examining responses of specific weather outcomes. Figure 4 shows that the specification successfully captures the targeted weather patterns of decreased Atlantic hurricane activity, increased precipitation in the southern regions (from the west to the southeast), and milder winter temperatures in the northeast and northwest.

5 Price results

In Figure 5, I present estimated impacts of a mean very strong El Niño episode on the main PCE price categories. Each series shows the response in terms of contribution to PCE price changes,

⁵The mean $RONI_EN_{yr}$ value that I use to rescale results is 13.

with shaded areas showing the 68 and 90 percent confidence intervals.

There are two key takeaways from Figure 5. First, it shows that prices respond quickly to developing El Niños, including what appear to be anticipation effects. This is consistent with Changnon (1999) who reports that in 1997, firms were already responding to El Niño forecasts by summer by changing order placements and other plans. For a mean very strong El Niño, headline PCE is elevated temporarily during the summer by about 30 basis points relative to April. This appears to be driven by a variety of factors, with energy goods and services, core services, and food all contributing a bit. Second, Figure 5 shows that a very strong El Niño may contribute up to about 1 percent of net growth to headline PCE growth over the calendar year following its onset. This increase is driven primarily by core services, with about 15-20 bps coming from food. The contribution from core goods is quite flat throughout.

The lagged response could be explained by some combination of (a) the heterogeneity in El Niño impacts by season, (b) the feature that El Niños typically peak around winter, and (c) the potential for anomalous weather to have lagged impacts on outcomes like food harvests, supply chains, and disaster recovery efforts. This would be consistent with findings in the literature. For example, Roth Tran and Wilson (2025) show that the responses to disasters of macroeconomic outcomes like employment can take several years to unfold. Similarly, Kruttli et al. (2025) show that it can take several months for financial markets to resolve uncertainty about firms hit by extreme weather events, with analyst call transcripts revealing that plant closures, supply chain issues, and insurance disputes can take significant time to resolve. However, my sensitivity analysis in section 5.1 suggests that the lagged responses in prices likely owe to the meteorological repercussions of El Niños for the following years.

What could be driving these effects? In Figure 6, I show estimates of contributions by PCE core services subcategories, the category in Figure 5 with the largest contributions. I find that the financial services and insurance category makes the largest contribution to PCE, with prices rising steadily to contribute about 20 bps in PCE price growth by December of the ENSO year before fluctuating in the following 12 months. Health care prices also contribute roughly 20 bps to the longer run rise in headline PCE, but start with a slightly negative contribution through the first December. In addition, the housing and utilities and the food services and accommodation categories also appear to make positive contributions by the end of the second December, making

the rise in prices relatively widespread in terms of services categories.

Food is a common concern in the public discourse about El Niño impacts. Although the contributions of food to the headline PCE effect shown in Figure 5 are relatively modest, this reflects the fact that food is a relatively small share of headline PCE. Focusing in on just the food series indicates that the mean very strong El Niño episode drives food prices up temporarily by roughly 1 percent by June, with the net increase in food prices over the 18-month period starting in May of the ENSO year amounts to roughly 2.5 percent.

Although the longer run overall contribution of energy to headline PCE is small, the series warrants further examination due to recent turmoil in energy markets. Figure 7 shows the contributions of energy subcategories. El Niño has a very small impact on PCE energy services and its electricity and natural gas components in terms of contributions to headline PCE. The boost to the energy goods and services is basically entirely driven by gasoline prices. Indeed, nearly half of the initial summer boost in headline PCE from El Niño can be explained by a temporary rise in gas prices. In Appendix Figure A2, I show that oil prices are elevated in May and June but then fall thereafter. While the initial bump in PCE gasoline prices is consistent with world oil prices, PCE gasoline prices do not decline thereafter like WTI oil prices do. This could be explained by the fact that strong El Niños are often followed by La Niñas, which tend to increase Atlantic hurricane activity that can disrupt Gulf Coast oil sector activity, which would affect refineries for the United States but not necessarily global oil markets.

5.1 Sensitivity of PCE Price Effects

As I describe in greater detail in Section 7, there are several important caveats that lead me to characterize the key takeaway on price effects as being that very strong El Niños introduce upside risk for inflation. In order to better understand the inflationary risks posed by El Niños, I have examined the sensitivity of the results to a variety of alternative empirical specifications. One choice in particular plays an important role and can help us better understand the results.

As can be seen a bit in Figures 1 and A1, strong El Niños are often followed in short order by La Niñas. This is a phenomenon that has been acknowledged by NOAA.⁶ In Figure 8, I show

⁶See NOAA. “El Niño and La Niña: Frequently asked questions” available at <https://www.climate.gov/news-features/understanding-climate/el-nino-and-la-nina-frequently-asked-questions>.

results from adding 1-year leads of the treatment variables $RONI_EN_{yr+1}$ and $RONI_LN_{yr+1}$ to equation (2). Adding these leads allows me to see how much of the effect could be driven by this phenomenon of La Niñas following El Niños. The figure shows that the second year increase in PCE headline goes away entirely when the treatment of the following year is included, indicating that the longer-run PCE price increase is driven by La Niñas that follow El Niños. I do not include these controls in my baseline specification because this channel is still an important part of the impulse response function for El Niños, which directly trigger the temporary initial price increases and the subsequent La Niña that triggers further price increases. Because $RONI_EN_{yr+1}$ and $RONI_LN_{yr+1}$ are plausibly caused by the El Niño, the baseline model reflects the total effect, while the model that includes the leads of the treatment measures show the direct effect. Because follow-on La Niñas play such an important role in the longer run effects of El Niños and cannot generally be forecast with accuracy until relatively late in the ENSO year, I characterize the main PCE finding as El Niños introducing significant uncertainty into PCE price forecasts for the following year.

In Appendix Figure A3, I present a heatmap with results for five additional alternative specifications. Diagonal stripes indicate that the coefficient estimates are not statistically significant based on a 68% confidence interval. Model 1 is the baseline model. Models 2-4 modify $X_{L(MAY, yr)}$, the vector of lagged controls, with model 2 using 6- and 12-month differences instead of the 3- and 12-month differences in the baseline and models 3 and 4 using specified lags of the levels of the controls. In model 5, I replace the annual $RONI_EN_{yr}$ and $RONI_LN_{yr}$ treatments with four quarterly values of RONI, also interacted with indicators for whether they are occurring as part of El Niño or La Niña episodes. Using quarterly values better captures varying timing of El Niño episodes but comes at the cost of a meaningful loss of degrees of freedom. Finally, model 6 shows the Figure 8 results, which add 1-year leads of $RONI_EN_{yr}$ and $RONI_LN_{yr}$ as controls. These models all yield positive point estimates for early increases in PCE prices, though some are not statistically significant. All models except model 6 yield positive effects on PCE prices in the later horizons, though the model 5 estimates are not statistically significant.⁷ At the same time, models 2 and 3 show stronger longer-run effects than the baseline model. Together, these sensitivity analyses

⁷This could reflect that by using eight rather than two treatment variables, the season-specific treatment model lacks statistical power.

show that although the statistical significance of the results are somewhat sensitive to alternative specifications, which is unsurprising given the short time series, the positive point estimates are consistent if I don't include the following year's treatment.

6 Real Economic Activity Results

In Figure 9, I show results from regressions for three distinct real economic outcomes: total nonfarm payrolls, industrial production, and housing starts. The results indicate that El Niños help boost labor markets and industrial production in the following year and provide a temporary boost to construction in the initial year. Unlike in the case of PCE, these results are not qualitatively sensitive to the inclusion of one-year leads of the treatment variables, indicating that they are not contingent on experiencing a La Niña the next year (see Appendix Figure A4).

The boost to payrolls shown in Figure 9 is sizeable. Appendix Figure A5 shows that these long-run results are not sensitive to alternative specifications. Indeed, some specifications show even stronger and more statistically significant positive responses. Consistent with this finding, in Appendix Figure A2, I also find that unemployment declines. The finding is consistent with Roth Tran and Wilson (2025), which shows that disasters result in boosts in employment that can be explained by recovery efforts that are funded by transfers and insurance.

To examine how widespread the employment effects are, in Figures 10 and 11, I show results from sector- and state-level analyses, respectively. Figure 10 shows that the lack of an initial effect masks offsetting effects across sectors. In particular, construction sees an early boost, while education and health services, financial services, and mining and logging decline by May, while an increase in information sector employment by August offsets decreases in financial services and mining and logging. In contrast, the longer increase in employment is widespread with several sectors seeing boosts on the order of several percentage points by the end of the 18-month period being considered. The mining and logging industry is a prominent outlier. This sector faces a fairly persistent decline that commences at the start of the ENSO year and could potentially be explained with the Appendix Figure A2 decline in oil prices and the decline in winter heating degree days (see Figure 4).⁸

⁸The decline in oil prices is consistent with Gallegati et al. (2026), which applies time-varying local projections to monthly oil price data going back to 1983. Using monthly shocks and distinguishing between El Niño and La Niñas,

Figure 11 shows a similar pattern of offsetting early effects followed by widespread positive longer-run effects in the geographic dimension. In particular, panel (a) shows that there are relatively modest but offsetting employment effects by August of the ENSO year, with some states exhibiting increases and others declines. Panels (c) and (d) show that by May of the following year, employment increases are quite widespread and persisting at least through that November.

The magnitude of the increase in single family starts shown in Figure 9 is consistent with anecdotal data on past episodes. Changnon (1999) explains that in the 1997-1998 El Niño episode, starts increased 6 percent from January to February and that “income and employment in the construction industry from December through February had increased 25%.” The boost in the figure also peaks during the winter months. This increase in construction activity in winter is consistent with milder winter weather in the northeast and northwest, where construction activity tends to be slowed by adverse weather conditions in winter. Because of the seasonality of starts, relatively small changes in the number of units can result in outsize increases in percentage terms. This could also help explain how large the estimated response is.

On the whole, it appears that El Niños lead to meaningful and widespread increases in employment and real economic activity. Unlike the price effects, these responses are not sensitive to whether there is a La Niña in the year that follows.

7 Caveats

I have characterized the findings of this analysis as El Niños introducing upside risk to inflation and employment because there are multiple sources of uncertainty. Thus far I have focused on sensitivity to alternative specifications and the uncertainty arising from whether or not a La Niña follows the El Niño. The following are additional key caveats to keep in mind when considering how to interpret the results presented herein.

Non-linearities and tipping points. There could be non-linearities or tipping points that are not captured in this analysis. Although the current treatment measure does to some extent magnify differences between weak and very strong El Niños by taking the integral of RONI values above 0.5 (versus just above 0), the empirical specification does not explicitly model non-linearities in

the paper finds that El Niño anomalies result in lower oil future and spot prices.

order to remain parsimonious. This means the results may not accurately reflect non-linearities or tipping points. For example, while a moderate increase in precipitation in the southern parts of the United States may be beneficial, too much precipitation causes flooding. Particularly strong El Niños like the currently still developing 2026-2027 episode could cause large-scale or widespread disasters that are disruptive and damaging in a manner not reflected in this analysis.

Treatment measures. RONI, the measure NOAA uses to identify El Niño events, is not the only ENSO measure available. Alternative measures, which handle smoothing and detrending differently or draw from different data sources, could yield different results. However, I work with RONI because it has data that go back to 1950. This contrasts with daily measures now available that are based on satellite data and only go back to the 1980s, leaving a much reduced sample size for these annual phenomena.

Context. A lot has changed since the 1950s. When it comes to El Niños, forecast quality and lead time have improved dramatically since then. In many ways, our system may be better prepared to respond to negative effects since the start of my sample, as our modern building codes and other efforts leave us more resilient to extreme events. At the same time, our economy may be more sensitive to global supply shocks given how much of our production occurs overseas. Developments like the recent disruptions to the fertilizer market, energy supply chain disruptions, and record-setting weather events could also interact with El Niño episodes in unexpected ways.

8 Conclusion

In this paper, I have applied a new approach to estimating the El Niño impacts on macroeconomic outcomes that accommodates the fact that El Niños are predictable, slow-moving, global events with strong seasonality and heterogeneous impacts by season. Using data going back to the 1950s, I find that El Niños present material upside risk for PCE prices and employment in the United States. The findings are consistent with extreme weather disruptions arising in the southern parts of the United States due to flooding and with milder winter weather in the northern parts being conducive to economic activity.

I have also discussed important caveats, including the potential for non-linearities and tipping points that may not be appropriately captured in my model and the changing context since the

start of my sample. These concerns combined with the finding that the PCE effects depend to a great extent on whether a La Niña follows an El Niño lead me to characterize the findings as pointing to heightened uncertainty in outcomes due to El Niños.

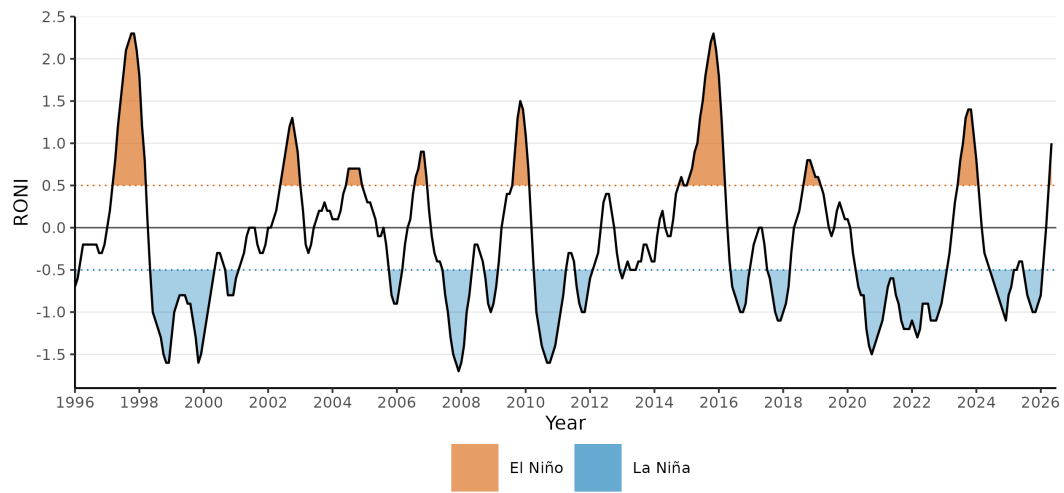
The magnitude of the estimated outcomes is large. The good news is that because El Niños are predictable, households, firms, and local governments can prepare for the potential impacts. However, such responses are likely already reflected somewhat in the data in this analysis. Thus, the results in this analysis indicate that policymakers at the national level need to at least consider that very strong El Niños can have potentially large impacts on employment and inflation.

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9 Figures and Tables



Source: NOAA.

Figure 1: Relative Oceanic Niño Index

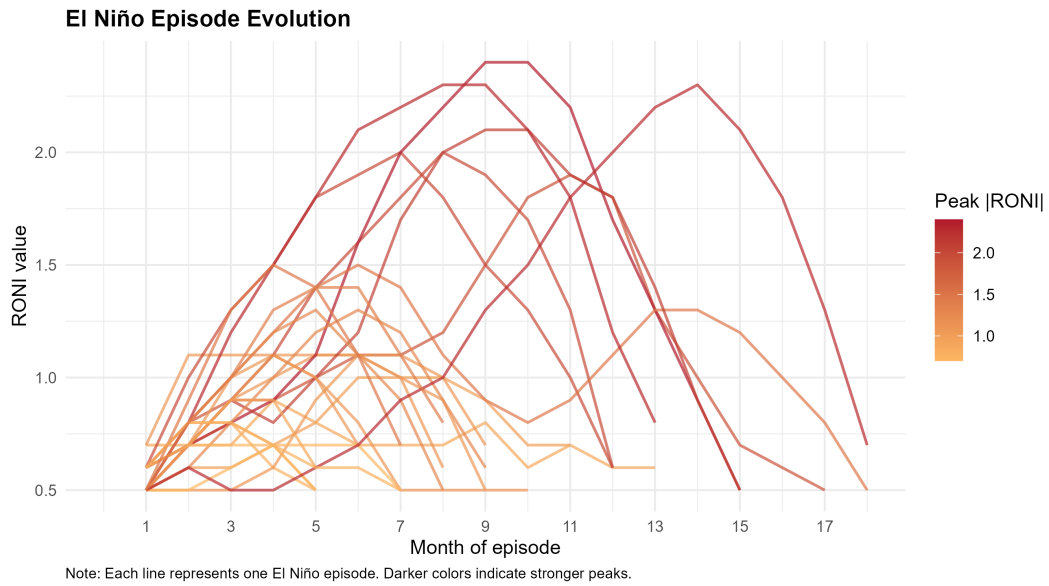


Figure 2: Duration of El Niño episodes

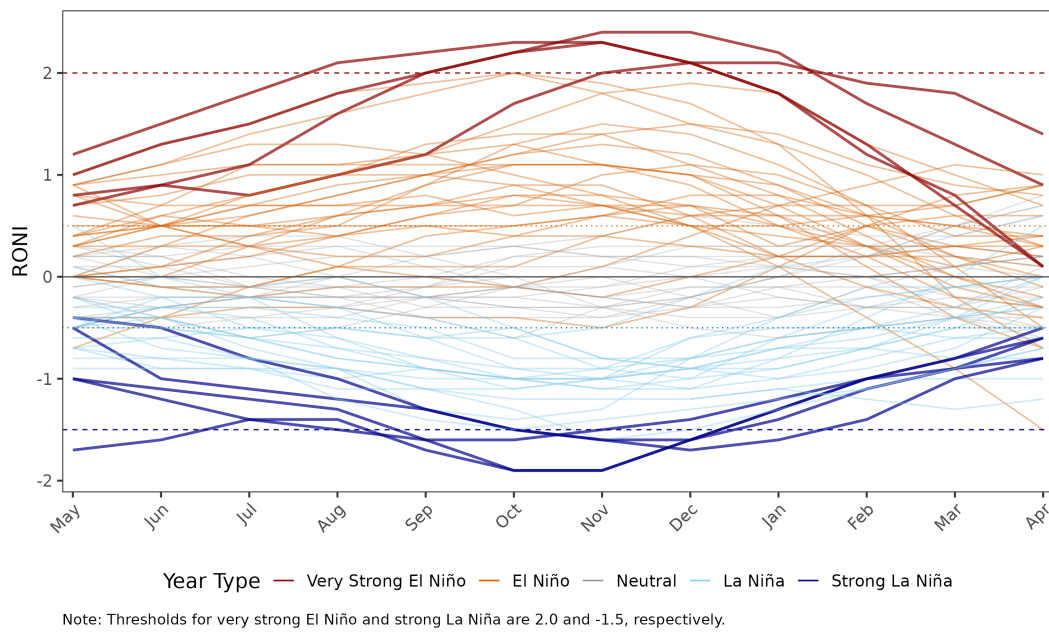


Figure 3: Seasonality of El Niño events

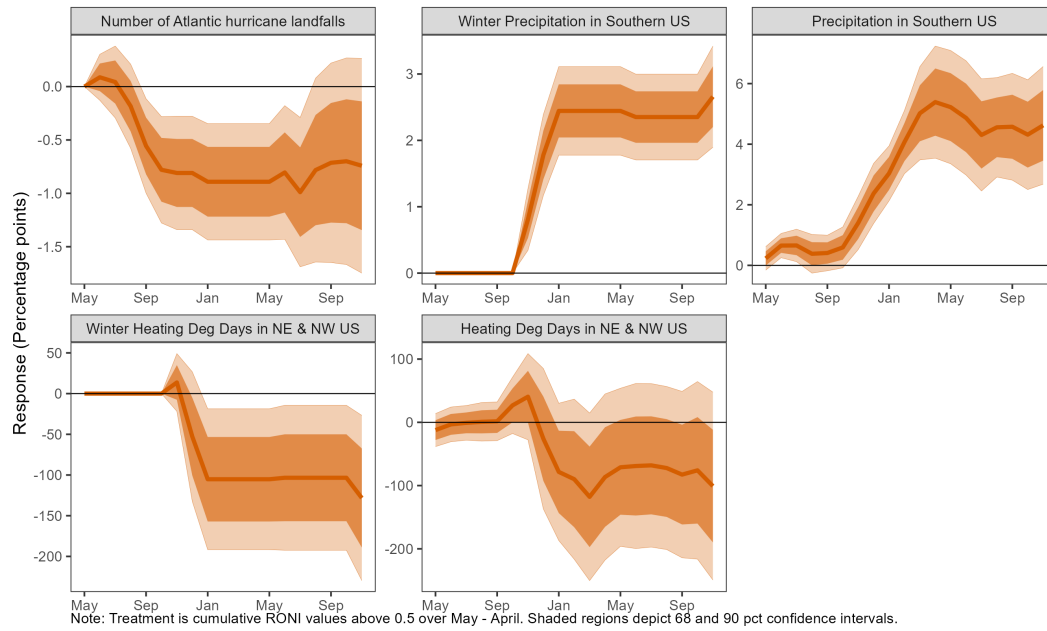


Figure 4: Responses of targeted weather outcomes validate model

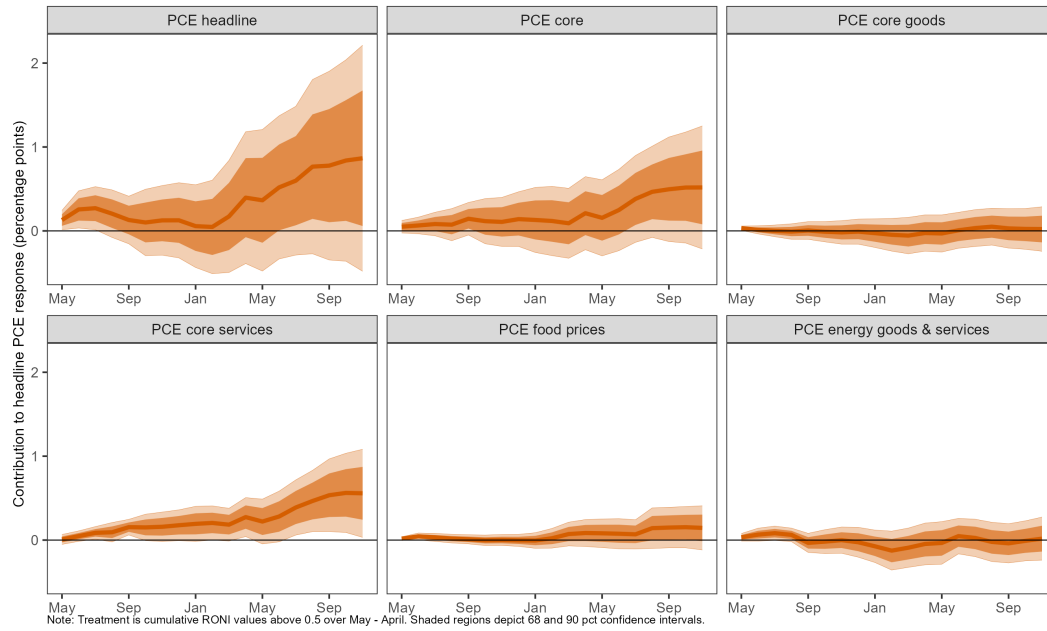


Figure 5: PCE price responses to very strong El Niño

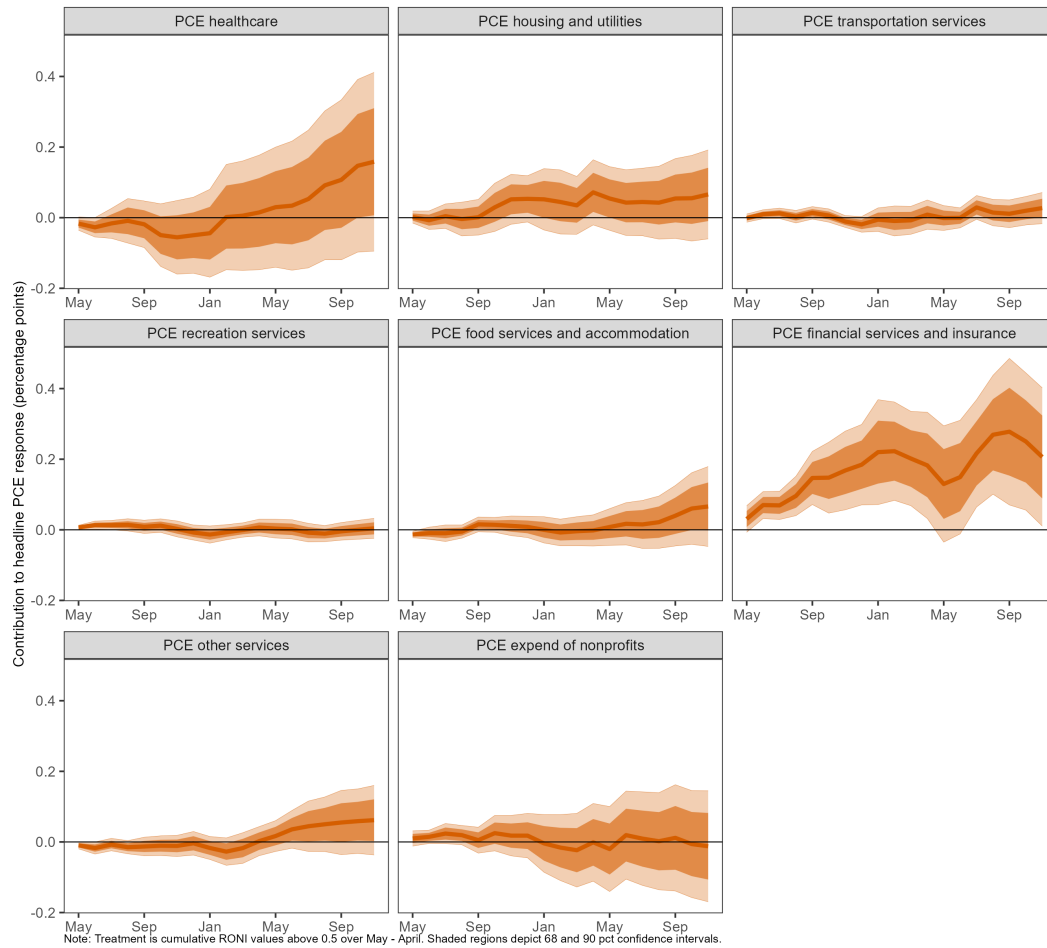


Figure 6: PCE Services Impulse Response Functions

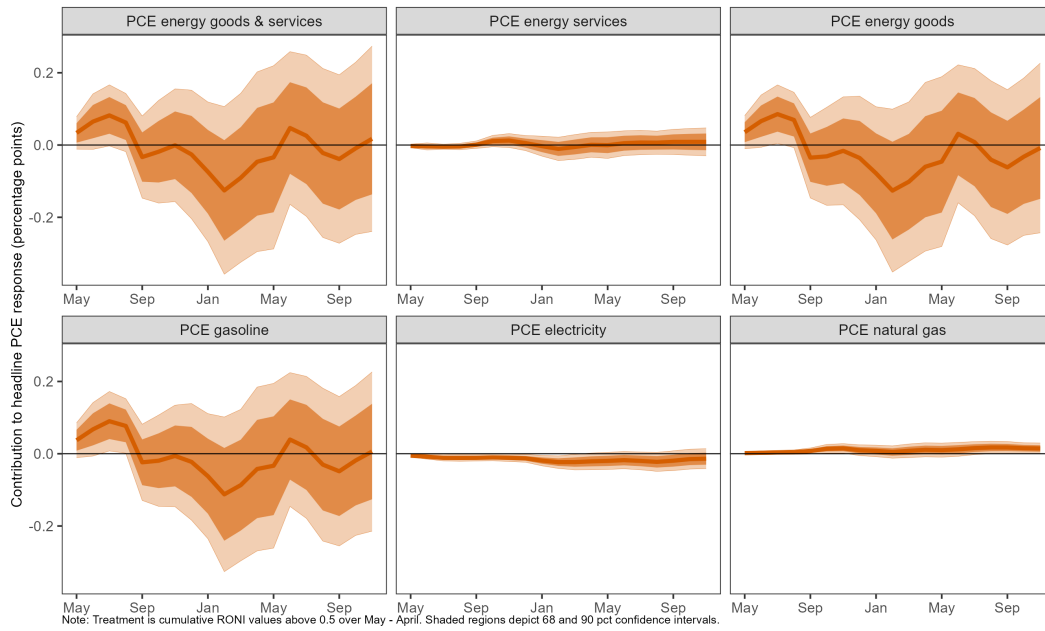


Figure 7: PCE Energy Impuls Response Functions

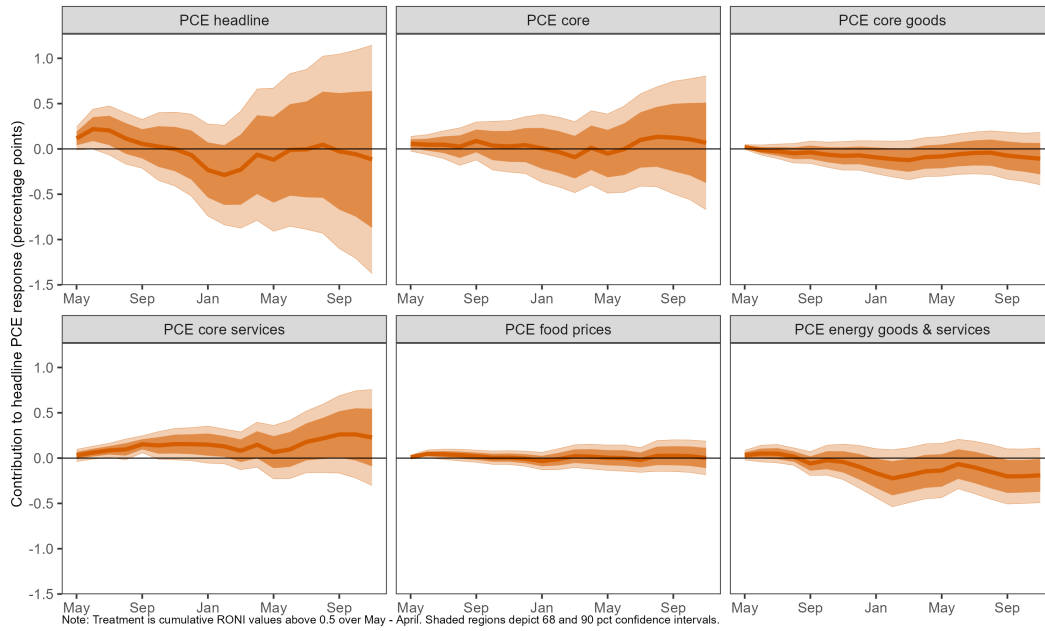


Figure 8: PCE price impulse responses when controlling for the following ENSO year treatment

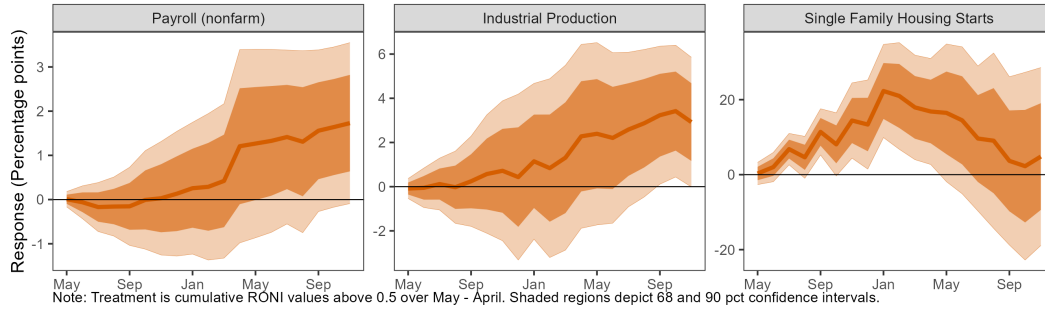
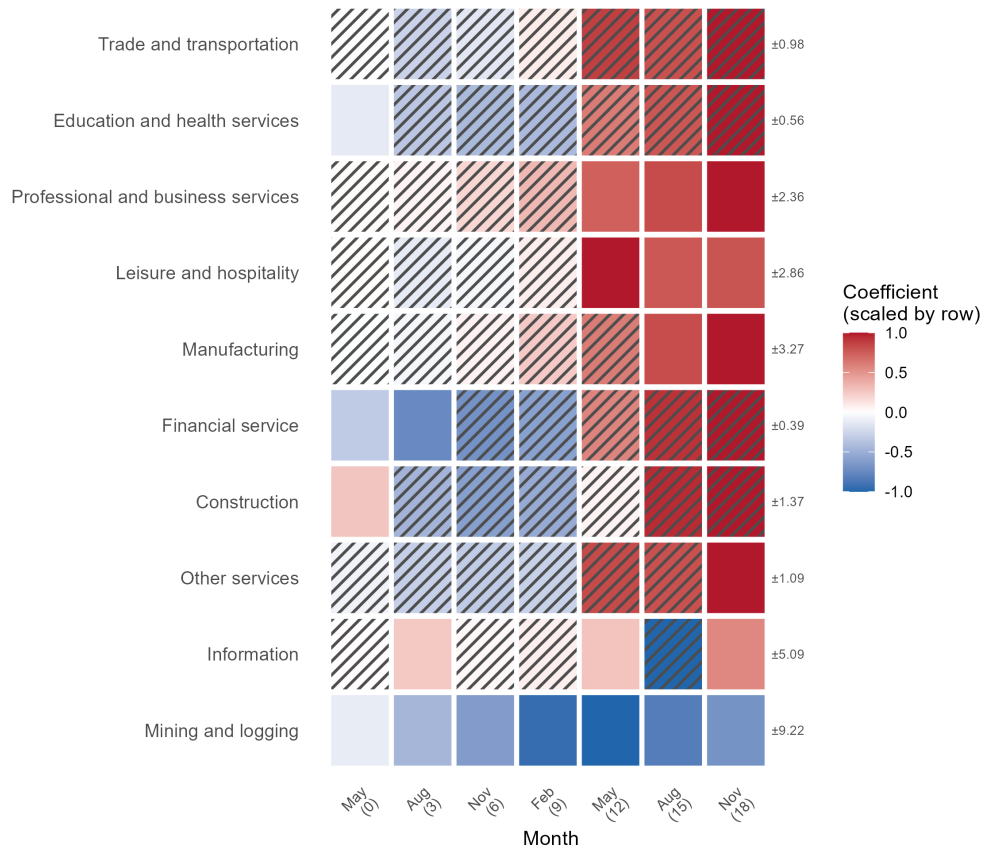
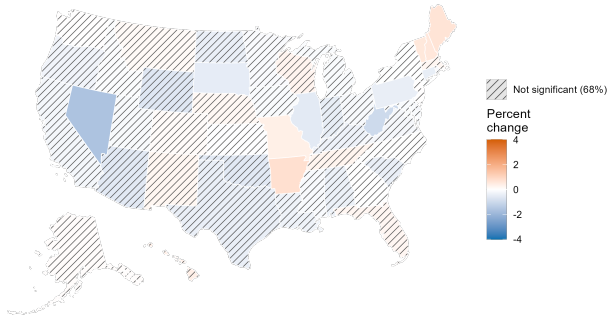


Figure 9: Impulse response functions for real economic activity

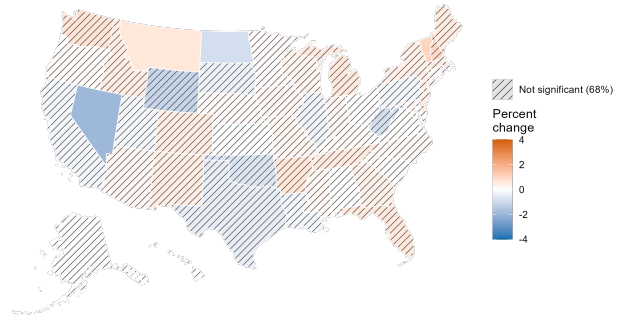


Diagonal stripes indicate a coefficient point estimate is not statistically significant based on a threshold of $p < 0.32$. Each row is scaled independently to its own maximum magnitude, listed to the right of each row. The numbers in parentheses below each month indicate the number of months from the start of the El Niño 'year.'

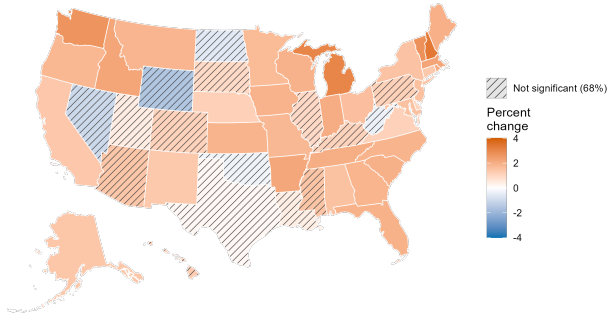
Figure 10: Sector-specific employment impulse response functions



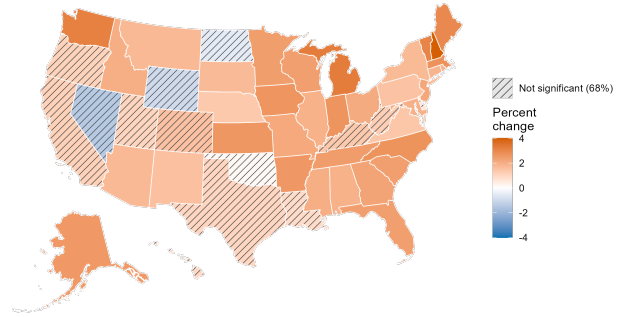
(a) August: $h = 3$



(b) November: $h = 6$



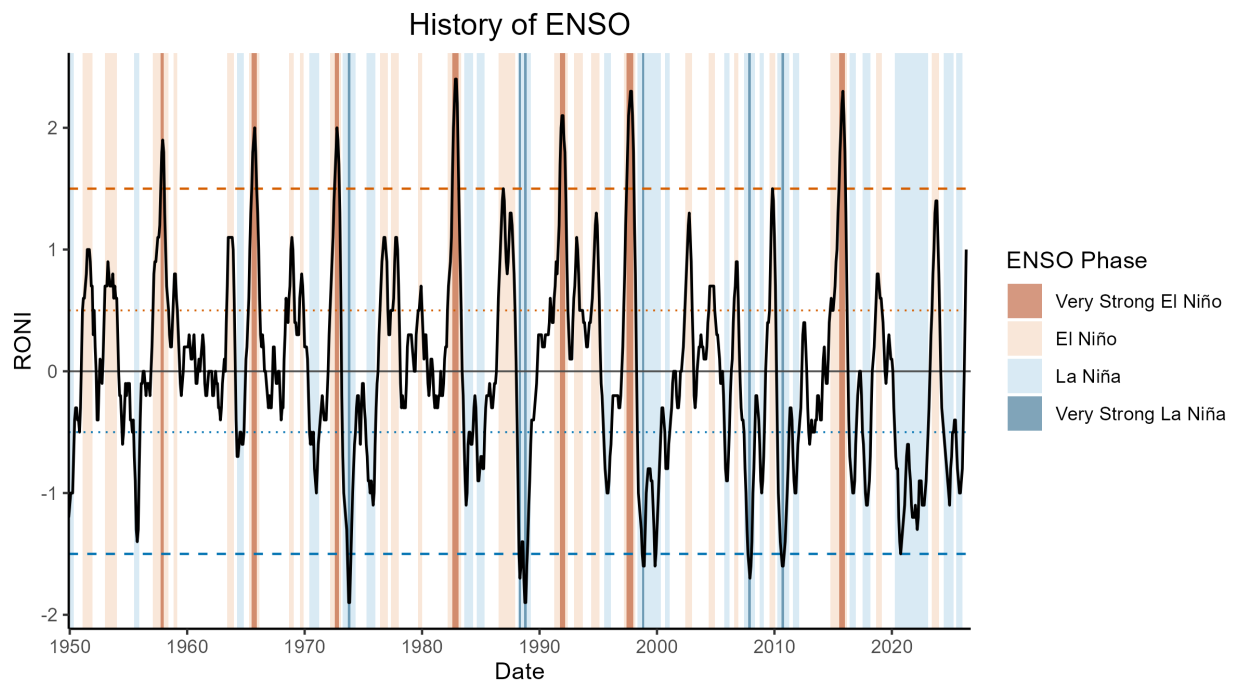
(c) May, following year: $h = 12$



(d) November, following year: $h = 18$

Figure 11: State employment impulse response function results at specific horizons ($h = 3, 6, 12, 18$).

Appendix



Source: NOAA.

Note: Thresholds for very strong El Niño and La Niña are 1.5 and -1.5, respectively.

Figure A1: RONI history to 1950

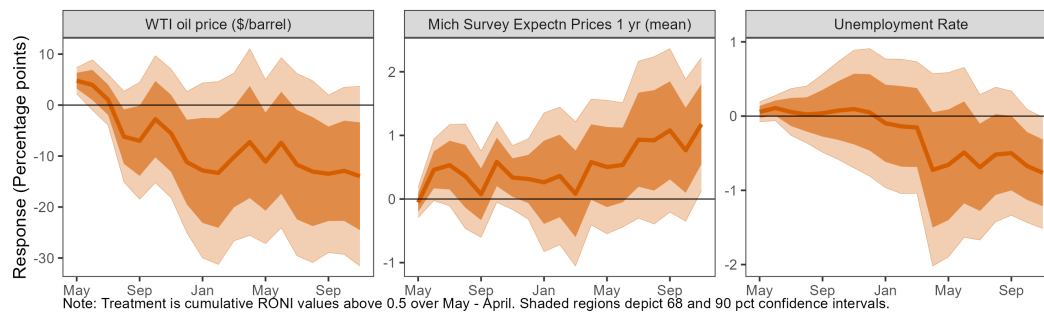
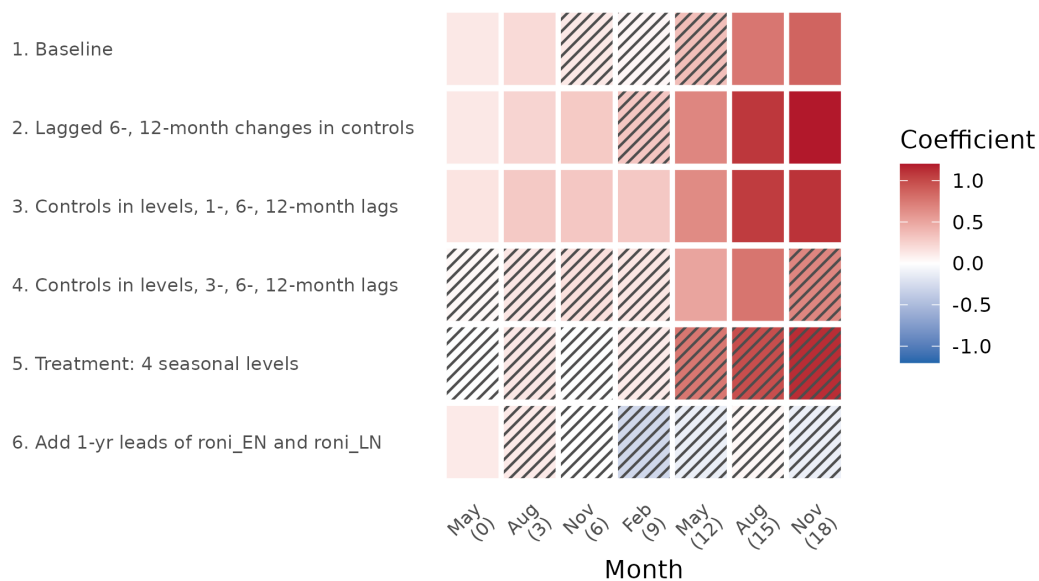


Figure A2: Impulse response functions for various outcomes



Note: Diagonal stripes indicate coefficient is not statistically significant based on max p-val of 0.32

Figure A3: Sensitivity of PCE price response to alternative models

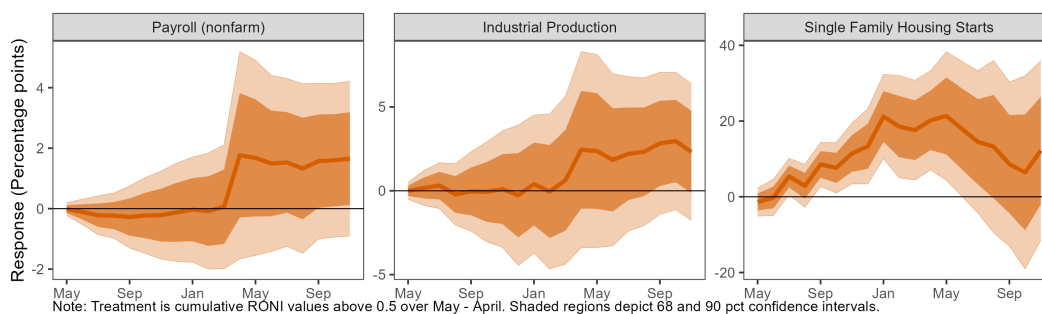
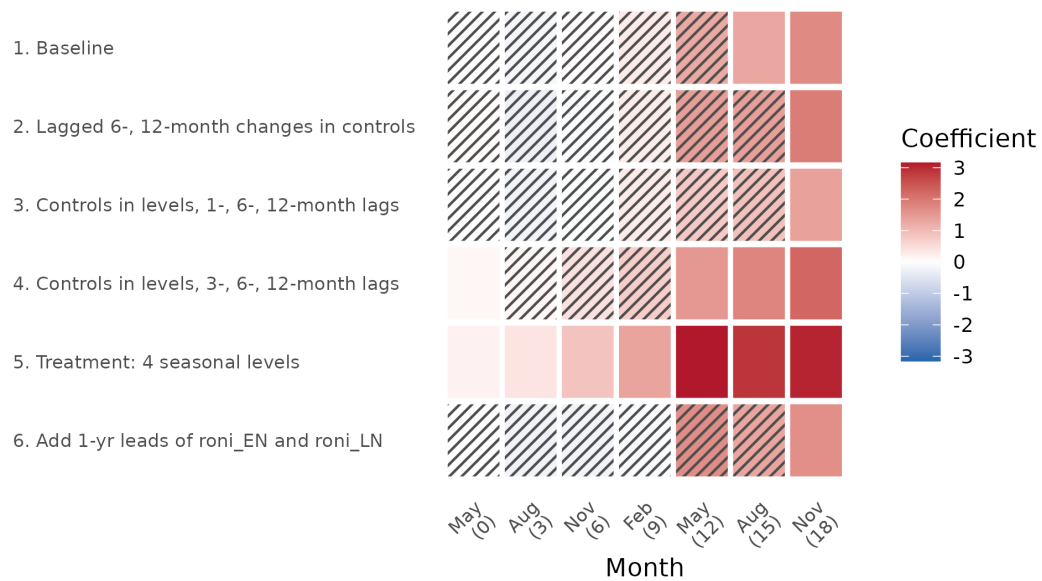


Figure A4: Impulse Response Function when controlling for the following year treatment



Note: Diagonal stripes indicate coefficient is not statistically significant based on max p-val of 0.32

Figure A5: Sensitivity of payroll results to alternative specifications