

# Natural Disasters, Regional Economic Structure and Commercial Real Estate\*

Shaun A. Bond<sup>1</sup>, Shawn J. McCoy<sup>2</sup>, and Ian K. McDonough<sup>2</sup>

<sup>1</sup>UQ Business School, The University of Queensland

<sup>2</sup>Department of Economics, University of Nevada, Las Vegas

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## Abstract

The economic consequences of weather and climate disasters in the United States are of significant concern to institutional investors. In this paper we study commercial real estate market outcomes in response to natural disasters. In particular, we draw on recent research examining resilient regions and show how measures of resiliency may predict which markets and property types recover more quickly from natural disasters. We first investigate the price and cash flow impacts of a natural disaster to understand how market signals are responding to the occurrence of extreme climate events. Second, we consider how investors are responding to, and potentially mitigating, evolving climate risks by examining capital expenditure strategies in areas before and after extreme events occur. In each case we investigate these questions in the context of the economic resiliency of the region in which the property is located.

**Keywords:** Commercial Real Estate, Economic Diversity, Natural Disasters, Resiliency

**JEL codes:** P25, Q51, R33

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# 1 Introduction

The economic consequences of weather and climate disasters in the United State are unprecedented. Since 1980, the US has experienced over 298 such disasters where the values of overall damages from each event exceeded \$1 billion. Eight distinct billion-dollar weather and climate disaster events impacted the United States during the first six months of 2021, alone. The overall cost of these disasters since 1980 is estimated to exceed approximately \$2.16 trillion (NCEI, NOAA 2022). Further, the National Climate Assessment states that such disasters are likely to increase in terms of both number and overall cost due to the increased exposure of assets, more vulnerability and an increasing frequency of extreme climate events (USGCRP 2018, Hong et al 2020).

Motivated by these trends, academic researchers have increasingly turned their attention to understanding the economic and financial implications of climate-related events and risks (Giglio et al 2021). However, less attention is devoted to understanding how commercial real estate markets respond to natural disasters which is surprising given the size of US commercial real estate was estimated at around \$16 trillion by NAREIT in 2018 (NAREIT 2019). Similarly, from the perspective of the financial services sector, commercial mortgages represent one of the largest category of debt on the balance sheet for commercial banks and life insurance companies. Even less research exists that examines strategies policy makers can take to improve the resilience of commercial real estate markets to catastrophic shocks. Among existing studies, much of the emphasis is on physical, pre-disaster mitigative efforts such as rapid assessment of structural vulnerabilities and the assurance of mechanical and electrical equipment

While clearly important, these types of pre-disaster mitigation strategies may ultimately may be insufficient tools to achieve resiliency since the value of commercial real estate depends on both current and expected future streams of income. These income streams, in turn, are inexorably linked to the strength of the local economy. A commercial property located within a city that is hit by a natural disaster may witness economic losses even in

a situation where it is not physically affected by the disaster if the disaster leads to broader scale market-level disruptions. These disruptions may include, for example, reductions in the demand for goods and services and changes in employment and income. In a study of the United States using almost a century of data, Boustan, et al. (2020) find that severe natural disasters can reduce household income, increase out-migration rates for an impacted county by 1.5 percentage points, and reduce house prices and rents by 2.5% to 5%. If these types of regional economic disruptions manifest in changes in the value of commercial real estate, resiliency may not only depend on the suite of pre-disaster mitigation strategies property owners undertake but on the degree of economic resilience of the city in which the property is located within as well.

These observations motivate our interest in two inter-related questions. First, we study how severe natural disasters influence commercial real estate market outcomes. We address this question by empirically estimating the impact of presidentially-declared hurricanes and typhoons on changes in market valuation, net operating income and leasing activity using a micro-level dataset recording property-level metrics on a quarterly basis for a large sample of commercial properties in the U.S. We draw on recent research examining resilient regions and show how responses across each market outcome vary based on property sub-type. This study will focus on hurricanes and typhoons as the specific natural disaster studied. However, it is expected that this methodology can provide a framework to study other natural disasters such as the current Covid-19 crisis, floods, and wildfires. All of which are critically important for commercial real estate investors.

Second, we study what types of regional economic structures attenuate or exacerbate property-level responses to natural disasters. We are particularly interested in understanding what features of regional economies improve the ability of local businesses to withstand the economic impacts associated with a natural disaster striking the metropolitan area they belong too. While there exists a broad spectrum of regional economic characteristics that may promote resiliency, in this paper we focus on the role of the composition of industries

within cities as features that may promote resiliency in the US commercial real estate market. Our interest in the role of industrial composition stems from the idea that ex-ante we cannot assume that a natural disaster will have a homogeneous impact on all industry types. For example, one might conjecture that an economy based heavily based on tourism would be relatively more susceptible to larger scale labor market disruptions when natural disasters strike.

We provide a systematic investigation of which types of industries within a city tend to improve or worsen commercial real estate cash flows and valuation in the wake of a shock. We do this by incorporating data from the BEA's Quarterly Census of Employment and Wages which measures total employment and wages at the county by year by quarter level by NAICS supersector. These data allow us to measure the size of any given supersector in a U.S. county expressed in terms of county-level shares. We then show how the estimated impact of a natural disaster changes when restricting attention to counties whose overall economic base is concentrated in any given industry.

Relatedly, researchers and policy makers also argue that industry-mix, or economic diversification, may play a key role in promoting regional economic stability (Coulson et al., 2020). The idea that industrial diversification can promote resiliency is of course longstanding. Barth et al. (2015) argue that as it would be suggested by standard portfolio theory, a diverse array of industry employment ought to lead to decreases in volatility in metro-level employment to the extent that industrial diversification may serve to tamp down the covariances of sectoral employment manifesting in reductions in aggregate employment volatility. This idea dates back to as early as 1977 with Lucas (1977) noting that disaggregating an economy into smaller sectors may serve to dampen the overall effects of a disturbance to any one sector.

The idea that diversity may be a driver of resiliency was subsequently challenged by Carvalho (2014) who shows using a multisector general equilibrium model that whether or not diversity catalyzes resiliency may ultimately depend on the structure of input-output

linkages between sectors in an economy. In effect, diversity may promote resiliency but only if industries within cities tend to be horizontally integrated. Nonetheless, the empirical work conducted by Coulson, McCoy, and McDonough (2020) show that the impact on real estate prices from a natural disaster is related to the economic diversity of an area. In areas with a high degree of economic concentration, the reduction in real estate prices could be closer to 5% with the effects lasting for almost two years. However the price impact is moderated in regions with more economic diversity. This finding seems to suggest there ought to exist a similar response in commercial real estate markets. However to date, no formal empirical evidence exists which documents the linkage between heightened regional economic diversification and heightened resiliency in the US Commercial Real Estate Market. In this paper we fill this gap by measuring the degree of regional economic diversity for each county in our study area. Given localized measures of diversity, we then estimate how commercial real estate market responses to natural disasters change when we restrict attention to properties located within highly concentrated cities or properties located within highly diversified cities.

With this said, the principal contribution of this study is showing not just how commercial real estate market outcomes change in response to natural disasters, but describing how the composition of industries within cities expressed in terms of both industrial-mix and industrial-dominance predicts the degree to which commercial real estate markets will react. In this sense, our paper contributes to a much broader literature sitting at the nexus of climate change and adaptation by adding a systematic discussion centered more closely on steps local policy makers might take to improve the economic resilience of commercial real estate markets by targeting the industrial composition of cities.

Collectively, our empirical results suggest that while natural disasters, on average, lead to significant and rather immediate reductions in market valuations as well as leasing activity, irrespective of which property type we consider, these responses substantially attenuate when regional economies are economically diverse. In turn, this finding suggests that the strength of a local economy as measured by its industrial composition may be an important factor

explaining the economic resiliency of income producing properties. It is well accepted that promoting physical resiliency via the appropriate set of pre-disaster mitigation strategies is important to protect commercial establishments, but as we allude to previously, these types of strategies may only be partially satisfactory approaches to promoting economic resiliency amongst commercial establishments that may respond indirectly to a disaster in terms of key market outcomes that might be particularly sensitive to broader (e.g. regional) scale economic disruptions.

The remainder of the paper is organized as follows. First, we review the existing literature and background information related to commercial real estate, climate and natural disasters, and regional economic diversity. Second, we describe the data and empirical strategy used for the analysis. Finally, we discuss the results and conclude.

## 2 Background

Giglio, Kelly and Stroebel (2021) provide a comprehensive review of the emerging area of climate risk. They distinguish two distinct stands of this literature identifying physical climate risk that includes potential impairment of cash flows and stranded asset risk in the transition to a low-carbon economy. Our paper is closely aligned with the first category of climate risk.

While there is a rapidly emerging literature on climate risks in finance, the study of climate risks and commercial real estate markets is more limited. Clayton et al (2021) provide a literature survey of this emerging area with a focus on providing guidance to industry professionals. An important finding from their summary is that value impacts tend to be *“modest and short-lived in locations where there is strong awareness of, and experience with, extreme weather-related events (particularly flooding and exposure to hurricanes/cyclones)”*. Their conclusion highlights the issue of risk salience, which is a central element of research related to the economic and financial impacts of nature disaster. The significance of risk

salience and natural disasters is well discussed by Dessaint and Matray (2017) for corporate cash holdings, Huang, et al (2022) for ESG disclosures, and McCoy and Walsh (2018) and McCoy and Zhao (2018) in the context of housing markets.

In research closely related to our work, Fisher and Rutledge (2021) also examine commercial real estate market outcomes following hurricanes. They investigated the impact of 19 hurricane making landfall in the US between 1989 and 2017. Using panel data regression their results suggest declines of around 40-46% in average property values relative to unaffected properties after three years, depending on property type. The negative value impact was observed to persist for five years following the hurricane. Not reported in this study are cash flow impacts arising from the hurricane. The econometric study may be subject concerns about unobserved heterogeneity at the property level and whether the pre-trend assumption is fully satisfied.

Addoum, et al (2021) investigate the impact of flood risk associated with Hurricane Sandy on New York, Boston, and Chicago commercial real estate. They find residual price impacts for up to five years after flooding and document a reduction in price growth for New York property of around 21%. Over the same period the reduction in price growth of similar water front property in Boston is around 7%. The authors suggest that the mechanism by which prices are impacted is through capitalization rates, as occupancy does not appear to have been affected. These findings give weight to the importance of this topic and suggest that a more complete study beyond the findings of one region after one extreme weather event has considerable merit.

The impacts of Hurricane Sandy on New York have also been studied by Meltzer, et al (2021). Their focus is on the occupiers of commercial real estate and they evaluate the impact on establishment survival, employment and sales review following the hurricane. Because it is a localized study on New York the results may be difficult to generalize. However, one of their key findings is that *“Consistent with theoretical expectations, losses are primarily concentrated among customer-facing retail businesses...”*. They also note the immediate

impact of review loss faced by businesses and in some cases this loss lingered for more than four years. They also note the lower rate of new business creation, along with indirect effects from lower revenue due to displaced residents and the reduced agglomeration benefits.

### **3 Data**

The main data set used in this paper come from the National Council of Real Estate Investment Fiduciaries (NCREIF). NCREIF is an organization of institutional investment managers who invest in U.S. commercial real estate and was formed to track the performance of commercial real estate. The data, which spans 2000 to the first quarter of 2021 includes quarterly, parcel-level data for five types of commercial properties (apartments, hotel, industrial, office and retail): quarterly net operating income, quarterly appraised property value, the percentage of the property leased in any given quarter, the year each property was built, the square footage of each property, and the U.S. County each property is located in. Observations with missing values for the variables year built, square footage, property type, percent leased, market value, and net operating income (NOI) were dropped prior to conducting analysis.

As we allude to previously, the first stage of our empirical analysis first seeks to identify the effect a natural disaster has on commercial property outcomes (e.g. market values, lease rates, and NOI), over time. The second stage of our analysis describes how the dynamic treatment effect of a disasters varies based on the level of economic diversification of the regional market (which we define as a US county) for which each property belongs to.

#### **3.1 Measuring Economic Diversity**

With the goal of ultimately measuring how economically diverse the local economy for which a given property belongs to is, we construct a measure of economic diversity using 2000-2020 industry level wage data from the Bureau of Labor Statistics' Quarterly Census of



Employment and Wages (QCEW). The data track total wages (e.g. total compensation paid to employees within each North American Industry Classification System (NAICS) supersector<sup>1</sup> for each county at a year by quarter time-step<sup>2</sup>. Given the data, we compute the usual measure of economic diversity,

$$DIV_{ct} = 1 - \sum_{s \in S} \left[ Share_{st}^i \right]^2, \quad (1)$$

where  $Share_{st}^i$  denotes the share of labor market income for industry  $s$  within county  $i$  at time  $t$ . We subsequently standardize the index mean zero, standard deviation one. In this sense, higher(lower) values of the index represent more(less) diverse regions. For example, a hypothetical value of 1.5 represents a county that is 1.5 standard deviations above the mean level of diversity.

### 3.2 Natural Disasters

We treat federally declared hurricanes and typhoons as exogenous shocks to commercial real estate markets. Data describing these events are sourced from FEMA's National Emergency Management Information System (NEMIS). NEMIS records the impacted county as well as the month, day, and year each disaster began. Our panel data-set spans the years 2000 to 2020 and as we discuss in more depth below, identifying the impact of a hurricane requires pre- and post-hurricane observations. We are thus unable to identify the impact of a hurri-

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<sup>1</sup>NAICS Supersectors are synonymous with two digit NAICS codes and represent the top-level industry groupings in the United States. The set of NAICS supersectors includes: Sector 11: Agriculture, Forestry, Fishing and Hunting; Sector 21: Mining, Quarrying, and Oil and Gas Extraction; Sector 22: Utilities; Sector 23: Construction; Sector 31-33: Manufacturing; Sector 42: Wholesale Trade; Sector 44-45: Retail Trade; Sector 48-49: Transportation and Warehousing; Sector 51: Information; Sector 52: Finance and Insurance; Sector 53: Real Estate and Rental and Leasing; Sector 54: Professional, Scientific, and Technical Services; Sector 55: Management of Companies and Enterprises; Sector 56: Administrative and Support and Waste Management and Remediation Services; Sector 61: Educational Services; Sector 62: Health Care and Social Assistance; Sector 71: Arts, Entertainment, and Recreation; Sector 72: Accommodation and Food Services; Sector 81: Other Services (except Public Administration); Sector 92: Public Administration.

<sup>2</sup>In cases where total county level wages for a particular industry are suppressed by the Bureau of Economic Analysis (BEA), we impute wages by multiplying the share of total state level establishments located in the given county of interest by total state quarterly wages of said industry.

cane that initiates in, for example, the first quarter of 2000. As we also discuss, the validity of our identification strategy is supported by documenting similar pre-treatment trends between properties in impacted vs. non-impacted counties. To increase the credibility of this approach, we seek to establish similar pre-treatment trends over a reasonably long (e.g. 3-year) period of time leading up to a disaster. Likewise, we also seek to estimate how the impact of a hurricane varies over time following the shock which we cannot do for disasters commencing at the end of our panel. Along these lines, given the universe of disasters, we first restrict attention to disasters occurring between 2003 and 2018 which ensures that we have at least 3 years of pre- and post-disaster data for each observation in our sample (e.g. property  $i$  located in county  $c$  observed at time  $t$ ).

As we discuss in more depth below, we estimate the impact of natural disasters on commercial real estate market outcomes using the group-time average treatment effect estimator based on Callaway and Sant’Anna (2021). This estimator estimates all group-specific average treatment effects on the treated for each group group and for each time period – denoted formally below as  $ATT(g,t)$  – and thus implementing this estimator using data sets with long time horizons and/or with many treated groups may not be computationally feasible. Along these lines, we make use of two data normalizations to improve the computational feasibility of our empirical approach and to maintain coherence with respect to treatment intensity across the multiple disasters. First, we restrict the natural disaster data to the top 10 costliest disasters as defined by the NOAA’s National Center’s for Environmental Information often times referred to as ”Billion-Dollar Weather and Climate Disasters.” This normalization both reduces the number of treated groups as well as attempts to minimize the difference in treatment intensity across treated groups. The resultant set of hurricanes considered in this study include Hurricanes: Sandy, Harvey, Maria, Ike, Irma, Katrina, Wilma, Rita, Charley, and Ivan.

Second, we drop commercial properties that intermittently report quarterly data within 3 year windows of each treatment date. This latter normalization serves the additional

purpose of attempting to ensure that when group-time average treatment effects on the treated are compared over time that actual differences in these effects are not conflated with any difference due to changes in the composition of commercial properties that are ultimately retained in the estimation sample.

## 4 Empirics

A traditional view on how to proceed in estimating the dynamic treatment effects associated with natural disasters and the various outcomes of interest related to commercial real estate is to employ an event study framework with the inclusion of both property and time fixed effects (e.g. Coulson et al., 2020). However, recent work has demonstrated that the causal parameters of interest in this setting may not be identified in the presence of heterogeneous treatment effects coupled with staggered timing in treatment adoption (Goodman-Bacon, 2021; Callaway Sant’Anna, 2021). Using the standard two way fixed-effects (TWFE) approach to recover causal parameters in this particular commercial real estate setting is complicated since the properties subject to natural disasters early on in the sample frame could serve as controls for those those commercial properties treated at a later point in time. This staggered treatment adoption can potentially induce bias in the estimated causal parameters of interest (Baker, Larker, and Wang 2021). As such, we implement the difference-in-differences approach as outlined in Callaway and Sant’Anna (2021) to identify the group-time average treatment effects on the treated and use various aggregation schemes to summarize our findings.

### 4.1 Setup and Identification

Following the notation in Callaway and Sant’Anna (2021), the group-time average treatment effect parameter, defined here as the average treatment effect for commercial real estate properties that belong to group  $g$  in time period  $t$ , can be denoted by

$$ATT(g, t) = E[Y_t(g) - Y_t(0) | G_g = 1] \quad (2)$$

where  $g$  is defined by the time period when a property is first treated,  $G_g$  is a binary indicator equal to 1 when a property is first treated in time period  $g$ ,  $Y_t(g)$  is the potential outcome that properties would realize at time  $t$ ,  $t = 1, \dots, \mathcal{T}$ , had the properties first been treated in time period  $g$ ,  $Y_t(0)$  is the potential outcome for untreated properties in time  $t$  under the condition that these properties remain untreated throughout all time periods. Next, let  $C$  be defined as a binary indicator that is equal to one for properties that are *never* exposed to a natural disaster in any time period (i.e. never treated).

For each property, then, exactly one of  $G_g$ ,  $g = 1, \dots, T$  or  $C$  should be set equal to 1. The generalized propensity score equation can be defined as  $p_g(X) = P(G_g = 1 | X, G_g + C = 1)$ , which represents the probability that a property is subject to a natural disaster conditional on both having covariates  $X$  and belonging to the group of properties treated in time  $g$  or belonging to the control group of properties never treated denoted by  $C$ . Assuming that parallel trends holds conditional on  $X$ , that treatment is irreversible, and that there is common support across control and treatment groups, the  $ATT(g, t)$  can be identified semiparametrically by

$$ATT(g, t) = E \left[ \left( \frac{G_g}{E[G_g]} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{E\left[\frac{p_g(X)C}{1-p_g(X)}\right]} \right) (Y_t - Y_{g-1}) \right]. \quad (3)$$

Once (3) is estimated for every treatment group  $g$ , we further follow Callaway and Sant’Anna (2021) to aggregate the many parameters via a dynamic aggregation approach allowing us to discuss and plot treatment effect heterogeneity with respect to time since treatment exposure.<sup>3</sup> We follow bootstrap inference procedures provided Callaway and Sant’Anna (2021) and report simultaneous 95% confidence bands for the group-time average treatment effects while clustering the standard errors at the county level.

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<sup>3</sup>We explore other aggregation methods in Callaway and Sant’Anna (2021) including with results available upon request.

## 5 Results

We first present our main results by having estimated the impact of a natural disaster on three commercial property market outcomes: the natural log of the appraised quarterly valuation of each property; the natural log of the percentage of the property leased in any given year-quarter; and the natural log of quarterly net operating income. Specifically, for every quarter relative to the actual quarter of treatment, we estimate the  $ATT(g, t)$  for each group  $g$  that corresponds to each quarter by year in the panel. A weighted average of the  $ATT$ s, weighting by group size with a group being defined as a cohort of properties treated at the same point in time, is constructed and plotted against an x-axis representing exposure to treatment relative to event time  $e$  where  $e = t - g$ . For example,  $e = 2$  represents two periods post a disaster while  $e = -2$  represents two periods prior to a disaster. For clarity, it should be noted that each  $ATT$  for a particular group  $g$  in the post periods are interpreted with respect to the period prior to being impacted by a natural disaster,  $g - 1$ , with the actual period prior to the disaster varying along  $g$  given the staggered treatment timing. Thus, the aggregated effects in the post-disaster periods are the weighted average of the dynamic  $ATT$ s across event time  $e$ .

After having presented our main findings as outlined above, we present results across the same outcomes, and in the same fashion, as noted above but now decompose the main results along various dimensions of heterogeneity. Specifically, we refine our results by decomposing the main findings by property type *and* regional economic diversity.

Table A1 displays the main characteristics of the properties that are used in the estimation procedure. As can be observed, our careful balancing of the data around the natural disasters results in a sample of treated properties that closely match to the never-treated properties (control) properties.

## 5.1 Main Results

We begin our formal empirical analysis by presenting estimates of (2) estimated separately for each market outcome of interest (market valuation, lease rates, and NOI) in Figure 1. Periods relative to treatment are represented on the x-axis. Estimated *ATTs* by period are represented on the y-axis along with 95 percent confidence intervals.

As we allude to previously, one identifying assumption of the model is that of parallel trends. That is, in the absence of treatment, changes in outcomes among the set of control units over time following a disaster are proportional to the changes in outcomes among the set of treated units that would have happened in the absence of treatment. While we cannot formally test this assumption, we can provide evidence supporting the credibility of it by investigating estimated *ATTs* in the three-years prior to treatment. Intuitively, this set of *ATTs* represent differences in market outcomes between treated and control units over time in the periods of time leading up to a disaster. Along these lines, *ATTs* for are statistically insignificantly in every pre-treatment time period for every market outcome. This finding engenders confidence regarding the validity of the parallel trends assumption.

Inspection of Figure 1 indicates there exists much heterogeneity in the magnitude of responses over time across the market valuation outcome. We estimated relatively immediate declines in market valuation that begin one quarter following a hurricane. Albeit, for the first year following a shock, these estimates are relatively small of the order of 1% to 2%. Interestingly, we do not find any statistically significant response on net operating income, but we do find that after approximately one year, the occupancy rates (percentage leased) of buildings in impacted areas decline. The time-lag for lease rates seem plausible given that we would not expect ex-ante to see immediate reductions in leasing activity given the nature of leasing contracts most of which generally do not expire less than one year. This finding also suggests a broader economic impact from the disaster plays out in the local economy. Nonetheless, what remains puzzling is why the results for market value and lease rates differ from our estimated results for net operating income.

To help rationalize these findings, it is perhaps important to note that for income producing properties, valuations typically capture investors' short and longer term assessment of income flows. As such, valuations today may adjust to reflect contemporaneous changes in local market conditions as well as expectations of future market conditions. Additionally, in our dataset we do not observe estimated changes in effective market-level rents. Lastly, given the nature of our data, properties that are completely destroyed by a hurricane or sold by the entities that report to NCREIF (and hence are no longer reported in our data) and that do not have post-treatment data would not appear in the data.

Thus - and keeping in mind our result that NOI is unresponsive to a disaster - in the short term (e.g. first three years following a shock) it is possible that the supply of leaseable properties in markets affected by hurricanes declines placing upward pressure on rent; an effect that may partially offset the reduction in NOI that would have otherwise occurred had rents remained stable and occupancy rates declined. Moreover, investors may be aware that these supply side responses may be ultimately short-lived as destroyed properties become repaired or renovated. If investors believe that demand side responses (e.g. reductions in the demand for lease-able space) is relatively more persistent than shorter-term supply side disruptions (and again recalling that valuations today are driven by expectations of future income flows over time) demand-side disruptions are most likely driving the reduction in market valuations we observe in the data.

Changes in risk-salience may be another potential mechanism at play. Our analysis focuses on the top 10 most severe disasters spanning our study window. These relatively rarer types of extreme events may result in certain types of market disruptions that previous investors failed to completely internalize prior to the onset of the disaster. For example, even if investors held accurate beliefs regarding the probability of a severe disaster occurring, it may be a relatively more challenging task ex-ante to predict the spatial extent (and intensity) of a hurricane damage in a specific geographic area; information that becomes more salient once a disaster ultimately strikes an area. If severe hurricanes do in fact lead investors to

update their baseline (e.g. pre-event) perception of disaster risk, said changes will ultimately be reflected in present-day reductions in the market value for commercial real estate.

## 5.2 Results Decomposed by Property Type *and* Regional Economic Diversity

We next decompose the above results across the dimension of property type, including apartments, office, industrial, and retail properties, as well as by our measure of regional economic diversification. Specifically, we explore results along the dimension of property type focusing on the bottom quartile interval and top quartile interval of the economic diversity distribution. As before, periods relative to treatment are represented on the x-axis, and estimated *ATT*s by period are represented on the y-axis along with 95% confidence intervals.

A few results emerge when looking at Figures 2 through 5. First, results for market value seem to be driven, in a statistically meaningful way, by apartment and industrial properties located in counties within in the bottom quartile interval of the distribution of economic diversity. Specifically for apartments (Figure 2), we see declines in market value, on average, of approximately 1% to 2% in the first two quarters following a natural disaster to about an 8% decline two years out. At the end of three-years post disaster, apartment values in these least-diverse areas are almost 15% below their pre-disaster values. At the top end of the economic diversity distribution, however, there are no estimated changes in market values for apartment properties that are statistically discernible at  $\alpha = 0.05$ . Indeed, if anything, there is a suggestion that the market values for apartments may actually be increasing in these areas. This suggests the trajectory of recovery in economically diverse areas as well as the interactions of demand and supply for housing in impacted areas is fundamentally different from the least diverse regions.

A similar story for market value emerges for industrial properties and market values (Figure 4). Specifically, we find an estimated decline in market values ranging, on average,



from approximately 10% two years out from a natural disaster to approximately 20% three years out from a natural disaster. Similar to what was found with apartments, no statistically significant results (at  $\alpha = 0.05$ ) in the market value of industrial properties is detected at the top end of regional economic diversification following a natural disaster.

Second, and with respect to occupancy rates, it is broadly difficult to ascertain what is driving the main results presented earlier with the exception, perhaps, of industrial properties (Figure 4) located in counties within the bottom quartile interval of regional economic diversity. Specifically, and relative to the period prior to the disaster, lease rates for properties located in counties within the first quartile interval of economic diversity experience approximately an average decline of 12% in lease rates two years after a disaster, relative to the quarter prior to the natural disaster, with these declines hovering around 12% to 13% through three years after experiencing a natural disaster.

Lastly, there is some evidence, though not precisely estimated, that NOI declines over the periods following a natural disaster in non-diversified regions with these declines reaching, on average, approximately 25% ten quarters afterwards. We find nothing meaningful as it relates to the impact of disasters on NOI across the other property types at either end of the distribution of economic diversity.

### 5.3 Results by Industry Exposure

The previous section of results highlights how the impact of natural disasters on various commercial real estate outcomes varied across the distribution of economic diversity. One aspect lost in this exercise is the idea that there could be multiple geographic regions with similar levels of economic diversity while at the same time having differential exposure to very specific industries. To get a sense of how natural disasters impact the various commercial real estate outcomes of interest while considering the differential exposure that counties have to specific industries, we re-estimate (1) multiple times again focusing on market value, leasing rates, and NOI as the outcomes of interest and specifically focus on the differential exposure

that counties have to 19 different industries as classified by NAICS. Specifically we focus on counties with relatively low exposure to particular industries (the bottom 25% of exposure) and counties with relatively high exposure (the top 25% of exposure) to particular industries. And while admittedly not comprehensive and more of a broad view of the interplay between specific industry exposure and the impact of natural disasters on the various outcomes of interest, we focus on some of the more obvious findings that emerge. With that said, all results from this exercise can be found in appendix Figures A1-A19.

The most of the meaningful responses that we find are with respect to our market valuation outcome. Specifically, those counties in the top 25% of exposure to the industries of Real Estate and Rental and Leasing, Construction, Finance and Insurance, Retail Trade, Manufacturing, Arts and Entertainment, Agriculture, Forestry, Fishing, and Hunting, Wholesale Trade, and Administrative and Support and Waste Management and Remediation Services all seemed to experience more of a muted effect on market valuation over time relative to those regions in the bottom 25% of exposure to these industries (appendix Figures A1-A9). Interestingly, we find the opposite result when looking at exposure to the industries of Utilities, Educational Services, and Professional, Scientific, and Technical Services. Here those counties with relatively high exposure to these industries appear to be more negatively impacted market valuations compared to those counties with relatively low exposure (appendix Figures A10-A12). As well, this pattern of being more negatively impacted with exposure to Educational Services and Professional, Scientific, and Technical Services also emerges when looking at the outcome of occupancy rates (appendix Figures A11-A12) . Again with respect to occupancy rates, counties with relatively high exposure to Health Care and Social Assistance experiences less of an impact, in absolute value, in occupancy rates relative to those counties with relatively low exposure to this industry (appendix Figure A13). Lastly, and across all industries, nothing of note is apparent when looking at the results related to the NOI outcome measure.

Overall, taking into both these and prior presented results, it becomes clear that there

is a real, complicated overlap between the areas of finance and urban economics with the results presented here making clear the extraordinarily complex interactions between cash flows/market valuations related to commercial properties and the underlying structure of a regional economy.

## 6 Discussion and Conclusion

The discrepancy with respect to the impacts on market value, occupancy rates, and NOI across property types is at first puzzling and warrants discussion. As noted above, we estimate declines in market valuations for apartment properties while at the same time finding that NOI and occupancy rates are unaffected. Taking into account both the supply-side and demand-side disruptions stemming from being exposed to a natural disaster, it may just be the case the the supply-side disruptions are relatively more significant for apartment properties (and residential properties more broadly) given their geographic location relative to regional floodplains. When apartment buildings are impacted by natural disasters, supply of apartment properties potentially fall due to destruction/damage; holding everything else constant, this places upward pressure on rents and contemporaneous changes in NOI. In light of investors recalibrating medium to long term expectations in demand once restoration of damaged properties is complete (which is synonymous with rightward shifts in the supply curve over time), investors may simply be (a) updating beliefs about future risk with these beliefs being reflected in present day market valuations and/or (b) updating present day market valuations to account for expectations of future supply increases coupled with relatively more persistent reductions in the demand for living in properties located in counties that experienced a shock.

With respect to industrial properties, it might simply be the case that far fewer industrial properties are actually being sufficiently damaged or destroyed. If this is in fact the case, then the supply-side disruptions would be minimal relative to the reductions in demand for

these properties. Given a modest short-term response on the supply side, the overall negative demand shock to the regional economy stemming places downward pressure on occupancy rates and/or rents manifest in overall reductions in NOI.

With respect to the role of regional economic diversity, our conceptual framework on the mechanism by which diversity can increase economic resiliency is through bolstering demand side changes (e.g. making the regional economy more robust to a shock). At the same time, it is reasonable to think that increasing the diversity of a regional economy does nothing to mitigate properties being damaged by disasters. Thus in diverse economies, changes in market outcomes may be driven more so, in relative terms, by supply-side disruptions. This can be clearly observed in the top end of regional economic diversity for apartment properties where we observed some evidence of increases in market value. What is potentially occurring here is that rising rents, stemming from a reduction in supply due to the disaster, is failing to be offset by overall reductions in market demand.

In contrast to the above, and when focusing on economically diverse regions, market valuations for industrial properties tend not to increase after a disaster-based shock. As before, we continue to expect demand to be more stable in economically diverse regions. The fact that we do not observe increases in market values seems to suggest that industrial properties are, perhaps, more resilient to supply-side disruptions. This idea is consistent with the response estimated for industrial properties located in the bottom quartile interval of the economic diversity distribution. Supply of industrial properties is stable but demand drops leading to declines in market valuations, occupancy rates, and NOI.

Finally, office and retail properties appear to be surprisingly resilient assets. However, one should keep in mind that office and retail properties are going to be situated in systematically different geographic regions relative to apartment and industrial properties. It is possible that these sub-regions are simply less likely to be directly impacted by a hurricane once it makes landfall. As well, the nature of the business conducted by firms in office and retail properties are simply different than the business associated with industrial properties. With

industrial properties, space is rented and retrofitted with the capital needed to produce and ship physical goods; physical re-location within a city is perhaps less important (on the margin) for this asset category than office and retail. Retailers, on the other hand, generate revenue from patrons visiting their businesses. A retailers revenue, then, is very dependent on both the nature of the products they sell *and* where they physically sell the products. Thus, temporary closures and re-locations may be inherently cost prohibitive. Thus, office and retail space leaseholders may simply find it more beneficial in the long term to stay put. If so, we would expect less response across the dimension of occupancy rates and by extension, NOI.

Overall, our empirical results suggest that being subject to natural disasters, on average, leads to an immediate and non-trivial reduction in commercial property market valuations and occupancy rates. With that said, and regardless of which property type is considered, the negative responses in these outcomes are muted when regional economies are diverse along the dimension of industrial composition. These findings support the idea that industrial diversification at the local level is arguably an important factor in explaining the economic durability of income producing commercial properties. Lastly, and in addition to the level of economic diversity, the degree to which certain regions are exposed to particular industries may further enhance the resiliency in various commercial property-related outcomes.

## References

- [1] Addoum, J., Eichholtz, P., Steiner, E., & Yönder, E. (2019). Climate Change and Commercial Real Estate: Evidence from Hurricane Sandy. Working paper.
- [2] Baker, A., Larcker, D. F., & Wang, C. C. (2021). How much should we trust staggered difference-in-differences estimates? Available at SSRN 3794018.
- [3] Barth, J.R., Benefield, J.D., & Hollans, H. (2015). Industry concentration and regional housing market performance. *Regional Analysis and Policy*, 45(2), 126-140.
- [4] Boustan, L. P., Kahn, M. E., Rhode, P. W., & Yanguas, M. L. (2020). The effect of natural disasters on economic activity in US counties: A century of data. *Journal of Urban Economics*, 118, 103257.
- [5] Callaway, B., & Sant’Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200-230.
- [6] Carvalho, V.M. (2014). From micro to macro via production networks. *Journal of Economics Perspectives*, 28(4), 23-48.
- [7] Clayton, J.; Devaney, S.; Sayce, S. & van de Wetering, J. (2021) Climate Risk and Commercial Property Values: a review and analysis of the literature. *UN Environment Program: Finance initiative*.
- [8] Coulson, N. E., McCoy, S. J., & McDonough, I. K. (2020). Economic diversification and the resiliency hypothesis: Evidence from the impact of natural disasters on regional housing values. *Regional Science and Urban Economics*, 85, 103581.
- [9] Dessaint, O. & Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics*, 126, 97-121.
- [10] Fisher, J.D., & Rutledge, S.R. (2021). The impact of hurricanes on the value of commercial real estate. *Business Economics*, 56, 129-145.

- [11] Giglio, S., Kelly, B. & Stroebe, J. (2021). Climate Finance. *Annual Review of Financial Economics*, 13, 15-36.
- [12] Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254-277.
- [13] Hong, H., Karolyi, G.A., & Scheinkman, J.A. (2020). Climate Finance, *Review of Financial Studies*, 33(3), 1011-1023.
- [14] Huang, Q., Li, Y., Lin, M., & McBrayer, G.A. (2022). Natural disasters, risk salience, and corporate ESG disclosure. *Journal of Corporate Finance*, 22, 102152.
- [15] Lucas, R. (1977) Understanding business cycles. *Carnegie-Rochester Conference Series on Public Policy*, 5, 7-29.
- [16] NAREIT (2019). Estimating the size of the commercial real estate market in the U.S. Available at <https://www.reit.com/data-research/research/nareit-research/estimating-size-commercial-real-estate-market-us>.
- [17] NCEI, NOAA (2022). Billion-dollar weather and climate disasters. Available at <https://www.ncdc.noaa.gov/billions>.
- [18] Meltzer, R., Gould Ellen, I., & Li, X. (2021). Localized commercial effects from natural disasters: The case of Hurricane Sandy and New York City', *Regional Science and Urban Economics*, 86, 103608.

# Figures

Figure 1: DID event plots aggregated across all property types

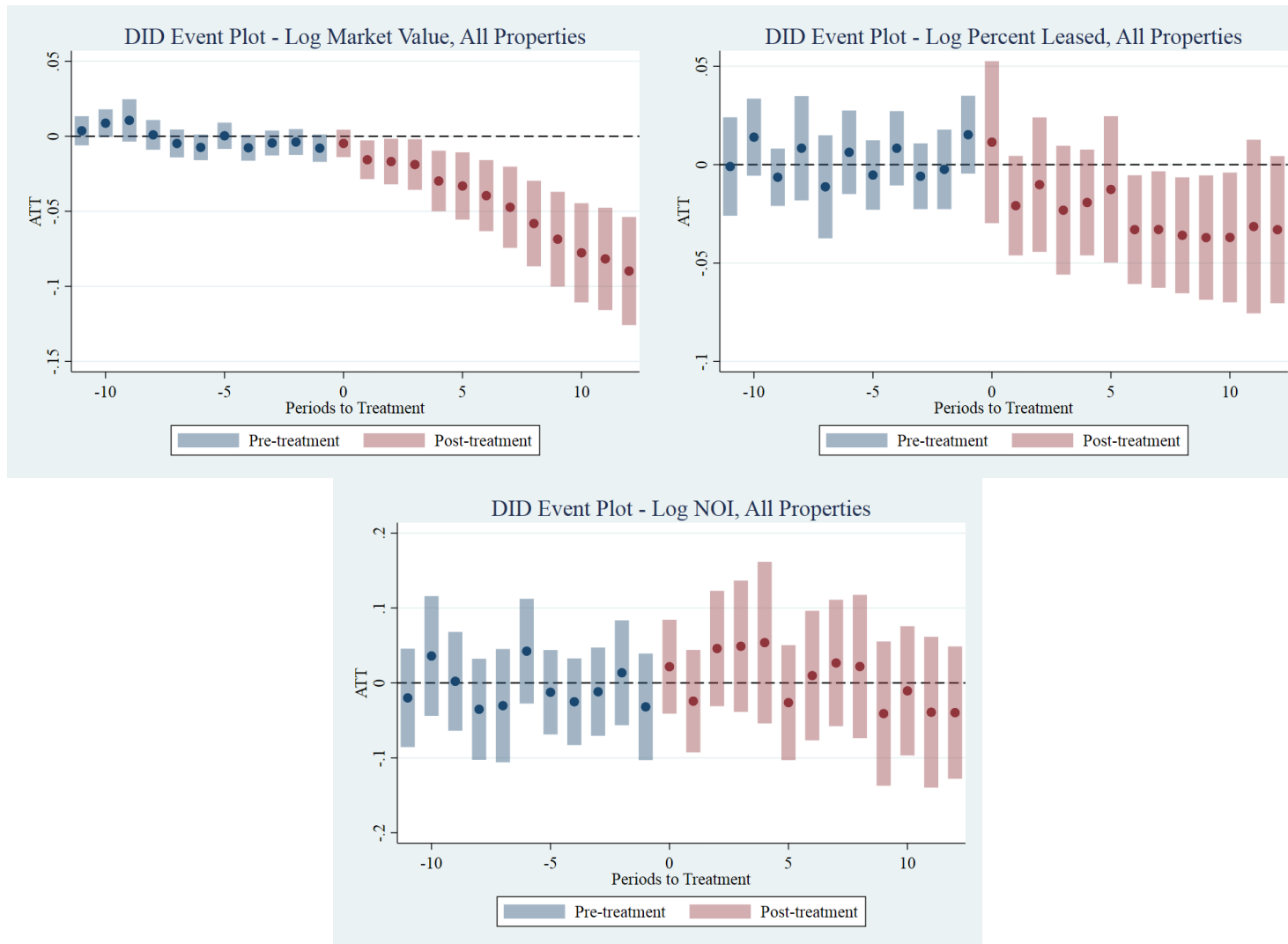




Figure 2: DID event plots for apartment properties estimated across the distribution of diversity

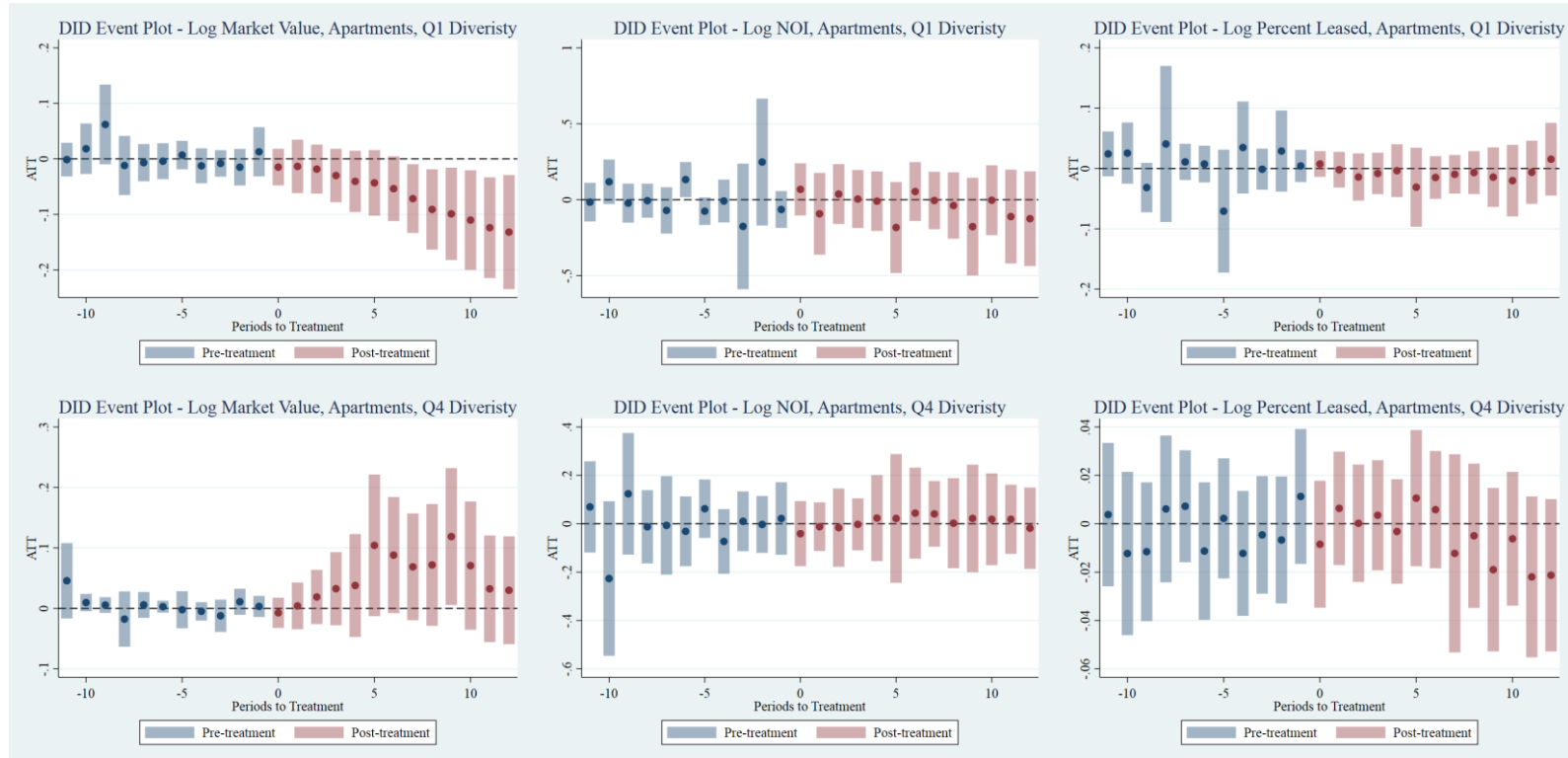


Figure 3: DID event plots for office properties estimated across the distribution of diversity

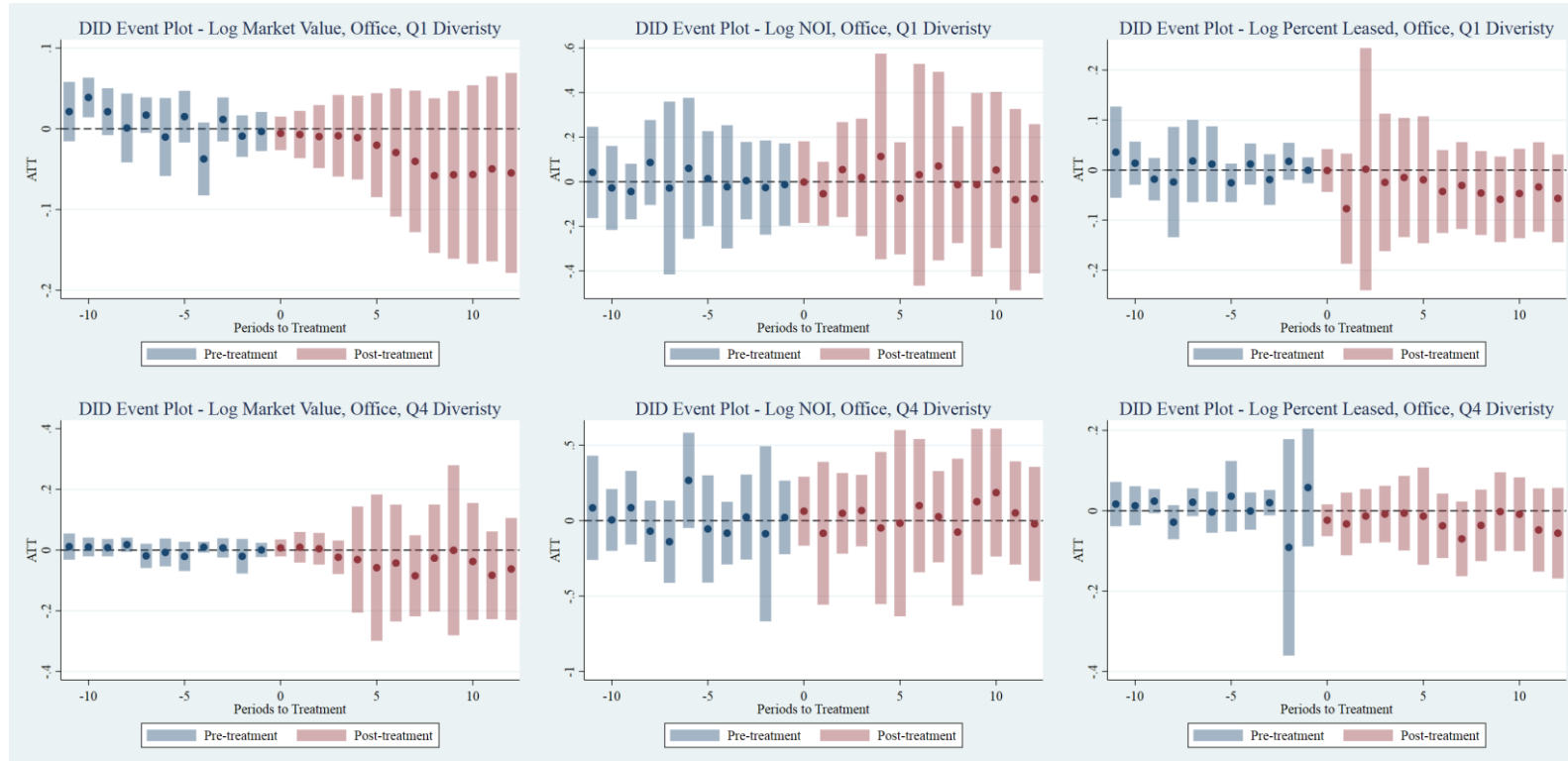


Figure 4: DID event plots for industrial properties estimated across the distribution of diversity

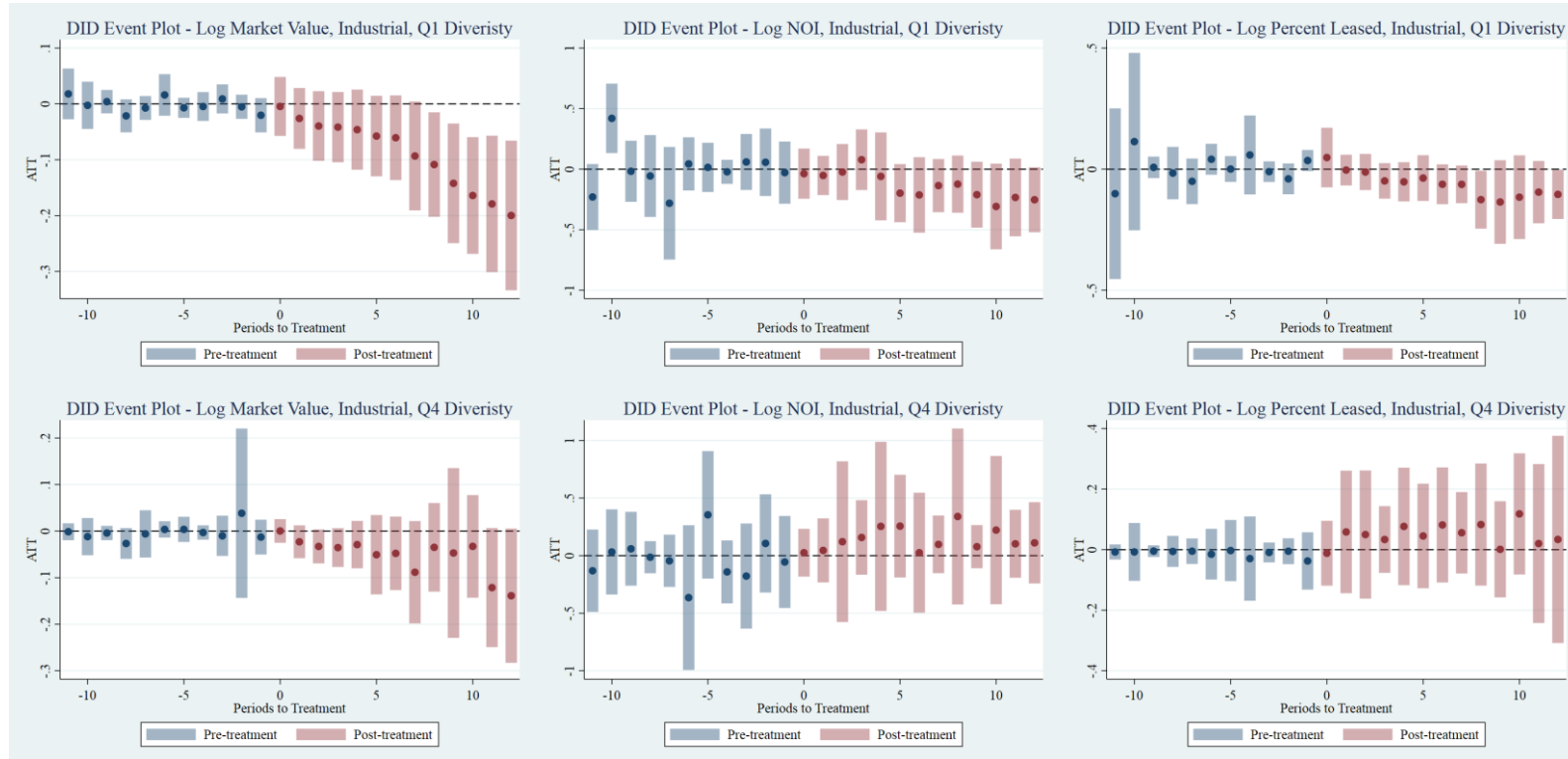
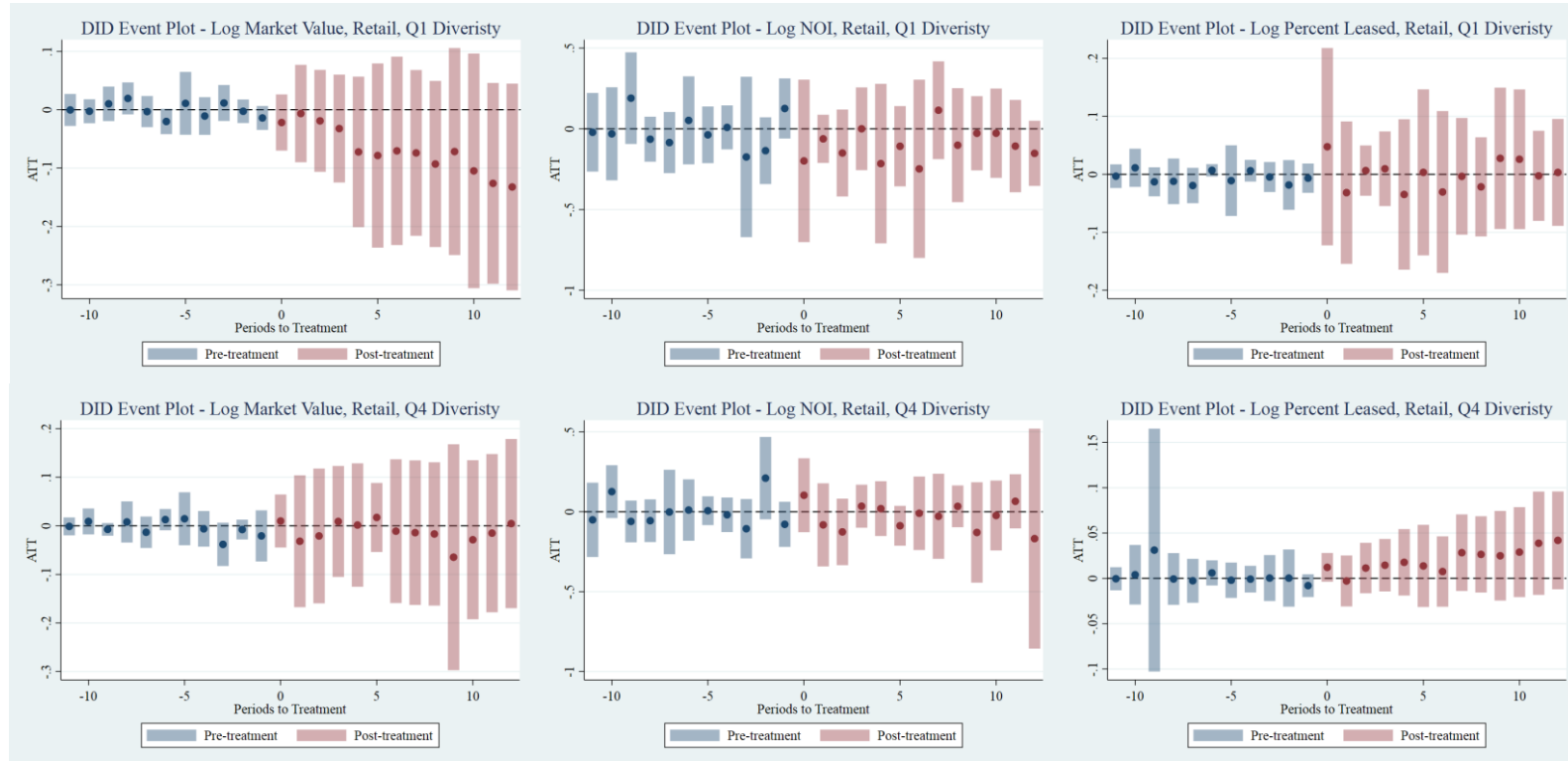


Figure 5: DID event plots for retail properties estimated across the distribution of diversity



# Appendix

Table A1: Summary Statistics

Variable	Treated Properties	Never Treated Properties
ln(Market Value)	17.36 (1.17)	17.52 (1.19)
Percent Leased	.92 (.12)	.93 (.11)
ln(NOI)	13.18 (1.14)	13.23 (1.14)
Diversity	.89 (.04)	.90 (.03)
Square Feet	353,207.90 (658,225.00)	400,849.00 (406,372.10)
Year Built	1988 (16.35)	1988 (12.81)
Number Properties	553	225

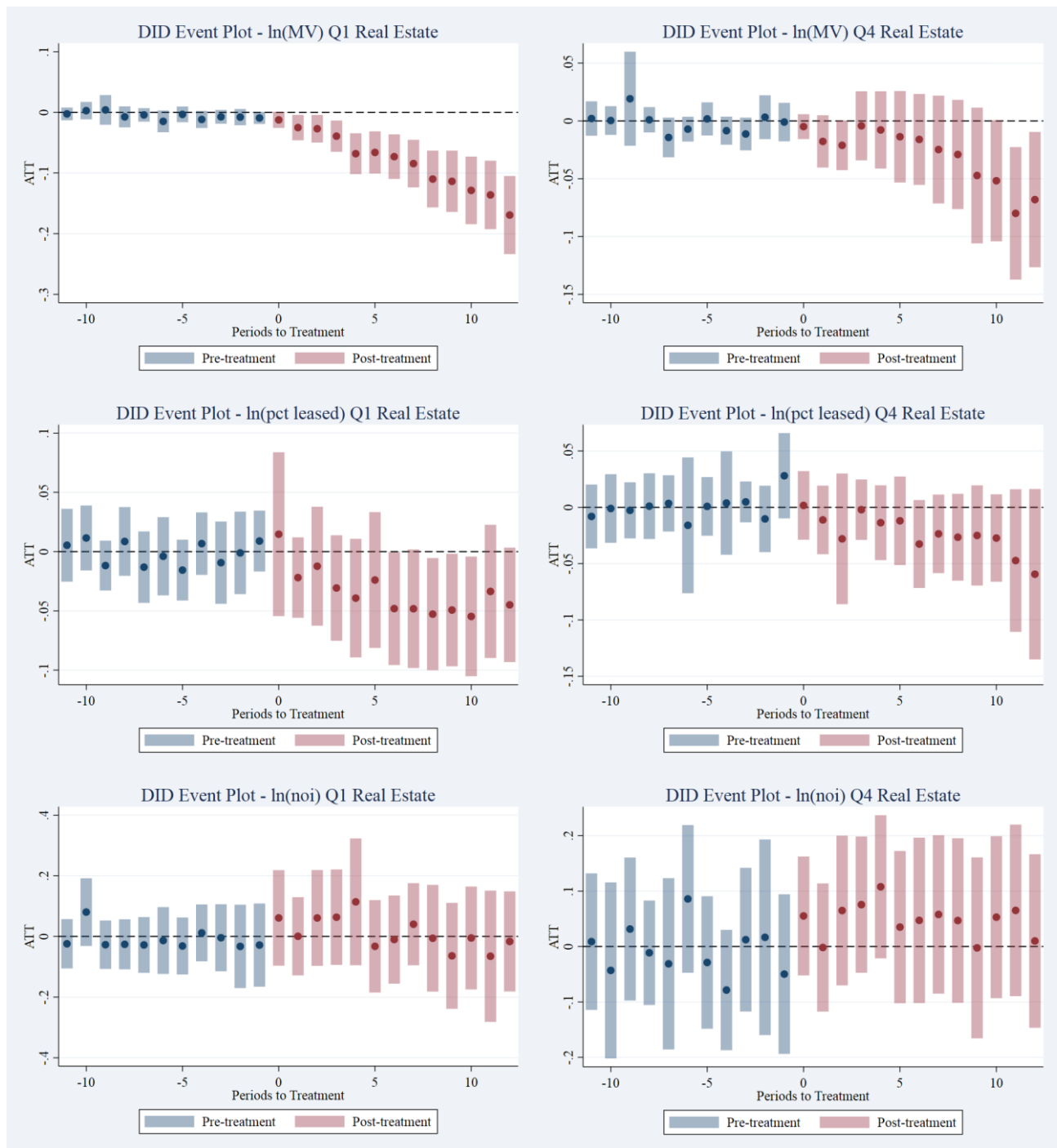


Figure A1: Real Estate and Rental and Leasing

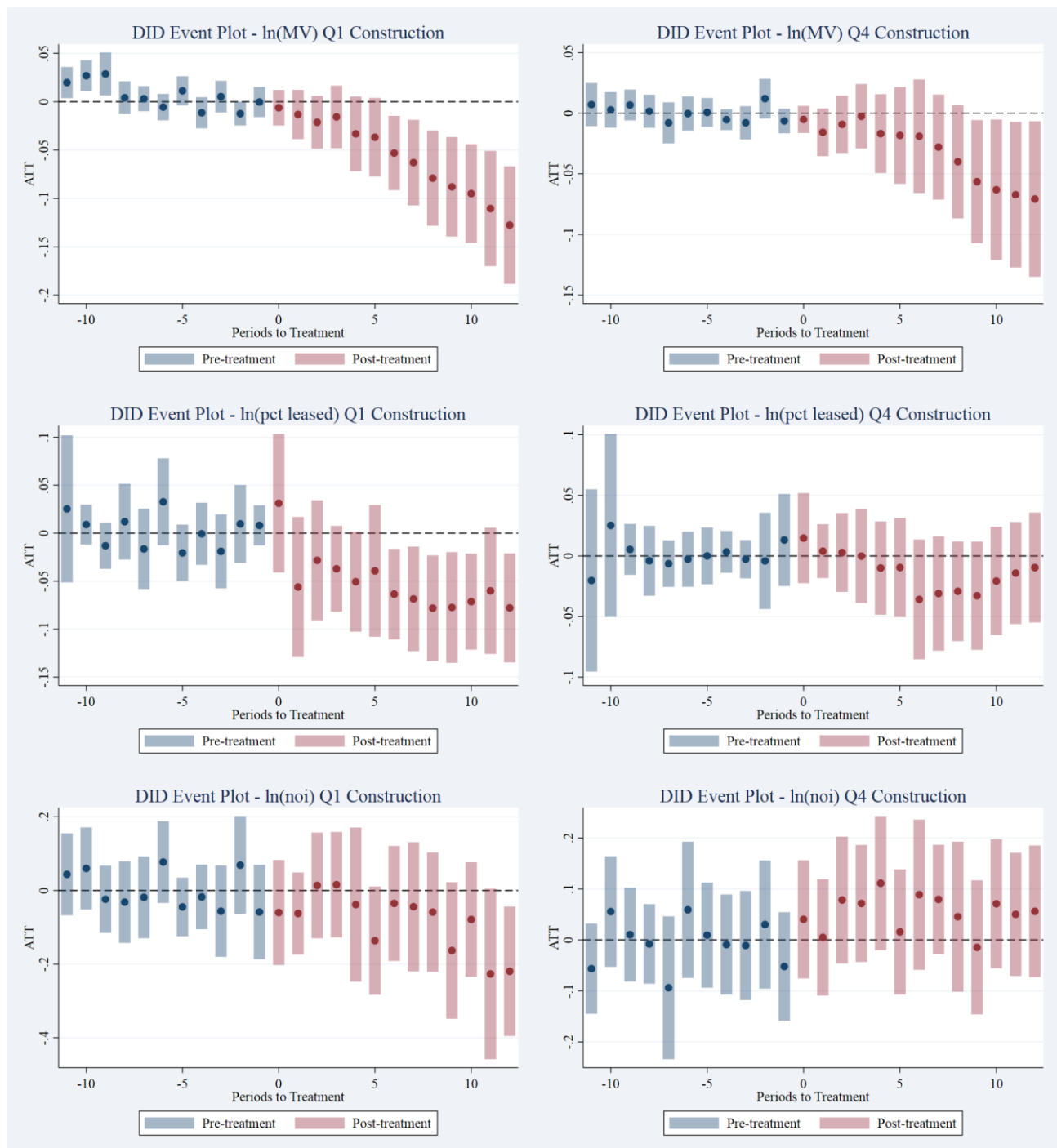


Figure A2: Construction

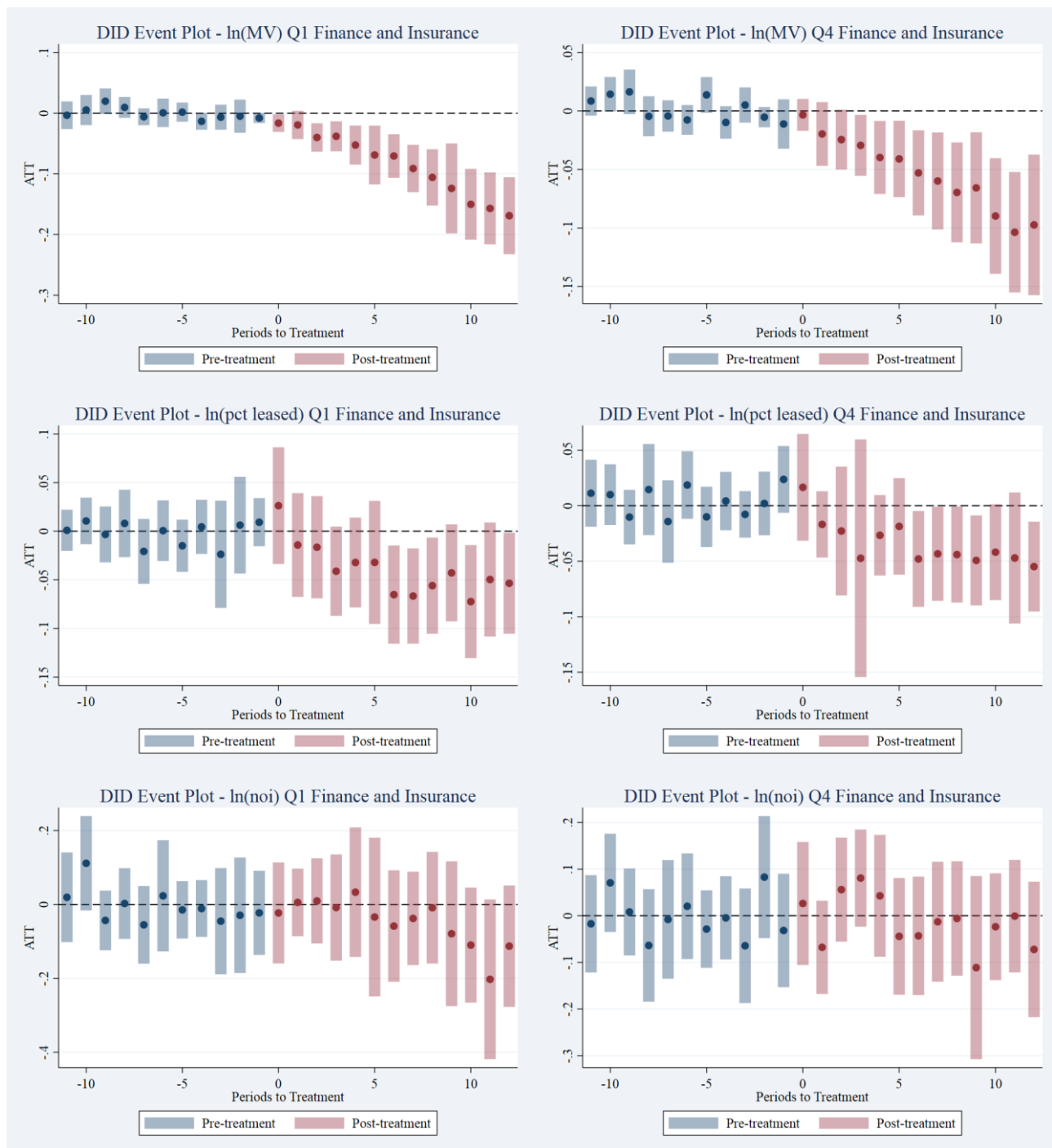


Figure A3: Finance and Insurance



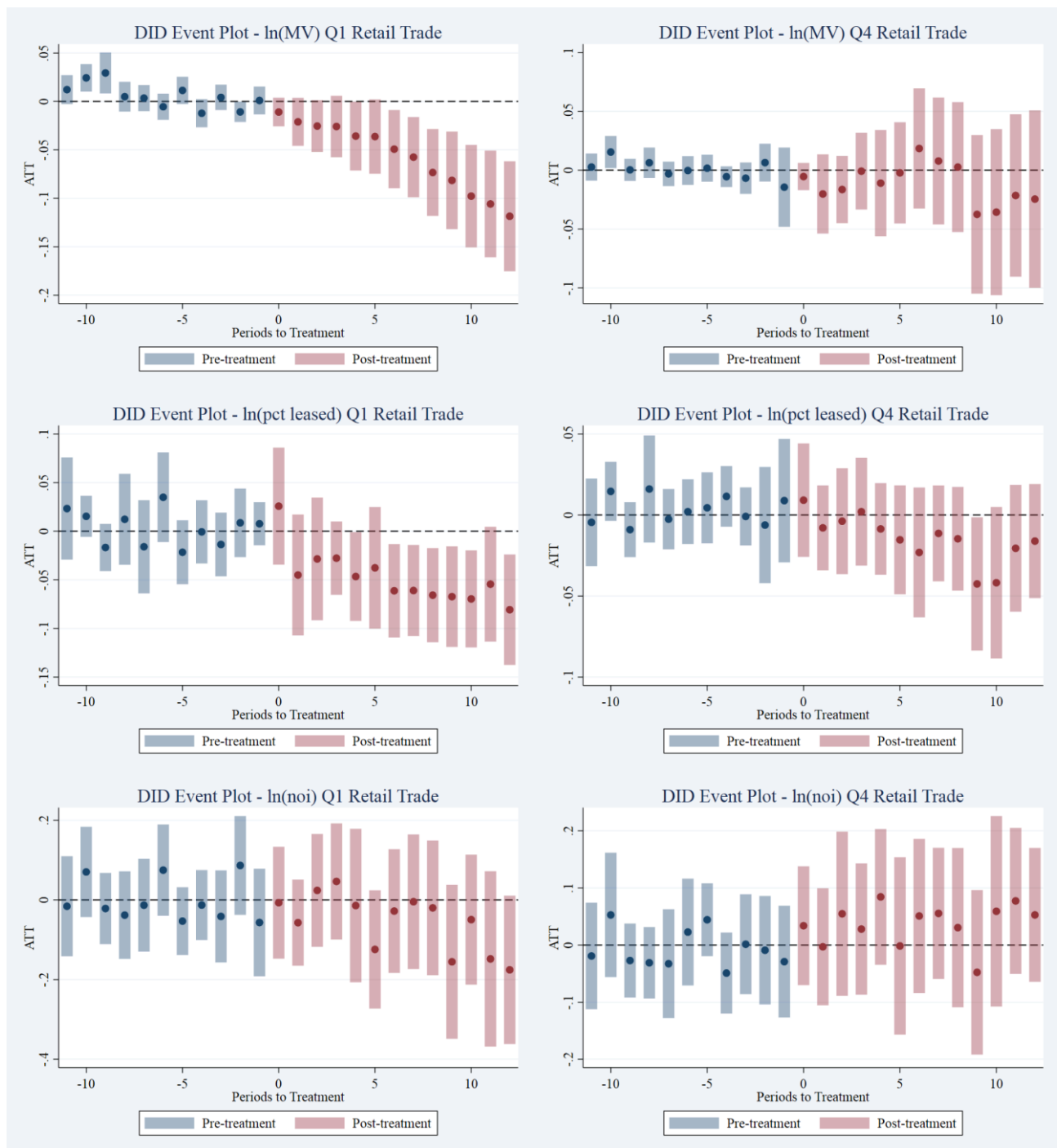


Figure A4: Retail Trade

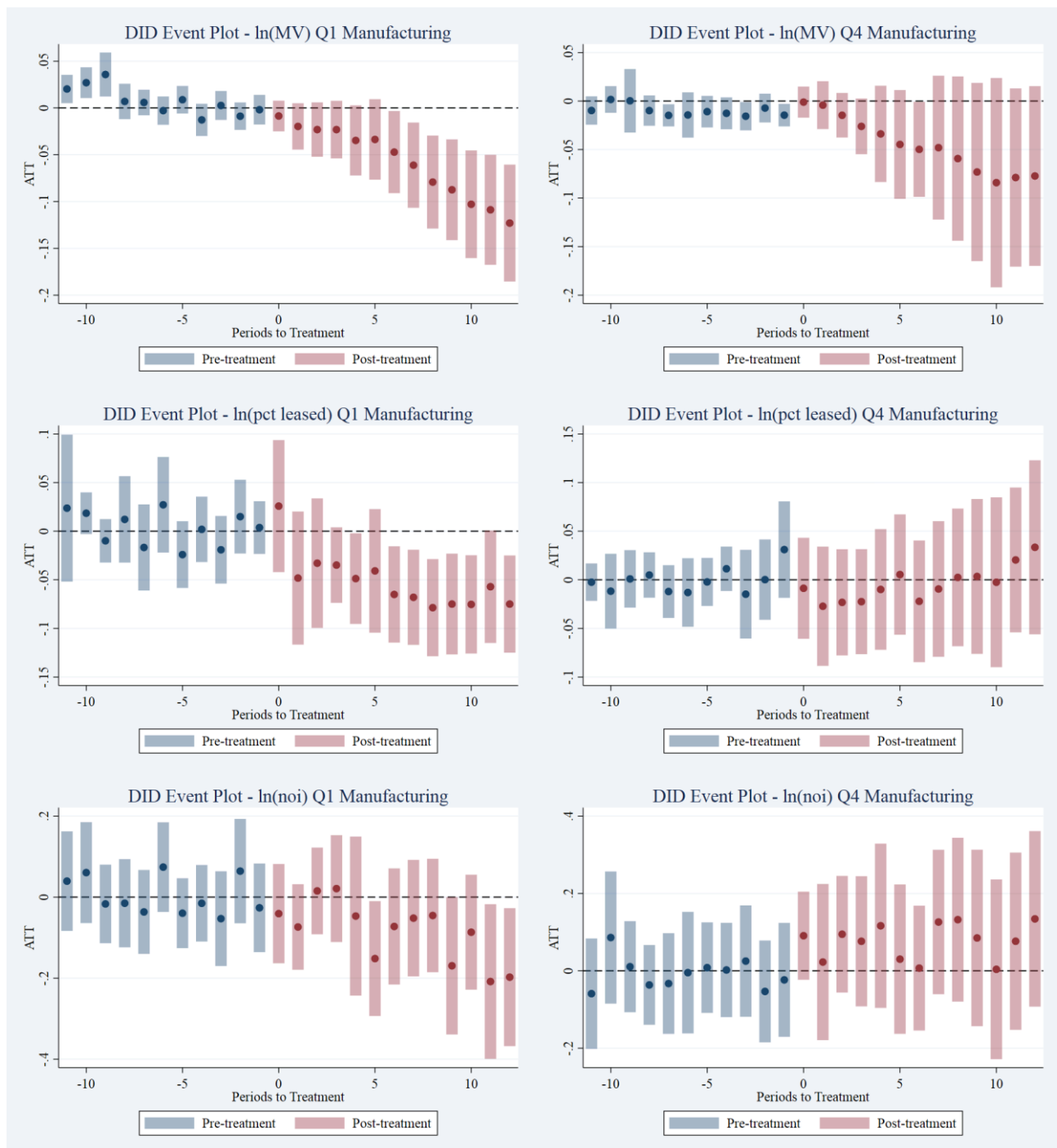


Figure A5: Manufacturing

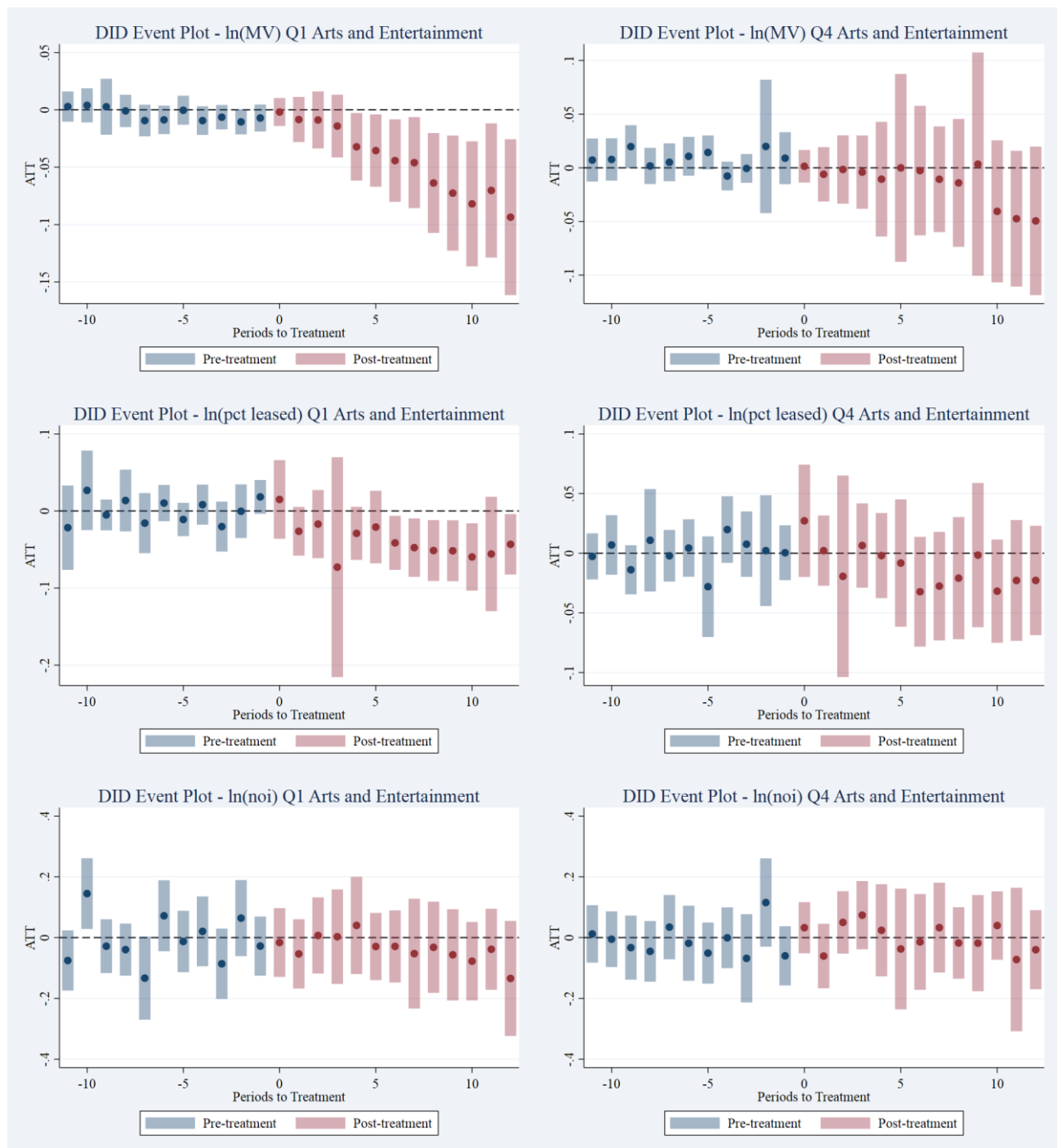


Figure A6: Arts and Entertainment

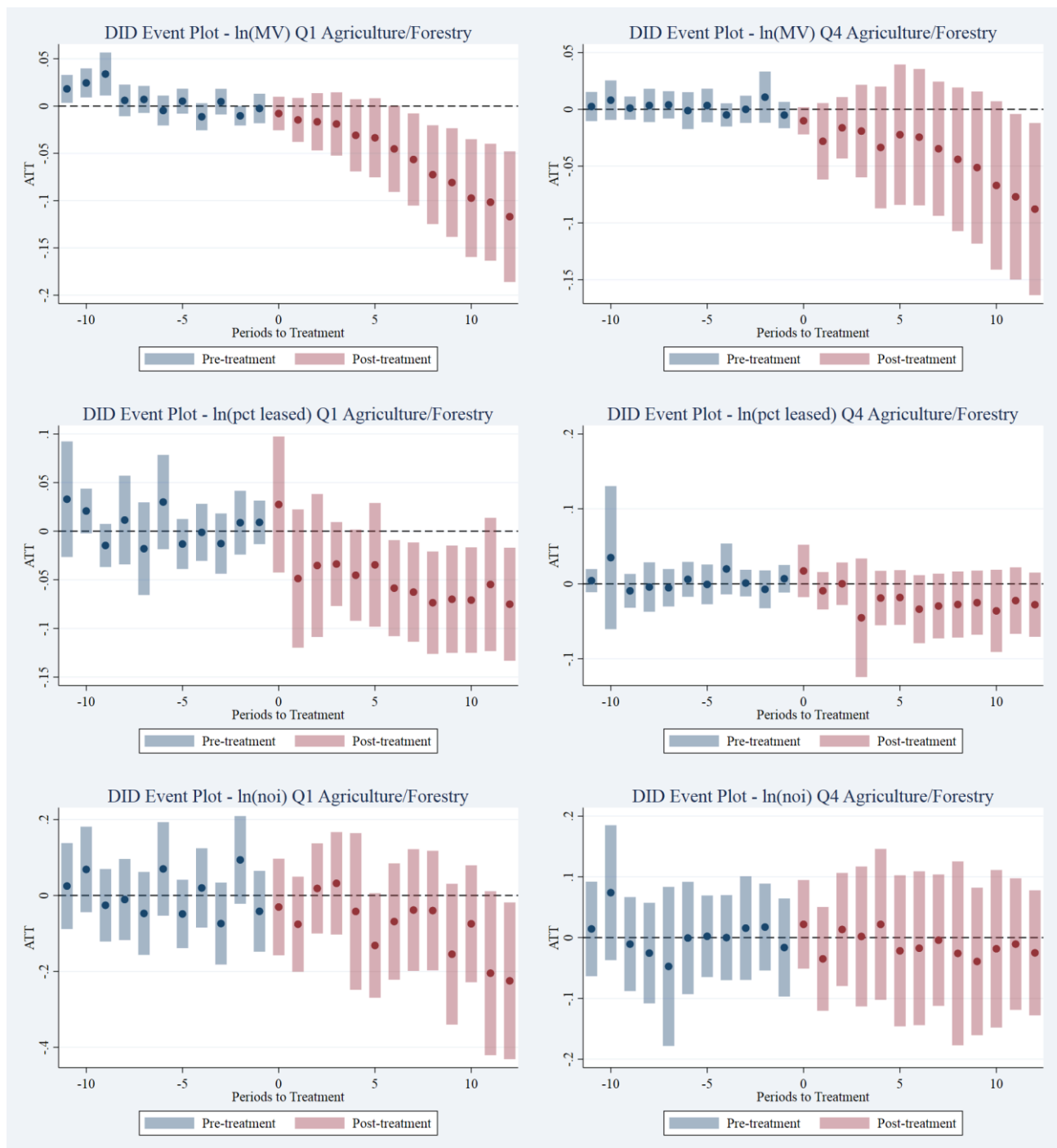


Figure A7: Agriculture, Forestry, Fishing and Hunting

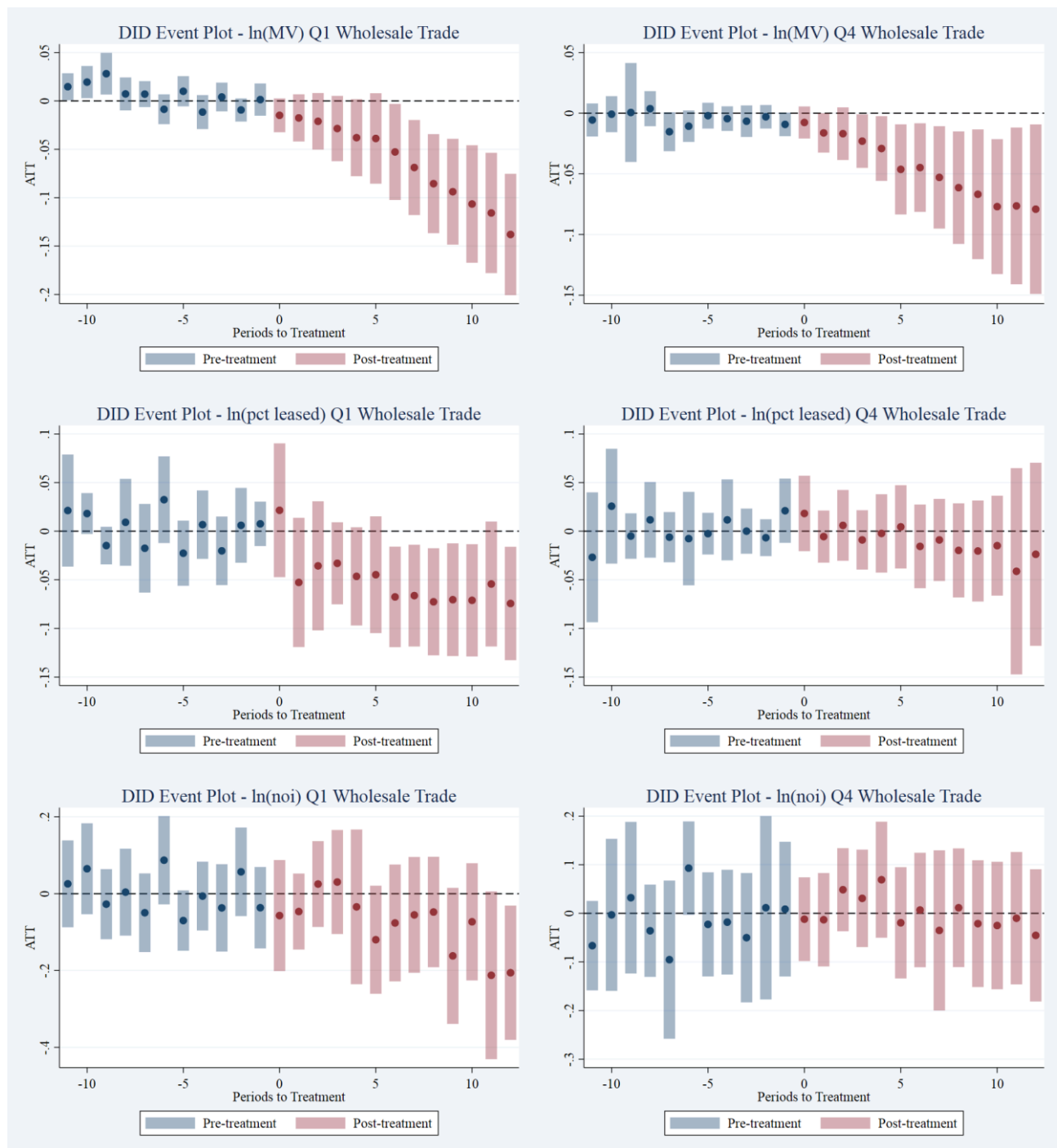


Figure A8: Wholesale Trade

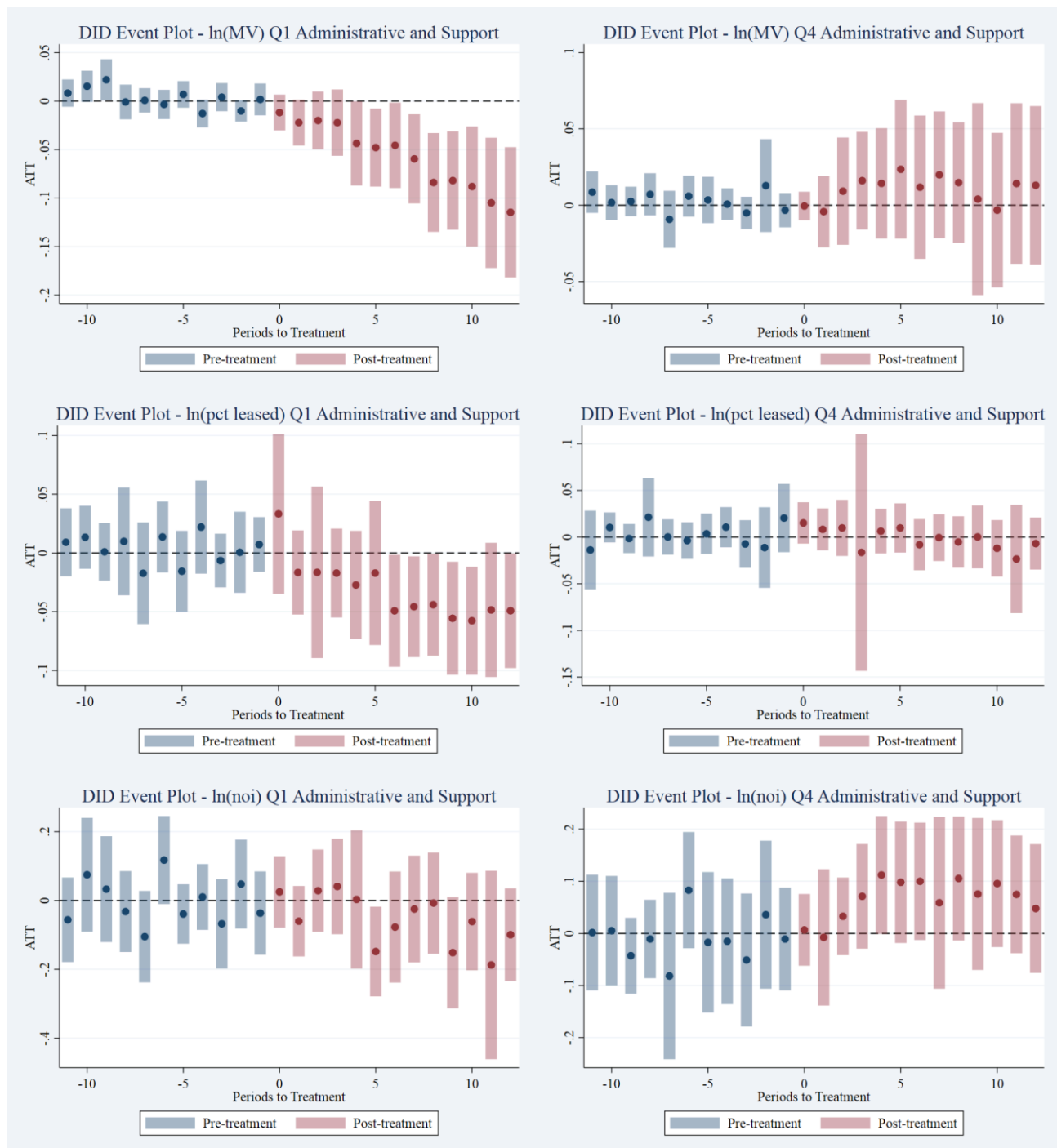


Figure A9: Administrative and Support and Waste Management and Remediation Services

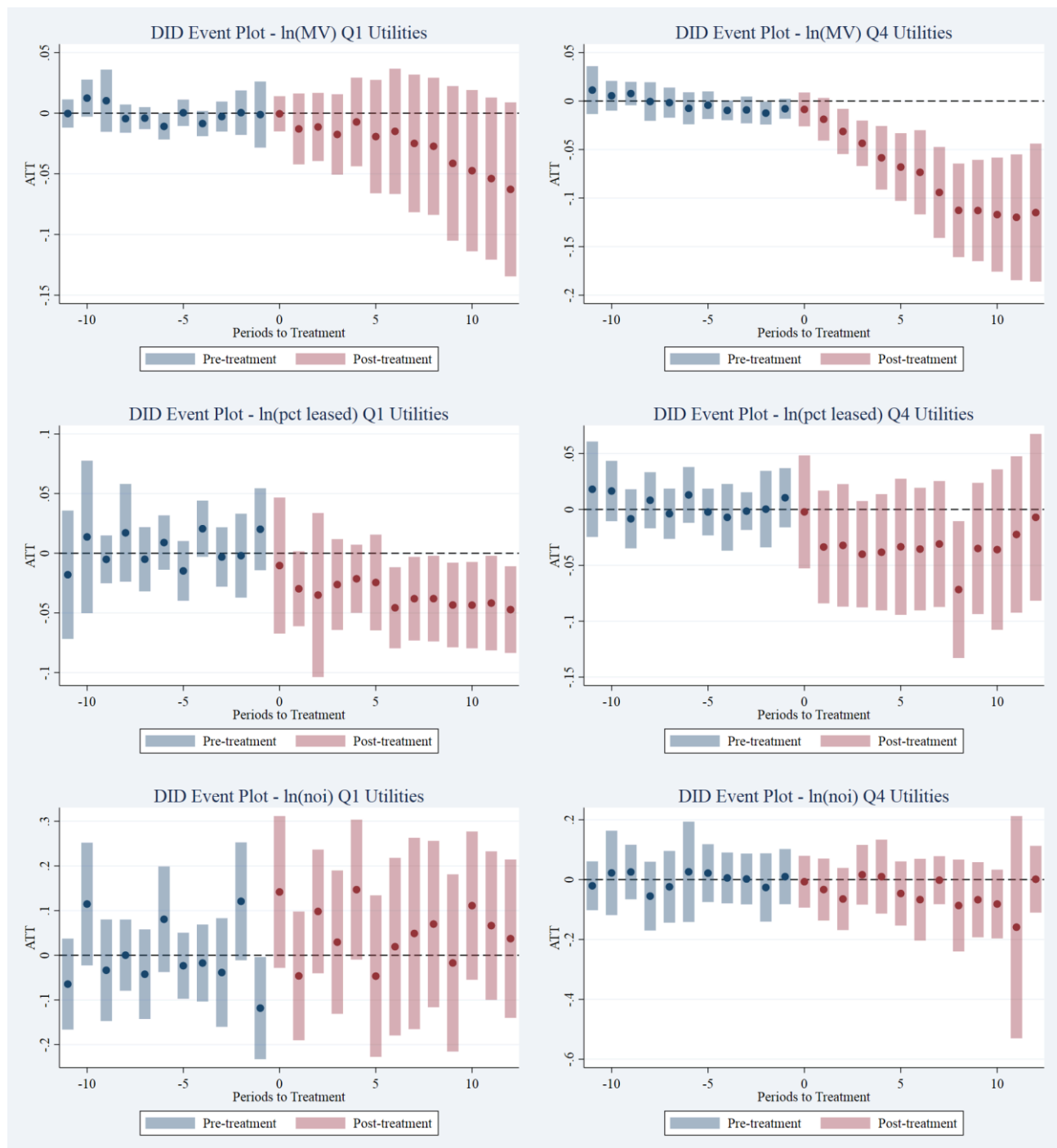


Figure A10: Utilities

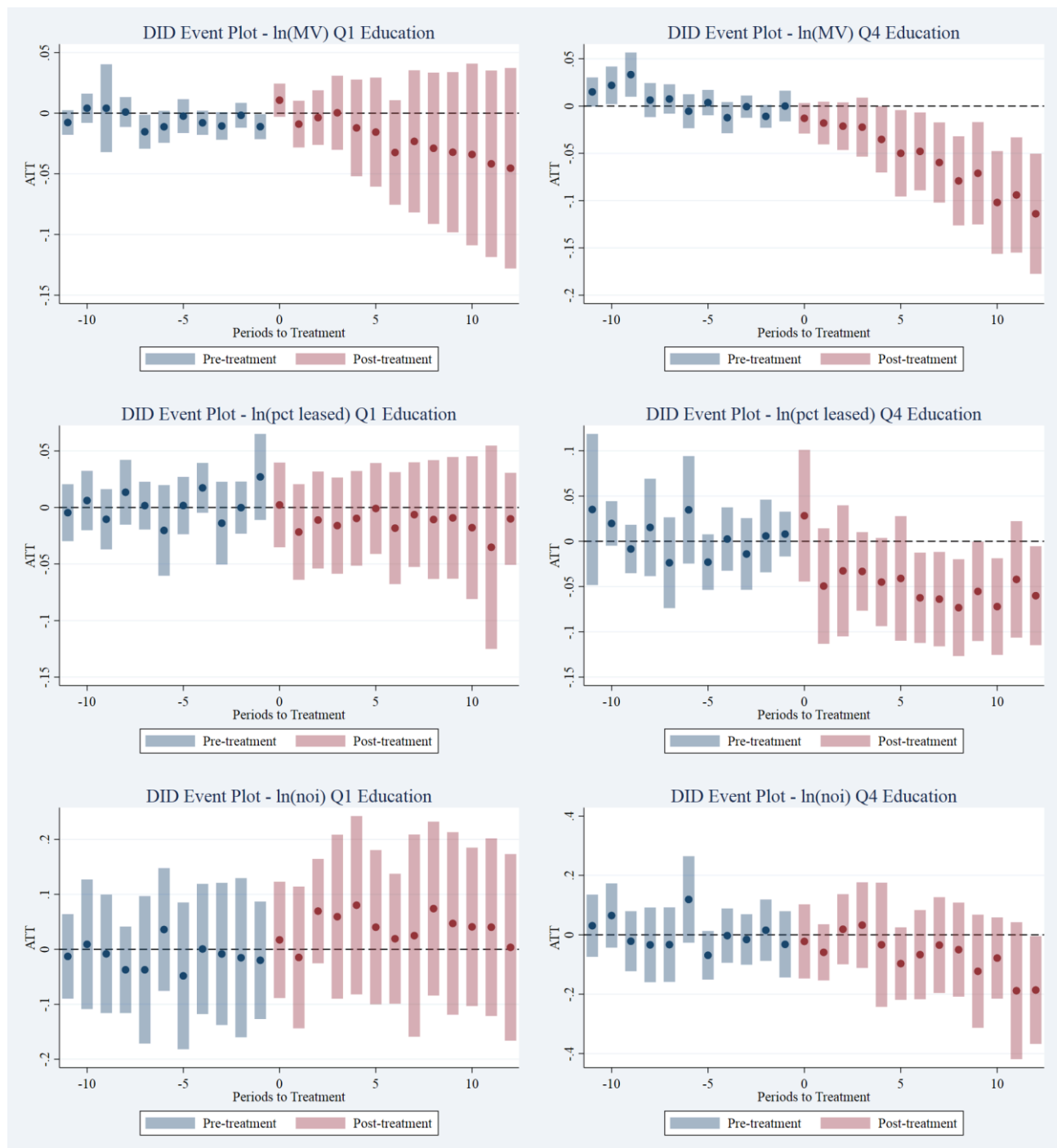


Figure A11: Educational Services



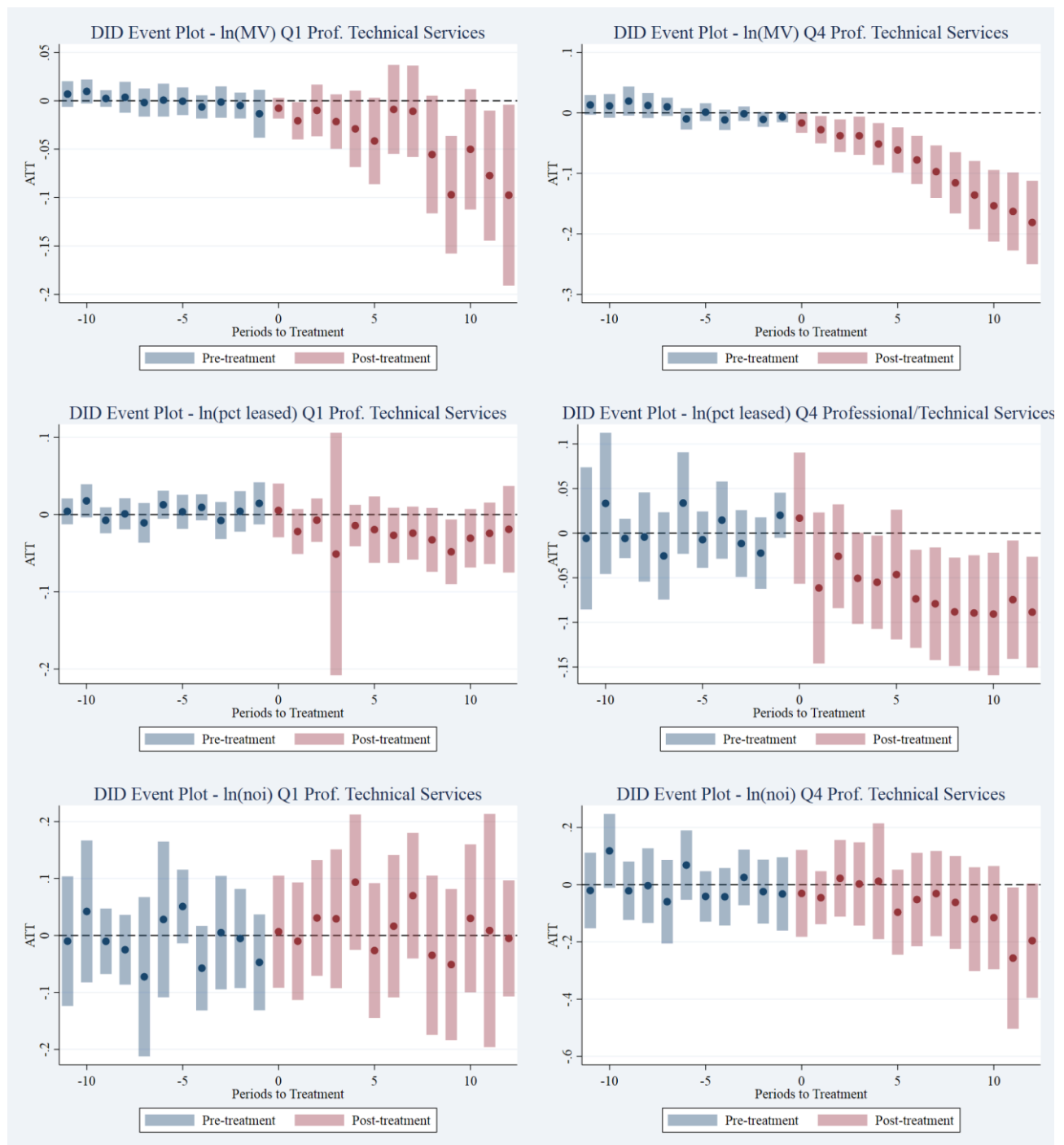


Figure A12: Professional, Scientific, and Technical Services

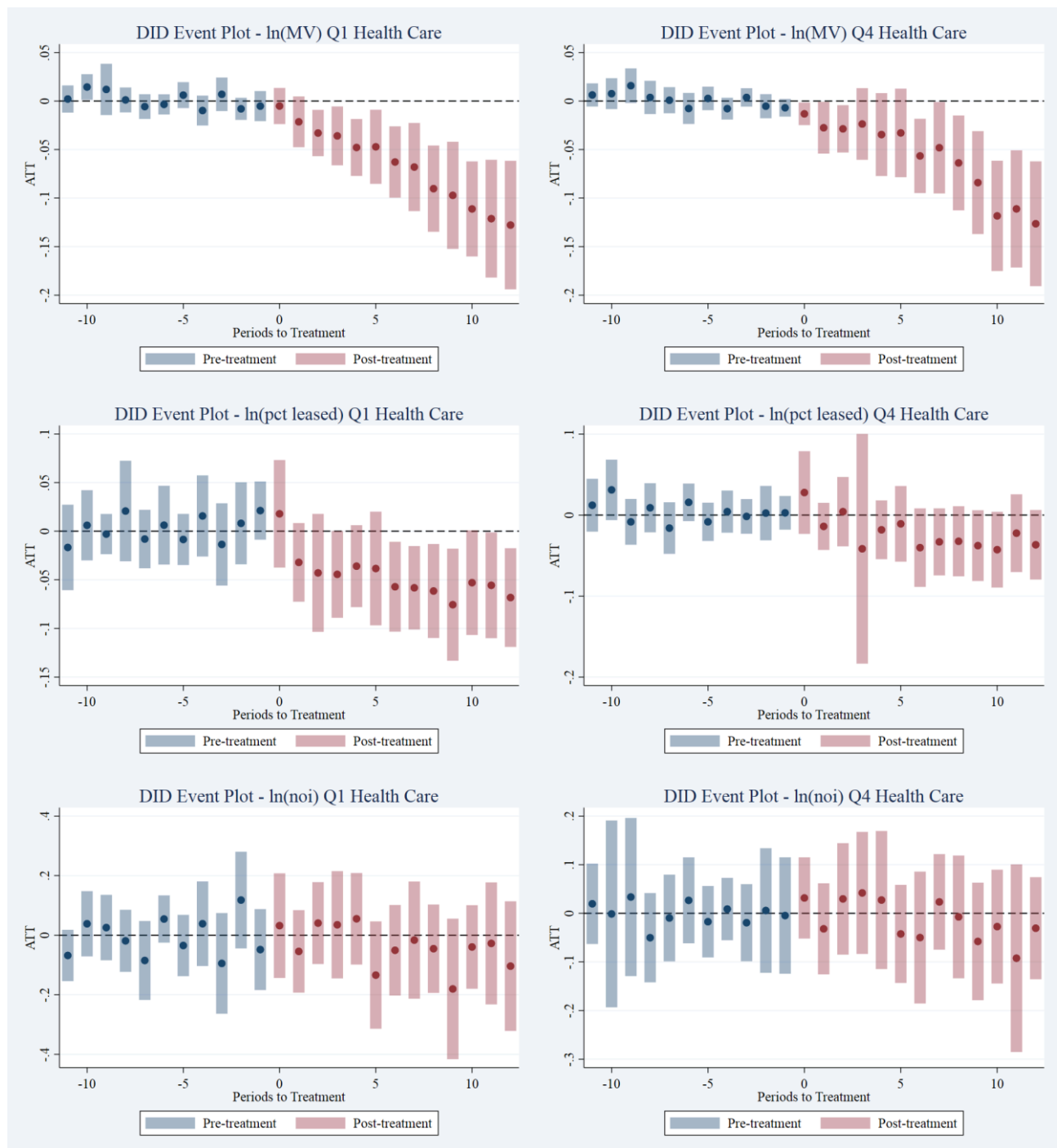


Figure A13: Health Care and Social Assistance

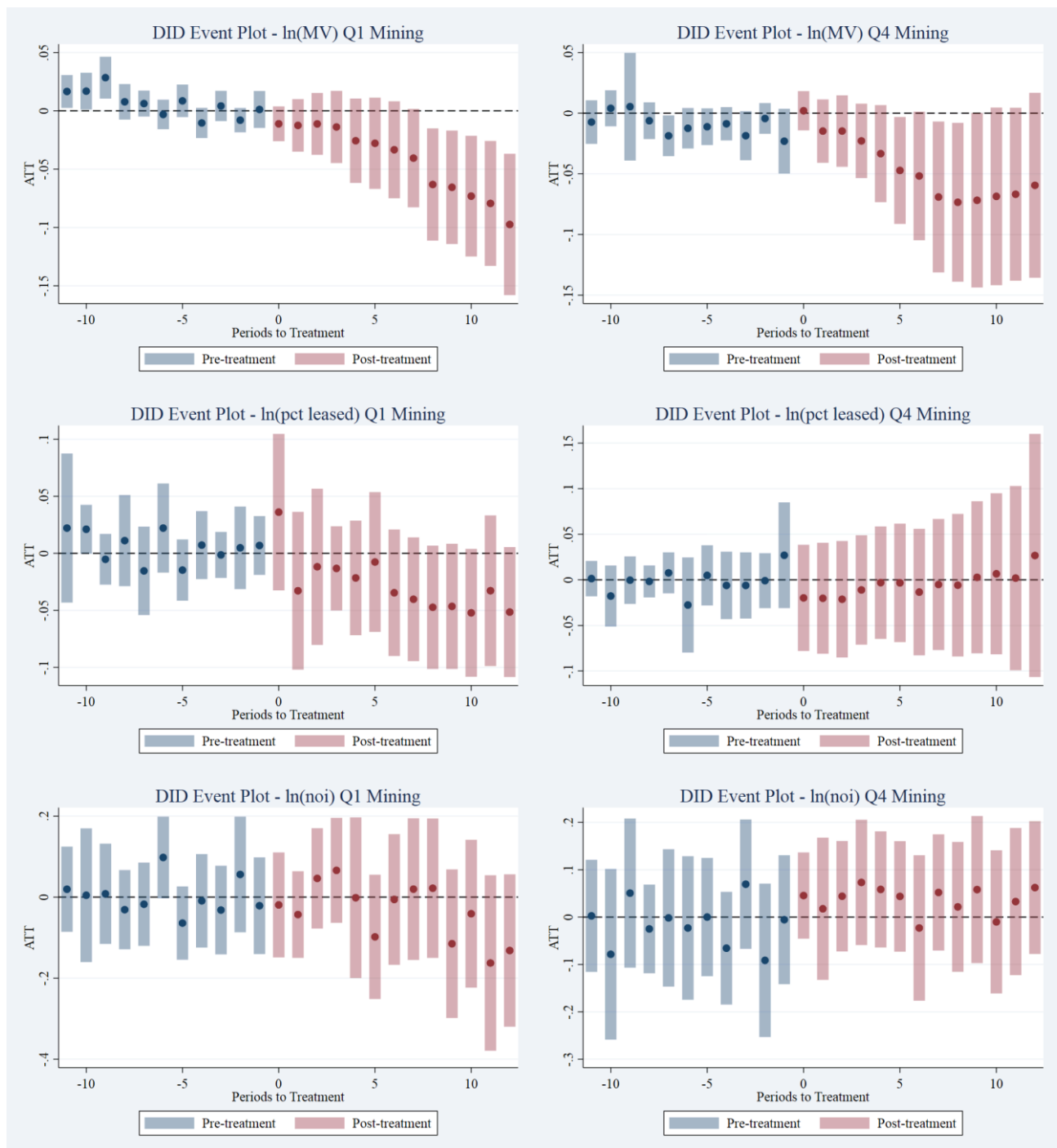


Figure 14: Mining, Quarrying, and Oil and Gas Extraction

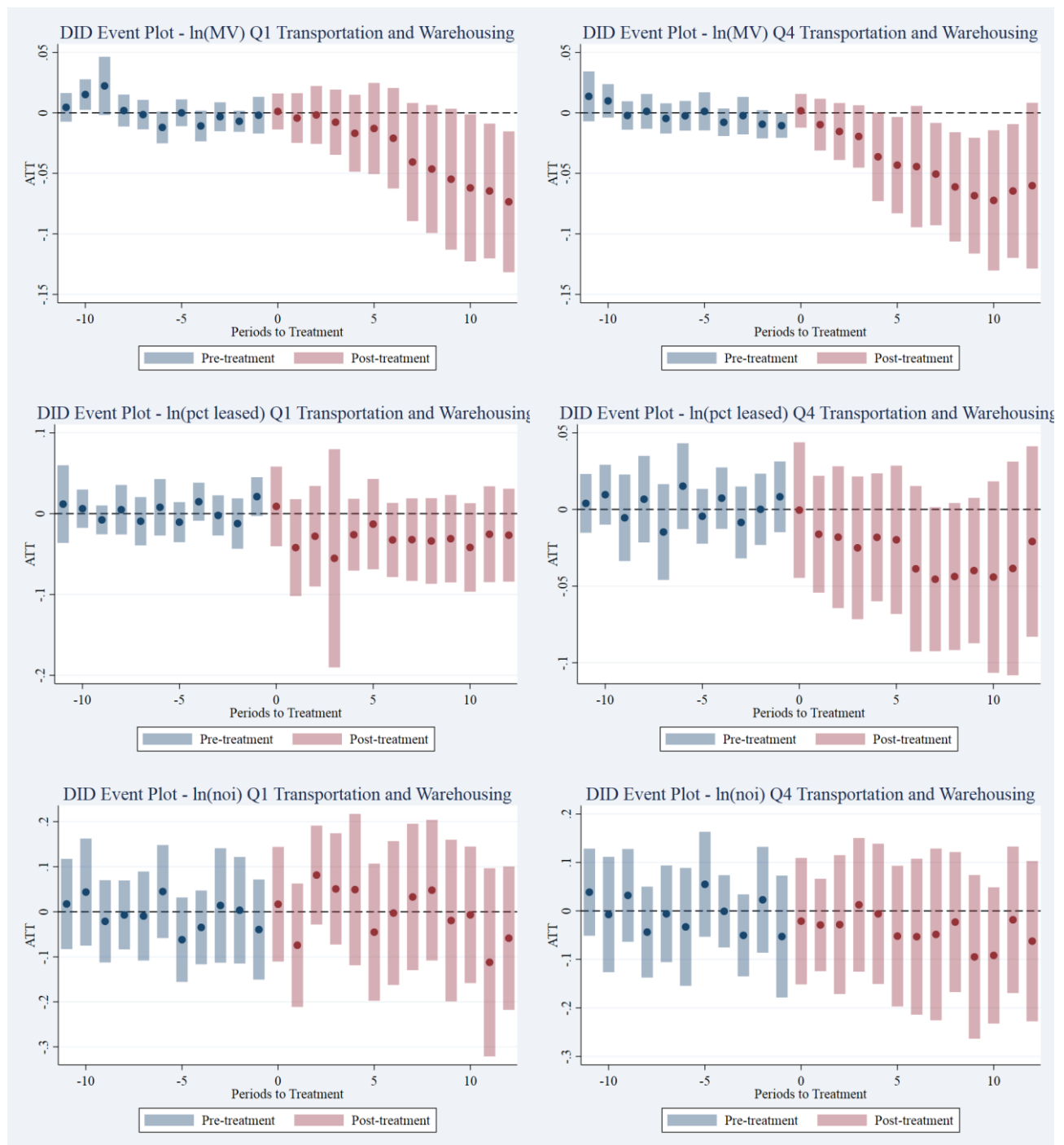


Figure A15: Transportation and Warehousing

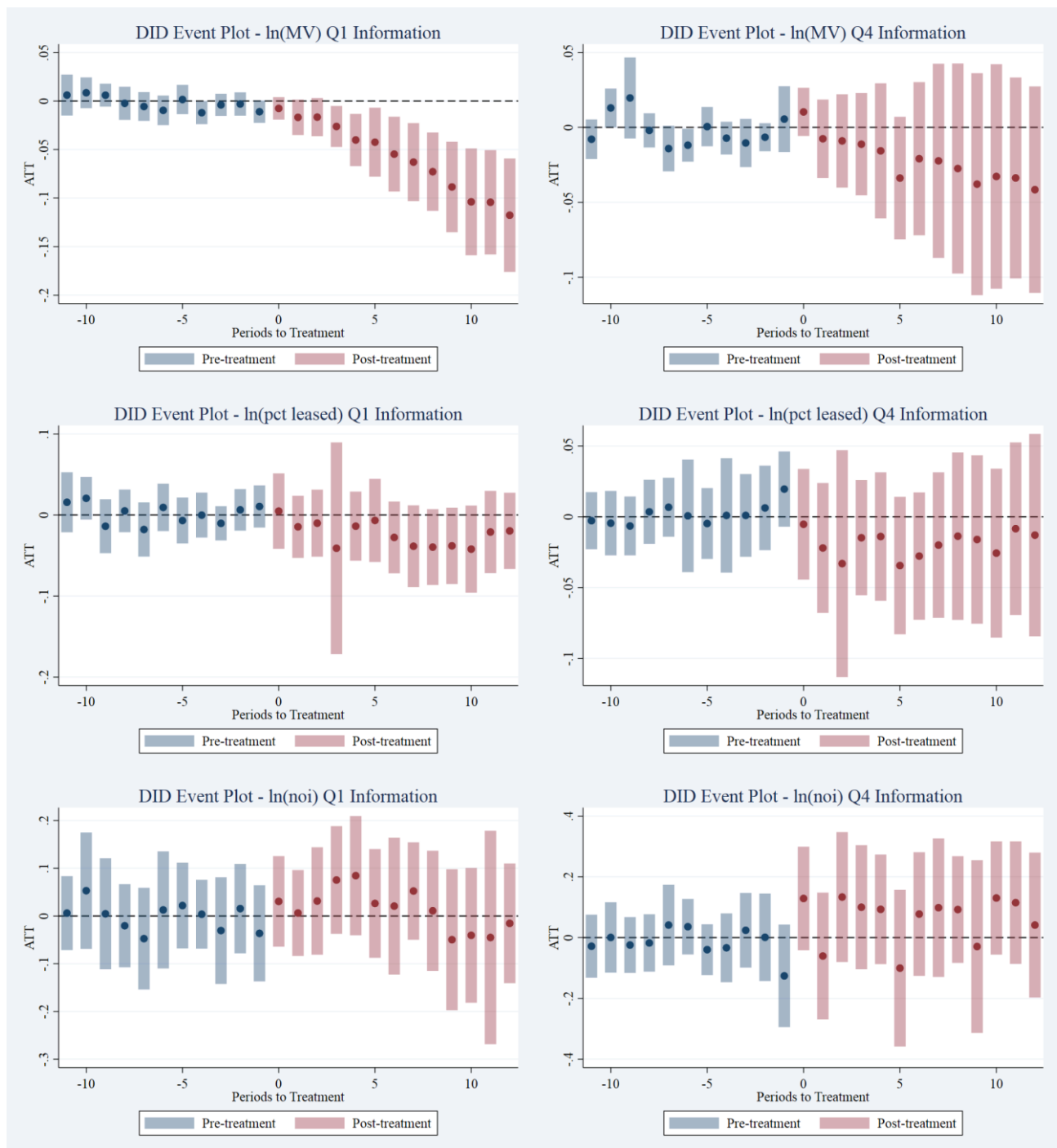


Figure A16: Information

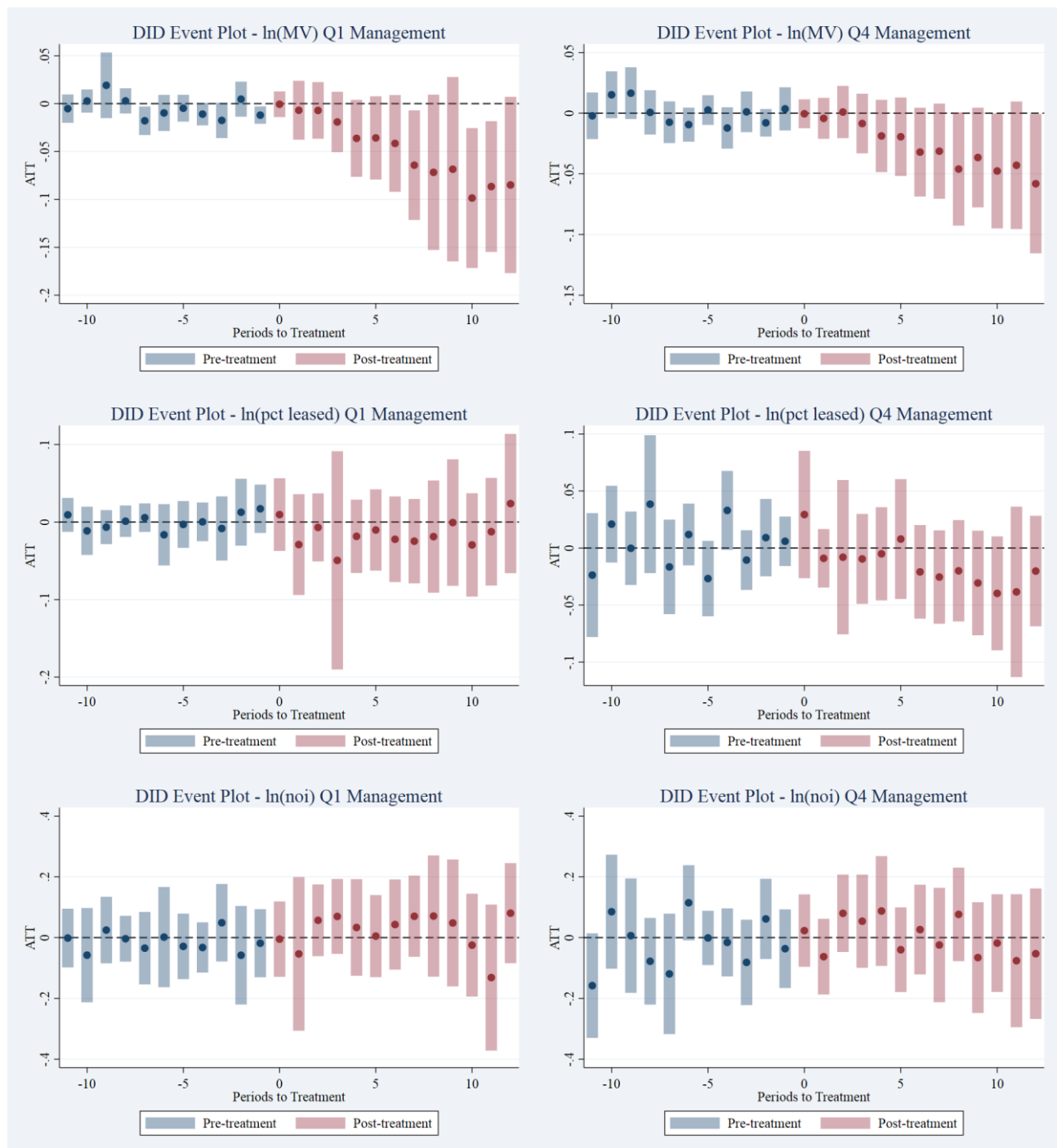


Figure A17: Management of Companies and Enterprises

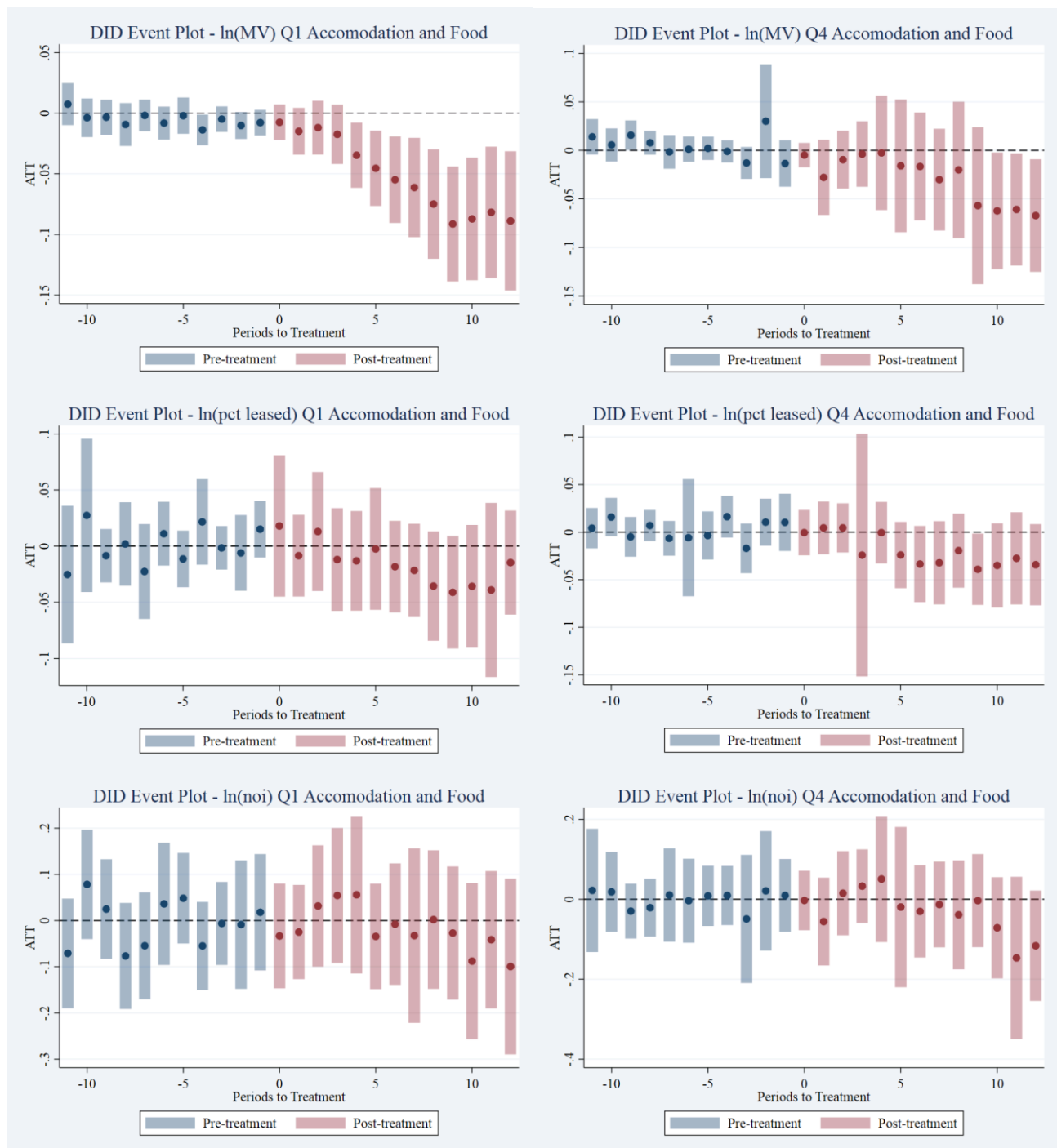


Figure A18: Accommodation and Food

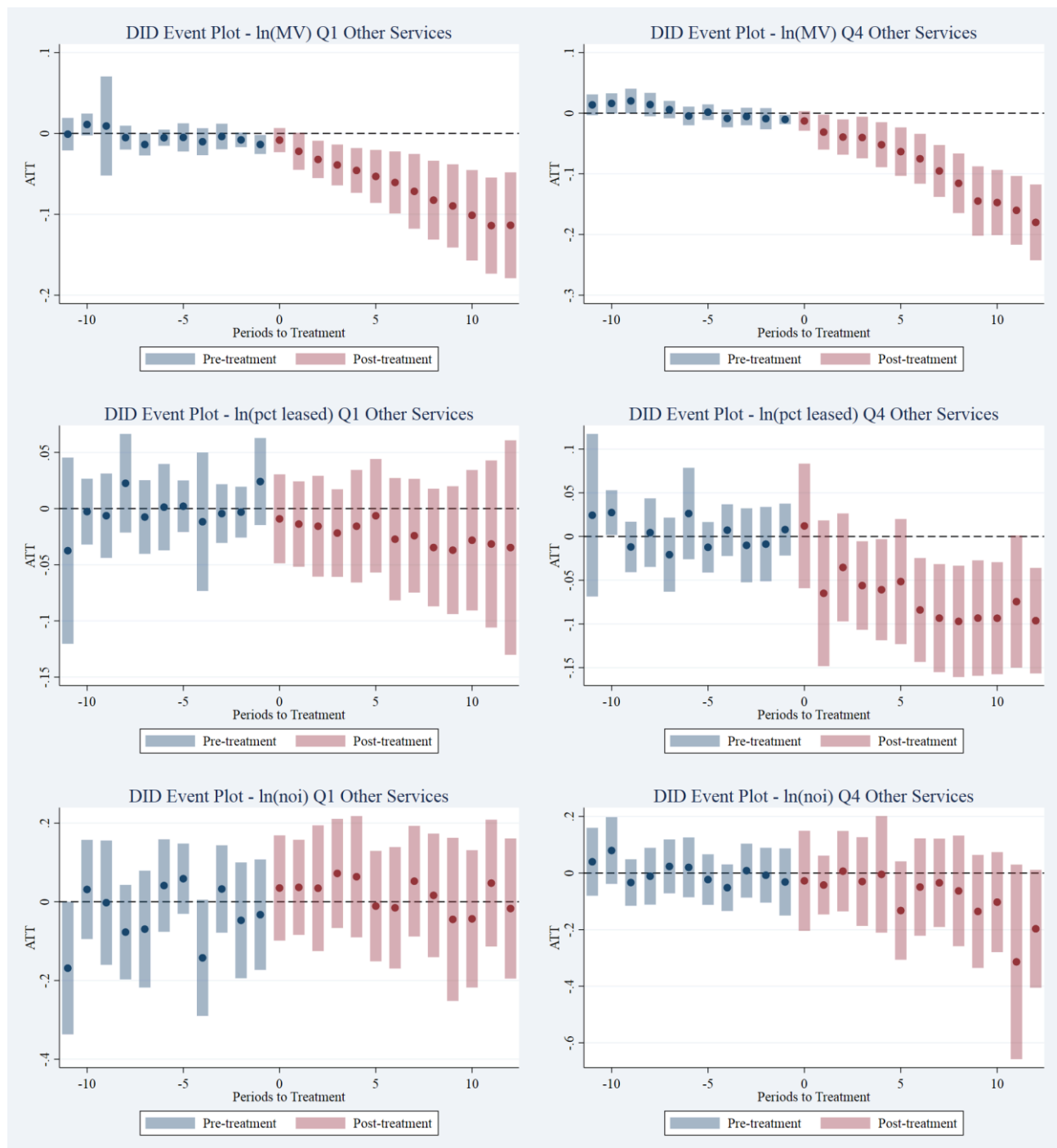


Figure A19: Other Services