# CLIMATE CHANGE IMPACT:
# ACCOUNTING FOR NONLINEAR AND HETEROGENEOUS RESPONSES ACROSS INDUSTRIES IN UNITED STATES

A Thesis

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by

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ABSTRACT

The relationship between weather and human society was discovered a long time ago. Recently, rising awareness of climate change has spurred many analyses on the cost of such change from various channels. Using a disaggregated approach, this paper examines the nonlinear impact of warming temperature on twenty economic sectors, meanwhile accounting for heterogeneity in the responses. The results suggest that, while most sectors will incur a loss under different scenarios of climate change, the aggregated impact on the entire United States economy is moderate.

## BIOGRAPHICAL SKETCH

Qingrun Meng was born May 14, 1993 in Nanchang, China. He attended the University of Wisconsin, Madison for his undergraduate studies in Agricultural and Applied Economics. After gaining the degree in 2015, he is now a Master of Science candidate in the Applied Economics and Management at Cornell University and has accepted a position as an Analyst in an economic consulting firm named Analysis Group (AG) in Boston.

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# CHAPTER I

# INTRODUCTION

## *1.1 Background*

As one of the critical factors in the formation of human society, climate has been affecting our lives in all aspects since we ever existed. The relationship between weather conditions and human activities was documented a long time ago, according to the ancient Greek records of people being unproductive under high temperature (Dell, Jones, & Olken, 2014). Early scientific studies estimating such relationships date back to at least the 1900s, and were summarized into one of the earliest comprehensive reviews named *Climate and Civilization* (Huntington, 1915), not only covering the impact of historical weather but also hypothesizing possible adaptations and changes to happen under the shifting climate. Besides showing high temperature causes low income, the book identified various components of our economies (e.g. seasonality, education, development) being affected by cross-sectional weather variation across the global landscape, which became the foundation for future researchers examining different ways by which humans and the climate are linked together.

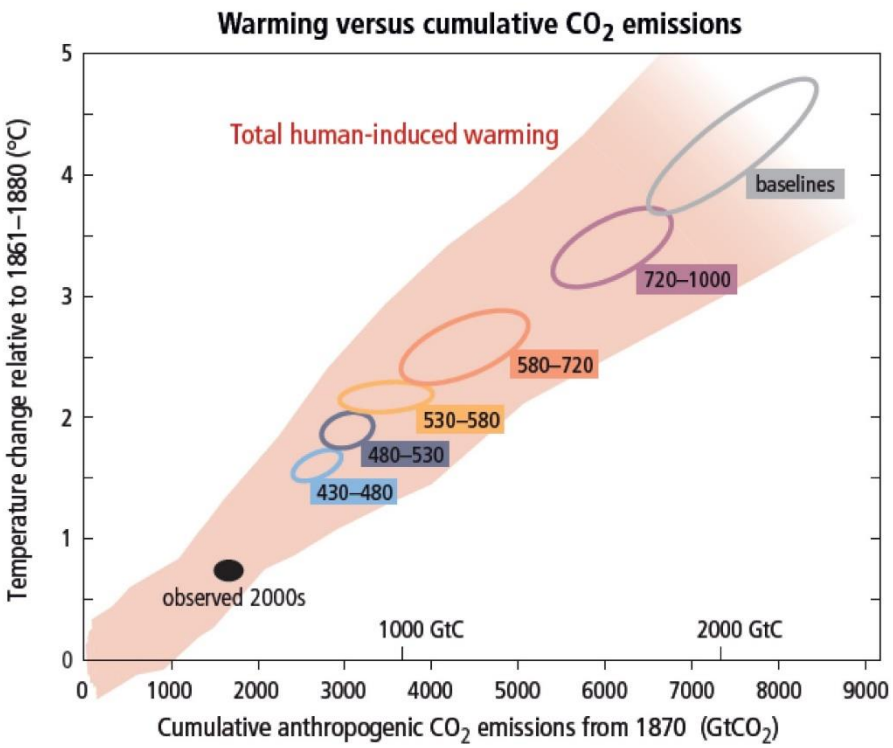
With the improvements made in statistical methodology as well as data collection, a growing amount of recent studies were conducted, many suggesting far-reaching costs of climate change through different channels, including agricultural production, labor productivity, mortality and birth rate, economic growth, migration, civil conflict, and energy consumption. These channels can be broken down into two categories: the ones affecting people, and the ones affecting the elements of the society that was built around people. This paper studies the impact of weather

somewhere in between these two categories.

### *1.2 Background on Impact of Climate*

Observed climate change in the past and projected change in the future have been documented by many researchers in different fields. According to the Intergovernmental Panel on Climate Change (IPCC), climate change will bring more than just a rising temperature, but also other unpleasant weather events, such as higher frequency of heat waves and extreme precipitation, many of which are irreversible.

*Figure 1. Climate Change Scenarios from IPCC*




The figure above illustrates that, with 1°C of warming already observed, continued emission of green-house gas (GHG) will cause further warming anywhere from 2 to 5°C, depending on the scenarios. While this paper aims at quantifying the effects of the warming temperature, analyses using other independent variables tend to find consistent results but with less statistical precision.

(Dell et al., 2014)

Humans respond to suboptimal weather conditions in many ways, for example, by lowering their mental and physical performance, shifting timing for conception and giving birth (Campbell & Wood, 1994), even rising aggression and death rate (Deschênes & Greenstone, 2011). Experimental evidence suggests about 1-2% reduction in cognitive function per Celsius degree over 25°C, in office and classroom environments (Niemelä, Hannula, Rautio, Reijula, & Railio, 2002; Wargocki & Wyon, 2007; Witterseh, Wyon, & Clausen, 2004). Similar studies conducted on an industry scale also find an 8% decrease in the United States (US) automobile factories production during hot weeks (Cachon, Gallino, & Olivares, 2012). Besides taking away our merits, weather can also magnify human flaws. People have higher tendency for interpersonal violence under high temperature (Rotton & Cohn, 2004), which eventually leads to aggravated criminal activities even in rich nations like the US (Ranson, 2014). While a consistent estimate of the temperature effect is still under debate, it is undeniable that weather can have immediate, first order impacts upon human beings.

The consequences of weather variations on our society, however, are more complex, as they account for human reactions and adaptations. For instance, labor supply comes from an individual's decision of balancing the utility gained from work and leisure, which would respond to weather shocks differently than how labor productivity does (Zivin & Neidell, 2010). Similarly, while agricultural production is strongly tied to climate conditions all over the world and for all kinds of crops (Deschênes & Greenstone, 2012; Feng, Krueger, & Oppenheimer, 2010; Kumar & Parikh, 2001; Schlenker & Roberts, 2009; Welch et al., 2010; Wolfram Schlenker and

David B Lobell, 2010), the income of agriculture sector does not necessarily respond to weather the same way, due to the buffering mechanisms (e.g. insurance, future contracts) we invented. Negative income effects may lead to migrations (Feng, Oppenheimer, & Schlenker, 2012; Jessoe, Manning, & Taylor, 2016), which can intensify the above mentioned rising aggression and conflict between people, leading to civil conflicts and unstable institutions (Hsiang, Burke, & Miguel, 2013; Miguel & Satyanath, 2011), or it may stimulate innovations and changes that leave us better off (P. J. Burke & Leigh, 2010). Although the reason for having different consequences from similar shocks is less clear from current literature, it is important to note that the reactions of people, as well as the feedback loops constructed in the economy, together will imply the outcomes of climate change on our society.

Given the sheer possibilities of links between weather and humans, it is not surprising that, ultimately, national income or even global income hinges on a pleasant climate condition. Both cross-sectional and panel studies have found substantial reduction in income growth caused by several types of weather variations, among which the major ones are temperature and precipitation (M. Burke, Hsiang, & Miguel, 2015; Dell, Jones, & Olken, 2009, 2012; Deryugina & Hsiang, 2014; Loayza, Olaberría, Rigolini, & Christiaensen, 2012). Many researchers predict acute costs of climate change in developing regions due to a less diversified economic portfolio, yet reaching no consensus on how wealthier countries would be affected by warming. What we do know is that if we fail to manage and adapt to the changing climate, more severe consequences will fall upon us, such as worsening of income disequilibrium and enduring post-shock damage (Anttila-Hughes & Hsiang, 2013; Miljkovic & Miljkovic, 2014).

### *1.3 Statement of the Problem*

Although a vast number of studies have been conducted, there are still important gaps in the literature. This paper focuses on three of them. Firstly, the scale of past research concentrates on two ends – either the micro-level responses of each individual or the macro-level responses of overall economic growth – but how do the small effects recombine and aggregate within the complex society, working their way through to eventually showing impacts on the national GDP, remain poorly understood. Most higher-order[1] empirical research applies a one-sector approach (Loayza et al., 2012), while one should never expect the weather to affect different industries, such as agriculture and shoes manufacturing, in similar ways. If looking at the impact only from an aggregated perspective, it may lead to ambiguous conclusion by conflating the heterogeneous responses across different sectors. A study of 28 Caribbean countries shows that the positive effect of a cyclone on construction sector offsets the negative effects on utility and mining sectors, thus having no net effect on national income (Hsiang, 2010). Meanwhile, most of past research which tried breaking down GDP into different components were not being exhaustive enough to go beyond the simple characterization of gross output into agricultural, industrial and service outputs. Thus, a comprehensive examination on all sectors of the economy is needed, given the existence of such heterogeneity. To accomplish this, my analysis examined 20 sectors, which exhaustively sum up to GDP, with minor adjustments. The sectors were characterized using the North American Industry Classification System (NAICS) and can be further broken

[1] First-order impacts are the direct and immediate ones, while second- and higher-order impacts are indirect and at more aggregate scales.

down into 113 industries. By conducting the analysis on sectoral rather than industrial level, I am quantifying the impact of weather variation at a medium scale which comes after encompassing all the first-order effects, but before they aggregate onto final GDP. Twenty carefully defined sectors will allow me to have a systematic recognition of how different industries react to weather through different channels. A full list of the sectors with their NAICS code and corresponding descriptions can be found in the first two columns of Supplementary Table 1.

Secondly, heterogeneous response to weather fluctuation is more than the above-mentioned different impacts on different industries. It can occur with regard to many other variables, both climate and non-climate ones. For example, a positive temperature shock is likely to be more damaging in hot areas, and be even worse during an already hot month[2]. Moreover, different regions would be affected in various manners, depending on their current characteristics such as stage of development as well as population and industry composition. Across the world, studies found poor countries, hot regions, and agriculture-intense economies most sensitive to weather changes, but I am not aware of any analysis comparing such heterogeneity within rich, well-diversified nations like the US. This study answers the above problem by interacting weather variables with dummies variables that capture group characteristics. Given the economic structure of the US, it's reasonable to group counties into states, or larger geographical area. By following the spatial definitions from the census, the counties were characterized into 49 continental states, nine divisions, and four regions. I also considered the timing of shocks to play a role, by examining how annual output responds to the weather during each month or season in

[2] The opposite can also be argued: hot temperature is less damaging in hot places due to adaptations.

that year.

Third, few studies have tried to quantify the non-linear damage brought by severe weather conditions, especially from temperature, by assuming more flexible functional forms on weather variables. On one hand, examination of the first-order impacts sometimes follow already established biological and ecological theories, aggregating temperatures into growing degree days (GDD) and harmful degree days (HDD) with arbitrary cutoffs (Deschênes & Greenstone, 2012), but this would not work well beyond the agriculture sector, where no theory dictates a threshold before and after which temperature can be beneficial or harmful. On the other hand, analyses of higher-order impacts often simply use average temperature, or a binary indicator for climatic events (e.g. droughts, floods, hurricanes), with corresponding quadratic terms to allow for some flexibility (Dell et al., 2012), but these are far from being able to capture the true non-linearity of the impact of weather fluctuations. As climate change brings a right-shift in temperature distribution, a disproportionate increase in the number of hot days further emphasizes the importance of taking such non-linearity into account, as it can lead to huge divergence, some up to 200% (Burke et al., 2015), in the estimation of projected damages. In order to precisely calculate the response at each temperature level, I use fine temperature bins (hours per month spent in each Celsius degree from -15°C to 60°C) and tried three types of semi-parametric functional forms, each with varying flexibility, following the practices in Schlenker & Roberts (2009). Temperature bins are aggregated using step functions of different width, polynomials of different orders, and piecewise spline functions of different number of knots. These allow me to find the best fitting specification for each industry, which will then be

used to plot non-linear response curves that track the relationship between economic performance and temperature.

### *1.4 Organization of Thesis*

The rest of this paper is organized in the following manner. Section II takes a closer look at the existing literature on the impact climate change on economic growth. Section III covers information about data, including sources, and how I treat, aggregate, and merge the dependent and independent variables; summary statistics will also be presented. Section IV explains the empirical framework applied in this analysis. Section V discusses and summarizes my findings. Section VI concludes this paper and points direction for future research.

# CHAPTER II

# LITERATURE REVIEW

There are many studies on the relationship between climate conditions and components of societies. This section highlights past analyses looking at the impact of weather on income, and how my study complements or improve them.

This paper adds to the growing body of literature on how economic production responds to weather fluctuations. Historical investigations of this problem were mostly cross-sectional in nature. For instance, an early study on economic growth between 1965 and 1990 found countries located in tropical regions to have 0.9 less percentage point in annual growth rate (Gallup, Sachs, & Mellinger, 1999). The cross-sectional approach used however, is vulnerable to omitted variable bias, such as time-invariant country-specific characteristics. To reduce the amount of bias from such a simple cross-country comparison, researchers have preferred to examine within-country variations. Dell et al. (2009) claim that the within-country cross-sectional relationship between temperature and income is weaker than the 8.5 percent decline per degree Celsius they found across the world, falling between 1.2-1.9 percent per degree. Such inconsistency confirms the existence of bias from omitted country-specific characteristics, but still, suggests a significant correlation of economically substantial magnitude. Meanwhile, recent enhancement in the quality and quantity of data has shifted scholars' attention onto causative panel studies, emphasizing the weather variation over time within a given area. In a panel involving 125 countries over 55 years, Dell et al. (2012) showed that 1℃ warming in a given year decreases per capita income of poor nations by 1.39 percent. Such large short-run impact

implies that it would only take 7 years to reach the 8.5 percent per Celsius degree long-run impact found in cross-sectional studies, thus further implying that, in reality, adaptation and convergence forces have helped to mitigate the adverse effect over time[3]. Although they did not find wealthy countries to be affected by high temperature, Burke et al. (2015) pointed out that with better data and a different model design, all countries appear to be responding to temperature shocks. Based on the above evidence, my paper can shed light on the resilience of developed nations by carefully examining the sensitivity to weather variation of different industries in the US.

Secondly, this paper develops insights on two relatively less explored dimensions of the impact of temperature simultaneously: heterogeneity and nonlinearity. Some scholars (Dell et al., 2012; Loayza et al., 2012) tackle the heterogeneous response question by comparing three major economic sectors – agriculture, industry, and services – and discovered that while severe weather condition imposes strong negative impact on the former two sectors, weather shocks actually induce faster growth in the following periods by propelling reconstruction and upgrade of the capital stock. Others have tried to investigate a broader collection of industries, learning that weather affects the performance of agricultural and light manufacturing businesses, but not heavy industries or production of raw materials (Jones & Olken, 2010). None of these studies, however, accounts for the nonlinear response by going beyond the usage of simple average temperatures and indicator variables for weather anomalies. A possible explanation for this

[3] Cross-sectional analysis shows the impact of temperature in the medium- and long-run, while panel analysis reflects short-run effects. One should be cautious when interpreting short-term marginal impact in long-term time frame, because potential adaptations as well as intensifications of climate shocks can either mitigate or amplify the effect.

phenomena is that, since higher-order impacts tend to be less sensitive than first-order impacts, most researchers adopt flexible functional forms only when examining granular fundamental economic elements or a single industry (Deryugina & Hsiang, 2014). For instance, Schlenker & Roberts (2009) found a substantial nonlinear relationship between yields and temperature using step functions, polynomials, and piecewise splines simultaneously. Moreover, they estimated the upper thresholds for beneficial output effect on agricultural production to be around 29-32℃, depending on the type of crop. Similarly, for studies conducted at a more aggregate scale, few have considered heterogeneity and nonlinearity simultaneously. For example, Burke et al. (2015) identified a strong nonlinear relationship between global output and temperature using quadratic function of annual average temperature, while adopting a simple differentiation between rich and poor countries to capture the different responsiveness. I am not aware of other analyses that are as comprehensive as this thesis in terms of applying more flexible functional forms, considering more subsamples, and adding more interaction terms, which makes this paper the first to extensively investigate the outcomes of climate change from a variety of perspectives.

Furthermore, by having more accurate measurements of climate's impact, this paper improves the construction of damage functions, one of the four essential pieces of Integrated Assessment Models (IAMs) that play a central role in environmental policy, such as the pricing of carbon emissions. The insights on sectors' various levels of resilience to higher temperature can also inform contemporary policies regarding the design of buffering mechanisms to help smooth out short-run damages. This mitigation can be accomplished partially by building up safety net solutions, such as insurance and transfer payments, and partially by having the winners

help offset the losers resulting from weather shocks. Last but not the least, this paper raises awareness regarding the vulnerability of various sectors of the economy, which may help business and governments prioritize their efforts to improve climate resilience.

# CHAPTER III

# DATA DESCRIPTION

## *3.1 Dependent Variable*

The variation explained in this study is the change in the growth rate of each industry's total output in the US. The original data was retrieved from Bureau of Economic Analysis (BEA) of US Department of Commerce. Specifically, I obtained the Local Area Personal Income accounts dataset, named CA5N, from BEA's Regional Economic Accounts[4]. Income consists of three essential parts: wages or wage equivalents, dividend from owning financial assets, and transfers from government or business. Formally, BEA defines income of each industry as " the sum of wages and salaries, supplements to wages and salaries, proprietors' income, dividends, interest, and rent, and personal current transfer receipts, less contributions for government social insurance", which is statistically and conceptually equivalent to the estimates in the National Income and Product Accounts (NIPA), whose annual county-level values sums up to national GDP, with minor adjustments.

This study focuses on 19 of the 20 sectors that NAICS classifies (i.e. excluding Public Administration), with the agricultural sector broken down into the "farming" industry and the "forestry, fishing and related activities" industry. Therefore, this analysis ended up having 18 sectors and 2 industries, which are listed in Supplementary Table 1. This paper uses the words "sector" and "industry" interchangeably to mean each sub-category. Based on data from Internal

[4] The CA5N dataset consists of income data from 2001 to 2015 by industries coded in NAICS, while the parallel version CA5 dataset goes from 1969 to 2001 with industries coded in SIC. Due to the difficulty of consistently matching between NAICS and SIC, this study was conducted using more recent data from CA5N.

Revenue Service (IRS) as well as several censuses[5] and surveys[6], BEA maintains the aggregation procedure for each sector consistently across years.

To improve the consistency of my study, I restrictively selected income data from 3,080 counties in 48 continental states (i.e. excluding Alaska, District of Columbia, and Hawaii), which are then deflated based on Consumer Price Index for All Urban Consumers (CPI-U). Next, I computed the growth rate of income, and within each sector, the top and bottom 1% of observations are dropped, which often occurs due to counties having a small industry that varies a lot from year to year. I rely on a balanced panel in my regression analysis[7]. The final sample size for each sector is shown as the "Number of observations" or "Nobs" in Supplementary Table 1, with the locations of the observed counties presented in the maps in Supplementary Figure 1.

Descriptive statistics of income growth during the entire period of 2001-2015 are presented in the main body of Supplementary Table 1, which show substantial differences in the variance of growth rate across sectors, with farming being the most volatile industry, and health care being the most stable sector. Supplementary Table 2 further breaks down this growth by year. To visualize the growth rates, Supplementary Figure 2 plots them by region, from which three main facts are observed: (i) for all sectors during the period, there are no clear evidence of a linear or quadratic trend in growth rate[8]; (ii) all sectors follow a similar business cycle, and are affected by country-wide economic shocks (e.g. 2008 crisis); (iii) the growth rate of the four regions

[5] Census of Population and Housing; Census of Agriculture; Quarterly Census of Employment and Wages.
[6] American Community Survey; Current Population Survey; Annual Survey of Public Pensions; (monthly) Current Employment Statistics Survey; Survey of Current Business.
[7] I also tried using unbalanced data, which produces similar findings but with much higher uncertainties. This suggest that the growth rate in those dropped counties behave so irregularly that even the data in the years that are not dropped cannot improve the precision of our model.
[8] This calls for the use of more flexible time-varying controls, such as the state-year fixed effect adopted in this paper.

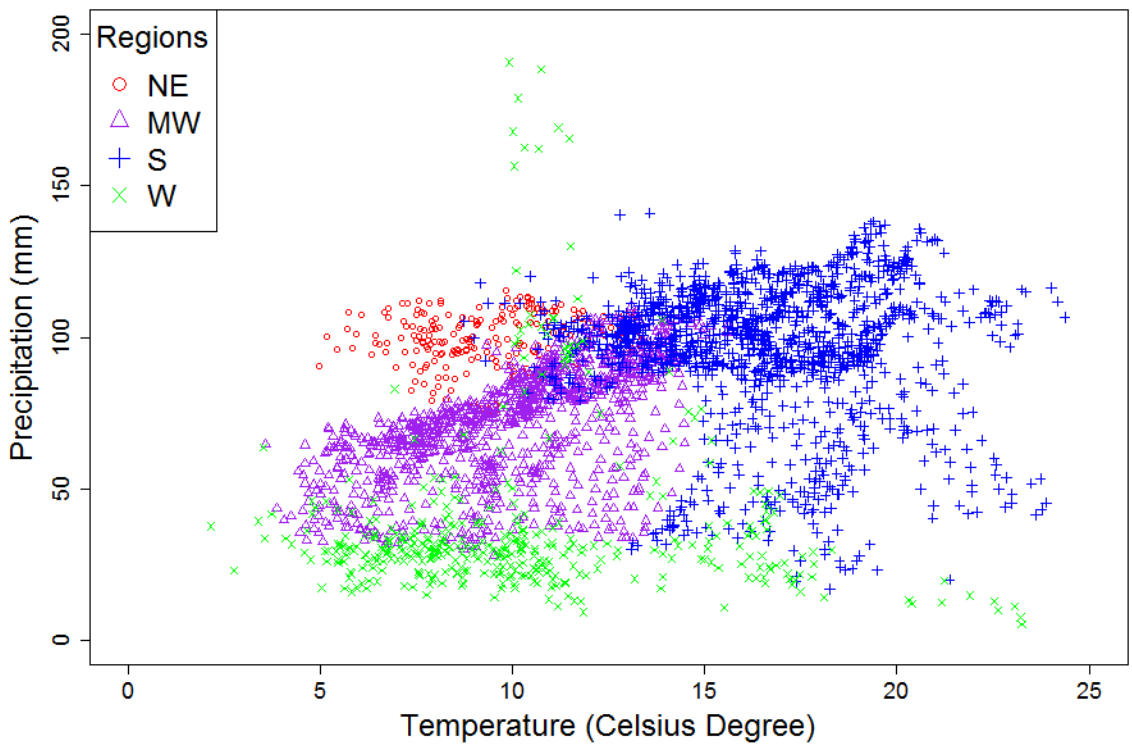
sometimes diverge markedly, especially for farming, information, and management industries.

### *3.2 Explanatory Variables*

Another major component of the data is the monthly county-level temperature and precipitation measurements from the PRISM Climate Group at Oregon State University[9]. To examine the relationship between temperature and precipitation, the figure below portrays county averages from 2001 to 2012, where the 3080 counties are grouped into one of the four census regions of US and plotted with different colors.

*Figure 2. Temperature and Precipitation during 2001-2012*

*(County-level Averages by Region)*




Comparing across regions, the Northeast (NE) and Midwest (MW) tends to be colder than

[9] The hourly temperature bins are obtained by fitting a sine curve on the gridded (4km) daily maximum and minimum temperature observations. These gridded bins were then aggregated onto county-level using cropland weights.

South (S), while NE and S receives more precipitation than the other two regions in general. When looking at just the S and MW, there is a strong correlation between hot temperatures and rain, but this relationship doesn't hold for the entire US. The West (W) region is geographically the largest, defined as the combination of Pacific and Mountain divisions. As the figure above shows, the broad distribution of W marks (green) across both dimension is consistent with West's wide longitude and latitude coverage.

Most of the counties on the hot end are located in Florida and Texas in the South, or California and Arizona in the West. West also possesses the coldest counties in Colorado and Wyoming, while other very cold locations are in Indiana, Minnesota, and North Dakota (MW). Not surprisingly, the most amount of rain is seen in Oregon and Washington (W), from which some counties receive almost 200mm of annual precipitation. Besides the West, Georgia and North Carolina in the South region also tend to have more rains. Consistent with expectations, Arizona, California, Nevada, New Mexico, as well as Texas are the driest locations.

Weather condition is not only spatially correlated, as Figure 2 illustrates, but are also highly consistent within each year (i.e. a hot year for New York City usually implies a hot year for Miami). Thus, questions are raised when controls for fixed effects yearly and regionally are applied (Burke et al., 2015), can potentially wipe out a big portion of the variations in weather variables. When the weather data quality is high enough, however, there will still be significant residual variations in weather even after applying the fixed effects. I further examine this potentially diminished variability by counting the proportion of weather observations deviating from their means by various levels, which are summarized in Table 1.

Table 1: Observed Average Temperature and Precipitation Variation, 2001-2012

| | Proportion of county-months with temperature degrees above/below county monthly mean | | | | | |
|---|---|---|---|---|---|---|
| | 0.25 | 0.5 | 1 | 1.5 | 2 | 3 |
| Raw data | 0.8752 | 0.7519 | 0.5299 | 0.3452 | 0.2125 | 0.0648 |
| Remove year FE | 0.8705 | 0.7455 | 0.5239 | 0.3367 | 0.1989 | 0.0561 |
| Remove year*region FE | 0.8699 | 0.7432 | 0.5156 | 0.3289 | 0.1950 | 0.0532 |
| Remove year*division FE | 0.8717 | 0.7452 | 0.5140 | 0.3267 | 0.1916 | 0.0511 |
| Remove year*state FE | 0.8708 | 0.7439 | 0.5134 | 0.3246 | 0.1884 | 0.0501 |

| | Proportion of county-months with precipitation millimeters above/below county monthly mean | | | | | | |
|---|---|---|---|---|---|---|---|
| | 10 | 20 | 30 | 40 | 50 | 75 | 100 |
| Raw data | 0.7510 | 0.5553 | 0.4063 | 0.2900 | 0.2044 | 0.0833 | 0.0373 |
| Remove year FE | 0.7583 | 0.5585 | 0.4061 | 0.2892 | 0.2016 | 0.0816 | 0.0361 |
| Remove year*region FE | 0.7530 | 0.5552 | 0.4030 | 0.2864 | 0.1990 | 0.0797 | 0.0345 |
| Remove year*division FE | 0.7509 | 0.5504 | 0.3967 | 0.2811 | 0.1951 | 0.0775 | 0.0329 |
| Remove year*state FE | 0.7493 | 0.5463 | 0.3935 | 0.2786 | 0.1924 | 0.0755 | 0.0309 |

As the table above shows, when more controls and interactions are added, the decay of the variability in monthly county-level weather data is quite slow. For instance, observed county's monthly mean temperature can deviate 2°C from its mean during the sample years once every 4.7 years or 5.3 years before or after demeaning[10]. The precipitation inside the US is less volatile than temperature, although the opposite is found when looking at different countries on the entire earth (Dell et al., 2012). Table 1 shows that deviations from monthly mean of 100 millimeters occur once every 26.8 years or 32.4 years before and after demeaning[11], respectively. In other words, removing spatial and temporal fixed effects only takes away relatively small portions of the useful variations in my weather data.

[10] $1/0.2125 \approx 4.7$ years; $1/0.1884 \approx 5.3$ years

[11] $1/0.0373 \approx 26.8$ years; $1/0.0309 \approx 32.4$ years.

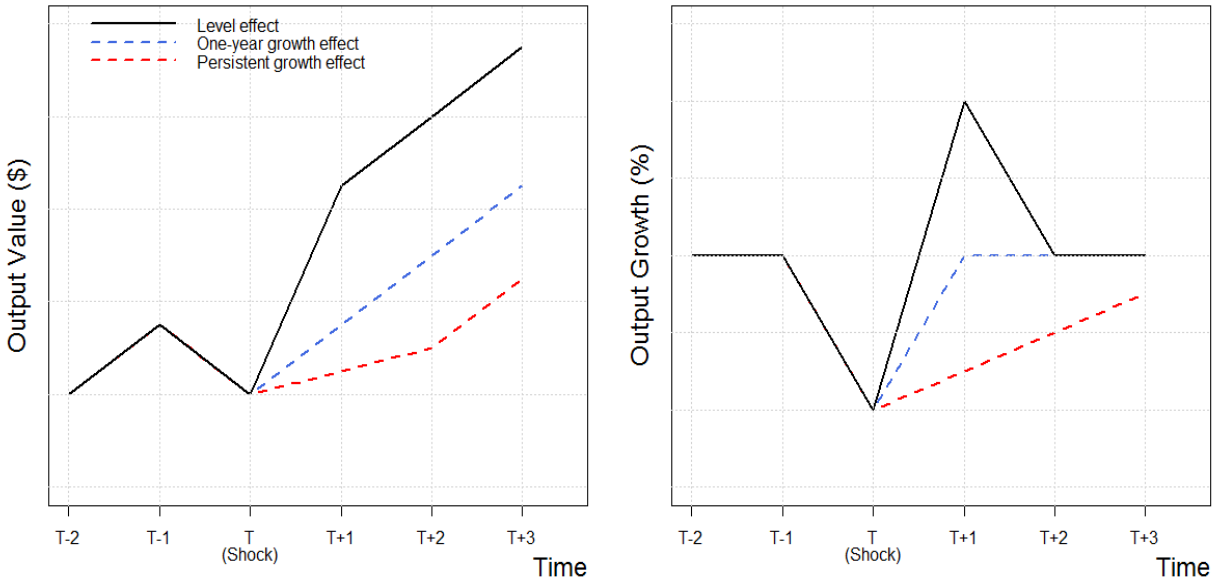
CHAPTER IV

METHODOLOGY

### *4.1 Growth versus Level Effects*

When studying the impact of weather on economic growth rate, researchers in the past distinguished two types of effects – the level effect, which is immediate but disappears in the next period, or the growth effect, which is persistent over several periods. The figure below compares the difference between these two effects on both the level and the growth rate of income over the years.

*Figure 3. Growth versus Level Effect*




During a level effect, the growth rate reverses and the income coverts back to its original trajectory after the period of the shock. Under a growth effect of one or more periods, however, the income path is permanently altered. When compounded over many decades, these two effects could result in a substantial difference in the estimated cost of climate change (M. Burke et al.,

2015; Dell et al., 2009, 2014).

### *4.2 Model without Lagged Temperature Variables*

Based on the strengths and weaknesses of existing empirical frameworks that target the link between income and climate variables, my methodology adopts a panel design with income growth as the dependent variable, and precipitation as well as temperature as the main explanatory variables. There are two reasons for choosing *growth* over *level* of income to be the left-hand-side variable: (i) the level of income has an extremely right-skewed distribution, making it incomparable across different counties and industries; (ii) it is challenging to account for upward trend and serial correlation when studying the level of income, while using year fixed effect in growth of income is a simply solution. For the weather variables, since it has been shown that models using anomaly-based deviations tend to produce similar results but with less statistical power (Dell et al., 2014), I rely on temperature and precipitation, which are observed with high frequency and quality in the US. Each industry is represented by the following equation:

$$g_{it} = \boldsymbol{\beta}_1 \cdot f\left(\boldsymbol{T}_{it}\right) + \boldsymbol{\beta}_2 \cdot f\left(\boldsymbol{T}_{it}\right) \times \boldsymbol{\gamma}_j + \beta_3 \cdot prec_{it} + \beta_4 \cdot prec_{it}^2 + \mu_i + \tau_{st} + \epsilon_{it}$$

(1)

where $g_{it}$ is the growth rate of the corresponding industry in county $i$ and year $t$. The state-year fixed effect $\tau_{st}$ controls for any business cycle, or time-varying shocks, within each state. $Prec_{it}$ is the total precipitation during the chosen month or season of year $t$, with a quadratic functional form to capture its inverse U-shape marginal effect consistently found in similar studies. All other unobserved time-invariant characteristics of each county are accounted for by the

individual fixed effect $\mu_i$. Errors are corrected with spatially decaying correlation within 100 miles, following the methods developed by Conley (1999).

$\boldsymbol{T}_{it}$ represents the temperature bins[12] recording the number of hours that each county has spent at each bin level during the chosen month or season in year *t*. These bins are transformed into various forms before entering into the equation. I applied a broad range of flexible functional forms, including (i) step functions with each step having 3-7℃; (ii) polynomials with degrees of freedom from 2 to 7; (iii) piecewise natural splines with numbers of knots from 1 to 6[13].

Finally, the transformed temperature variables are interacted with area dummies $\gamma_j$ to allow for heterogeneous sensitivities across different places. I also explore different groupings of the counties – the lower 48 states[14], or 9 divisions, or 4 regions[15] following the definitions of the census[16].

In this model without lagged regressors, failing to reject that the coefficients of temperature variables are statistically different from zero would suggest that temperature has no impact at all on income growth, while significant coefficients imply the existence of contemporary effects in the same period during which the weather deviation occurs. But whether these effects would reverse or continue to perpetuate in following periods cannot be answered from this model alone.

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[12] The original temperature bins have 66 levels going from -15℃ to 50℃. The bins on two ends, which often have values of 0, are aggregated using a 0.5% threshold to make the extreme bins more representative and easier for interpretation.
[13] The number of knots equals the degree of freedom minus 1.
[14] There are 50 states in US, consist of Hawaii and 49 continental states, formed by Alaska and 48 southern (or lower) states, which are included in this study.
[15] The 4 regions (9 divisions) are Northeast (New England & Middle Atlantic), Midwest (East North Central & West North Central), South (South Atlantic, East South Central & West South Central), and West (Mountain & Pacific).
[16] https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf

### *4.3 Model with Lagged Temperature Variables*

Some studies find climate shocks to have persistent damage on economic growth by including past weather condition, mainly in less developed countries. I am interested in knowing if such situations happen in rich countries, as well as whether well-diversified economies have the ability to recover from shocks by experiencing faster growth in later periods. Acknowledging the heterogeneous response across locations and types of businesses, I have the following lagged model for each region and industry:

$$g_{it} = \sum_{l=0}^{L} \boldsymbol{\rho}_l f\left(T_{i(t-l)}\right) + \beta_3 \cdot prec_{it} + \beta_4 \cdot prec_{it}^2 + \mu_i + \tau_{st} + \epsilon_{it} \qquad (2)$$

The weather variables no longer interact with area dummies because I am running the above model for each of the four census regions. When $L = 0$, this is similar to the model without lag. When $L > 0$, I can test for immediate effects of temperature through $\rho_0$, as well as the cumulative effect by summarizing the coefficients: $\sum_{l=0}^{L} \boldsymbol{\rho}_l$. A failure to distinguish the cumulative impact from zero suggests full recovery, thus making the impact of temperature a *level* effect, while the opposite suggests *growth* effect for one or more periods. Figure 3 demonstrates the difference between these effects in one and more periods.

# CHAPTER V

# RESULTS & DISCUSSIONS

## *5.1 Finding the Optimal Regression Model*

The results from this study are the damage functions for each sector of the economy, as well as for the entire US, under different warming scenarios. Many steps are taken before that: (i) finding the best model design by comparing the improvement in forecasting accuracy across all specifications, which will determine when, where, and how does weather variations matter; (ii) running the preferred model to get the response functions, which traces the impact of temperature on the growth rate at each degree level; (iii) simulating a shift of the underlying temperature distribution, and tracing the difference (usually loss) caused by this shift over the next five decades to get the income projection; (iv) repeat the last step for various cases of global warming to compute the damage functions.

### *5.1.1 General Procedure: K-fold Cross-validation*

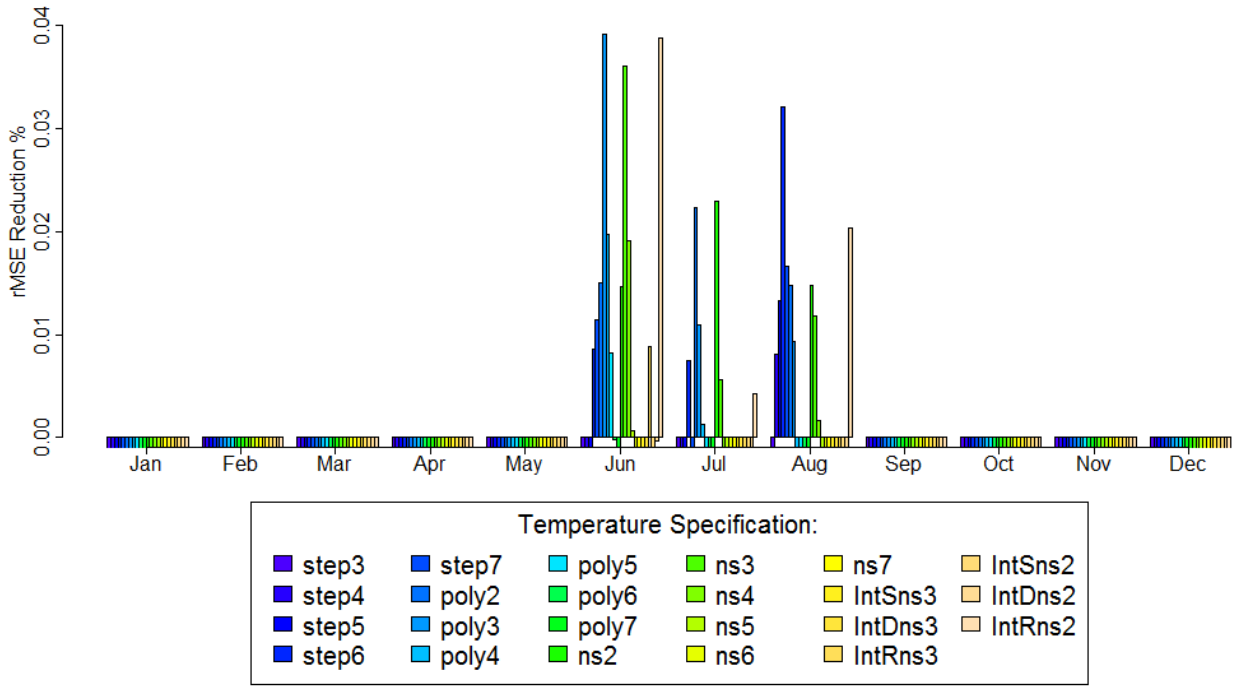
In order to understand which specification does a better job of explaining industry growth, I first conducted an out-of-sample prediction comparison based on the reduction of root-mean-squared error (RMS) between the baseline model and the full model[17]. Moreover, weather data in different time windows are used to capture the difference in temporal sensitivity. To avoid spurious results from random sampling, this comparison was made under the procedure of 11-fold cross-validation[18] by breaking down the total sample into 11 subsamples. The

[17] The base-line model has all and only the fixed effects; while in the full model, I added weather variables. A model is better fitting if it reduces prediction error more than the others do.

[18] I have income data from 2001-2012, thus growth data from 2002-2012. Leaving out 1 year for out-of-sample prediction each time, I ended up with 11 folds.

following figure (Figure 4) visualizes the results for the agricultural industry using the monthly model, where reductions in RMS by 17 temperature specifications and 6 spatially interacted specifications are compared across models using each month's temperature data. It is clear that temperature in June, July, and August help to improve the forecast of agricultural income growth. Moreover, the high RMS reduction by models with regional interactions calls for the need to account for spatial differences.

*Figure 4. 11-fold cross-validation for farming industry*




It is worth pointing out that, though the RMS reductions appear to be small in comparison to the reductions found in studies using other dependent variables, it is consistent with my expectations as well as similar analyses in the literature. There are two primary reasons causing such phenomenon: (i) theoretically, as higher-order elements, income growth of a sector should be less responsive to weather variations than lower-order elements (e.g. yield, revenue, profit of

a company), because it comes after all the mitigation mechanisms in our economy, either for ensuring revenue and profit, or for smoothing consumption; when running the same analysis on corn yields by states, I find July's temperature and precipitation reduces RMS by more than 20% in Illinois, matching the results found by Schlenker & Roberts (2009); but when looking at agricultural income, the buffering from government and private sectors wipes away a great portion of the variation; (ii) empirically, past researchers have found it challenging to perform out-of-sample forecasting in aggregate-level analysis, such as inflation, exchange rate, and GDP (Hamilton, 2016); when I replicate the global GDP growth analysis by Burke et al. (2015), the percentage changes in RMS between the full model and baseline model (i.e. model with only fixed effects) range between -0.05% to 0.04% in various trials (see Table 2). Across all k-fold analysis on my growth data, the highest RMS reduction is 3.43% found on the growth of farm income in the Midwest in June. Therefore, my model predicts up to 80 times more residual variation in farm income than their global analysis does.

Table 2: Replication of Burke et al. 2015

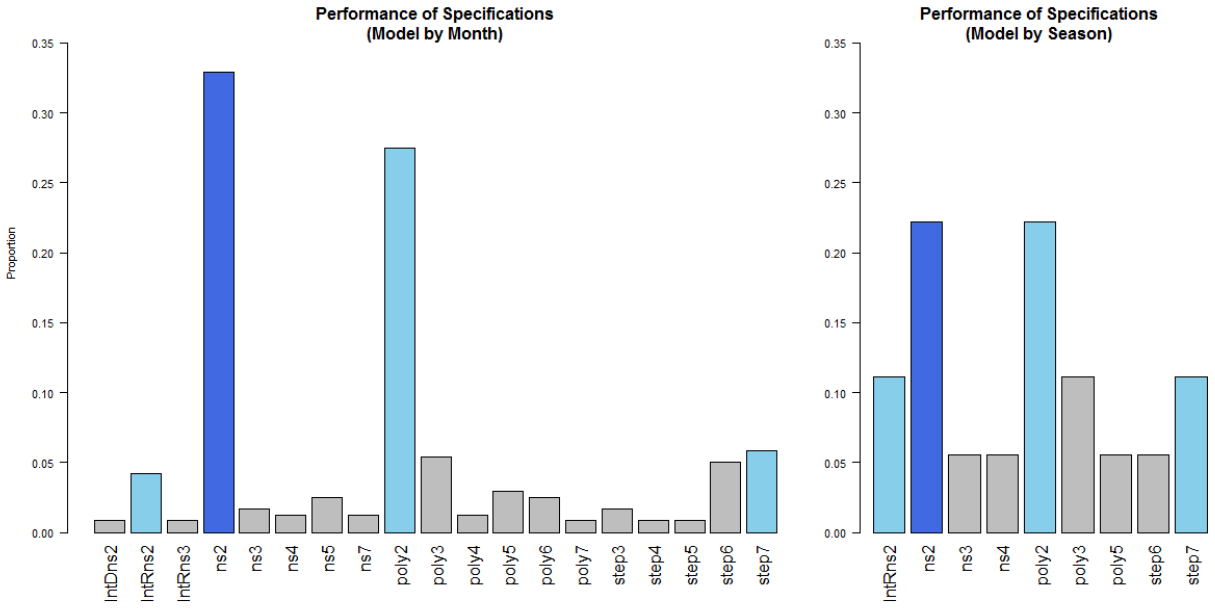
| Folds (K) | RMS | | RMS Reduction |
|---|---|---|---|
| | Baseline | Full Model | (%) |
| 5 | 0.65535 | 0.65508 | 0.04 |
| 10 | 0.65299 | 0.65331 | -0.05 |
| 15 | 0.65337 | 0.65326 | 0.02 |
| 20 | 0.64437 | 0.64423 | 0.02 |
| 50 | 0.63267 | 0.63273 | -0.01 |

### *5.1.2 Which Specification Fits Better?*

Consistent with other out-of-sample forecasting studies, I find models with a more simple structure predict more accurately. Within each category of the three types of functional forms (i.e. step, polynomial, spline), the specifications using fewer number of variables (i.e. polynomial and spline with the lowest degree, and step function with the largest width) perform better than others. The bar charts below summarize the proportion of times that each corresponding specification

results in the smallest RMS (i.e. the best prediction performance) in the k-fold analysis for all sectors[19].

*Figure 5. Performance of specifications*




In both models, transforming the temperature bins into the form of 2-degree polynomial generates significant RMS reduction, which is quite consistent with the functional form other scholars adopted when examining nonlinear temperature impact (e.g. Burke et al., 2015). Given that a natural spline is similar but generally more flexible than a polynomial, it is not surprising to see that spline with higher degree always outperforms polynomial with the same degree. Possessing both simplicity and flexibility, spline with two degrees of freedom serves as the best and the second best specification in monthly and seasonally models, correspondingly. Among the interacted specifications, interaction with states was always inferior, but interaction with census regions as well as divisions turns out to be relevant. In order to account for heterogeneity as

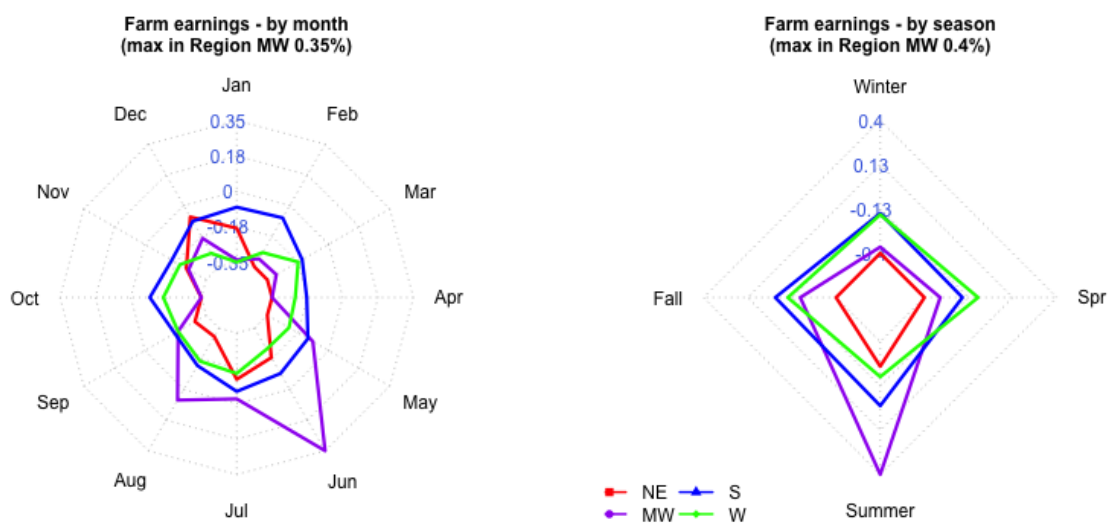
[19] The results are not dominated by a single sector.

much as possible, my primary model runs the analysis by region for each industry, using 2-degree spline transformation of temperature variables.

### *5.1.3 Which Time of the Year Matters More?*

Based on the preferred model, I calculated the reduction[20] in RMS achieved by including weather variables during different time-windows. The following radar charts present the results for farming industry, which includes both animal and crop productions. The full results for all sectors for both models are included in Supplementary Figure 3 and 4.

*Figure 6. Relevance of months and seasons for farming industry*




Among the four census regions, Midwest is clearly the one being most dependent on climate conditions. In monthly models, weather variables from May to September explain a larger

[20] In case where adding weather variables does not give better prediction, the RMS reduction is negative. But even so, during more relevant months, the magnitude of such negative reduction would be closer to zero (i.e. being less bad) than during other non-relevant months. Since I am trying to understand whether the timing of weather variation matters, I report these negative values to fully compare the performance across different months and seasons.

portion of growth variation, with June being the most relevant single month, likely due to the fact that the Midwest is more reliant on rain-fed agriculture than other parts of the country. When running the monthly analysis without state-year fixed effect, June's weather can improve RMS by as much as 3.43% in the corn-belt[21] area. Seasonal models show a similar but smoother pattern, where Midwest still appears to be more vulnerable to weather fluctuations during summer time. The farming industry in the Northeast is affected by weather during the same months as in the Midwest while being less sensitive in general. The South and West, however, do not show strong dependency on the weather during any specific time of the year, suggesting adaptation to hot climate in the South and reliance on irrigated agriculture in the West.

Among all 20 sectors, agriculture is, as expected, the most sensitive to weather changes. In the monthly models, mining, utilities, and construction sectors also appear to be responsive to climate condition, while the growth in real estate, administrative, and accommodation sectors are not modeled any better with weather variables. The seasonal models, though being slightly better off in forecasting income from agriculture, give less consistent results for other industries, indicating that arbitrarily selected cutoffs for the farming sector may not fit business cycles elsewhere (Supplementary Figure 3 and 4).

#### *5.1.4 Placebo Test*

As explained above, the magnitudes of RMS reductions appear small to match theoretical and empirical expectations. To further demonstrate that the results are reliable rather than simply spurious, a placebo test was carried on the income growth of agricultural sector using 1- to

[21] The corn-belt here consists of Iowa, Illinois, Indiana, Michigan, Ohio, Nebraska, Kansas, Minnesota, and Missouri.

3-period lagged and leading weather data, with the full results presented in the appendix (Supplementary Figure 5). I choose to examine the agriculture industry not only because it has the most RMS improvement in all k-fold analyses, but also because I can use the results of research in other areas (e.g. biological and ecological) to confirm my findings. The following figure compares the test of using 1-period lagged and leading weather.

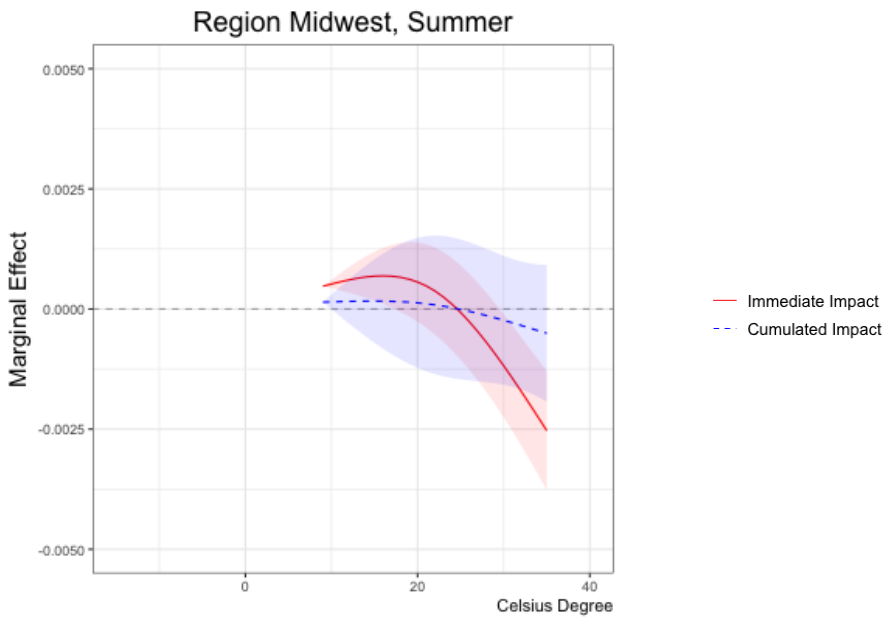
*Figure 7. 1-Period placebo test for farming industry*


As the bar charts in Figure 7 show, neither past nor future weather is able to explain as much of the variation as contemporary weather variables. A similar structure was also found in the results from the seasonal models, reassuring that the models are explaining meaningful variations in income growth.

### *5.1.5 Growth versus Level Effect*

Taking a closer look at Supplementary Figure 5, it's not hard to see that even the temperature and precipitation during the summer two years ago can still explain a small portion of Midwest's farming growth, suggesting the possibility of persistent impacts from unusual weather conditions. Still, focusing on the agricultural sector in Midwest, a comparison was made between the contemporary response curve and the cumulated response curve[22], where the latter is the sum of the impact of temperature during current and previous year's season.

*Figure 8. Growth vs. level effect for farming industry in summer*




According to the preferred model, hotter summer temperatures in Midwest bring significant damage to farming income of that year. Point estimates of the cumulative impact suggest a certain extent of growth impact, but the estimate was quite imprecise. This result is consistent

[22] The response curves in Figure 8 are centered following the procedure of exposure-weighting in Schlenker & Roberts (2009), so that if future temperature turns out to be exactly the same as the observed average during 2001-2012, the marginal impact on income growth from temperature would be zero.

with other studies finding no evidence of persistent impacts from bad weather in developed countries (Dell et al., 2012). Supplementary Figure 6 in the appendix contains agricultural sector's current and cumulative response curves for other regions and seasons. Among the 16 combinations, only the summer in the Northeast shows support for a possible growth effect. As a further check, the same comparison was made for the other 19 sectors (not presented), all of which show little evidence of a growth effect[23]. Therefore, I concluded that, within the US, weather does not bring long-lasting losses.

By combining the findings of the above out-of-sample prediction analyses, the preferred model is concluded and shown below, on which the rest of this paper is built:

$$g_{it} = \boldsymbol{\gamma}_j \times \Big[ ns2\big(T_{it(winter)}\big) + ns2\big(T_{it(spring)}\big) + ns2\big(T_{it(summer)}\big) + ns2\big(T_{it(fall)}\big) + prec_{it} + prec_{it}^2 \Big] + \mu_{st} + \epsilon_{it} \qquad (2)$$

For each sector of the economy, I have a county-level panel regression of growth on climate data and controls. The temperature variables are transformed using natural spline of 2-degrees of freedom, separated into four seasons, and together with precipitation interacted by regional dummies. In addition, state-year fixed effects are adopted and errors are corrected with spatially decaying correlation within 100 miles.

### *5.2 Response Function*

With a better grasp of the relevance of time and location of weather impacts, I now turn to the question of how temperature affects income growth of different sectors across seasons and

[23] It should be noted that the weather in US varies largely from year to year, thus making it difficult to tell if there would be growth effect when unexpected weather rolls out consecutively, a possible situation which climate change can bring.

regions. Supplementary Figure 7 in the appendix presents all the results, where the heterogeneous responses with regard to several aspects are well illustrated: (i) for the income of each sector, the four regions can be affected by temperature in drastically different ways; for instance, a colder fall season leads to agricultural loss in the Northeast, Midwest, and South, while being beneficial to farms in the West; (ii) the timing of temperature deviation plays an important role in determining the direction of impact; for example, a warmer winter is healthful to agriculture in the Midwest and South, while a hotter summer brings substantial damages; (iii) besides having various levels of sensitivity, sectors can either prefer cold or hot temperatures; an example would be that, while a cold winter hurts manufacturing businesses, the utility industry gains due to higher energy demand.

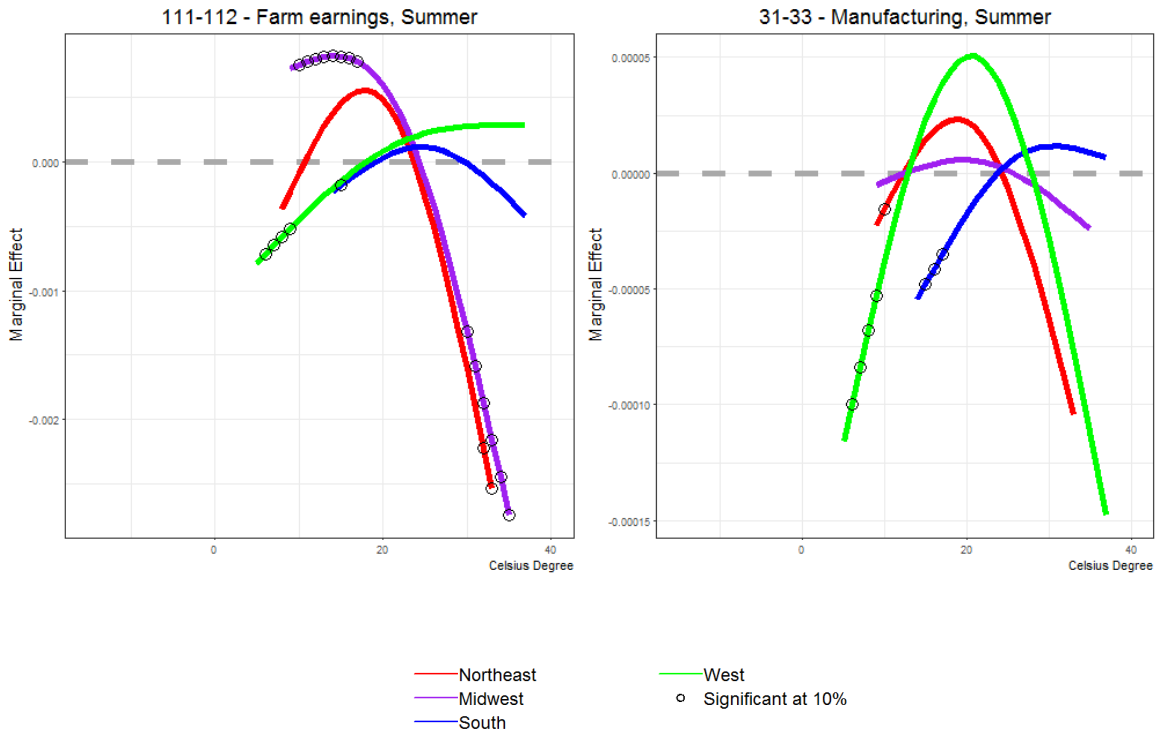
The phenomena that, not only the magnitudes but also the signs of the effects vary substantially across time and location, emphasizes the necessity of taking heterogeneity into account when examining the impact of climate change. There are, however, situations where a more aggregated approach would produce similar results. I have selected two of these cases to show in Figure 9.

During the four seasons, summer is the one in which the highest consistency across the 20 sectors is found, as most industries are harmed by higher temperature. Looking at the general shape of these response curves, it's not surprising to see that spending more time on the hot end is detrimental to crops in most places. The marginal damage dealt to agriculture in the Midwest becomes statistically significant starting at 30℃[24], which matches the findings of other

[24] To interpret the results: if the Midwest spends an extra day at 35℃ rather than at 23℃ during the summer, its annual income

agricultural research (Schlenker & Roberts, 2009). Similar inverse-U shapes are observed in the manufacturing sector. The optima located around 20℃ for the three regions are extremely consistent with the individual-level studies linking temperature and productivity of human beings. Such consistency between micro- and macro-level evidence is reported by other scholars as well (Dell et al., 2014), together giving us more confidence when estimating the impact of climate change. Furthermore, it is interesting to see that the manufacturing sector in the South is more resistant to heat, a phenomenon likely due to the adaptation occurred in this region (e.g. air conditioning in assembly factories), which effectively increases its tolerance of hot temperature by almost 10℃.

*Figure 9. Selected response functions*

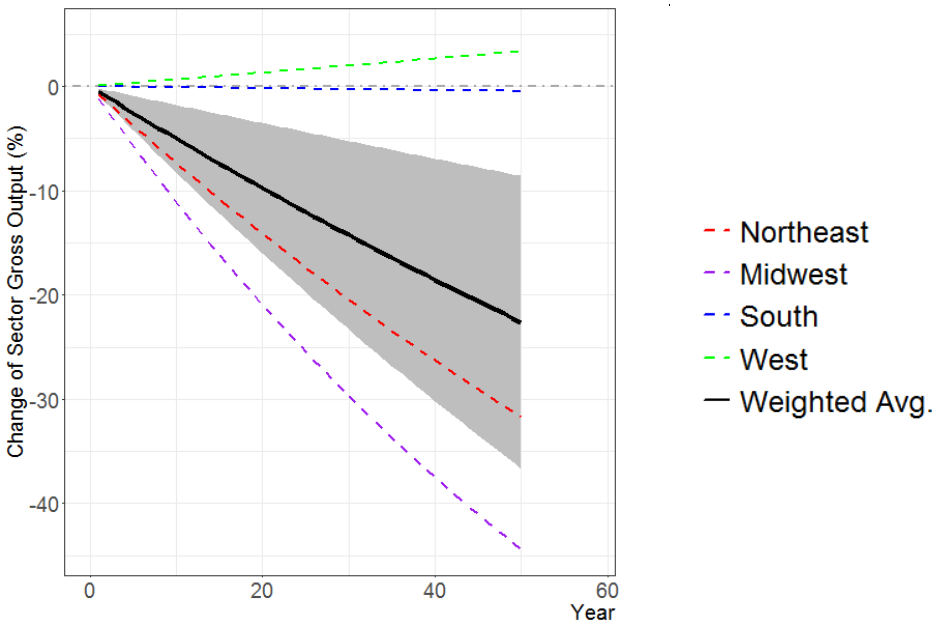



growth rate will be lowered by 0.06 percentage point (-0.0025×24).

### *5.3 Income Projection*

To explore the full range of possible impacts beyond the general circulation model (GCM) projections, in my study I conducted simple simulations for cases where the temperature rises (in comparison to the base periods) immediately in the next period and stays at the raised level forever. For each sector in each region, the average growth rate observed in 2001-2012 was assumed to be the base trend under the situation of no climate shift. An annual deviation of the growth rate, calculated by multiplying the marginal responses with the raised temperature bins, was added to the base rate. Then, the income with and without climate change for the next 50 years is projected and compared to generate a trace of relative loss over these years. Finally, assuming the proportions of sectoral income from the four regions remain stable, a weighted average income trajectory and 95% confidence interval are computed for each industry. Note that here I assume the sectors are not adapting and their sensitivity to weather shocks remains constant, thus making the following estimation the most negative outlook to the future. The results for the farming sector under the case of 2℃ warming is illustrated below, and full results can be found in the appendix (Supplementary Figure 8).

*Figure 10. Projected income for farming industry under 2 ℃ warming*




Expectedly, global warming incurs a loss in agriculture across the country, with the Midwest region being the most sensitive, resulting in a 44% reduction in gross income by the end of a half century. The farms in the South and West are more resilient towards warming, likely due to the adaptations spurred by historically frequent high temperature and dry weather, which can be done by either switching into different farming activities or upgrading to heat or drought-resistant cropping system. The income trajectories are roughly linear, but slightly convex due to the underlying mathematical property of the projection estimation, suggesting that the value of income loss would increase due to compounding effect, but at a decreasing speed. Further explanations of the convexity can be found in the step-by-step derivations in the appendix (Supplementary Figure 9).

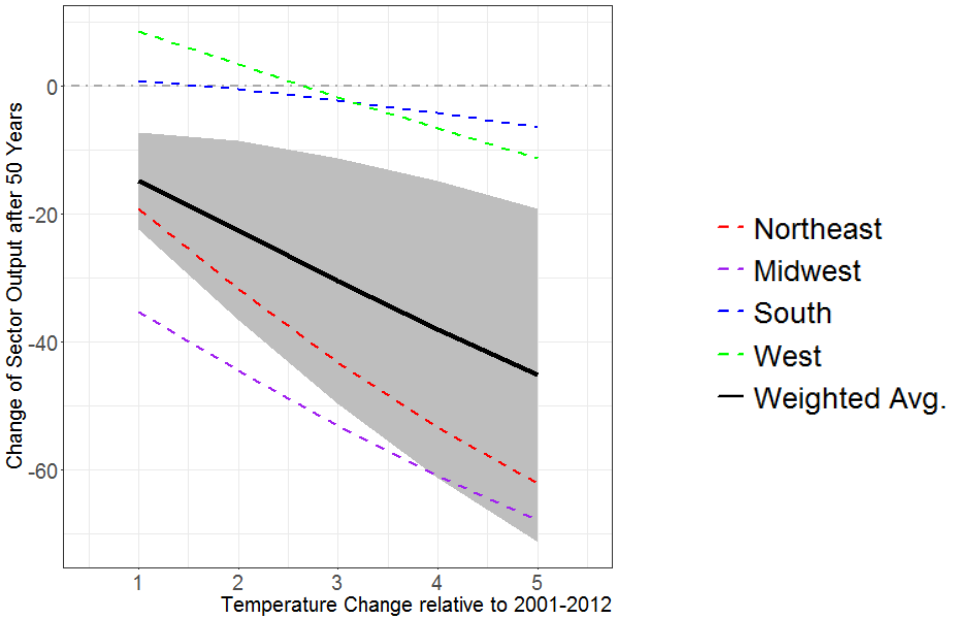
Given that the relative contributions to US agricultural sector are 38% by the Midwest, 30% by West, 27% by the South, and 5% by the Northeast, the weighted income reduction will be

roughly 22% on the entire sector, suggesting that the impact of climate change on gross profit is much smaller than what it does to micro-level elements, such as yields (Schlenker & Roberts, 2009). Furthermore, for all 20 sectors, agriculture was the only one losing more than 10% in five decades. Most other sectors would be harmed by a 2°C warming, but the aggregated loss is within 5%, not to mention that there are sectors showing almost no impact, as well as the transportation sector that would even benefit from such temperature shift. The aggregate impact on the entire US will be highlighted later.

### *5.4 Damage Function for Sectors*

Understanding what would happen given moderate temperature change, I am also interested in knowing how these impacts evolve under different extents of climate shifts. For each industry, a damage function showing the relative change in income from 1 to 5°C warming is computed, with full results presented in the appendix (Supplementary Figure 10).

*Figure 11. Damage function for farming industry*



As the graph above shows, extreme warming results in substantial losses in the agricultural sector for all regions, with the Midwest and Northeast losing almost 65% if temperatures increases by 5℃. Keep in mind that climate change causes a right shift of the entire temperature distribution which leads to higher exposure on the hot end. The phenomena that, the Northeast's damage function bends downwards and gets closer to Midwest's damage function as warming increases, is driven by the Northeast's high sensitivity to the hot temperature shown in the response curves (Figure 9), making it increasingly vulnerable as the underlying exposure distribution shifts towards the hot end. In other words, the convexity of damage function depends on the region's marginal responses as well as the way in which temperature shift happens. Nevertheless, the curvature of the weighted average damage function further depends on the relative shares of regional contributions, which are assumed to be constant in this analysis.

It is interesting to see that, among the sectors that are not responsive to warming, all of the four regions respond divergently. It is the weighting and balancing between the regions that make the final aggregate impact small. This suggests that traditional one-sector and one-region approach hide the tradeoffs across space and industries, leading to an overestimation of the damage brought by climate change. On top of this, if behavioral adaptation is allowed in which the most vulnerable region can respond as the region that incurs the least loss in each case, it would further lower the total cost of climate change. Although accounting for adaptation is beyond the scope of this study, I have shown the promising possibility of not only resisting, but also possibly being able to take advantages of the rising temperature in the future.

### *5.5 Damage Function for the US*

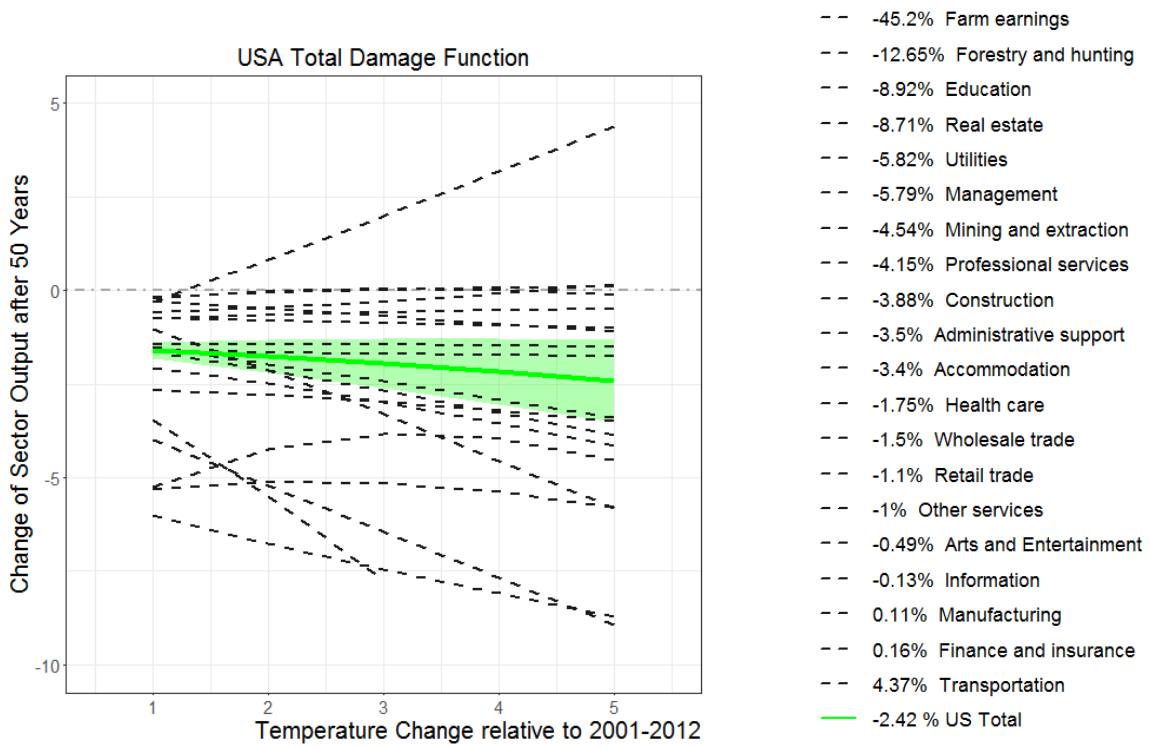
The sector analysis above shows that, although climate change is harmful to most industries, the magnitude of the loss under different warming scenarios are all within a moderate range, except for agricultural sector. This is partially due to the way the model is constructed, and partially because farming is the most sensitive business to weather fluctuations.

Table 3: Weights of Sectors in US Economy

| Sector | Share (%) | Sector | Share (%) | Sector | Share (%) | Sector | Share (%) |
|---|---|---|---|---|---|---|---|
| 111-112 | 1.0 | 31-33 | 13.4 | 52 | 8.7 | 61 | 1.8 |
| 113-115 | 0.3 | 42 | 6.2 | 53 | 2.3 | 62 | 12.3 |
| 21 | 1.5 | 44-45 | 7.8 | 54 | 11.2 | 71 | 1.3 |
| 22 | 1.0 | 48-49 | 4.1 | 55 | 2.8 | 72 | 3.7 |
| 23 | 7.5 | 51 | 4.1 | 56 | 4.7 | 81 | 4.5 |

Assuming the weight of each sector to stay the same within the US in the next five decades (see Table 3), I aggregate the results of all sectors to show the impact of global warming on a national level. The final result with 95% confidence interval is presented in Figure 12. While most sectors would incur losses, entertainment, information, manufacturing, and finance do not respond to climate change. Transportation is the only industry that benefits significantly from warming since it has upright-U shape response functions centered at 0℃ reflecting the damage from icy road condition (see Supplementary Figure x). Finally, consistent with the conclusions of many macro-level studies (Dell et al., 2014), in a wealthy and well-diversified economy such as the US, I find the total loss from global warming to be as small as 2.42%.

*Figure 12. Aggregated Damage Function*



# CHAPTER VI

# CONCLUSIONS

The objective of this study is to understand the impact of climate change through a disaggregated approach by decomposing the US economy into sectors, then aggregate the results back onto a national level to measure the total effect brought by the warming temperature. The model developed in this paper builds on the existing frameworks of similar studies and is further refined through comparing the performance of out-of-sample prediction.

Besides allowing each sector to respond differently to weather variations, the k-fold analysis suggests the importance of taking into account the temporal as well as regional differences. Moreover, nonlinear response exists in all cases, most of which have inverse-U shape response function, reflecting people's preference towards moderate climate condition.

By aggregating the four regions, this study has shown that, while many sectors will be affected by future warming, the entire US economy would incur only a 2.42% loss comparing to the case of no climate change. It is important to note that this number should be a lower bound estimate of the damages (i.e. the worst possible estimates), since neither inter-regional nor inter-sector adaptation is allowed in the model, while in reality, technological improvement, as well as behavioral adjustments, will take place to further reduce the damage of brought by climate change.

## *6.1 Concluding Comments*

This paper provides the response functions for each sector and each region, without needing to understand the underlying mechanisms driving such shapes of those functions. In some cases,

research in other fields can be informative. For instance, biological and ecological studies tell us why the rain-fed farming industry is hurt by hot temperatures above 30℃, and labor supply studies explain why the turning point of both manufacturing and construction sector are located around 25℃. With deeper knowledge on the mechanisms, I can make the estimations more accurate by fixing the place of knots during natural-spline transformation. The government can design more effective policies to tackle climate change by directly targeting the underlying mechanisms with this additional knowledge.

Sub-industry level income data would be useful so that the same analysis can be carried at even finer scales. For now, heterogeneous responses still exist within each sector. For example, the farming industry consists of both crop and animal production, which are further complicated by having crop varieties and land types. Each individual business is bound to respond slightly differently to weather fluctuations. On top of that, when considering interactions between countries, any weather shock can be imported or exported (i.e. spill-over effects), therefore making the change on general equilibrium much more difficult to estimate, let alone the possibility of adaptations spurred by future shocks.

Finally, climate change alters more than just the temperature, which can also bring variations that are beyond the range of our historical experiences. Some shocks, such as a rising sea level, might reach the limit of our ability to react, thus causing unexpected impacts.

In spite of the above limitations, this paper offers insights into the cost of climate change on all sectors as well as the entire US, by simultaneously accounting for non-linearity and heterogeneity lying in the responses. Besides concluding that global warming only results in

moderate damages on most industries, the regional, temporal, as well as inter-sector differences imply the tremendous potential for a well-developed society to deal with future climate change.

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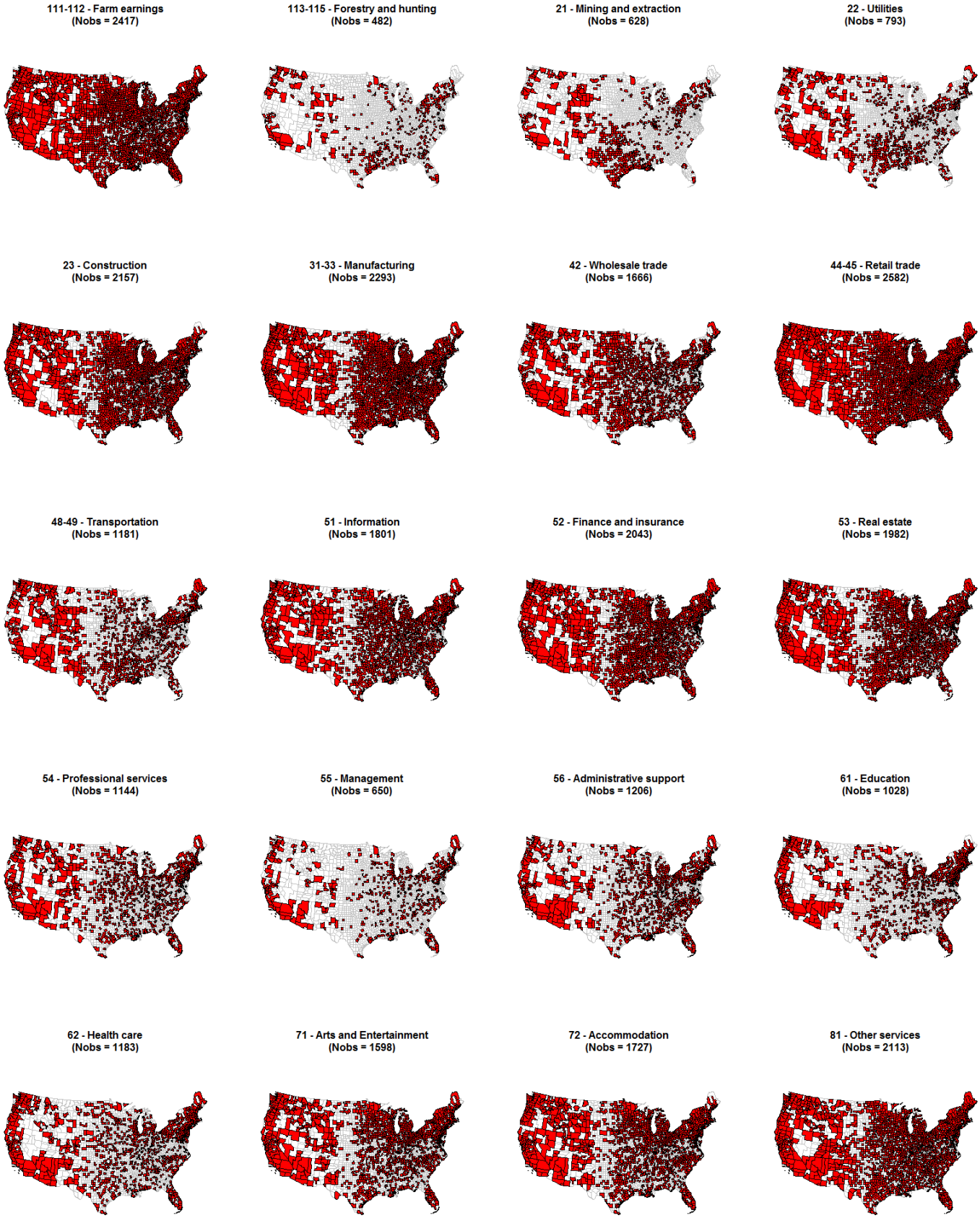
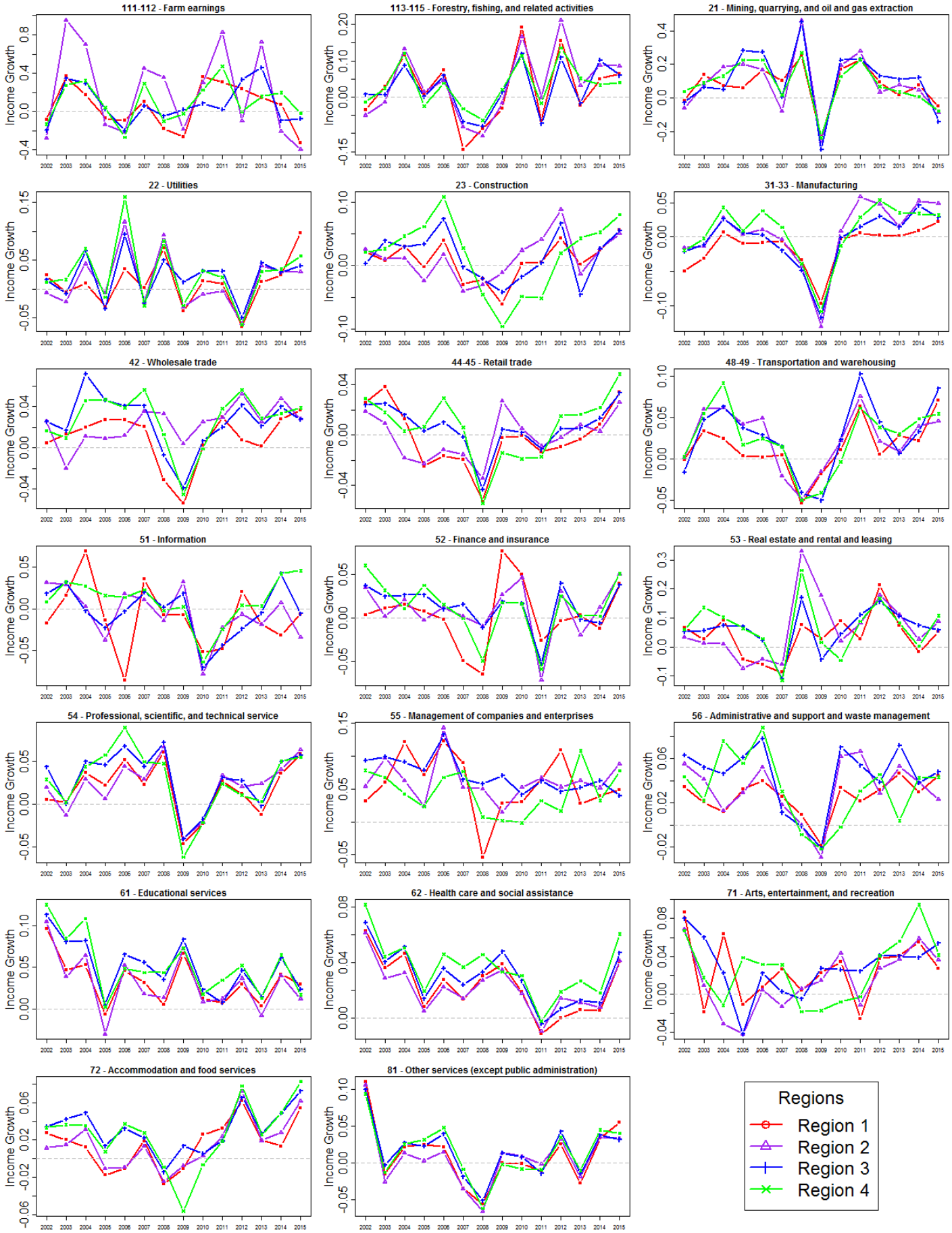
# APPENDICES

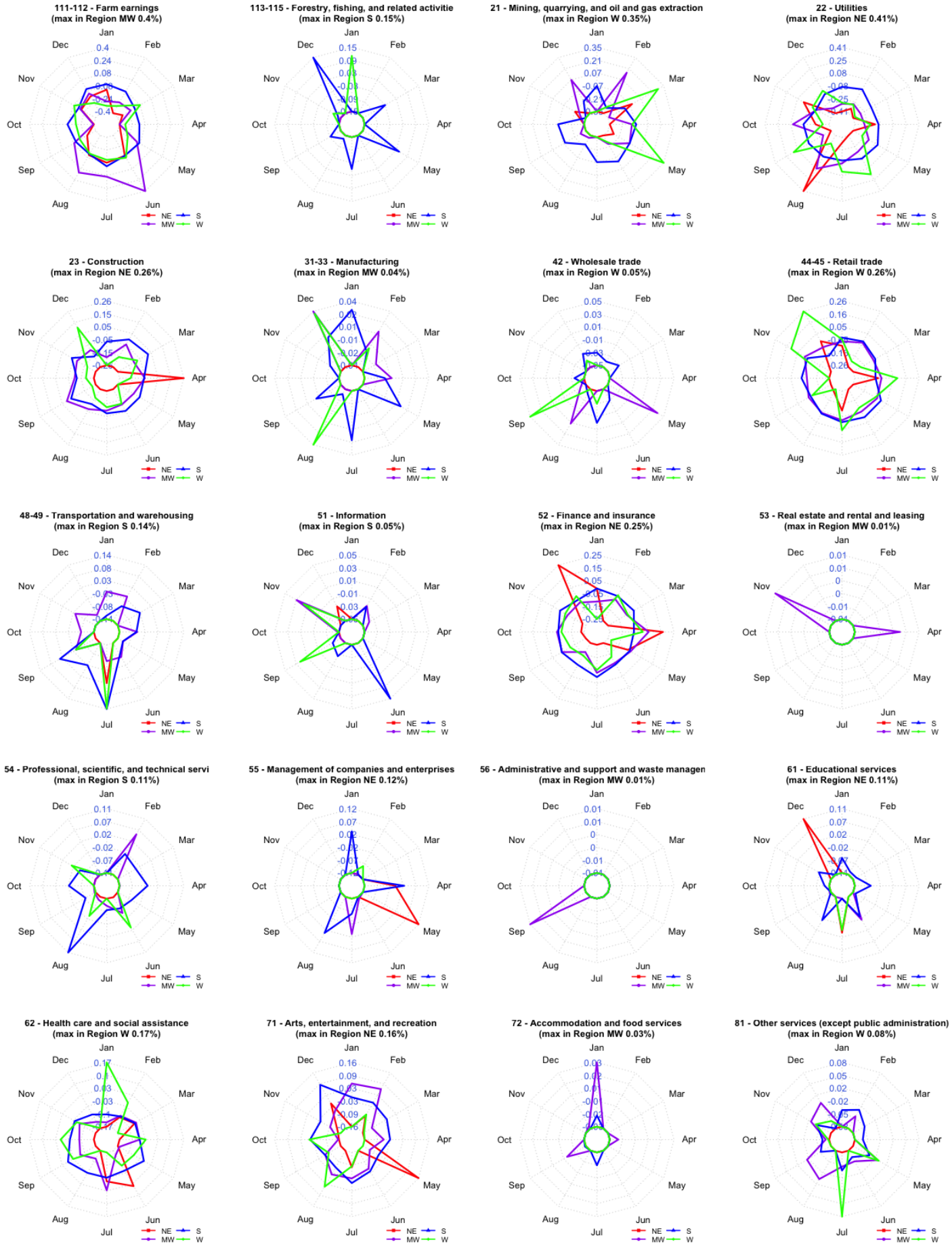
*Supplementary Figure 1. Maps for number of observations*



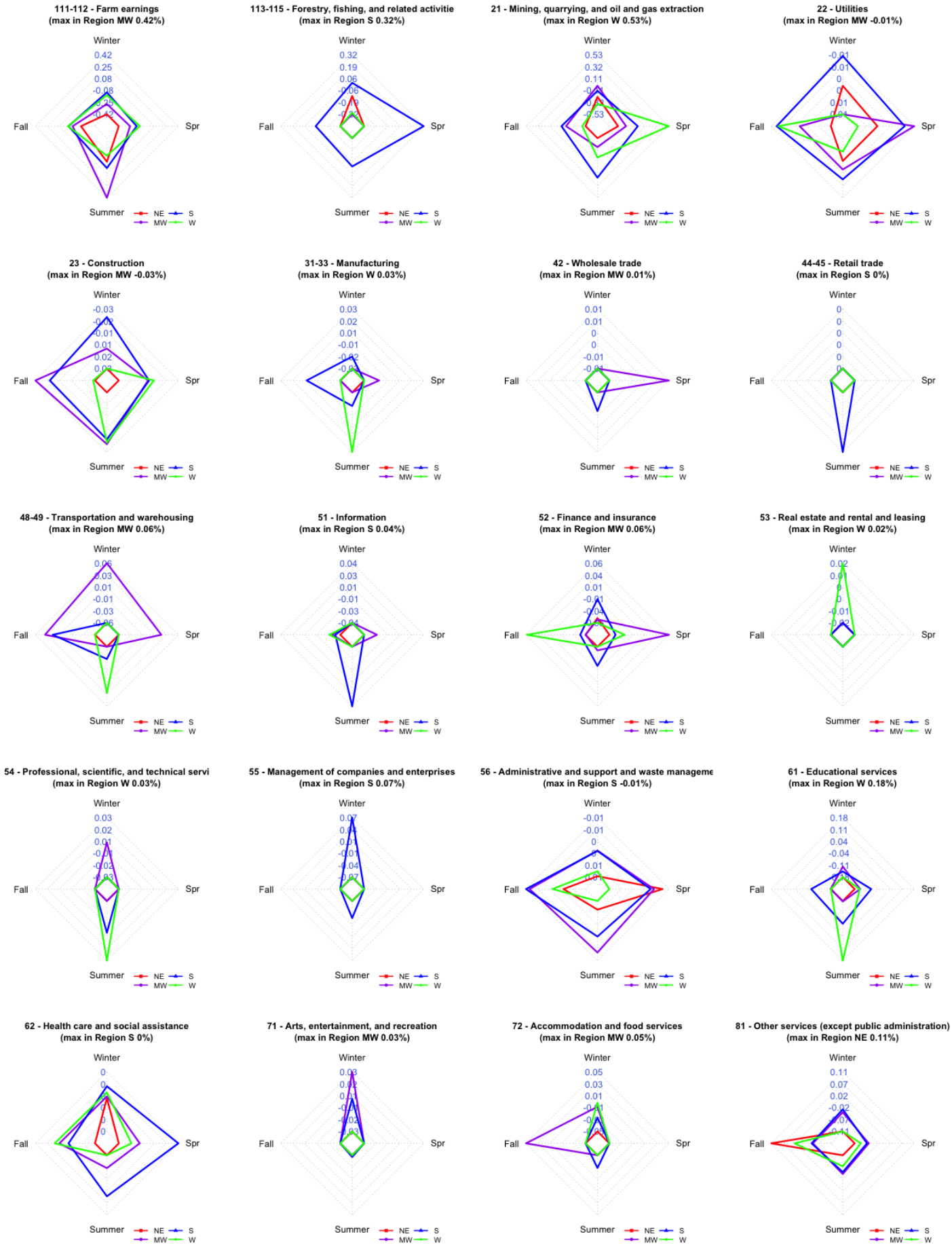
*Supplementary Figure 2. Industry growth by region*



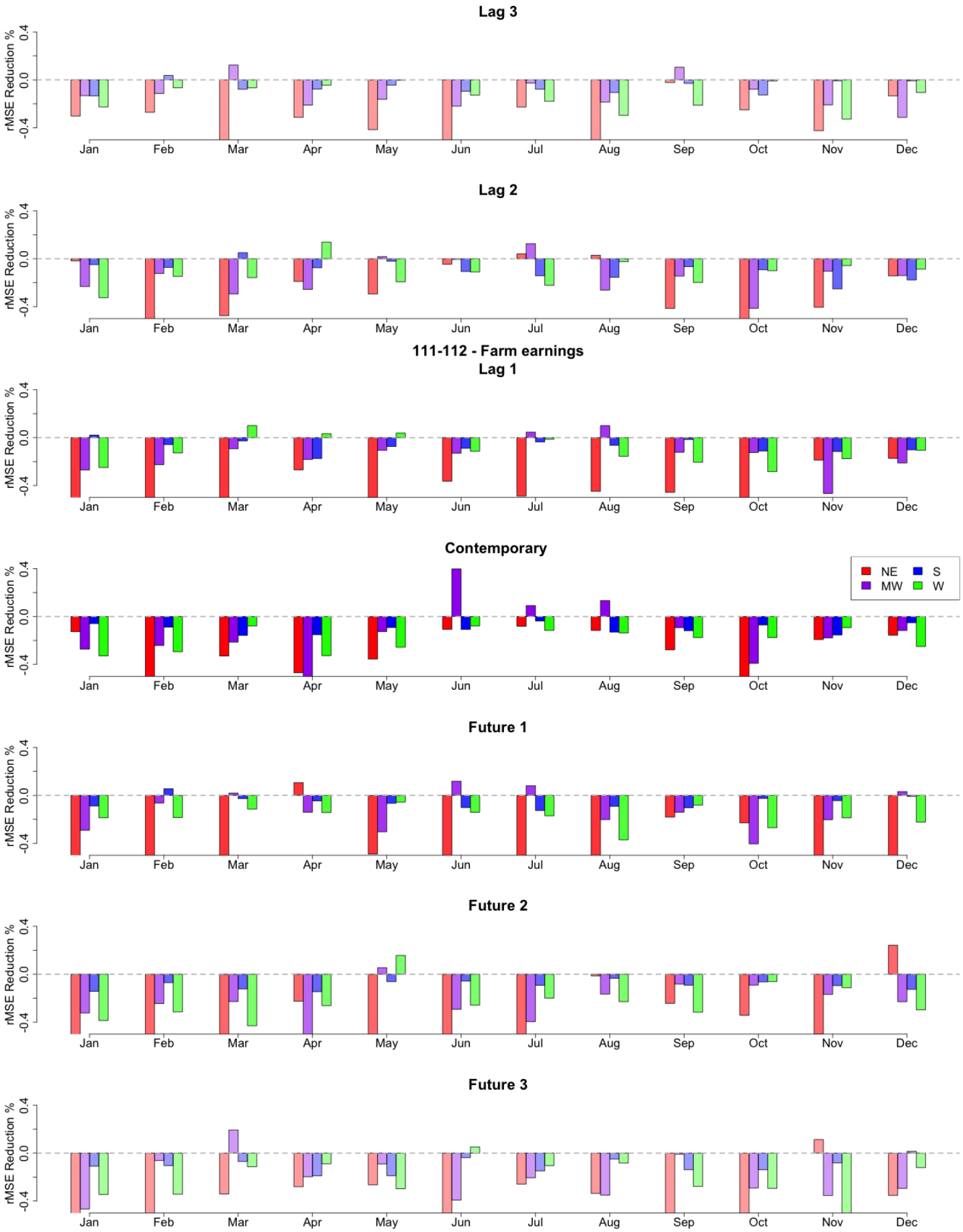
*Supplementary Figure 3. Relevance of months*



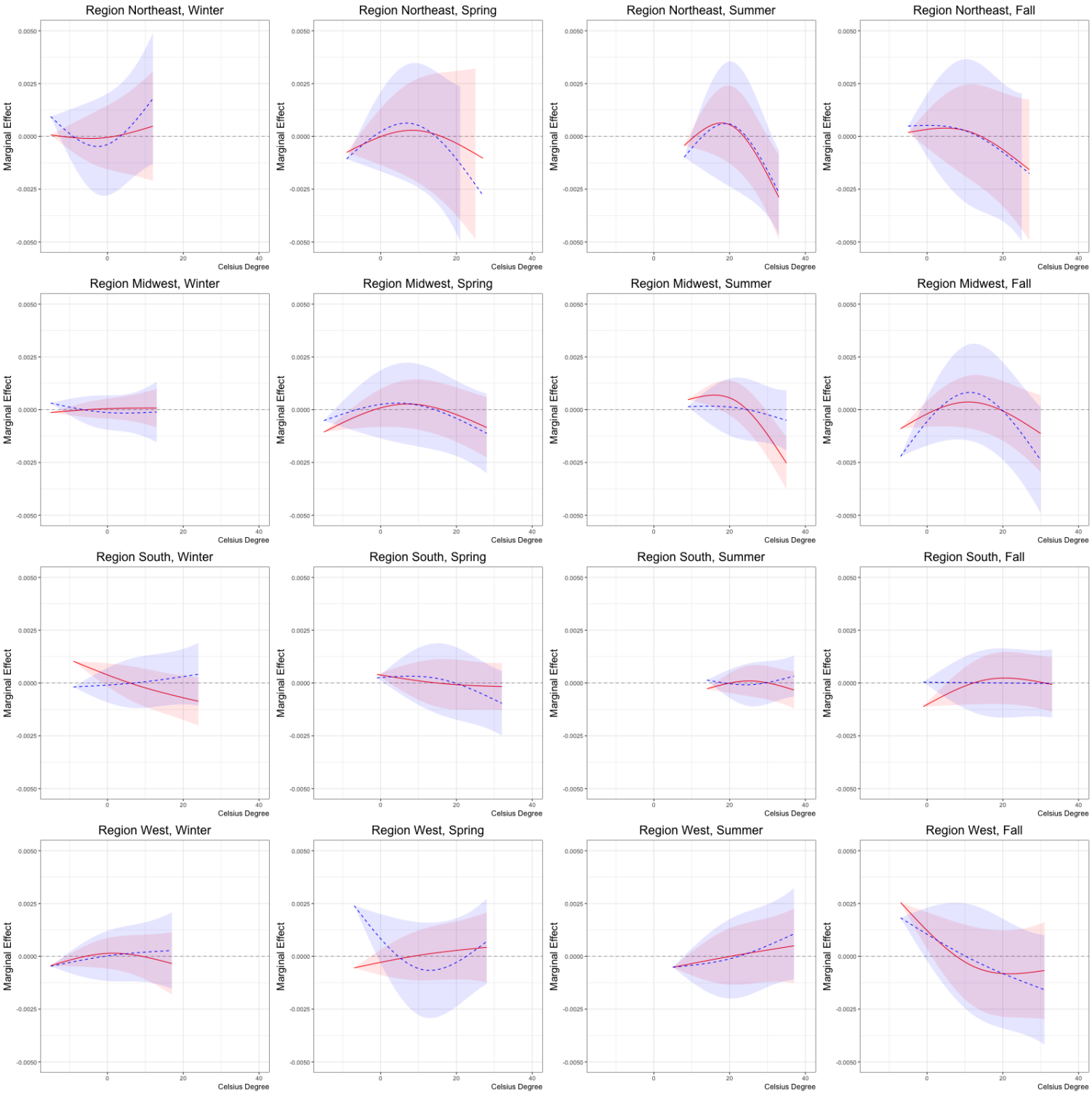
*Supplementary Figure 4. Relevance of seasons*



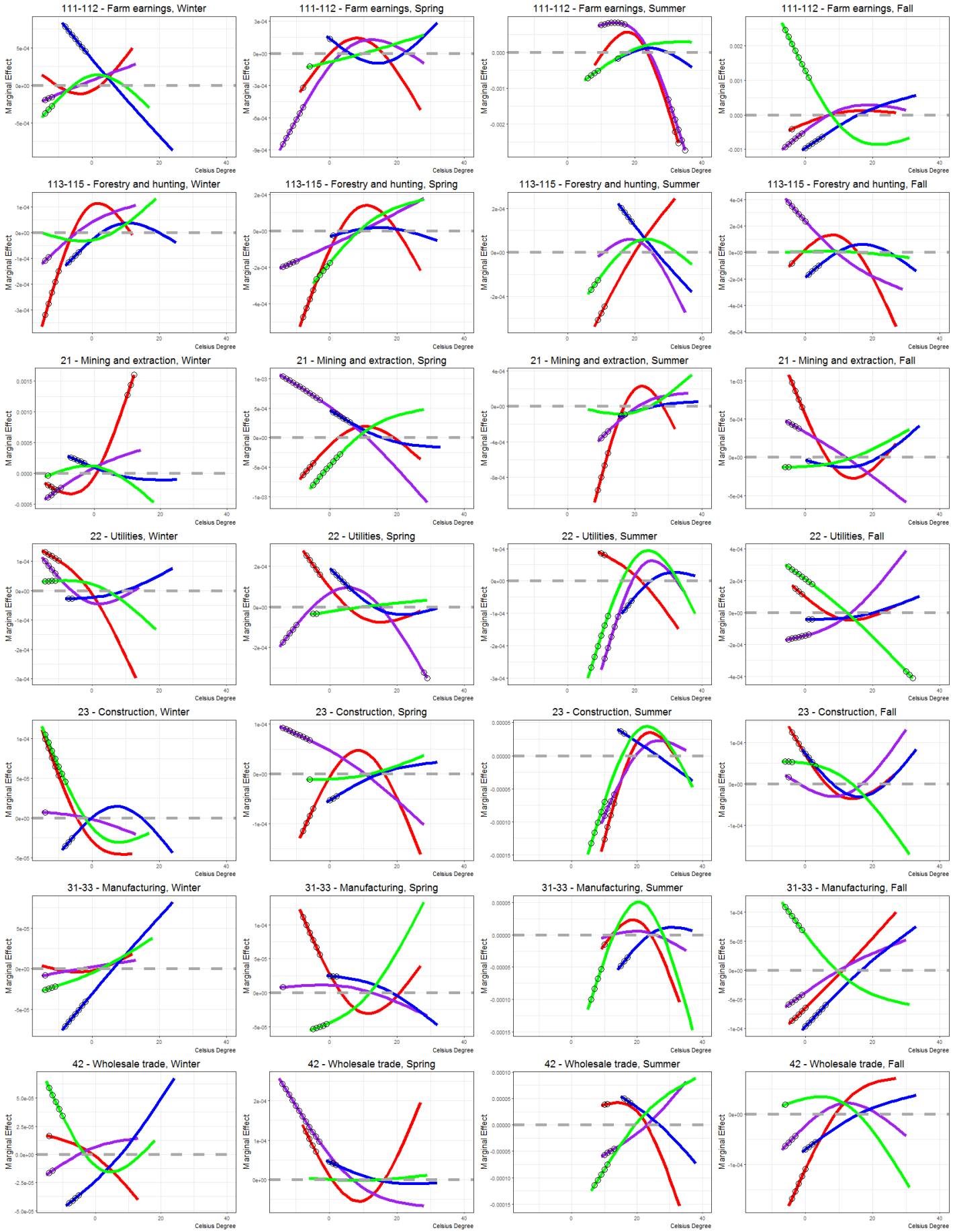
*Supplementary Figure 5. 3-Periods placebo test*

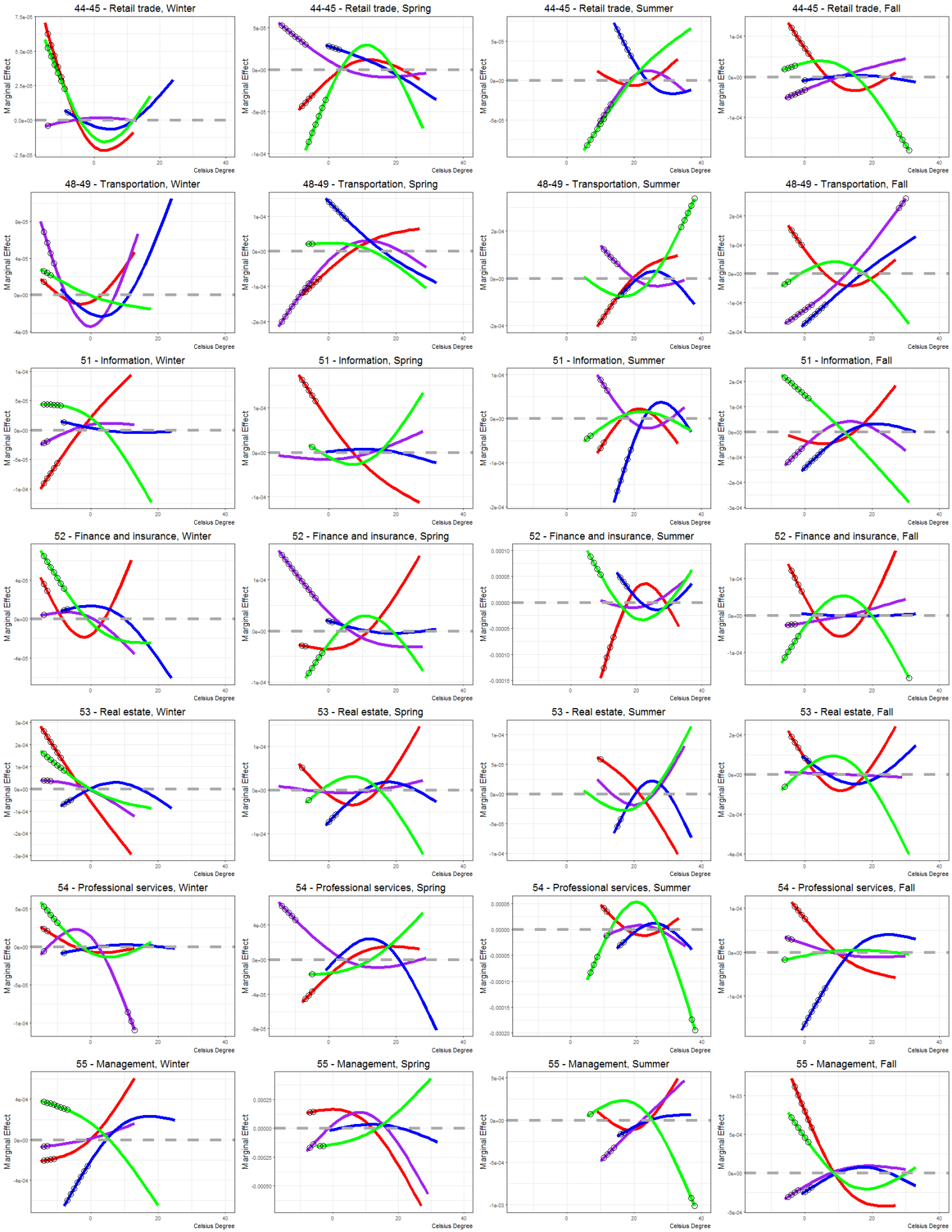


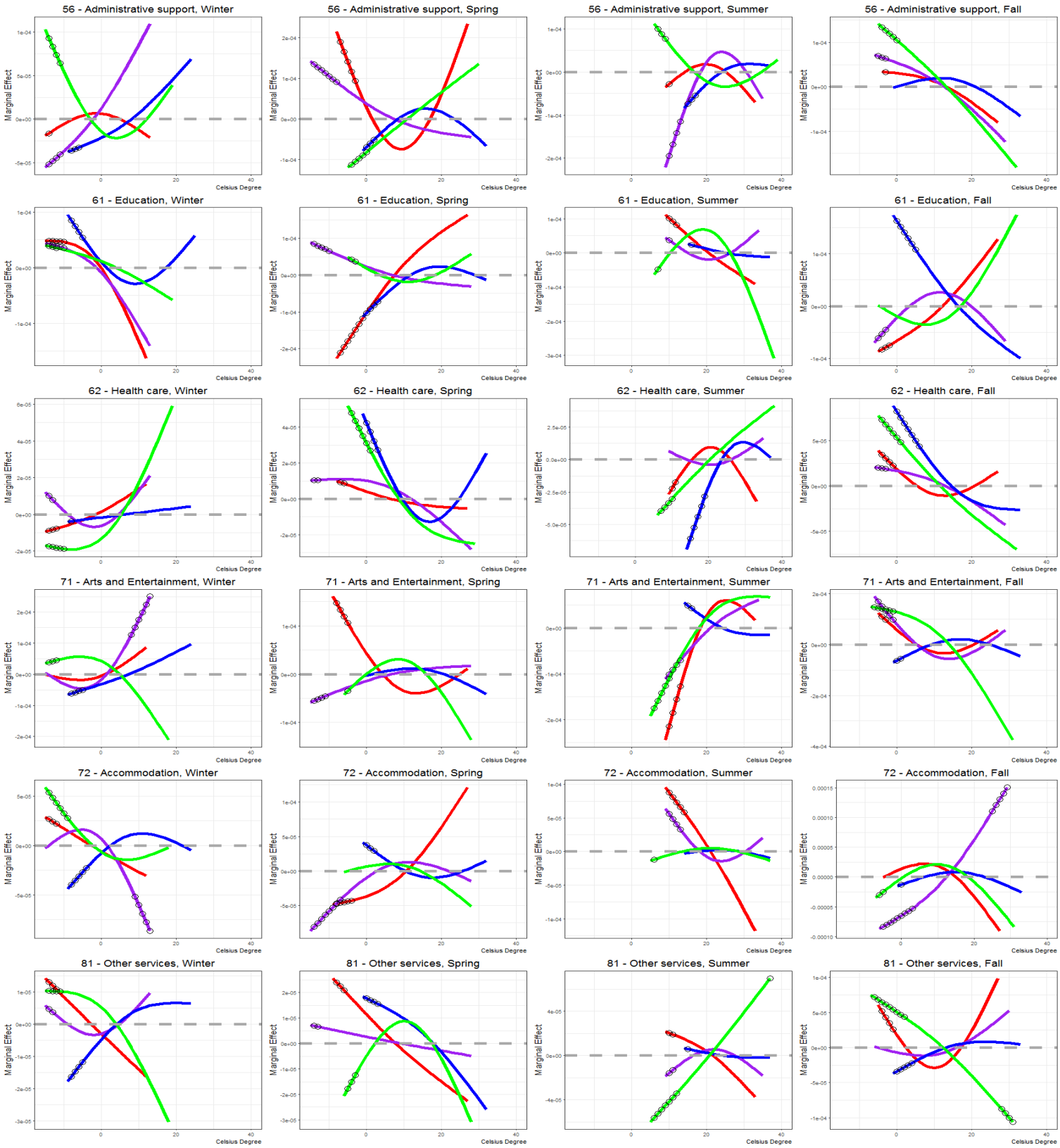
*Supplementary Figure 6. Growth vs level effect for farming industry*



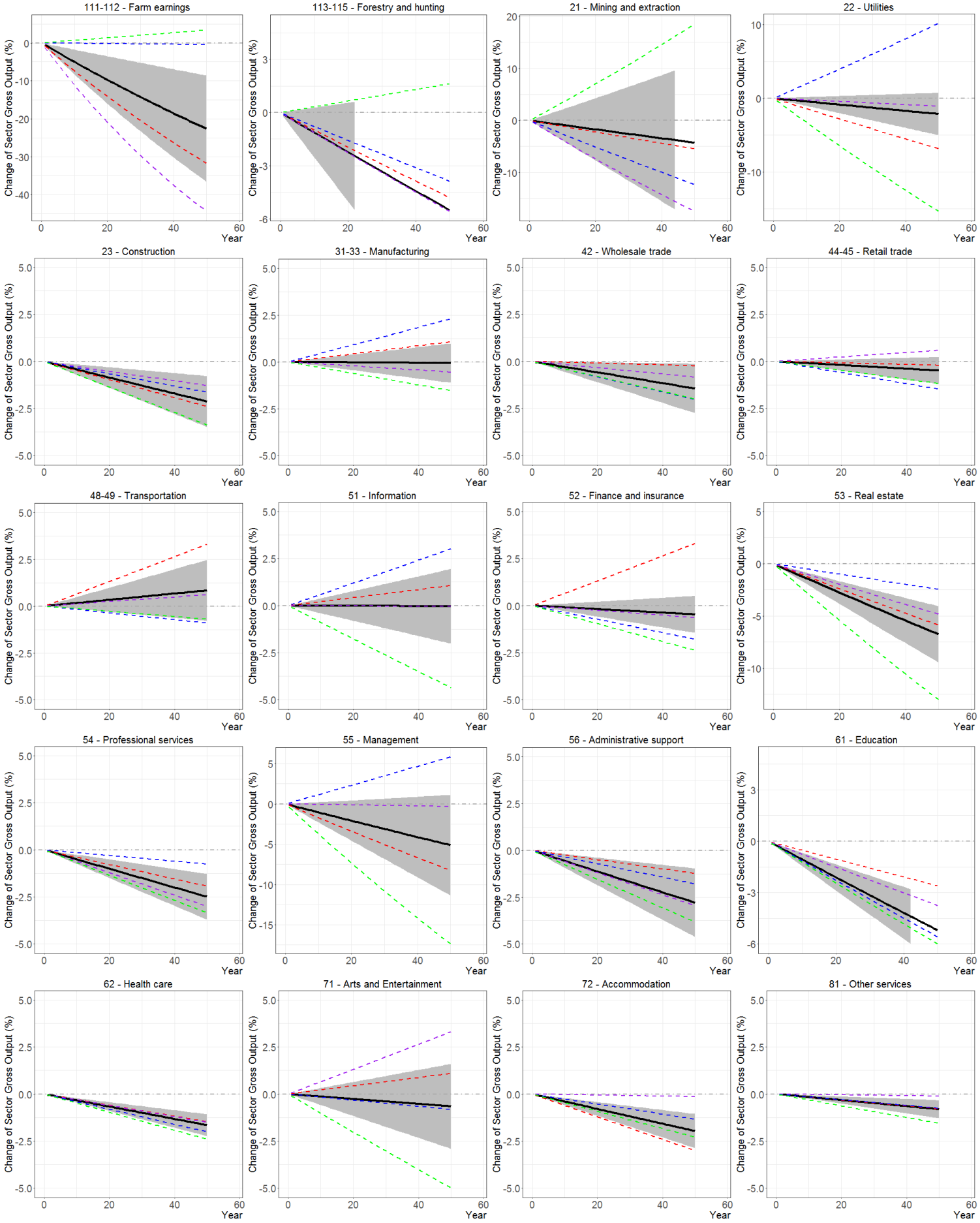
*Supplementary Figure 7. Response functions for 20 sectors*



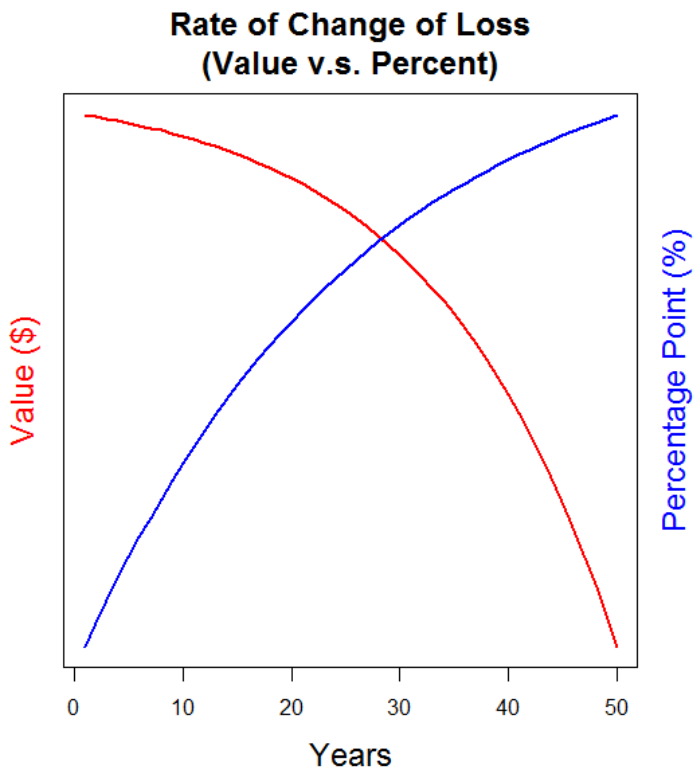

44-45 - Retail trade, Winter
44-45 - Retail trade, Spring
44-45 - Retail trade, Summer
44-45 - Retail trade, Fall
48-49 - Transportation, Winter
48-49 - Transportation, Spring
48-49 - Transportation, Summer
48-49 - Transportation, Fall
51 - Information, Winter
51 - Information, Spring
51 - Information, Summer
51 - Information, Fall
52 - Finance and insurance, Winter
52 - Finance and insurance, Spring
52 - Finance and insurance, Summer
52 - Finance and insurance, Fall
53 - Real estate, Winter
53 - Real estate, Spring
53 - Real estate, Summer
53 - Real estate, Fall
54 - Professional services, Winter
54 - Professional services, Spring
54 - Professional services, Summer
54 - Professional services, Fall
55 - Management, Winter
55 - Management, Spring
55 - Management, Summer
55 - Management, Fall
Marginal Effect
Celsius Degree


56 - Administrative support, Winter
56 - Administrative support, Spring
56 - Administrative support, Summer
56 - Administrative support, Fall
61 - Education, Winter
61 - Education, Spring
61 - Education, Summer
61 - Education, Fall
62 - Health care, Winter
62 - Health care, Spring
62 - Health care, Summer
62 - Health care, Fall
71 - Arts and Entertainment, Winter
71 - Arts and Entertainment, Spring
71 - Arts and Entertainment, Summer
71 - Arts and Entertainment, Fall
72 - Accommodation, Winter
72 - Accommodation, Spring
72 - Accommodation, Summer
72 - Accommodation, Fall
81 - Other services, Winter
81 - Other services, Spring
81 - Other services, Summer
81 - Other services, Fall
Marginal Effect
Celsius Degree

*Supplementary Figure 8. Projected income under 2 ℃ warming*



*Supplementary Figure 9. Percentage loss increases at decreasing speed*




Let:

$a$ = growth rate under climate change
$b$ = growth rate without climate change
$x$ = years from now

**Value of loss:**

$$Value = (1+a)^x - (1+b)^x$$

Rate of change of value:

$$\frac{d[(1+a)^x - (1+b)^x]}{dx} = (1+a)^x \cdot \log(1+a) - (1+b)^x \cdot \log(1+b)$$

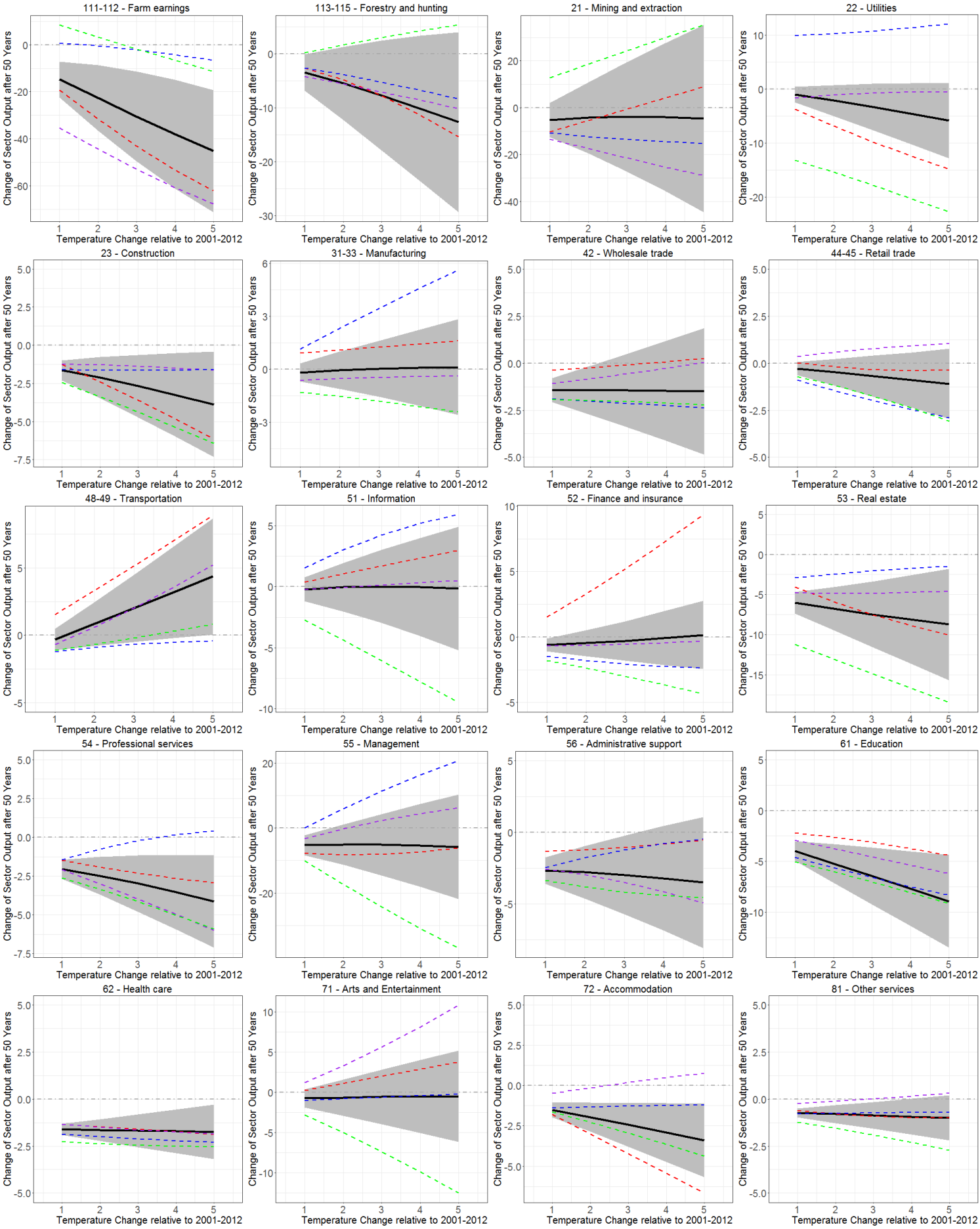
**Percentage of loss:**

$$Percent = \frac{(1+a)^x - (1+b)^x}{(1+b)^x} = (1+a)^x \cdot (1+b)^{-x} - 1$$

Rage of change of percent:

$$\frac{d[(1+a)^x \cdot (1+b)^{-x} - 1]}{dx} = (\frac{1+a}{1+b})^x \cdot log(\frac{1+a}{1+b})$$

*Supplementary Figure 10. Damage functions for 20 sectors*



Supplementary Table 1: Industry Growth Summary Statistics 2002-2012

| NAICS.Code | Description | Mean | Std.Dev | Max | Min | Nobs |
|---|---|---|---|---|---|---|
| 111-112 | Farm earnings | 0.121 | 1.097 | 8.847 | -6.988 | 2365 |
| 113-115 | Forestry fishing and related activities | 0.027 | 0.185 | 1.091 | -0.558 | 475 |
| 21 | Mining quarrying and oil and gas extraction | 0.094 | 0.370 | 3.456 | -1.198 | 629 |
| 22 | Utilities | 0.020 | 0.138 | 1.162 | -0.571 | 789 |
| 23 | Construction | 0.014 | 0.123 | 0.719 | -0.393 | 2116 |
| 31-33 | Manufacturing | 0.000 | 0.109 | 0.778 | -0.453 | 2281 |
| 42 | Wholesale trade | 0.023 | 0.113 | 0.698 | -0.404 | 1631 |
| 44-45 | Retail trade | 0.003 | 0.069 | 0.329 | -0.250 | 2572 |
| 48-49 | Transportation and warehousing | 0.024 | 0.126 | 0.844 | -0.383 | 1158 |
| 51 | Information | -0.003 | 0.147 | 0.966 | -0.555 | 1730 |
| 52 | Finance and insurance | 0.011 | 0.088 | 0.434 | -0.337 | 2021 |
| 53 | Real estate and rental and leasing | 0.061 | 0.265 | 1.897 | -0.757 | 1957 |
| 54 | Professional scientific and technical services | 0.025 | 0.093 | 0.728 | -0.353 | 1111 |
| 55 | Management of companies and enterprises | 0.062 | 0.295 | 3.022 | -1.160 | 680 |
| 56 | Administrative and support and waste management and remediation services | 0.036 | 0.139 | 1.122 | -0.477 | 1199 |
| 61 | Educational services | 0.042 | 0.120 | 1.041 | -0.536 | 1034 |
| 62 | Health care and social assistance | 0.027 | 0.050 | 0.393 | -0.208 | 1181 |
| 71 | Arts entertainment and recreation | 0.023 | 0.178 | 1.467 | -0.797 | 1562 |
| 72 | Accommodation and food services | 0.023 | 0.077 | 0.454 | -0.284 | 1698 |
| 81 | Other services (except public administration) | 0.013 | 0.058 | 0.239 | -0.183 | 2038 |

Supplementary Table 2: Summary Statistics on Income Growth

| | Year | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Industry | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | No. obs |
| 111-112 - Farm | -0.207 | 0.556 | 0.434 | -0.04 | -0.205 | 0.233 | 0.079 | -0.082 | 0.205 | 0.394 | 0.126 | 0.488 | -0.083 | -0.204 | 2365 |
| 113-115 - Fores | -0.012 | 0.01 | 0.105 | -0.001 | 0.055 | -0.075 | -0.082 | 0.004 | 0.137 | -0.049 | 0.137 | 0.003 | 0.078 | 0.061 | 475 |
| 21 - Mining, qu | -0.021 | 0.082 | 0.098 | 0.229 | 0.229 | 0.001 | 0.397 | -0.275 | 0.195 | 0.242 | 0.094 | 0.079 | 0.079 | -0.107 | 629 |
| 22 - Utilities | 0.011 | -0.006 | 0.055 | -0.023 | 0.105 | -0.021 | 0.069 | -0.011 | 0.020 | 0.018 | -0.055 | 0.038 | 0.030 | 0.047 | 789 |
| 23 - Constructi | 0.015 | 0.024 | 0.026 | 0.014 | 0.055 | -0.014 | -0.027 | -0.040 | -0.005 | 0.010 | 0.066 | -0.019 | 0.030 | 0.057 | 2116 |
| 31-33 - Manufac | -0.021 | -0.012 | 0.027 | 0.004 | 0.009 | -0.009 | -0.044 | -0.119 | 0.001 | 0.031 | 0.037 | 0.017 | 0.044 | 0.036 | 2281 |
| 42 - Wholesale | 0.022 | 0.002 | 0.041 | 0.031 | 0.028 | 0.039 | 0.008 | -0.025 | 0.012 | 0.027 | 0.044 | 0.022 | 0.041 | 0.030 | 1631 |
| 44-45 - Retail | 0.023 | 0.020 | 0.002 | -0.008 | 0.003 | -0.007 | -0.043 | 0.009 | 0.000 | -0.012 | 0.003 | 0.007 | 0.011 | 0.033 | 2572 |
| 48-49 - Transpo | -0.007 | 0.051 | 0.063 | 0.031 | 0.031 | 0.003 | -0.046 | -0.035 | 0.017 | 0.083 | 0.033 | 0.014 | 0.036 | 0.067 | 1158 |
| 51 - Informatio | 0.018 | 0.029 | 0.011 | -0.022 | -0.002 | 0.019 | -0.006 | 0.018 | -0.071 | -0.034 | -0.010 | -0.011 | 0.022 | -0.009 | 1730 |
| 52 - Finance an | 0.036 | 0.017 | 0.021 | 0.016 | 0.01 | 0.003 | -0.021 | 0.027 | 0.029 | -0.057 | 0.030 | -0.007 | 0.001 | 0.043 | 2021 |
| 53 - Real estat | 0.049 | 0.050 | 0.059 | 0.012 | -0.005 | -0.093 | 0.226 | 0.043 | 0.029 | 0.090 | 0.170 | 0.102 | 0.040 | 0.074 | 1957 |
| 54 - Profession | 0.028 | -0.003 | 0.041 | 0.032 | 0.062 | 0.037 | 0.065 | -0.045 | -0.020 | 0.030 | 0.020 | 0.006 | 0.045 | 0.059 | 1111 |
| 55 - Management | 0.070 | 0.087 | 0.08 | 0.053 | 0.123 | 0.067 | 0.029 | 0.036 | 0.035 | 0.059 | 0.053 | 0.061 | 0.051 | 0.061 | 680 |
| 56 - Administra | 0.054 | 0.040 | 0.036 | 0.046 | 0.066 | 0.018 | -0.001 | -0.023 | 0.053 | 0.050 | 0.035 | 0.053 | 0.038 | 0.039 | 1199 |
| 61 - Educationa | 0.110 | 0.063 | 0.076 | -0.008 | 0.055 | 0.039 | 0.025 | 0.075 | 0.016 | 0.013 | 0.041 | 0.006 | 0.052 | 0.020 | 1034 |
| 62 - Health car | 0.068 | 0.037 | 0.045 | 0.011 | 0.032 | 0.021 | 0.033 | 0.040 | 0.023 | -0.006 | 0.010 | 0.014 | 0.010 | 0.046 | 1181 |
| 71 - Arts, ente | 0.075 | 0.026 | 0.003 | -0.025 | 0.016 | 0.005 | -0.002 | 0.015 | 0.028 | 0.001 | 0.036 | 0.042 | 0.057 | 0.042 | 1562 |
| 72 - Accommodat | 0.025 | 0.029 | 0.036 | 0.001 | 0.014 | 0.020 | -0.018 | -0.007 | 0.005 | 0.022 | 0.069 | 0.024 | 0.038 | 0.068 | 1698 |
| 81 - Other serv | 0.102 | -0.013 | 0.022 | 0.017 | 0.030 | -0.025 | -0.058 | 0.010 | 0.005 | -0.009 | 0.036 | -0.017 | 0.037 | 0.036 | 2038 |