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From AEC to NRC:

A Paradigm Shift in U.S. Nuclear Energy Regulation and its Consequences for the Industry

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Abstract: Concerns over energy security and climate change are pushing countries to reconsider their stances on nuclear energy and plan new buildouts. The success of nuclear energy has historically varied greatly, depending to a great extent on the legal and regulatory environment. With the view that discerning which theory of regulatory impact is operative in the nuclear industry is important in developing an understanding of how the industry will behave in different regulatory contexts, this paper aims to ascertain the effect that the replacement of the Atomic Energy Commission by the Nuclear Regulatory Commission had on the U.S. nuclear industry. This is done by measuring the difference in log Tobin's Q and operating profit margins after depreciation before vs after the change of regulator, using data from the years 1966 through 1977. Both difference-in-differences and demeaned synthetic control methods are employed. The effect on log Tobin's Q is found to be either null or negative while a functioning model for operating margins cannot be identified with the data and methods used. The Granger test indicates some possibility of treatment anticipation but running the difference-in-differences model with earlier treatment years reveals that this is unlikely to account for the Granger test results.

Keywords: Regulation, nuclear energy, energy economics, industrial organization, synthetic control

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Introduction and Background

The objective of this thesis is to gain insight into how the U.S. nuclear industry was affected by the dissolution of the Atomic Energy Commission (AEC) and its replacement by the Nuclear Regulatory Commission (NRC) in January 1975. Construction of nuclear power plants slowed down and ground to a halt in the late 1970s, with the last plant to break ground for decades doing so in January 1978. Given this timing, the potential effects of the new regulator ought to be considered. While some theories of regulation imply that a regulatory intervention of this kind is likely to harm firms in the industry, others imply that incumbent firms could benefit under certain conditions. To establish which theory is most applicable in this context, I use two different methods, difference-in-differences and demeaned synthetic control, to track the log Tobin's Q and operating profit margins after depreciation of firms in the industry before and after the establishment of the NRC. These metrics have been used by Bessen (2016) as they can be a good proxy for sustained extraction of economic rents.

This subject is increasingly relevant in our time as, over the past several years, concern regarding climate change, and most recently the energy crisis, have caused many countries to reconsider their stances on nuclear energy. The French senate is evaluating a proposal to eliminate the existing mandate to reduce the country's proportion of nuclear in the electricity mix to 50% by 2035. South Korea recently elected a new president who has reversed the nuclear phaseout policy of the previous administration. Similarly, the British Energy Security Strategy now states that their government will scope and set up a new flagship body, Great British Nuclear (GBN), to enable nuclear projects and support the UK's nuclear industry. Countries with no existing power reactors, such as Poland, Uzbekistan, and Saudi Arabia, are now seeking to build them.

However, those seeking to develop nuclear energy, be they in the public or private sector, can only succeed if they are able to meet the requirements posed by the relevant regulatory and legal institutions. The prospect of an increasingly central role for nuclear energy in the world's electricity infrastructure highlights the importance of the quality of these institutions. If they are of high quality, they will ensure that plant designs and operational practices are sound, but also that nuclear does not become artificially costly relative to other energy technologies and that innovation is not deterred by excessively high entry costs. Failure to meet the latter two conditions may mean that companies in the nuclear industry pursue regulatory rents at the expense of expanding and developing nuclear energy technologies (Barrett, 1991; Brock and Evans, 1986; Porter, 1980, 1990).

Over the course of the past half century, overnight construction costs and construction times for nuclear power plants have risen substantially in many countries (Lovering, Yip, and Nordhaus, 2016; Lang, 2017). Correspondingly, the number of plants under construction in the West is now far lower than in the 1970s or '80s. In the United States, only one nuclear power plant currently commercially operating began construction after 1978 or began its initial licensing process after the establishment of the NRC in 1975. The establishment of the NRC constituted a significant event in the history of nuclear energy in the U.S. While its predecessor agency, the AEC, had been assigned a dual mandate, to promote and regulate the use of nuclear energy, the NRC was tasked by congress with the single mandate of regulation, as the previous arrangement was thought to be a conflict of interest. American companies involved in the industry have, by now, had to contend with little organic demand growth for an extended period of time. Given this state of affairs, the ways in which the regulatory environment affects firms in the industry is worth understanding.

Review of Literature

Numerous mechanisms have been proposed and discussed in the literature for how environmental regulation may affect new firm entry, much of which would make sense in the context of safety regulation as well. Some of these incentivize new entry while others deter it. Examples of the former include regulatory exclusions, asymmetries in enforcement, asymmetries in the actions of environmental groups, demand growth in pollution abatement equipment industries, and large firm divestiture of liability-generating activities. Examples of the latter include productive and administrative economies of compliance, learning curve impacts due to regulatory complexities, difficulties in siting and permitting new operations, and new/incumbent regulatory tiering (Dean and Brown, 1995). The authors find that the net effect appears to be in favor of entry deterrence.

It is important to note that greater entry of new firms into the nuclear energy space does not necessarily contribute to more innovation or more deployment of nuclear energy, for instance in the case of entry driven by greater demand for equipment or services mandated by additional regulation. There is also reason to expect that the extent of entry driven by additional demand for equipment and services of this kind may be minimal given certain assumptions. Utilities operating nuclear power plants cannot avoid the purchase of equipment and services, short of retiring their plants, if they are mandated by regulation. This makes demand for such equipment and services inherently inelastic. Because greater inelasticity allows firms to pass a larger proportion of the compliance costs on to consumers, these equipment and service providers should be expected to benefit from barrier-creating regulation more than would firms in industries where demand is more elastic (Carlton and Perloff, 1990). As nuclear power plant (NPP) vendors must compete with vendors of other types of power plants, we should expect demand for new NPPs to be more elastic than demand for mandated parts and services for existing NPPs. If this is the case, NPP vendors in countries that have experienced long periods with no new NPPs build, deriving more of their business from the provision of equipment and services, may benefit more from barrier-creating regulation than vendors in countries where new plants are still built.

The regulatory environment can affect industry dynamism not only through barriers to entry, but also through barriers to success. Maloney and McCormick, (1982) emphasize that it can be in the interest of a firm to encourage regulation of product standards that increase the costs of its rivals. This can hold even if the firm's own costs are increased by the new standards, so long as the impact of cost increases to the industry falls disproportionately on rivals. More precisely, Maloney and McCormick assert that at the original output, a sufficient condition for a strategy to be profitable is that it must shift the firm's residual demand curve up by more than it shifts its average cost curve up. Hence it easy to see how the entry-disincentivizing aspects of regulation outlined by Dean and Brown could also serve to constrain the size of the competitive fringe in an industry with a small handful of dominant firms.

An understanding that regulation affects market outcomes is not new. Quantifying regulatory complexity in a way that makes these effects feasible to pin down, however, has been a relatively recent development in the field. In particular, the Quantgov framework, which allows researchers to count the total number of restrictions, total number of words, Shannon entropy among other metrics of a corpus has made it easier to assess the complexity of regulations. Already, Regdata, which was assembled by Al-Ubaydli and McLaughlin (2015) using the Quantgov methods, has been used to demonstrate a positive association between regulatory complexity by industry and firm operating profit margins and Tobin's Q for the U.S. economy (Bessen, 2016). However, this effect was not present in all sectors and the overall effect was found to be driven by a select few sectors.

Other researchers have seized on this development for a similar purpose. Gutiérrez and Philippon, (2017) show increased regulatory complexity to be associated with significantly higher industry concentration, especially when outliers are eliminated from the data. Conversely, Goldschlag and Tabarrok, (2018) use measures of job creation and destruction as well as business start-up rates to show that a slowdown in business dynamism cannot be explained by increasing regulatory complexity. These conflicting results show that more research is needed to understand the nature of the relationship between regulation and market outcomes.

Other researchers have pointed out that the effects of regulation can also run in the opposite direction. McChesney (1987) points out that it can be in the interest of politicians to threaten punitive regulations on an industry and forbear after in response to campaign contributions or some other form of assistance. This, however, implies the possibility of such a treat being carried out if the expectations of the politician are not met. Further, Stigler (1971) observes that it is in the interest of industries with political power to influence the supply of substitutes and compliments. Hence, we should expect some less politically powerful industries to be hindered at the behest of more powerful substitute-producing industries. This may pertain to the nuclear industry if it is the case that other energy industries are more politically powerful than the nuclear industry. Stigler (1971) also notes that whether an industry tends to use its political capital to pursue barriers to entry or subsidies depends on the strength of existing barriers. If barriers are weak, subsidies will stimulate entry, whereas an already entry-protected industry would be able to capture the full value of any subsidies introduced. If demand growth in regulation mandated equipment and services affects demand in a way that is analogous to a subsidy, this would also have implications regarding the circumstances under which industry incumbents would find such regulation desirable. Niskanen (1968) posits that bureaucracies should be thought of as budget-maximizers. In this case, the fact that the NRC is a fee-based agency may be important, as more fees trivially equate to a larger budget in this instance.

Because this funding mechanism was not introduced to the NRC until 1986, it is possible that this dynamic was not operative, or was not as important before that time. Finally, Pigou (1938) conceives of regulation as a corrective to market failures such as monopoly power and externalities, which is also compatible with the view that we should expect regulation to be onerous to the firm.

Empirically, an OECD Nuclear Energy Agency (2008) report on market concentration in various branches of the nuclear industry found that globally, the Herfindahl-Hirschman index (HHI) for power plant vendors was around 1666 as of that year, with concentration dropping to 1448 if only plants completed after 2000 are accounted for. These concentration figures are moderately high but not considered to be of regulatory concern. The report gives HHI figures for other branches of the nuclear industry as well. For uranium mining, the figure given is 1208, also not especially concentrated. However, as with other mining industries, the number of producers, and hence market concentration, can be affected by volatile business cycles. Therefore, this estimate may be too old to be considered reliable. HHI for conversion, enrichment, and fabrication, all components of the uranium fuel supply chain, are given as 2286, 2690 and 1923 respectively and are all sufficiently high as to be of regulatory concern. Concentration in the nuclear waste management industry was not estimated. It is further important to note here that, for any of these branches of the nuclear industry, significant barriers to international commerce often exist. Import-export restrictions on nuclear power technology transfer in the U.S. and recent sanctions placed on Rosatom by the U.K. are examples of this. Hence, global estimated HHI figures should be treated as lower bounds of the effective HHI of these nuclear industry branches in any given country. On the other hand, while the report notes that the relationship between a power plant vendor and its customer is likely to continue well beyond the construction phase, companies other than the vendor also contribute to the provision of equipment and services to existing nuclear power plants. This makes the HHI among vendors a flawed proxy for that among providers of equipment and services.

Other attempts to measure concentration as HHI in the nuclear industry have been aimed at quantifying the degree of standardization that prevails in different geographies, in particular France vs. the U.S. (Berthélemy and Rangel, 2015; David and Rothwell, 1996). In this context, high HHI is considered desirable insofar as it is associated with more learning-by-doing, less supply chain risk and reduction in lead-time. David and Rothwell provide HHI estimates for nuclear steam supply system manufacturers, turbine-generator manufacturers, and architect-engineers in the United States which are 0.34, 0.46, and 0.16 (or 3,400, 4,600, and 1,600) respectively. Meanwhile, France employed a vertically integrated state company in its nuclear program, resulting in a state of near complete concentration in the industry. While this research shows many parts of the nuclear industry are fairly concentrated, it is difficult to ascertain the extent to which this this is indicative of regulatory barriers to entry vs natural economies of scale and multitudes in construction and supply chain development.

Data

Because the nuclear industry is both large and not especially concentrated there, the focus of this investigation will be the United States. The absolute number of relevant public companies with available data at a given time is nonetheless small due to the niche nature of the industry. The dependent variables of interest are operating profit margins after depreciation and Log Tobin's Qs.

The company level data used to calculate these variables is taken from Compustat North America, with only U.S. firms included. The Tobin's Qs are constructed by dividing the following sum, (market value of equity + liquidation value of preferred stock + book value of long-term debt and current liabilities – current assets + book value of inventory), by book value of total assets, as in Carter, Rogers, and Simkins (2006). Since data on market cap is unavailable for many of the companies for the years of interest, it is calculated manually by multiplying annual closing share price by number of common shares. The Tobin's Q figures used are in logs. Data on daily stock returns is taken from CRSP for all companies. Operating profit margins after depreciation are calculated by subtracting depreciation and amortization from operating income before depreciation and dividing the result by sales.

The companies used were all publicly traded during the period of interest. The treatment companies are all either NPP vendors, NPP equipment manufacturers or construction firms that have worked on NPPs. All have non-nuclear branches of their businesses. Utilities are not considered as their profit margins and stock price will have been affected by public utility commission policies that are not of interest here. They are also the customers of the treatment group firms, meaning that some effects might benefit treatment group firms at the expense of utilities or vice versa. The companies in the treatment group are General Electric Co., Westinghouse Electric Corp., Curtiss-Wright Corp., Babcock & Wilcox Co., Combustion Engineering Inc., Buffalo Forge Co., and Fluor Corp. This includes four of the five companies who have ever sold a nuclear reactor in the U.S., accounting for over 99% of all U.S. built commercial reactors.

Estimation Strategy

I employ first a difference-in-differences approach, then a demeaned synthetic control approach to measure the effect of the creation of the NRC on the log Tobin's Qs and operating profit margins after depreciation for the treatment firms. In particular, I use data from seven companies which have available data from the years 1966 to 1977. 1974, The year the Energy Reorganization Act, which established the NRC as the successor agency to the AEC, was passed, is used as the treatment year for the purposes of Tobin's Q. This is because the market capitalization used to calculate Tobin's Q here is the closing price for the year. Further, while the NRC could not have affected the business of companies in the industry before it was established on January 19th the following year, the efficient market hypothesis gives us reason to believe investors would have incorporated any expected change in market valuation due to its imminent establishment into share prices.

For Operating margins, the treatment year is 1975, as it is more difficult to make the case that the passage of the Energy Reorganization Act in October 1974 could have affected operating margins before the relevant provision had taken effect. Nonetheless, since the bill passed the U.S. House of Representatives as early as December 1973, and orders and cancellations could plausibly have been affected in advance of January 1975, I run both regressions with earlier treatment years as well.

Prior to 1966, the quality of data declines and the number of nuclear plants under construction in the U.S. was small as was the size of the early reactors. This means that these firms' nuclear divisions would be small relative to total firm value. Conversely, from 1979 onwards, the partial meltdown at Three Mile Island and its repercussions makes the attribution of any structural break in the trends of industry outcomes to the NRC implausible without positing the existence of a composition effect.

Since other countries either have vertically integrated nationalized nuclear industries, or simply have a very small number of companies in the industry with available data for any given year, there is no natural control group in any non-U.S. nuclear industry. For this reason, I construct a control out of other U.S. firms that are in the same Standard Industrial Classification (SIC) industries as the treatment firms. The SIC system was used during this period before its replacement by North American Industry Classification System (NAICS), hence it is preferred in this context. Since equipment, like pumps, valves and pressure vessels, that is used in the nuclear industry is also used in many other industries, albeit sometimes with slight differences, and treatment firms all have branches that engage in business outside the nuclear industry, these firms are a natural place to look to establish a counterfactual for how firms doing business in the nuclear industry might fare in the absence of nuclear-specific regulatory turbulence. The SIC codes for the firms chosen for the control group are 3728, 3564, 3569, 3510, 1600, 3634 and 3613. These correspond to aircraft parts and auxiliary equipment, industrial and commercial fans and blowers and air purification equipment, general industrial machinery and equipment, engines and turbines, heavy construction other than building construction contractors, electric housewares and fans, and manufacturing switchgear and switchboard apparatus respectively. For GE and Westinghouse, SIC codes are taken from the Center for Research in Security Prices (CRSP) as opposed to Compustat[1]. The number of firms available for the control group, matching one of the above listed SICs and having data for all the necessary outcome variables and covariates as far back as 1966, is 13. Since no annual report exists for Babcock & Wilcox for 1977, nor does any quarterly report for the final quarter, the first three quarters of data are used

[1] This is because GE is simply listed under a conglomerate code in Compustat, which is not particularly useful in identifying similar companies. Further, due to the naming conventions of Compustat, Westinghouse is listed as CBS, which it bought and appropriated the name of in 1997, in the data. This resulted in it being listed under the SIC for broadcasting companies.

and annualized to create a best approximation of the company's financials in what was their final year before being acquired.

Since all of the treatment firms were engaged in several industries, their SIC codes may not be representative of enough of their total business for a control assembled from firms in the same SIC industries to be appropriate. Hence, I also assemble a broader control group using information about the other industries in which these firms were engaged during the relevant period to assess the sensitivity to the choice of control group. This brings the total number of control group firms to 34 for the broader control models. The list of additional SIC industry codes and descriptions can be found in the appendix.

Four approaches are employed for each outcome variable. I first use firms from the SIC industries of the treatment group firms as a control. Similarly, I run a model wherein the control group is augmented with firms from a number of other industries that may be relevant as described above. I then use each control group in turn as donor pools for a demeaned synthetic control.

Long-term debt to assets ratio, a dummy variable for whether a dividend was paid that year, log of total assets, the ratio of tax loss carryforwards to total assets, the ratio of capital expenditure to sales, the Altman Z-score, which is the result of a credit-strength test measuring the likelihood of bankruptcy for a publicly traded manufacturing company, and the standard deviation of daily stock returns are used as covariates in both the difference-in-differences models and the demeaned synthetic control. The first six covariates are recommended by Carter, Rogers, and Simkins (2006) as predictors for log Tobin's Q while stock price volatility is used in Bessen (2016). I am also unable to control for intangible capital intensity due to insufficient data, however, due to the control and treatment firms being from the same handful of SIC industries, reliance on intangibles in unlikely to vary hugely between the groups. Industry concentration may be relevant here as well, but since the industries represented are in similar proportions in the control and treatment groups, including industry concentration would add little new information. Similarly, while Carter, Rogers, and Simkins (2006) recommend controlling for the cash to sales ratio and cash flow to sales ratio, poor data on these metrics for the relevant years makes this less tenable.

I employ a backwards stepwise selection procedure using fixed-effects panel data regressions with robust standard error to ascertain which covariates should be included in the regression for each specification. I use Bayesian information criterion (BIC) as the principal metric for informing the inclusion or omission of potential covariates. BIC is preferred to Akaike information criterion (AIC) due to the relatively small number of panels in the data. Nonetheless, I also run specifications with the lower AIC in cases where the two differ to assess the sensitivity to the choice of covariates. In one particular case, the specification which is essentially a compromise between AIC and BIC, having the second lowest value for each, is also included.

The resulting Difference-in-Differences model equations are as follows:

$ln(Tobin's\ Q)_{igt} = \alpha_1 + \alpha_2(Post\text{-}NRC)_t + \beta_1(Nuclear\ Firm)_g + \beta_2((Nuclear\ Firm)_g \times (Post\text{-}NRC)_t) + \gamma(Control\ Variables)_{igt} + \epsilon_{igt}$

$(Operating\ Margin\ after\ Depreciation)_{igt} = \alpha_1 + \alpha_2(Post\text{-}NRC)_t + \beta_1(Nuclear\ Firm)_g + \beta_2((Nuclear\ Firm)_g \times (Post\text{-}NRC)_t) + \gamma(Control\ Variables)_{igt} + \epsilon_{igt}$

After estimating the difference-in-differences regressions, I use the demeaned synthetic control (DSC) method described by Ferman and Pinto (2021) to ascertain whether it can provide a more reliable control for some models, or whether the estimates of treatment effect are sensitive to the estimation technique employed. This method involves subtracting the pre-treatment mean from each variable for each firm panel, thus creating a demeaned series. Hence, the estimator is denoted as follows,

$$\hat{\alpha}_{0t}^{SC'} = y_{0t} - \boldsymbol{y'}_{\boldsymbol{t}}\widehat{\boldsymbol{w}}^{SC'} - (\bar{y}_0 - \bar{\boldsymbol{y}}'\widehat{\boldsymbol{w}}^{\boldsymbol{SC'}})$$

with $\bar{y}_0$ being the pretreatment average of unit 0, while $\bar{\boldsymbol{y}}$ is an Jx1 vector with the pretreatment averages of the controls. The demeaned series are then used to construct the DSC estimator. The demeaned synthetic control is useful for several reasons. It can improve on the difference-in-differences estimator in terms of bias and variance and, unlike standard synthetic control, its unbiasedness does not depend on the weights recovering the time-invariant fixed effect of the treatment group. It is more robust than SC to imperfect pre-treatment fit and can even maintain its advantages over difference-in-differences under these circumstances.

Each DSC is accompanied by a placebo test plotting each donor pool unit as though it were treated and measuring the difference between its outcome variable trajectory and that of its synthetic control. For both the diff-in-diff and the DSC, the treatment group is a single unit which is an average of the relevant nuclear industry firms.

Finally, for diff-in-diff specifications where the parallel-trends hypothesis is not rejected, but the Granger causality test indicates that treatment anticipation may have been present, I run the specifications with earlier treatment years to assess whether genuine treatment anticipation is a plausible explanation for the Granger test results. Doing so may also help identify other potential threats to parallel trends, for instance events which may have affected the treatment and control groups differently during the pre-treatment period, as these can resemble treatment anticipation on the Granger causality test. Where these additional tests reveal the possibility of a parallel-trends violation, I run the relevant diff-in-diff specifications an additional time with a truncated post-treatment time-horizon to confirm whether there is a significant break in trends at that particular year.

Results

Difference-in-Differences

Outcome Variable: Tobin's Q

Treatment Year: 1974

Table 1: Difference-in-differences results for log Tobin's Q

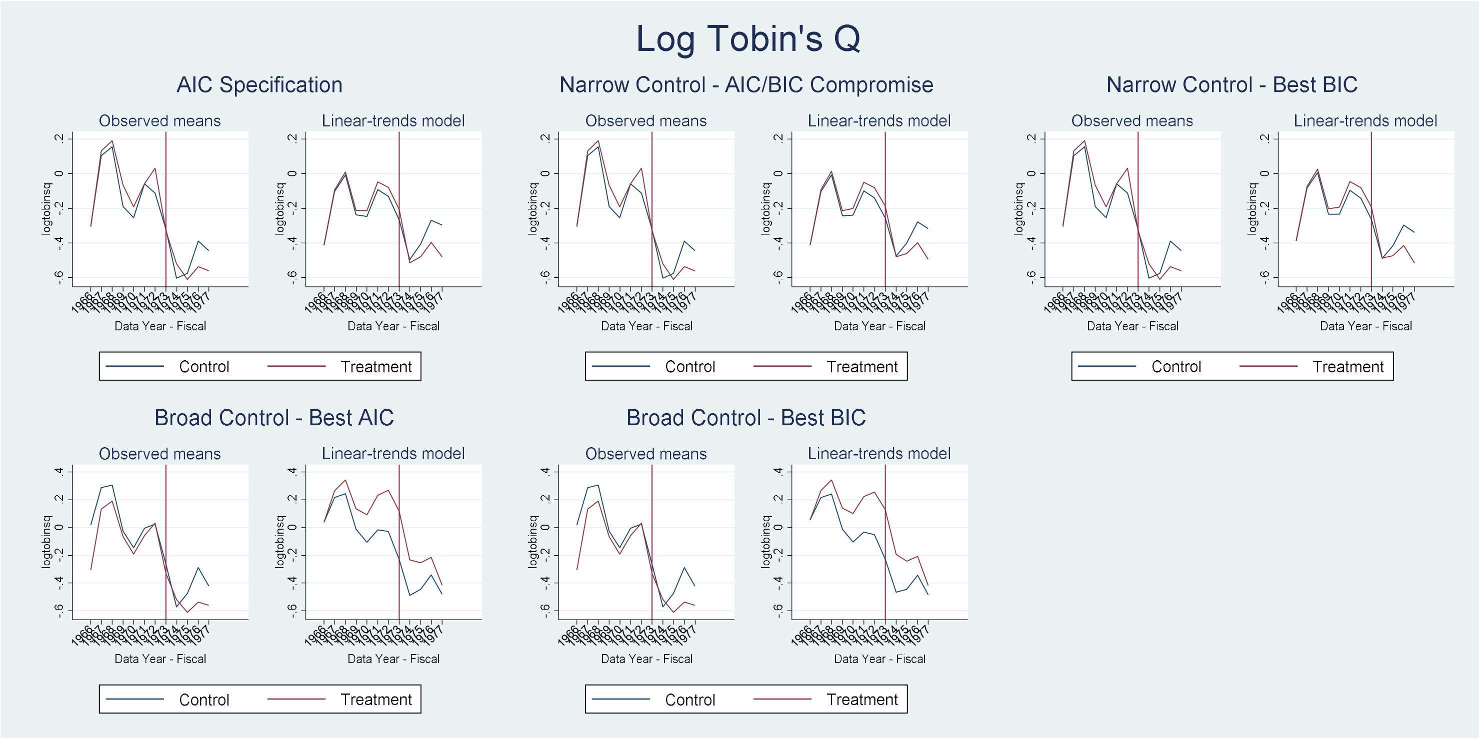
Diff-in-Diff Results for Log Tobin's Q

	(1) AIC NC	(2) cmp. NC	(3) BIC NC	(4) AIC BC	(5) BIC BC
ATET					
r1vs0._treated2	-0.131**	-0.125**	-0.124**	-0.0143	-0.00889
	(0.0520)	(0.0528)	(0.0527)	(0.0557)	(0.0572)
Controls					
logat	-0.0470	-0.0444		0.177*	0.152
	(0.108)	(0.106)		(0.0875)	(0.0915)
capexToSales	4.106***	3.982***	3.975***	1.901***	
	(0.818)	(0.799)	(0.809)	(0.619)	
z_score	0.137**	0.135**	0.137**	0.144***	0.144***
	(0.0573)	(0.0549)	(0.0545)	(0.0250)	(0.0254)
returnSD	2.796			-4.844	-6.572
	(5.172)			(5.912)	(5.839)
ltDebtRatio				0.983***	1.193***
				(0.314)	(0.315)
div				0.248*	0.236
				(0.146)	(0.142)
Constant	-0.966	-0.899	-1.121***	-2.001***	-1.730***
	(0.676)	(0.645)	(0.256)	(0.540)	(0.537)
Observations	168	168	168	420	420
ptrends_F	0.272	0.357	0.391	15.08	16.09
ptrends_p	0.611	0.560	0.542	0.000452	0.000313
granger_F	2.635	2.222	2.255	5.691	5.536
granger_p	0.0624	0.101	0.0976	0.000207	0.000259

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Figure 1: Observed means and linear-trends models for log Tobin's Q



These models make it clear that the control group assembled from the smaller basket of SIC industries, corresponding only to the SIC industries associated with the treatment firms in Compustat or CRSP, matches the average trend of the treatment firms better than the control group assembled from the larger basket of potentially relevant industries. Notably, the observed means of both control groups match those of the treatment group closely in both cases. When covariates are controlled for, however, the narrower control group clearly performs much better than the broader one, with the parallel-trends hypothesis being soundly rejected at any traditional level when the broad control group is used. All model specifications show a negative coefficient and all those where the narrower control group is used result in p-values significant at the 5% level. Similarly, the quantitative size of the coefficient is about an order of magnitude larger for the narrow control specifications than for the broad control ones.

Including log of total assets or log of total assets and standard deviation of daily stock return, as in the AIC/BIC compromise specification and the best AIC specification of the narrow control model respectively, leads to only very minor improvement in pre-treatment trends fit and are arguably inferior for being less parsimonious.

It would be prudent to exercise caution in interpreting the results which show significance here, as the Granger causality test indicates that treatment anticipation may have occurred. Even when the narrow control group is used, the F-statistic is significant at the 10% level in two of the three specifications and nearly so in the third. However, only the clearly inferior model using the broad control group yields results significant at the 5% or 1% level. The matter of whether genuine treatment anticipation is the cause of these results will be addressed later.

Outcome Variable: Operating Margin

Treatment Year: 1975

Table 2: Difference-in-differences results for operating margins

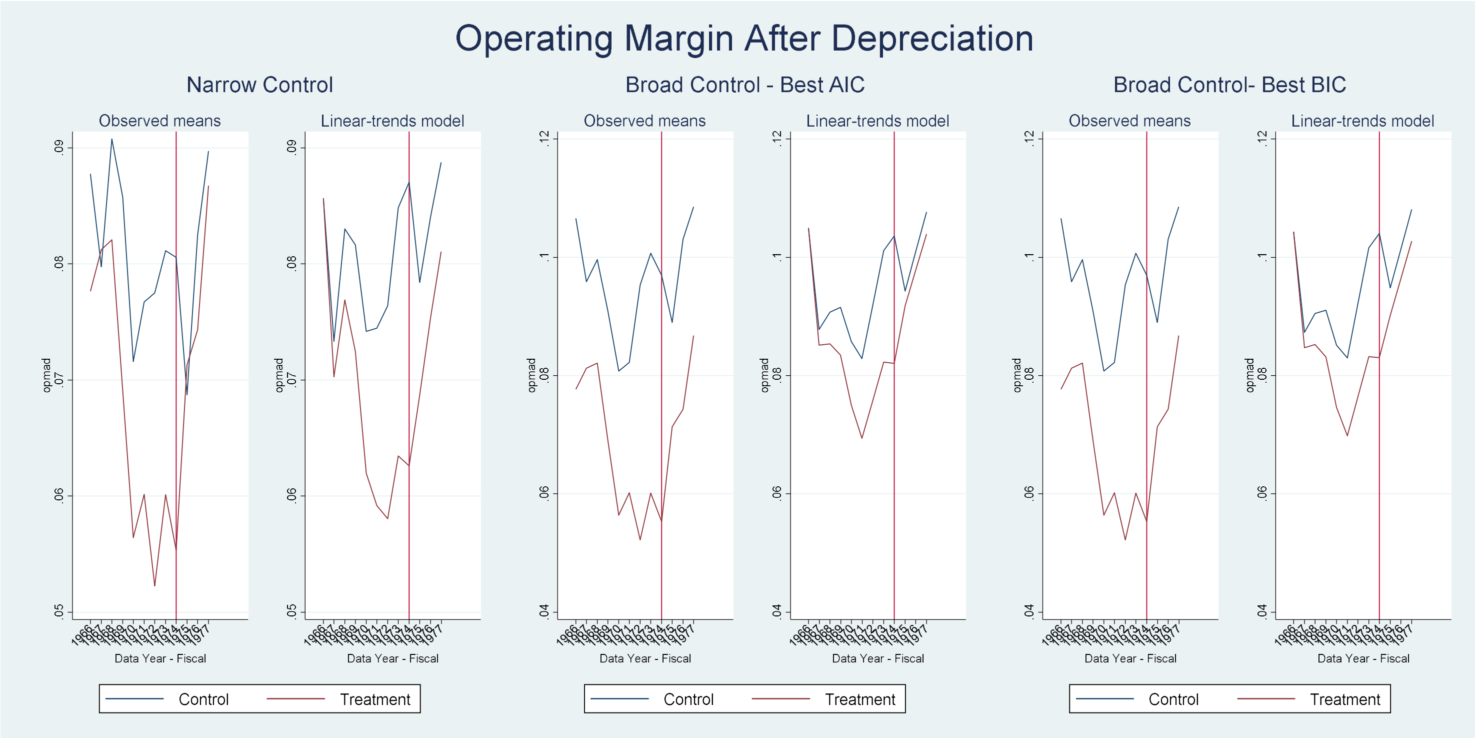
Diff-in-Diff Results for Operating Margins

	(1) NC	(2) AIC BC	(3) BIC BC
ATET			
r1vs0._treated	0.00371	0.00765	0.00555
	(0.00654)	(0.00563)	(0.00538)
Controls			
ltDebtRatio	-0.0665	-0.0640*	-0.0593
	(0.0661)	(0.0359)	(0.0371)
logat	0.00881*	0.0108	0.00944
	(0.00487)	(0.00830)	(0.00829)
div	0.0218	-0.0146	
	(0.0140)	(0.0135)	
capexToSales	0.167	0.146	0.150
	(0.151)	(0.125)	(0.125)
z_score	0.00813**	0.0133**	0.0133**
	(0.00303)	(0.00508)	(0.00514)
taxTa		-0.381	-0.331
		(0.243)	(0.244)
Constant	-0.0110	0.00364	-0.00411
	(0.0378)	(0.0509)	(0.0524)
Observations	168	420	420
ptrends_F	8.131	5.451	5.339
ptrends_p	0.0136	0.0256	0.0271
granger_F	6.529	4.044	3.836
granger_p	0.00160	0.00183	0.00262

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Figure 2: Observed means and linear-trends models for operating margins



My attempt to match the operating profit margin trends of the nuclear industry meets with failure in both the broad and narrow control cases, with the parallel-trends hypothesis being rejected at the 5% level in all cases. Bessen (2016) argues that, since stock prices are shaped by investors expectations of future profits, operating margins ought to be affected by regulation in a manner similar to that of Tobin's Q, but potentially with higher standard error. It is possible then, that this discrepancy is the result of shocks during the pre-treatment period that affected immediate profits of the industry much more than expected discounted present value of future profits. The Calvert Cliffs' Coordinating Committee, Inc. v. Atomic Energy Commission decision, which led the AEC to suspend the licensing of all new nuclear plants for 18 months while it adjusted its rules to comply with the National Environmental Policy Act (NEPA) (Thompson, 2010), could constitute such an event if investors believed that the industry would recover from this setback relatively quickly. This would be plausible if optimism about the technology's long-term potential was high enough and could explain why the operating margins of the treatment group might be lower than those of the control group, while Tobin's Q was relatively similar, which is what we see here. This could also be the cause of the apparently positive coefficients in these models.

Demeaned Synthetic Control

Outcome Variable: Tobin's Q

Treatment Year: 1974

Table 3: DSC demeaned log Tobin's Q effect sizes

Year	Best AIC; Narrow donor pool	AIC/BIC compromise; Narrow donor pool	Best BIC; Narrow donor pool	Best AIC; Broad donor pool	Best BIC; Broad donor pool
1966	-0.371	-0.292	-0.111	-0.388	-0.349
1967	-0.369	-0.248	-0.180	-0.0706	-0.0392
1968	-0.110	0.0173	-0.0361	-0.203	-0.0715
1969	0.110	0.109	0.0995	-0.0386	-0.0525
1970	0.222	0.131	0.0871	0.149	0.138
1971	0.207	0.104	0.0228	-0.0327	0.00567
1972	0.238	0.144	0.165	0.0862	-0.0105
1973	0.0723	0.0335	-0.0466	0.498	0.379
1974	-0.0844	0.0494	0.0144	0.562	0.363
1975	-0.114	-0.0767	-0.114	0.128	-0.0410
1976	-0.154	-0.270	-0.247	-0.0316	-0.140
1977	-0.122	-0.151	-0.210	0.102	0.0512

Table 4: DSC demeaned log Tobin's Q standardized p-values

	Best AIC; Narrow donor pool	AIC/BIC compromise; Narrow donor pool	Best BIC; Narrow donor pool	Best AIC; Broad donor pool	Best BIC; Broad donor pool
std. p-value	0.846	0.462	0.231	0.559	0.647

Figure 3: DSC demeaned log Tobin's Q vs demeaned synthetic control

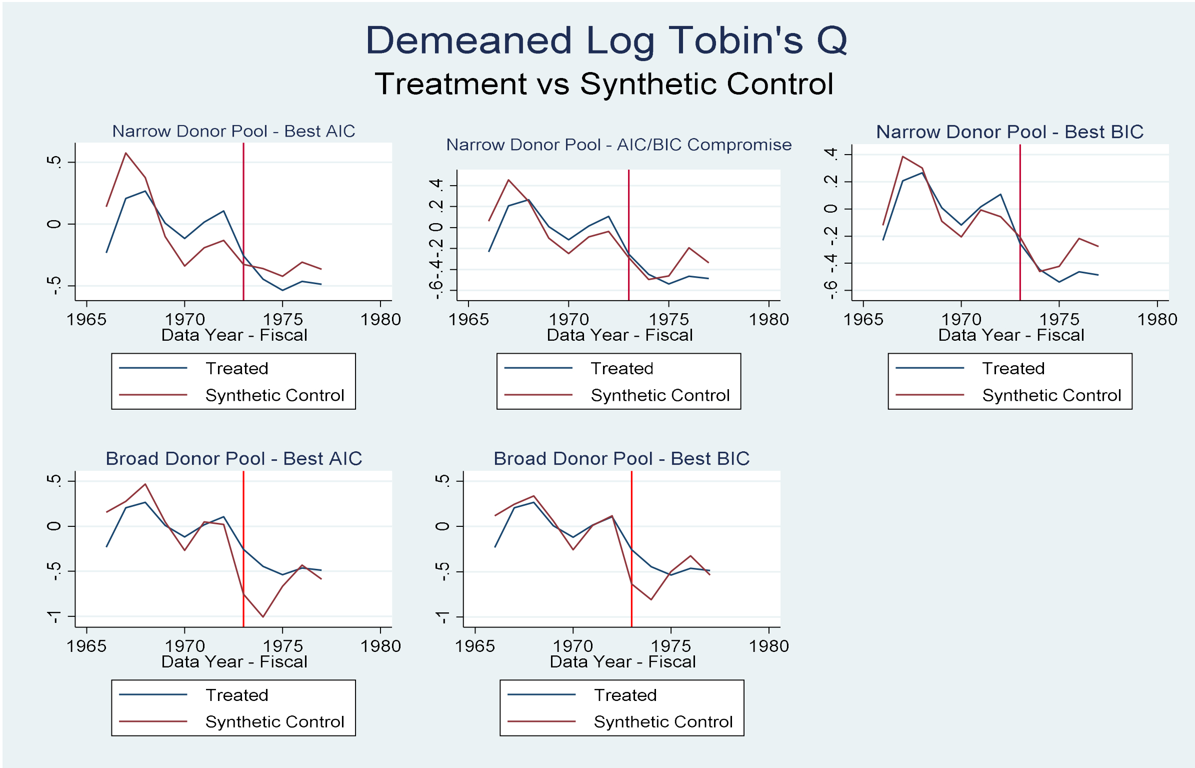


Figure 4: DSC demeaned log Tobin's Q effect sizes

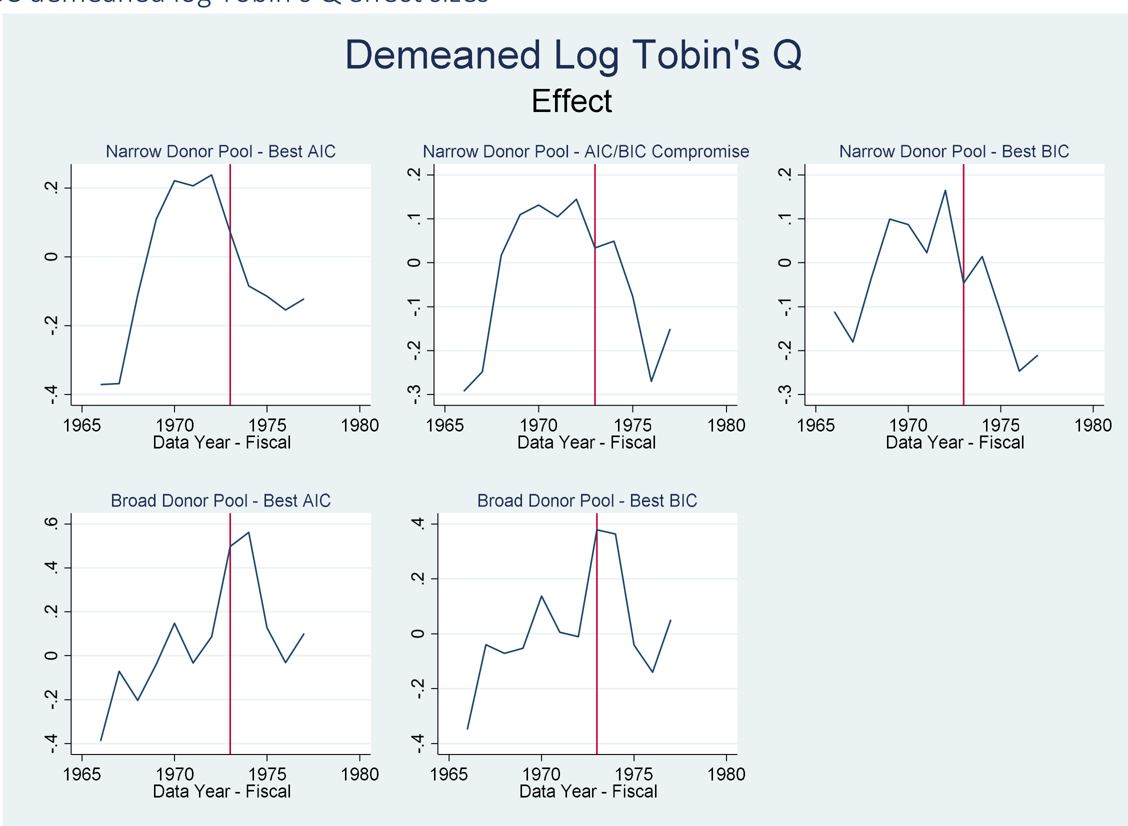
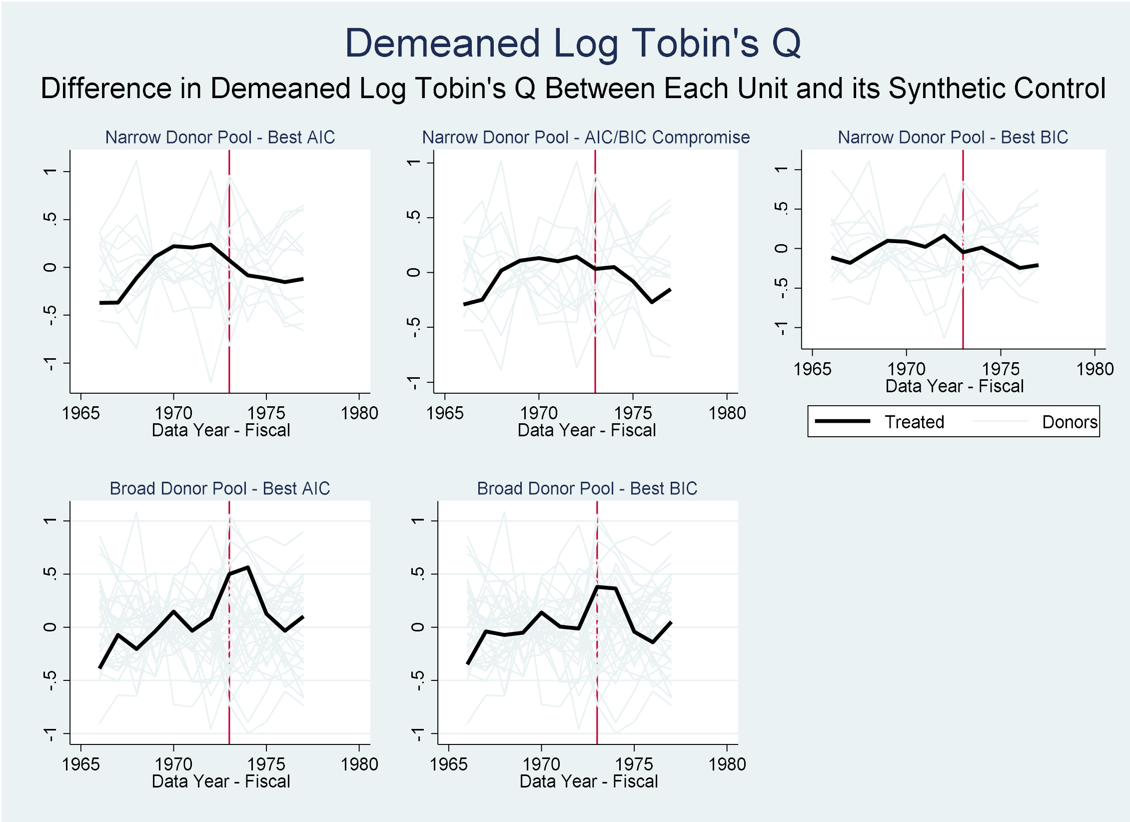


Figure 5: DSC demeaned log Tobin's Q Placebos



Using the control groups from the Log Tobin's Q diff-in-diff models as donor pools for a demeaned synthetic control results in distinctly different linear combinations of donor pool firms depending on the breadth of the donor pool and the covariates included. For four of the five specifications, the weights are sparse, providing good assurance that the synthetic control is not overfitted. Only in the case of the lowest BIC specification for the narrow donor pool model is each firm in the donor pool assigned a non-zero weight. Despite having the lowest pre-treatment root mean squared prediction error (RMSPE), this model should be viewed skeptically. The next lowest RMPSE is found in the specification using the AIC/BIC compromise specification, where log of total assets is included in the model as a covariate. This much sparser synthetic control consists of 0.689*Sundstrand Corporation and 0.311*Cummins Inc., where the former is a manufacturer of aerospace and industrial equipment, including turbines, while the latter manufactures engines, and filtration, and power generation systems. The broad donor pool synthetic controls do not allocate much weight to the firms included in the narrow donor pool, with the best AIC specification not doing so at all.

These models reveal that apparent treatment anticipation is not the only reason to question the diff-in-diff results which had the Log Tobin's Q coefficient as significant at the 5% level. While most of these specifications show the treatment effect to be negative, plotting the time path of the placebo treatment firms reveals that there is nothing particularly special about the nuclear firms, which fall near the middle of the distribution of placebos irrespective of the choice of donor pool or covariates.

On the other hand, the narrow donor pool – AIC/BIC compromise specification, which has sparse weights and second lowest RMSPE, also appears to show the largest negative treatment effect. Also potentially important is that the higher RMSPEs of the broad donor pool model specifications appear to be driven by breakdown in the fit of the synthetic controls in the final treatment year, 1973, before which they appear to fit the nuclear firm trajectory more closely than do the narrow donor pool derived synthetic controls. This is even more the case if the best BIC narrow donor pool synthetic control where overfitting appears present is discounted. Given that, everything else being equal, a larger donor pool ought to lead to a better synthetic control, it is possible that this result is pointing to an inflection in the trend of the Log Tobin's Qs of the nuclear firms before the treatment period, which could be interpreted as further evidence of treatment anticipation.

Outcome Variable: Operating Margin

Treatment Year: 1975

Table 5: DSC demeaned operating margin effect sizes

Year	Narrow donor pool	Best AIC; Broad donor pool	Best BIC; Broad donor pool
1966	0.00792	0.000342	0.000767
1967	0.00742	0.0173	0.0177
1968	-0.00103	0.0195	0.0194
1969	-0.00977	-0.0132	-0.0124
1970	-0.00992	-0.0220	-0.0207
1971	-0.00689	-0.00645	-0.00588
1972	-0.00837	-0.0191	-0.0192
1973	0.000841	0.00307	0.00188
1974	0.0198	0.0205	0.0184
1975	0.0322	0.0302	0.0292
1976	0.00658	0.0187	0.0170
1977	0.0219	0.0222	0.0203

Table 6: DSC demeaned operating margin standardized p-values

	Narrow donor pool	Best AIC; Broad donor pool	Best BIC; Broad donor pool
std. p-value	0.250	0.394	0.412

Figure 6: DSC demeaned operating margin vs demeaned synthetic control

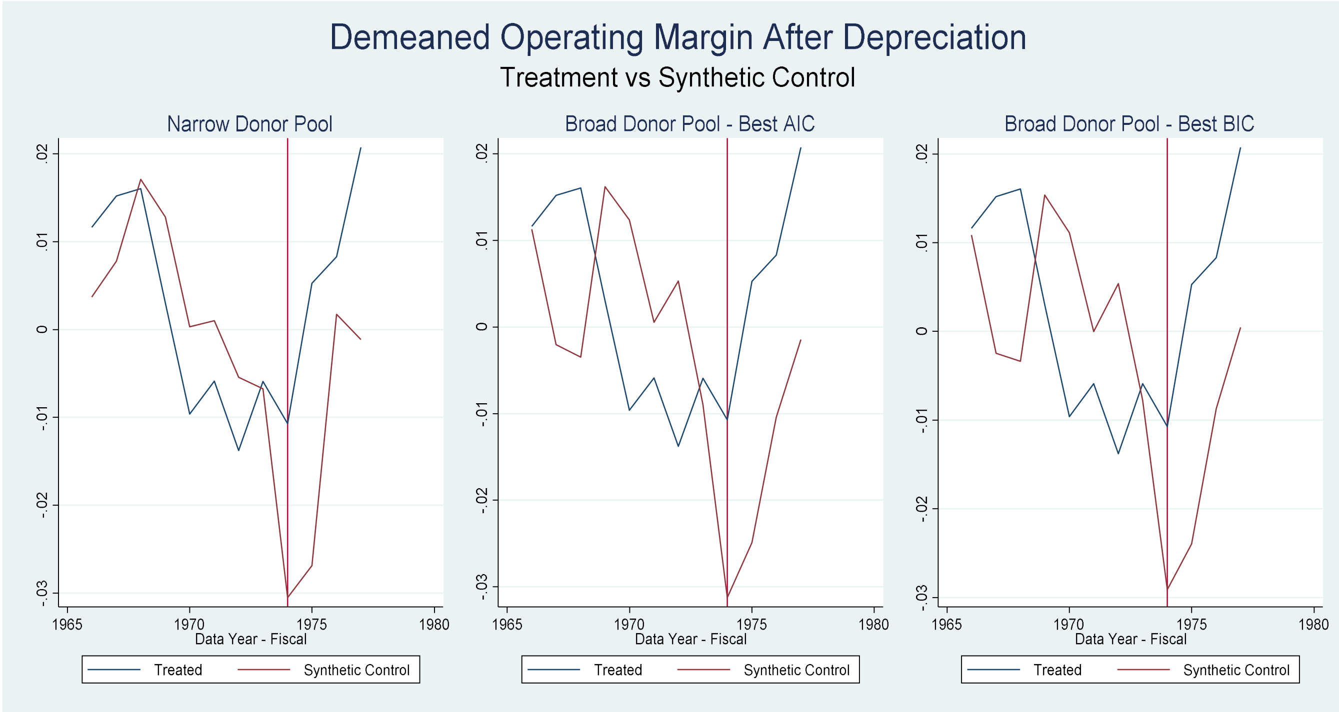


Figure 7: DSC demeaned operating margin effect sizes

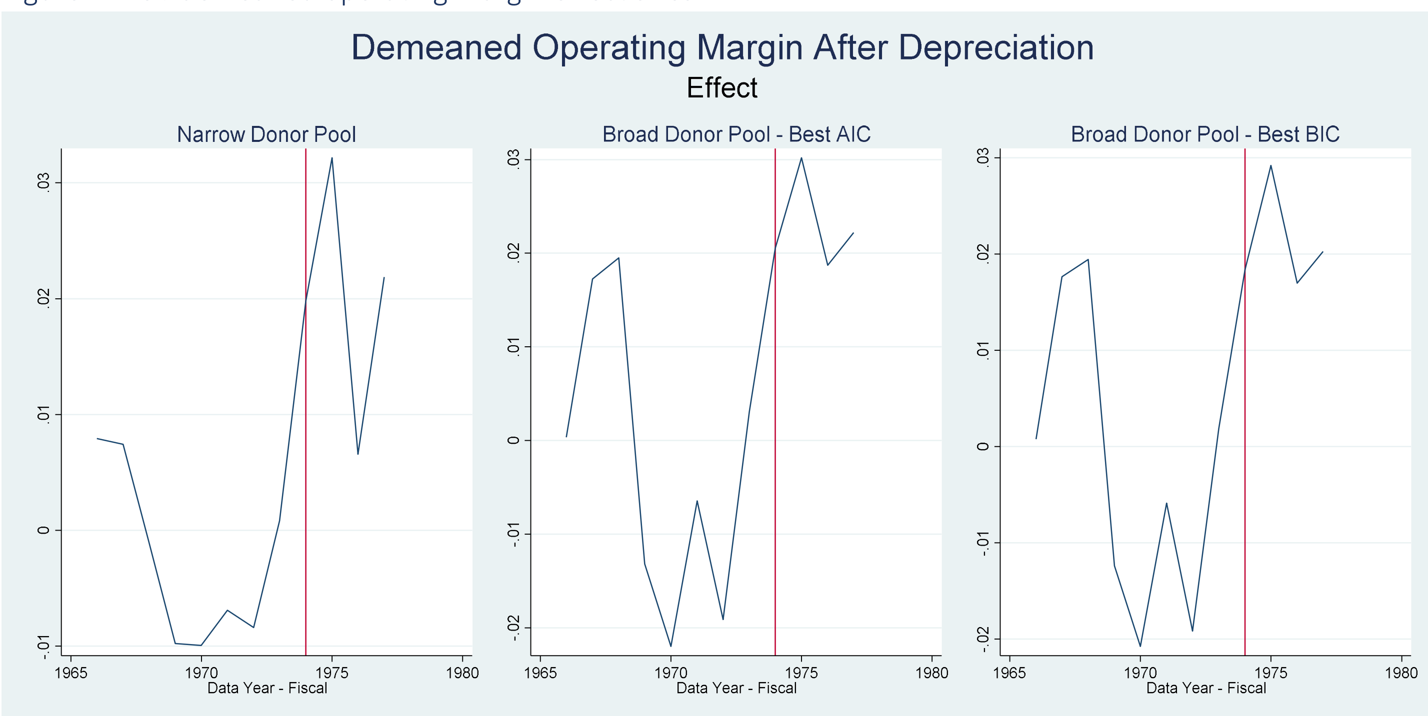
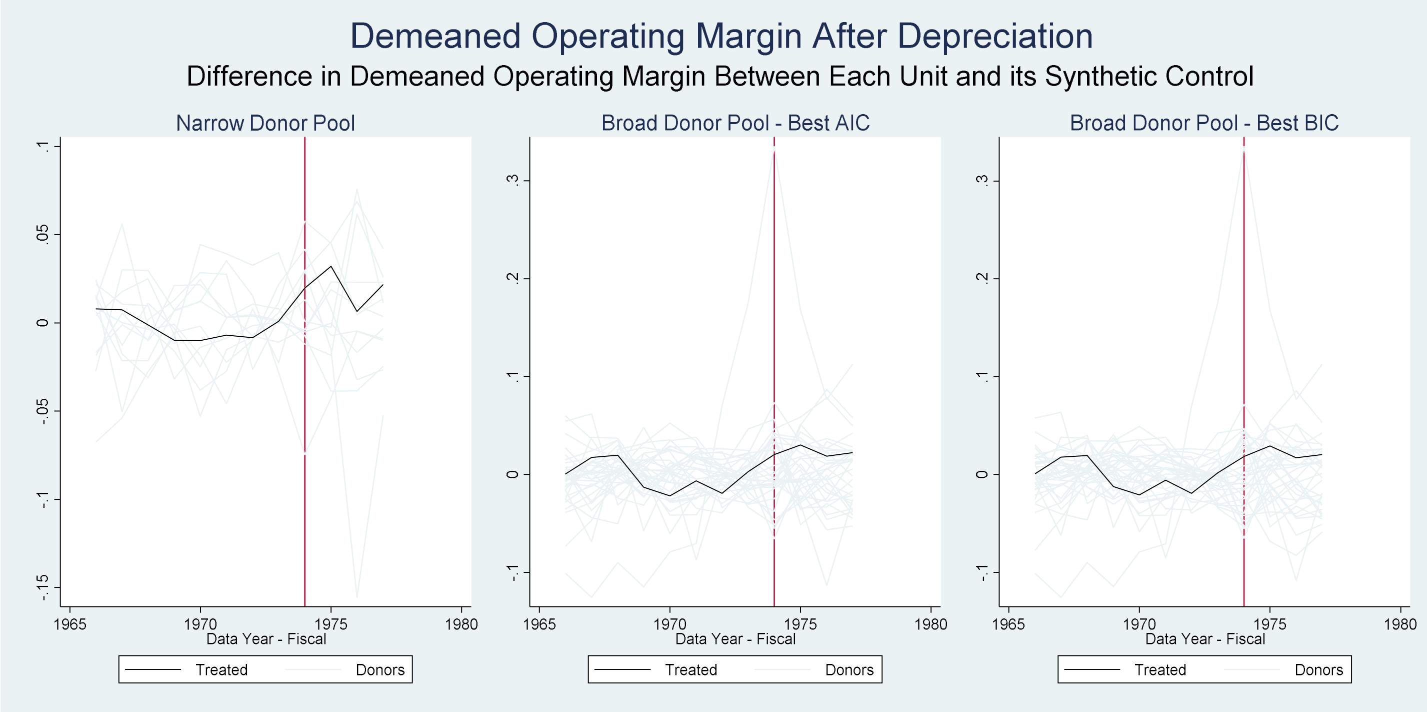


Figure 8: DSC demeaned operating margin Placebos



The demeaned synthetic control models for operating margins generate universally sparse weights, though not generally as sparse as was the case for log Tobin's Q. The best fitting model specification, which is again a narrow donor pool one, in the case the only such specification, is composed of 0.398*Phillips Industries Inc., 0.224*Pullman Inc., 0.218*Scovill Inc., and 0.159*Cummins Inc, the former three of which are a manufacturer of advanced electrical and air brake system components for large automotive vehicles, a railroad car manufacturer, and a manufacturer of consumer, housing and industrial products respectively.

Disappointingly, the DSC also has difficulty matching the pre-treatment trends for the nuclear firms. Much like most of the diff-in-diff models, these models cannot produce a control with sufficiently low operating margin values for much of the early 1970s. Though the narrow donor pool model comes closer than the broad donor pool one, with a RMSPE approximately two thirds the size of its broad counterpart, neither model is accurate enough to be of much use under any specification. The positive treatment effect is similar to what occurs in the diff-in-diff models, but the placebo tests, along with the poor pre-treatment fit, give ample reason to doubt that this has any natural interpretation.

Accounting for Granger Rejection

As many of the diff-in-diff results obtained were indicative of treatment anticipation, which could plausibly have occurred if firms in the industry or their customers were politically well connected enough to attain foreknowledge of upcoming legislation, I make an effort here to ascertain whether this is the most reasonable explanation for the Granger test results. If the result of the Granger test changes significantly when the treatment year is set to 1973, as opposed to 1974 or 1975, this may indicate that the passage of the Energy Reorganization Act of 1974 was anticipated while the bill was still pending or even shortly after President Nixon proposed the partitioning of the AEC in mid-1973. There are, however, other possibilities that may explain the Granger results for the original treatment years. For instance, small sample sizes can limit the ability of the Granger test to distinguish between treatment anticipation and random fluctuations as mentioned earlier. Another explanation would be that something occurred during the pre-treatment period that affected the treatment and control groups differently. The 1969-70 or 1973-75 recessions might be an example of such an event. The 1971 Calvert Cliffs decision could be another potential example.

A further possibility might be the inversion of the NPP learning curve, which happened early during pre-treatment period. Though both Lovering et al. (2016) and Lang (2017) have the inversion of the NPP learning curve in 1968, it is important to note that it is the date of construction start being measured in both cases, and hence the inflection point in construction costs could have occurred during one of several years during which this cohort of plants were being built. Joskow (1974) describes the incentives facing utilities, who are the customers of the treatment group firms, during this period. During the 1950s and most of the 1960s, utilities had a benign incentive to minimize costs as nominal rates remained constant in the face of decreasing costs. However, as elevated inflation began to drive increasing nominal costs irrespective of gains in efficiency, it became necessary for utilities to regularly engage in the rate of return review process to keep rates sufficiently high as to make a substantial return on capital, thus marking a switch from cost-minimization to Averch-Johnson capital bias. Joskow documents that the formal rate of return reviews processed by state regulatory commissions for electrical utilities climbed from five in 1968, to sixteen in 1969, to thirty-one in 1970, reaching fifty-three by 1972. This could have constituted an important disruption to the nuclear power plant business that was not accounted for in any of the control group configurations considered.

In order to glean as much information as possible about the potential origins of the Granger results from the original treatment periods, I iteratively run the model specifications where the parallel-trends hypothesis was not rejected at the 5% level originally, with treatment years as far back as 1969. Moving the treatment back further than this may not provide much useful information, as this would leave only one or two pre-treatment years, and therefore potentially insufficient information on pre-treatment trends. This is done even for specifications where the no-anticipation hypothesis was not technically rejected at the 5%, or even 10% level, because the only specification where the hypothesis was not rejected at the 10% level was extremely close to rejection, while the other specifications for the same control and treatment groups yielded rejection at the 10% level. This makes the possibility of type 2 error a concern here.

Table 7: Difference-in-differences results for log Tobin's Q of best AIC specification in all early treatment years

Early Treatment Diff-in-Diff Results for Log Tobin's Q - Best AIC; Narrow Control

	(1) 1973	(2) 1972	(3) 1971	(4) 1970	(5) 1969
ATET					
r1vs0._treated3	-0.132*				
	(0.0729)				
r1vs0._treated4		-0.0678			
		(0.0661)			
r1vs0._treated5			-0.0530		
			(0.0637)		
r1vs0._treated6				-0.0369	
				(0.0626)	
r1vs0._treated7					-0.000330
					(0.0629)
Controls					
logat	-0.0480	-0.0472	-0.0465	-0.0458	-0.0451
	(0.109)	(0.109)	(0.110)	(0.110)	(0.109)
capexToSales	4.090***	4.084***	4.085***	4.095***	4.099***
	(0.819)	(0.823)	(0.826)	(0.820)	(0.816)
z_score	0.137**	0.137**	0.137**	0.137**	0.136**
	(0.0573)	(0.0576)	(0.0578)	(0.0578)	(0.0580)
returnSD	2.778	2.702	2.652	2.603	2.458
	(5.167)	(5.200)	(5.254)	(5.272)	(5.282)
Constant	-0.960	-0.961	-0.962	-0.964	-0.964
	(0.677)	(0.680)	(0.680)	(0.678)	(0.678)
Observations	168	168	168	168	168
ptrends_F	1.745	0.545	1.477	1.535	0.0221
ptrends_p	0.209	0.473	0.246	0.237	0.884
granger_F	2.633	1.709	1.526	1.878	0.173
granger_p	0.0677	0.202	0.252	0.183	0.843

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 8: Difference-in-differences results for log Tobin's Q of AIC/BIC compromise specification in all early treatment years

Early Treatment Diff-in-Diff Results for Log Tobin's Q - AIC/BIC Compromise; Narrow Control

	(1) 1973	(2) 1972	(3) 1971	(4) 1970	(5) 1969
ATET					
r1vs0._treated3	-0.127				
	(0.0735)				
r1vs0._treated4		-0.0612			
		(0.0679)			
r1vs0._treated5			-0.0462		
			(0.0643)		
r1vs0._treated6				-0.0291	
				(0.0623)	
r1vs0._treated7					0.00546
					(0.0629)
Controls					
logat	-0.0455	-0.0446	-0.0440	-0.0433	-0.0429
	(0.106)	(0.107)	(0.107)	(0.107)	(0.106)
capexToSales	3.967***	3.966***	3.970***	3.981***	3.990***
	(0.802)	(0.810)	(0.816)	(0.811)	(0.807)
z_score	0.135**	0.135**	0.135**	0.135**	0.135**
	(0.0549)	(0.0552)	(0.0554)	(0.0555)	(0.0556)
Constant	-0.894	-0.897	-0.899	-0.903	-0.906
	(0.647)	(0.651)	(0.653)	(0.652)	(0.651)
Observations	168	168	168	168	168
ptrends_F	2.078	0.722	1.755	1.454	0.0233
ptrends_p	0.173	0.411	0.208	0.249	0.881
granger_F	2.263	1.786	1.592	1.839	0.210
granger_p	0.102	0.185	0.235	0.190	0.814

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 9: Difference-in-differences results for log Tobin's Q of best BIC specification in all early treatment years

Early Treatment Diff-in-Diff Results for Log Tobin's Q - Best BIC; Narrow Control

	(1) 1973	(2) 1972	(3) 1971	(4) 1970	(5) 1969
ATET					
r1vs0._treated3	-0.125				
	(0.0733)				
r1vs0._treated4		-0.0586			
		(0.0674)			
r1vs0._treated5			-0.0440		
			(0.0634)		
r1vs0._treated6				-0.0276	
				(0.0618)	
r1vs0._treated7					0.00659
					(0.0633)
Controls					
capexToSales	3.960***	3.960***	3.964***	3.975***	3.984***
	(0.812)	(0.819)	(0.825)	(0.821)	(0.817)
z_score	0.137**	0.137**	0.137**	0.137**	0.137**
	(0.0545)	(0.0548)	(0.0549)	(0.0550)	(0.0551)
Constant	-1.121***	-1.119***	-1.119***	-1.119***	-1.119***
	(0.256)	(0.257)	(0.258)	(0.258)	(0.258)
Observations	168	168	168	168	168
ptrends_F	2.171	0.716	1.744	1.583	0.0165
ptrends_p	0.164	0.413	0.209	0.230	0.900
granger_F	2.266	1.686	1.493	1.678	0.206
granger_p	0.102	0.207	0.261	0.221	0.817

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

The pattern for Log Tobin's Q is interesting but difficult to interpret. The Granger test yields a nearly identical result when the treatment year is moved back to 1973 but is comfortably far from rejection even at the 10% level when the treatment year is moved to 1972. Nonetheless, the disjuncture in the F-statistics from 1973 to 1972 is not especially large, with no p-values greater than 0.21. This does not offer especially strong evidence that anything fundamental is changing when the treatment year is moved by this increment. There is yet another small change in the p-values as the treatment year is moved to 1971, at which point all are at least 0.25, although moving back further to 1970 causes a decline back to approximately 1972 levels. When the treatment year is set to 1969, p-values for all three specifications abruptly rise above 0.81. This makes inferring the cause of the Graner test results for the original treatment year difficult. On the one hand, the absence of any serious shift in the Granger results when the treatment year is moved from 1974 to 1973 implies that genuine treatment anticipation is unlikely to account for them. On the other hand, it is not obvious what the most likely alternative mechanism might be.

The abrupt jump in the Granger test p-values for the 1969 treatment year may be of import here. Though the test failed to reject the no-anticipation hypothesis for several later years, the risk of type 2 error is larger for lower values than for higher ones, and the market conditions at the time give some reason to suspect that changes in nuclear industry business trends may have occurred that would not have been mirrored in the control group. As Burness, Montgomery, and Quirk (1980) document, GE and Westinghouse, the two largest reactor vendors, ceased offering to sell reactors under turnkey contracts in mid-1966, although plants built under these contracts were still under construction into the early 1970s. These plants lost money for the vendors, who Burness, Montgomery, and Quirk (1980) assert were making an investment in learning in order to capture rents later. The transition to cost-plus contracts allowed these firms to profit from reactor construction. Hence, as the portfolio of active construction projects transitioned from more turnkey projects to more cost-plus projects, we should expect the profitability of these firms to rise, everything else being equal. Since this development had no equivalent in the control group, this could constitute a threat to parallel-trends. To get a sense of whether a significant disruption to existing trends occurred in the nuclear industry that was not mirrored in the control group in 1969, I run yet another difference-in-differences model for the first five years of what was the pre-treatment period in the original model. I use 1969 as the treatment group and omit years 1971 and later, after which point the Calvert Cliff decision led to a pause in new reactor construction starts.

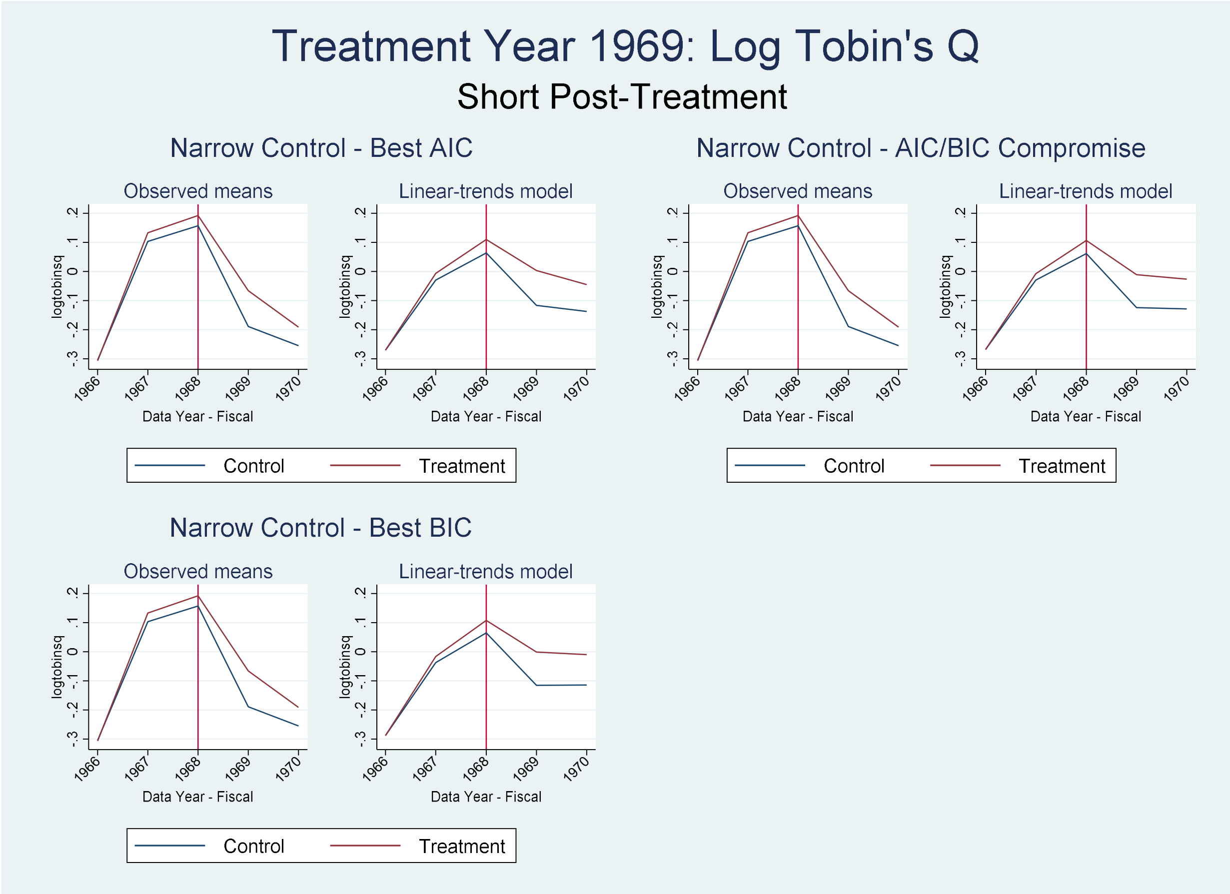
Table 10: Difference-in-differences results for log Tobin's Q of all narrow control model specifications with 1969-70 post-treatment period

Diff-in-Diff Results for Log Tobin's Q; 1969-70 Post-Treatment

	(1) AIC NC	(2) cmp. NC	(3) BIC NC
ATET			
r1vs0._treated7	0.0830*	0.0855*	0.0874**
	(0.0427)	(0.0411)	(0.0392)
Controls			
logat	0.0577	0.0723	
	(0.112)	(0.107)	
capexToSales	3.722***	3.595***	3.540***
	(1.108)	(1.019)	(0.967)
z_score	0.211**	0.210**	0.207**
	(0.0770)	(0.0744)	(0.0728)
returnSD	4.150		
	(8.041)		
Constant	-1.803**	-1.766**	-1.403***
	(0.737)	(0.687)	(0.371)
Observations	70	70	70
ptrends_F	0.269	0.264	0.228
ptrends_p	0.612	0.616	0.641
granger_F	0.138	0.140	0.120
granger_p	0.872	0.871	0.888

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Figure 9: Observed means and linear-trends models for log Tobin's Q for 1969-70 post-treatment period



Interestingly, all three specifications of this model have the treatment effect as positive, quantitatively about the same size, and significant at the 10% level. The lowest BIC model, which should be preferred with small sample sizes in general, even has the coefficient as significant at the 5% level. In stark contrast to the 1974 model, there is not a shred of evidence for treatment anticipation in any of the three specifications, although this may have something to do with the shorter pre-treatment period. Both the treatment and control groups are clearly affected by the 1969-70 recession, as both groups' Log Tobin's Qs decline from 1968 to 1969, but the decline is substantially gentler for the nuclear firms.

Discussion

These tests have offered some confidence that, over the time horizon measured, the treatment effect on log Tobin's Q is likely null or negative and too small to detect confidently. Though the apparently significant results in the first round of diff-in-diff regressions are interesting, they are called into question by the results of the Granger test and DSC placebo tests. A further test examining 1969 for a potential violation of parallel trends, following on earlier robustness checks and a theoretical basis for believing that disruptions specific to the nuclear industry may have occurred around that time, finds that there may indeed be a parallel-trends violation at this juncture.

Disappointingly little insight into the effect on operating profit margins has been gained over the course of this investigation. It is clear that the group of control firms considered is simply not capable of reproducing the pre-treatment trends of the operating margins of the treatment group well enough to offer much insight.

There are several alterations to my estimation strategy that might have remediated this issue. One might be finding more innovative ways to define the control group and donor pool for the diff-in-diff models and DSC models respectively, which would likely involve being more discerning about which SIC industries from the broad control group were ultimately appropriate to include. This could consist of, for instance, examining the balance of covariates vis-à-vis the treatment group on an industry-by-industry basis, and would hopefully result in a more representative control group or donor pool. Another possibility, which would be especially beneficial for the purposes of constructing a more appropriate DSC, would be to survey a broader pool of firms in heavy industry for similarity in terms of the covariates used, irrespective of whether the treatment firms were involved in such industries at the time. Finally, the inclusion of more or better covariates might lead to better pre-treatment fit. For instance, supposing that a more diverse cross section of industries was incorporated into the control group, it would make sense to include industry concentration as a covariate. These solutions might benefit the log Tobin's Q models as well as the operating margins models.

The evidence gathered here provides only weak support for the hypothesis that regulation should be onerous to the regulated industry, either because of budget-maximizing civil servants, because of competing industries seeking opportunities for substitution, or because Pigou's public interest theory holds. For the hypothesis that regulation ought to benefit the regulated industry's incumbents, either by creating barriers to entry or by inducing additional demand which can be capitalized on by an already entry-protected oligopoly, this investigation does not provide support. However, there are good reasons not to take the evidence provided here as definitive. One reason for this is that the presence of regulatory disruptions during the pre-treatment period may mean that any disruptions created by swapping out the AEC for the NRC may be more accurately viewed as a continuation of an existing trend. Beyond that, examining a post treatment as short as three or four years, depending on the outcome variable, may not be long enough to capture the capture the full effect on the nuclear industry. It is important to remember that the process of applying for a construction license, having it approved, building a plant, and obtaining an operating license, can take many years, and hence there may be long lag times before the impacts of some disruptions manifest in firm financial statements.

Conclusions

I've used the difference-in-differences and demeaned synthetic control methods here to try to determine whether the inception of the NRC affected the commercial success of nuclear industry firms using their Tobin's Q and operating profit margins after depreciation as dependent variables. I've also used earlier years as treatment periods in several diff-in-diff model specifications in an attempt to ascertain whether the rejection of the no-anticipation hypothesis by the Granger causality test at the 10% level should be interpreted as an indication of genuine treatment anticipation, and if not, what other mechanism might be responsible for these results. Though the Granger test p-values for some specifications and some earlier treatment years fail to reject the no-anticipation hypothesis, the pattern does not fit what should be expected if genuine treatment anticipation were present. Some evidence was uncovered that parallel trends between the treatment and control groups for the narrow control diff-in-diff model may have been disrupted in 1969. A convincing control, either natural or synthetic, for the operating margins of the treatment firms, could not be identified.

Thought both the difference-in-differences models and the demeaned synthetic control models suggest a negative treatment effect, the picture each model paints of how significant this finding is and what might constitute threats to its validity varies depending on the method employed. The diff-in-diff suggests that the coefficients are significant at the 5% level, but offers cause to be concerned about the validity of parallel trends due to the results of its Granger tests, while the DSC shows the time path of the difference between log Tobin's Q for the treatment firms and its synthetic control to be well within the range of trajectories of the analogous differences for the control firms and their respective synthetic controls.

Because ascertaining the effects of the regulatory environment on firms in the nuclear energy industry should provide a better understanding of how these firms are likely to behave in these different environments, which should, in turn, affect the way they deploy their resources, it is worth the time of future researchers to better understand this. To this end, better data, and perhaps different methods should be employed. In addition to finding a more appropriate group of firms to use in the difference-in-differences control and the DSC donor pool, future research could employ a framework more like that of Jayachandran, Lleras-Muney, and Smith (2010), who included a year term, and a year-treatment group interaction term. This would be a good way to incorporate a longer period of time, particularly as it pertains to the post-treatment period, and would give a better sense of long-term trends in an industry whose projects tend to have a long time-horizon. Additionally, other events that triggered a regulatory response from the history of the nuclear power industry could be used as treatments, both before and after the creation of the NRC. The Three Mile Island accident or the Calvert Cliffs decision could be examples of this. Finally, performing similar experiments examining the impacts of regulatory shocks on other industries using the relatively new demeaned synthetic control framework could provide new insights and help test different theories regarding the way in which regulation affects firms.

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Appendix 1: Backwards Stepwise Regression Procedure for Covariate Selection

Table 11: Fixed-effect regression results for log Tobin's Q backwards stepwise regression procedure

Backwards Stepwise Regression Procedure - Log Tobin's Q

	(1) 1 NC	(2) 2 NC	(3) 3 NC	(4) 4 NC	(5) 5 NC	(6) 6 NC	(7) 7 NC	(8) 1 BC	(9) 2 BC	(10) 3 BC	(11) 4 BC
ltDebtRatio	-0.458	-0.453		-0.388				1.687***	1.701***	1.838***	1.776***
	(0.608)	(0.595)		(0.567)				(0.467)	(0.471)	(0.456)	(0.469)
div	-0.107	-0.117	-0.00729					0.243*	0.267*	0.263*	
	(0.0870)	(0.0959)	(0.0846)					(0.141)	(0.157)	(0.147)	
logat	-0.0984	-0.0974	-0.158*	-0.105	-0.114	-0.111		-0.288***	-0.288***	-0.309***	-0.300***
	(0.0791)	(0.0793)	(0.0827)	(0.0761)	(0.0744)	(0.0750)		(0.0688)	(0.0676)	(0.0644)	(0.0627)
taxTa	0.610							-1.616			
	(2.632)							(1.669)			
capexToSales	3.856***	3.804***		3.634***	3.654***	3.761***	4.236***	1.268	1.338		
	(1.193)	(1.133)		(1.063)	(1.053)	(1.112)	(1.049)	(0.933)	(0.930)		
z_score	0.157**	0.158**	0.158**	0.156**	0.164**	0.173**	0.193***	0.155***	0.157***	0.157***	0.158***
	(0.0674)	(0.0672)	(0.0687)	(0.0655)	(0.0634)	(0.0611)	(0.0598)	(0.0275)	(0.0266)	(0.0267)	(0.0273)
returnSD	-5.027	-4.889	-6.507	-4.659	-5.541			-15.38***	-15.29***	-15.70***	-16.64***
	(4.511)	(4.620)	(4.436)	(4.848)	(4.609)			(3.381)	(3.264)	(3.204)	(3.201)
_treated2	-0.223***	-0.222***	-0.225***	-0.242***	-0.217***	-0.231***	-0.281***	-0.107**	-0.111**	-0.105**	-0.0563
	(0.0603)	(0.0601)	(0.0496)	(0.0574)	(0.0412)	(0.0424)	(0.0458)	(0.0467)	(0.0481)	(0.0487)	(0.0476)
Constant	-0.212	-0.210	0.147	-0.284	-0.319	-0.507	-1.209***	0.637	0.591	0.772	0.997**
	(0.651)	(0.648)	(0.688)	(0.686)	(0.681)	(0.585)	(0.221)	(0.502)	(0.492)	(0.467)	(0.455)
Observations	168	168	168	168	168	168	168	420	420	420	420
AIC	-3.586	-5.524	6.818	-6.568	-7.535	-6.970	-4.225	99.51	98.91	102.7	109.5
BIC	18.28	13.22	19.31	9.052	4.961	2.402	2.023	127.8	123.2	122.9	125.6

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 12: Fixed-effect regression results for operating margin backwards stepwise regression procedure

Backwards Stepwise Regression Procedure - Operating Margins

	(1) 1 NC	(2) 2 NC	(3) 3 NC	(4) 4 NC	(5) 5 NC	(6) 1 BC	(7) 2 BC	(8) 3 BC	(9) 4 BC	(10) 5 BC
ltDebtRatio	-0.0905	-0.0937	-0.0947	-0.0949		-0.0918**	-0.0914**	-0.0870**	-0.0852**	-0.0679
	(0.0615)	(0.0562)	(0.0568)	(0.0626)		(0.0354)	(0.0346)	(0.0354)	(0.0356)	(0.0497)
div	0.0203	0.0203*	0.0216**	0.0261**	0.0275**	-0.0156	-0.0158			
	(0.0115)	(0.0114)	(0.00984)	(0.00991)	(0.0124)	(0.0125)	(0.0133)			
logat	0.0119*	0.0120*	0.0119*	0.00937	0.00957	0.0180**	0.0179**	0.0174**	0.0176**	0.0143*
	(0.00560)	(0.00574)	(0.00577)	(0.00539)	(0.00645)	(0.00760)	(0.00731)	(0.00727)	(0.00777)	(0.00843)
taxTa	-0.0624	-0.0782				-0.378	-0.379	-0.325		-0.371
	(0.101)	(0.110)				(0.293)	(0.298)	(0.295)		(0.306)
capexToSales	0.187	0.188	0.195		0.195	0.190	0.189	0.193	0.206	
	(0.142)	(0.144)	(0.144)		(0.133)	(0.129)	(0.132)	(0.133)	(0.123)	
z_score	0.00680**	0.00693**	0.00694**	0.00658**	0.00907***	0.0127**	0.0127**	0.0127**	0.0132**	0.0126**
	(0.00286)	(0.00301)	(0.00302)	(0.00301)	(0.00288)	(0.00532)	(0.00500)	(0.00507)	(0.00555)	(0.00512)
returnSD	-0.144					0.0511				
	(0.346)					(0.656)				
_treated	0.00382	0.00390	0.00378	0.00185	0.00861*					
	(0.00452)	(0.00456)	(0.00440)	(0.00336)	(0.00461)					
_treated2						0.00648	0.00671	0.00403	0.00423	0.00453
						(0.00522)	(0.00442)	(0.00393)	(0.00386)	(0.00471)
Constant	-0.0203	-0.0244	-0.0252	-0.00528	-0.0438	-0.0432	-0.0416	-0.0545	-0.0596	-0.0300
	(0.0511)	(0.0556)	(0.0547)	(0.0498)	(0.0455)	(0.0727)	(0.0570)	(0.0607)	(0.0666)	(0.0652)
Observations	168	168	168	168	168	420	420	420	420	420
AIC	-862.8	-864.6	-866.4	-861.6	-858.1	-1852.1	-1854.1	-1852.8	-1848.7	-1842.6
BIC	-841.0	-845.8	-850.8	-849.1	-845.6	-1823.9	-1829.9	-1832.6	-1832.5	-1826.4

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Appendix 2: Unit weights and Pre-treatment RMSPEs for Demeaned Synthetic Control

Outcome Variable: Log Tobin's Q
Treatment Year: 1974

Table 13: Log Tobin's Q DSC with best AIC for narrow donor pool unit weights and pre-treatment RMSPE

Unit Weights:

Co_No	Unit_Weight
1387	0
1671	.362
2444	0
3613	0
3650	0
4864	0
5229	0
8545	0
8820	0
8968	0
9523	0
9965	0
10163	.638

Loss: Root Mean Squared Prediction Error

RMSPE	.2377364

Table 14: Log Tobin's Q DSC with AIC/BIC compromise for narrow donor pool unit weights and pre-treatment RMSPE

Unit Weights:

Co_No	Unit_Weight
1387	0
1671	0
2444	0
3613	0
3650	.311
4864	0
5229	0
8545	0
8820	0
8968	0
9523	0
9965	0
10163	.689

Loss: Root Mean Squared Prediction Error

RMSPE	.1617367

Table 15: Log Tobin's Q DSC with best BIC for narrow donor pool unit weights and pre-treatment RMSPE

Unit Weights:

Co_No	Unit_Weight
1387	.032
1671	.034
2444	.085
3613	.044
3650	.022
4864	.069
5229	.035
8545	.081
8820	.057
8968	.042
9523	.046
9965	.041
10163	.411

Loss: Root Mean Squared Prediction Error

RMSPE	.1078817

Table 16: Log Tobin's Q DSC with best AIC for broad donor pool unit weights and pre-treatment RMSPE

Unit Weights:

Co_No	Unit_Weight
1387	0
1409	0
1481	0
1671	0
2285	0
2444	0
2529	.483
2729	0
2789	.092
3506	0
3613	0
3650	0
4864	0
5046	0
5229	0
5439	0
5686	0
5959	0
6513	0
7298	.425
7985	0
8123	0
8545	0
8820	0
8968	0
9027	0
9217	0
9523	0
9965	0
10163	0
10581	0
10649	0
10983	0
11465	0

Loss: Root Mean Squared Prediction Error

RMSPE	.2440246

Table 17: Log Tobin's Q DSC with best BIC for broad donor pool unit weights and pre-treatment RMSPE

Unit Weights:

Co_No	Unit_Weight
1387	0
1409	0
1481	0
1671	0
2285	0
2444	0
2529	.525
2729	.236
2789	0
3506	0
3613	.208
3650	0
4864	0
5046	0
5229	0
5439	0
5686	0
5959	0
6513	0
7298	0
7985	0
8123	0
8545	0
8820	0
8968	0
9027	0
9217	0
9523	0
9965	0
10163	0
10581	.031
10649	0
10983	0
11465	0

Loss: Root Mean Squared Prediction Error

RMSPE	.1916068

Outcome Variable: Operating Margin
Treatment Year: 1975

Table 18: Operating margin DSC for narrow donor pool unit weights and pre-treatment RMSPE

Unit Weights:

Co_No	Unit_Weight
1387	0
1671	0
2444	0
3613	0
3650	.159
4864	0
5229	0
8545	.398
8820	.224
8968	0
9523	.218
9965	0
10163	0

Loss: Root Mean Squared Prediction Error

RMSPE	.0095722

Table 19: Operating margin DSC with best AIC for broad donor pool unit weights and pre-treatment RMSPE

Unit Weights:

Co_No	Unit_Weight
1387	0
1409	.124
1481	.283
1671	0
2285	0
2444	0
2529	0
2729	0
2789	0
3506	0
3613	0
3650	.001
4864	0
5046	0
5229	0
5439	0
5686	0
5959	0
6513	0
7298	0
7985	0
8123	0
8545	0
8820	0
8968	0
9027	0
9217	0
9523	.077
9965	0
10163	0
10581	0
10649	.515
10983	0
11465	0

Loss: Root Mean Squared Prediction Error

RMSPE	.0155447

Table 20: Operating margin DSC with best BIC for broad donor pool unit weights and pre-treatment RMSPE

Unit Weights:

Co_No	Unit_Weight
1387	0
1409	.136
1481	.281
1671	0
2285	0
2444	0
2529	0
2729	0
2789	0
3506	0
3613	0
3650	.001
4864	0
5046	0
5229	0
5439	0
5686	0
5959	0
6513	0
7298	0
7985	0
8123	0
8545	0
8820	0
8968	0
9027	0
9217	0
9523	.097
9965	0
10163	0
10581	0
10649	.485
10983	0
11465	0

Loss: Root Mean Squared Prediction Error

RMSPE	.0149648

Appendix 3: Accounting for Granger Results Regression Tables

Table 21: Difference-in-differences results for log Tobin's Q of broad control model with best AIC specification in all early treatment years

Early Treatment Diff-in-Diff Results for Log Tobin's Q - Best AIC; Broad Control

	(1) 1973	(2) 1972	(3) 1971	(4) 1970	(5) 1969
ATET					
r1vs0._treated3	0.0141				
	(0.0550)				
r1vs0._treated4		0.0809			
		(0.0505)			
r1vs0._treated5			0.114**		
			(0.0468)		
r1vs0._treated6				0.155***	
				(0.0507)	
r1vs0._treated7					0.183***
					(0.0498)
Controls					
ltDebtRatio	0.984***	0.989***	0.992***	0.998***	0.995***
	(0.313)	(0.313)	(0.313)	(0.314)	(0.313)
div	0.247*	0.245*	0.246*	0.246*	0.247*
	(0.145)	(0.144)	(0.144)	(0.144)	(0.144)
logat	0.177*	0.177*	0.177*	0.176*	0.176*
	(0.0875)	(0.0874)	(0.0873)	(0.0871)	(0.0871)
capexToSales	1.900***	1.900***	1.901***	1.898***	1.892***
	(0.619)	(0.620)	(0.621)	(0.622)	(0.622)
z_score	0.144***	0.144***	0.144***	0.144***	0.144***
	(0.0250)	(0.0251)	(0.0251)	(0.0251)	(0.0251)
returnSD	-4.891	-5.039	-5.082	-5.150	-5.099
	(5.897)	(5.904)	(5.898)	(5.894)	(5.866)
Constant	-1.999***	-1.995***	-1.994***	-1.991***	-1.992***
	(0.539)	(0.539)	(0.538)	(0.537)	(0.537)
Observations	420	420	420	420	420
ptrends_F	20.51	13.53	13.38	6.905	2.717
ptrends_p	0.0000694	0.000805	0.000853	0.0128	0.108
granger_F	6.642	4.650	5.596	5.236	1.760
granger_p	0.000103	0.00243	0.00143	0.00444	0.187

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 22: Difference-in-differences results for log Tobin's Q of broad control model with best BIC specification in all early treatment years

Early Treatment Diff-in-Diff Results for Log Tobin's Q - Best BIC; Broad Control

	(1) 1973	(2) 1972	(3) 1971	(4) 1970	(5) 1969
ATET					
r1vs0._treated3	0.0163				
	(0.0564)				
r1vs0._treated4		0.0826			
		(0.0524)			
r1vs0._treated5			0.113**		
			(0.0493)		
r1vs0._treated6				0.158***	
				(0.0534)	
r1vs0._treated7					0.191***
					(0.0522)
Controls					
ltDebtRatio	1.194***	1.199***	1.202***	1.208***	1.204***
	(0.314)	(0.314)	(0.314)	(0.314)	(0.313)
div	0.235	0.233	0.234	0.234	0.235
	(0.141)	(0.141)	(0.140)	(0.140)	(0.140)
logat	0.152	0.152	0.151	0.151	0.151
	(0.0915)	(0.0915)	(0.0913)	(0.0912)	(0.0912)
z_score	0.144***	0.144***	0.144***	0.145***	0.144***
	(0.0254)	(0.0255)	(0.0255)	(0.0256)	(0.0255)
returnSD	-6.612	-6.760	-6.799	-6.871	-6.820
	(5.826)	(5.833)	(5.828)	(5.826)	(5.800)
Constant	-1.728***	-1.724***	-1.723***	-1.720***	-1.722***
	(0.537)	(0.536)	(0.535)	(0.534)	(0.534)
Observations	420	420	420	420	420
ptrends_F	23.10	16.64	18.44	12.09	6.581
ptrends_p	0.0000306	0.000258	0.000138	0.00141	0.0149
granger_F	6.367	4.526	5.667	5.345	3.437
granger_p	0.000146	0.00286	0.00132	0.00399	0.0437

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 23: Difference-in-differences results for operating margin of narrow control model in all early treatment years

Early Treatment Diff-in-Diff Results for Operating Margins - Narrow Control

	(1) 1974	(2) 1973	(3) 1972	(4) 1971	(5) 1970	(6) 1969
ATET						
r1vs0._treated2	-0.00379					
	(0.00552)					
r1vs0._treated3		-0.00609				
		(0.00467)				
r1vs0._treated4			-0.00897**			
			(0.00360)			
r1vs0._treated5				-0.00814**		
				(0.00372)		
r1vs0._treated6					-0.0100*	
					(0.00554)	
r1vs0._treated7						-0.0118**
						(0.00491)
Controls						
ltDebtRatio	-0.0688	-0.0703	-0.0723	-0.0723	-0.0741	-0.0732
	(0.0664)	(0.0666)	(0.0668)	(0.0677)	(0.0695)	(0.0679)
logat	0.00886*	0.00878*	0.00865*	0.00866*	0.00868*	0.00870*
	(0.00486)	(0.00486)	(0.00486)	(0.00488)	(0.00489)	(0.00491)
div	0.0224	0.0222	0.0221	0.0217	0.0214	0.0213
	(0.0140)	(0.0137)	(0.0134)	(0.0133)	(0.0133)	(0.0133)
capexToSales	0.166	0.165	0.163	0.164	0.165	0.166
	(0.151)	(0.151)	(0.152)	(0.152)	(0.152)	(0.151)
z_score	0.00807**	0.00805**	0.00801**	0.00801**	0.00796**	0.00799**
	(0.00299)	(0.00297)	(0.00297)	(0.00299)	(0.00300)	(0.00298)
Constant	-0.0111	-0.0103	-0.00894	-0.00866	-0.00816	-0.00841
	(0.0379)	(0.0378)	(0.0378)	(0.0381)	(0.0386)	(0.0381)
Observations	168	168	168	168	168	168
ptrends_F	4.306	2.915	1.115	2.500	0.175	0.455
ptrends_p	0.0584	0.112	0.310	0.138	0.682	0.512
granger_F	7.464	8.653	2.199	2.683	2.392	1.624
granger_p	0.00102	0.000629	0.117	0.0788	0.116	0.235

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 24: Difference-in-differences results for operating margin of broad control model with best AIC specification in all early treatment years

Early Treatment Diff-in-Diff Results for Operating Margins - Best AIC; Broad Control

	(1) 1974	(2) 1973	(3) 1972	(4) 1971	(5) 1970	(6) 1969
ATET						
r1vs0._treated2	0.00222					
	(0.00587)					
r1vs0._treated3		-0.00321				
		(0.00568)				
r1vs0._treated4			-0.00880			
			(0.00575)			
r1vs0._treated5				-0.00819		
				(0.00557)		
r1vs0._treated6					-0.00827	
					(0.00554)	
r1vs0._treated7						-0.00786*
						(0.00449)
Controls						
ltDebtRatio	-0.0642*	-0.0644*	-0.0647*	-0.0648*	-0.0649*	-0.0647*
	(0.0359)	(0.0359)	(0.0358)	(0.0358)	(0.0359)	(0.0358)
div	-0.0145	-0.0143	-0.0142	-0.0143	-0.0144	-0.0144
	(0.0135)	(0.0134)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
logat	0.0108	0.0108	0.0108	0.0108	0.0109	0.0108
	(0.00832)	(0.00835)	(0.00839)	(0.00838)	(0.00838)	(0.00836)
taxTa	-0.381	-0.380	-0.380	-0.381	-0.381	-0.381
	(0.242)	(0.242)	(0.242)	(0.243)	(0.243)	(0.243)
capexToSales	0.146	0.146	0.146	0.145	0.146	0.146
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
z_score	0.0133**	0.0133**	0.0133**	0.0133**	0.0133**	0.0133**
	(0.00508)	(0.00507)	(0.00506)	(0.00506)	(0.00506)	(0.00506)
Constant	0.00346	0.00333	0.00345	0.00351	0.00342	0.00340
	(0.0510)	(0.0512)	(0.0514)	(0.0514)	(0.0514)	(0.0513)
Observations	420	420	420	420	420	420
ptrends_F	8.331	6.197	0.0254	0.402	1.459	5.162
ptrends_p	0.00673	0.0178	0.874	0.530	0.235	0.0295
granger_F	4.210	4.699	2.049	2.517	3.307	3.239
granger_p	0.00195	0.00140	0.0964	0.0594	0.0317	0.0516

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 25: Difference-in-differences results for operating margin of broad control model with best BIC specification in all early treatment years

Early Treatment Diff-in-Diff Results for Operating Margins - Best BIC; Broad Control

	(1) 1974	(2) 1973	(3) 1972	(4) 1971	(5) 1970	(6) 1969
ATET						
r1vs0._treated2	-0.000339					
	(0.00554)					
r1vs0._treated3		-0.00482				
		(0.00562)				
r1vs0._treated4			-0.00968			
			(0.00585)			
r1vs0._treated5				-0.00838		
				(0.00566)		
r1vs0._treated6					-0.00825	
					(0.00559)	
r1vs0._treated7						-0.00772*
						(0.00446)
Controls						
ltDebtRatio	-0.0596	-0.0598	-0.0602	-0.0601	-0.0602	-0.0600
	(0.0370)	(0.0370)	(0.0369)	(0.0370)	(0.0371)	(0.0369)
logat	0.00948	0.00949	0.00948	0.00949	0.00951	0.00950
	(0.00832)	(0.00835)	(0.00839)	(0.00838)	(0.00837)	(0.00835)
taxTa	-0.332	-0.332	-0.332	-0.332	-0.333	-0.332
	(0.244)	(0.243)	(0.243)	(0.244)	(0.244)	(0.244)
capexToSales	0.150	0.149	0.149	0.149	0.149	0.150
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
z_score	0.0133**	0.0133**	0.0133**	0.0133**	0.0133**	0.0133**
	(0.00513)	(0.00512)	(0.00511)	(0.00511)	(0.00512)	(0.00512)
Constant	-0.00420	-0.00419	-0.00402	-0.00405	-0.00416	-0.00419
	(0.0526)	(0.0527)	(0.0529)	(0.0528)	(0.0528)	(0.0527)
Observations	420	420	420	420	420	420
ptrends_F	7.031	4.506	0.326	0.523	1.458	4.912
ptrends_p	0.0121	0.0411	0.572	0.475	0.236	0.0335
granger_F	3.934	4.513	1.918	2.283	2.945	3.039
granger_p	0.00304	0.00183	0.117	0.0806	0.0467	0.0611

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Appendix 4: Accounting for Granger Results Graphs

Figure 10: Observed means and linear-trends models for log Tobin's Q with 1973 treatment

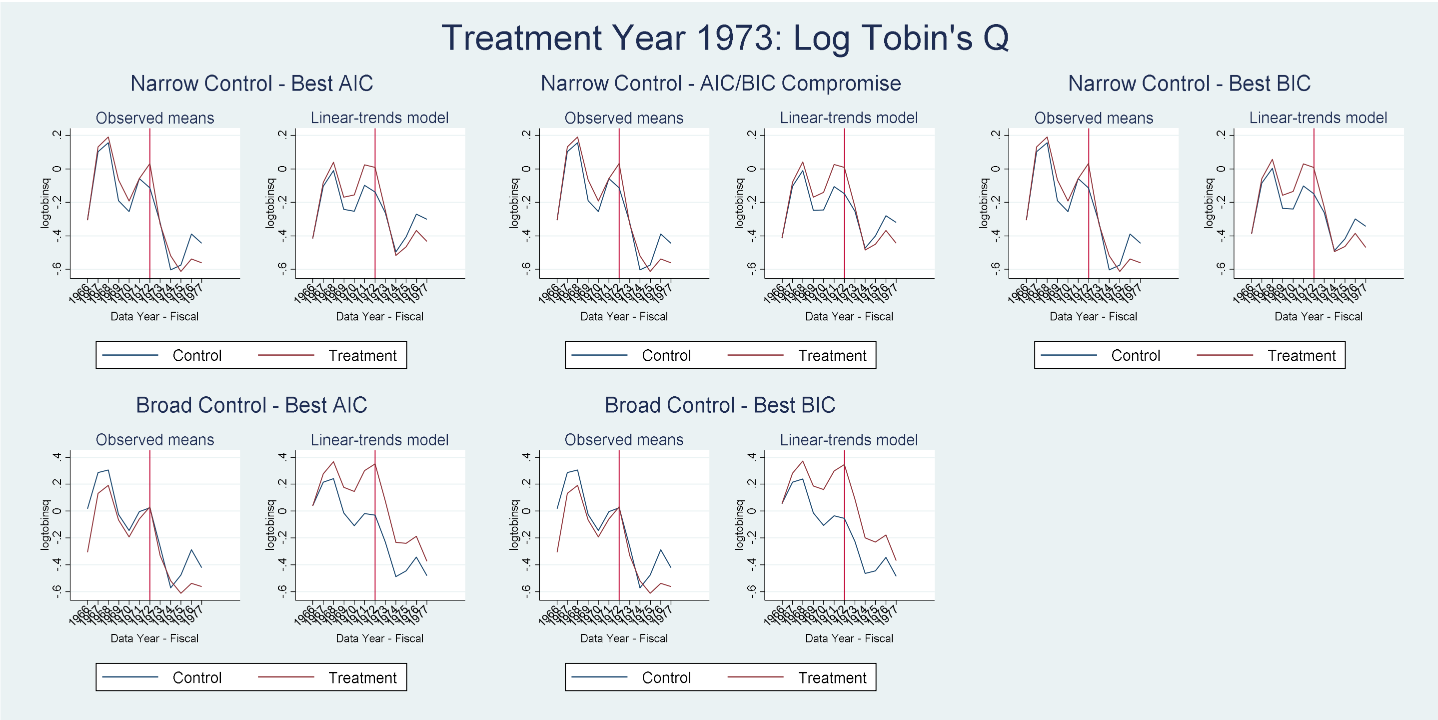


Figure 11: Observed means and linear-trends models for log Tobin's Q with 1972 treatment

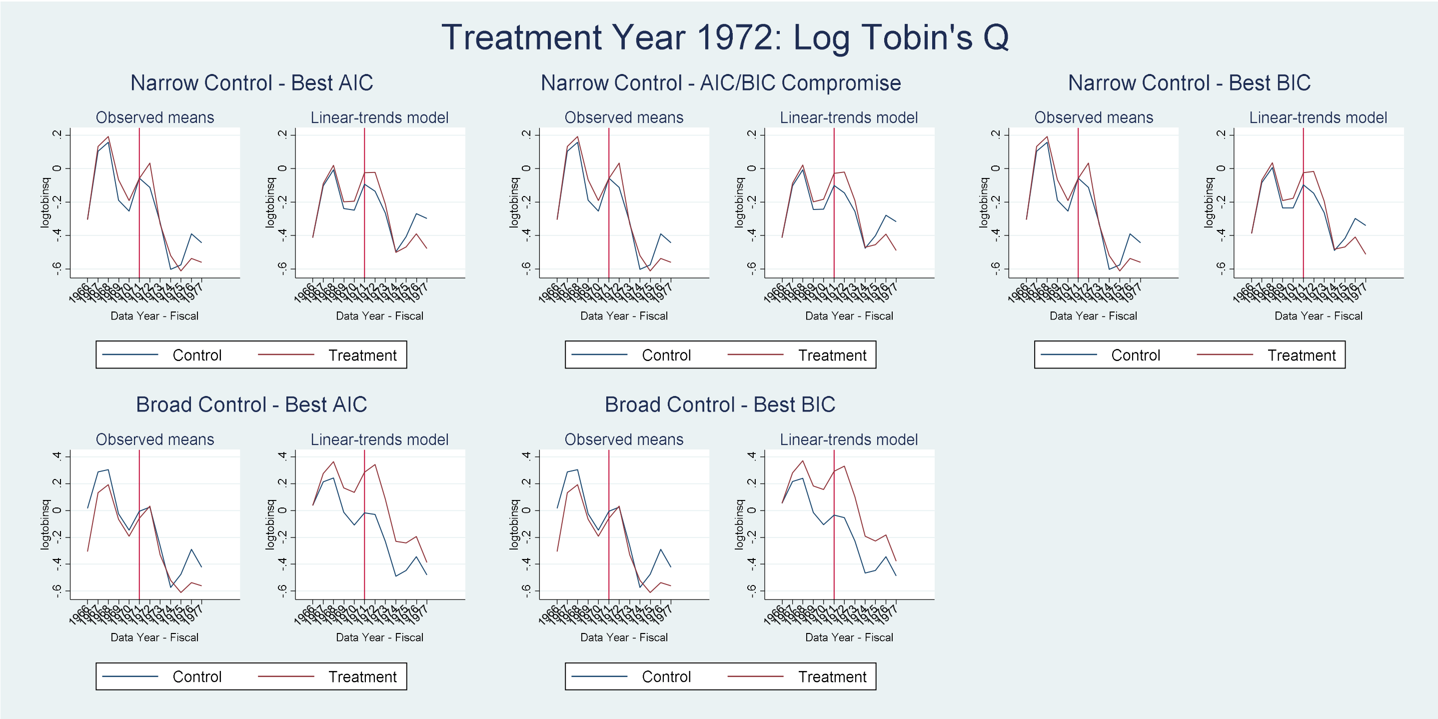


Figure 12: Observed means and linear-trends models for log Tobin's Q with 1971 treatment

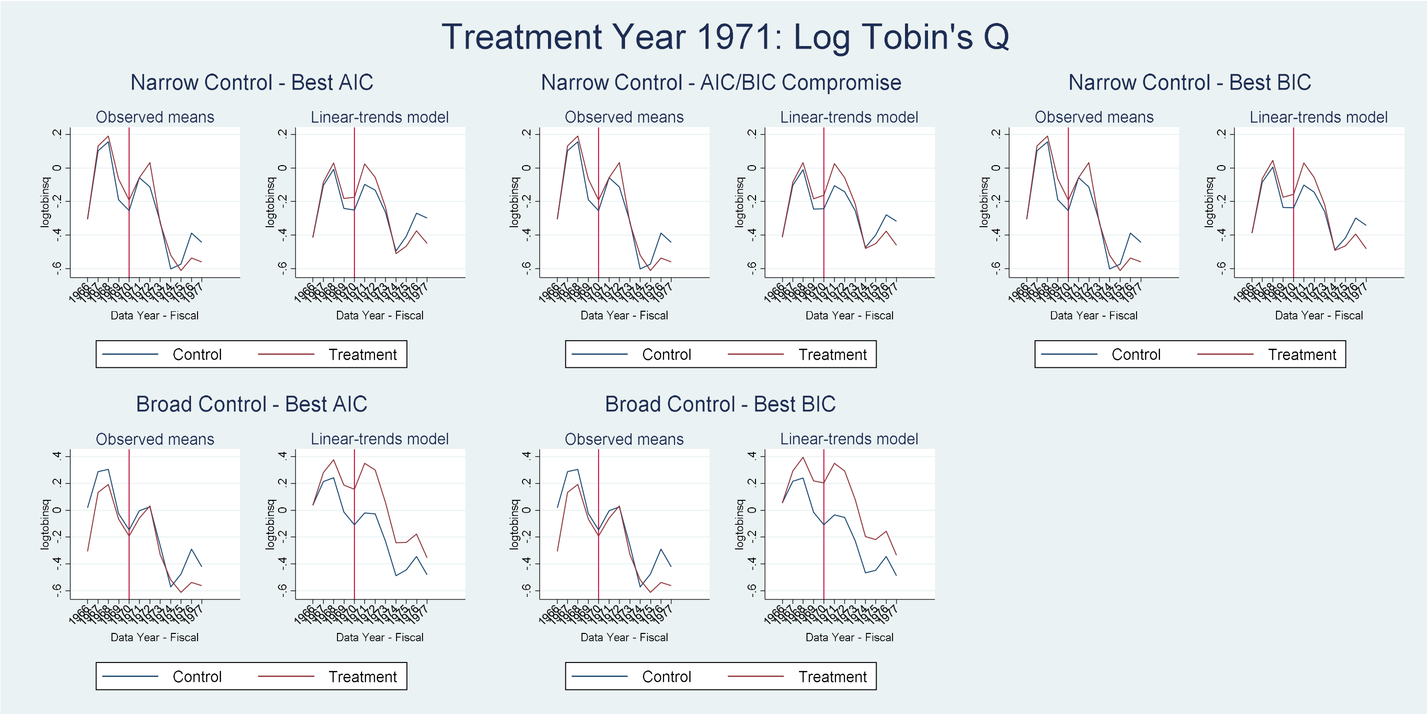


Figure 13: Observed means and linear-trends models for log Tobin's Q with 1970 treatment

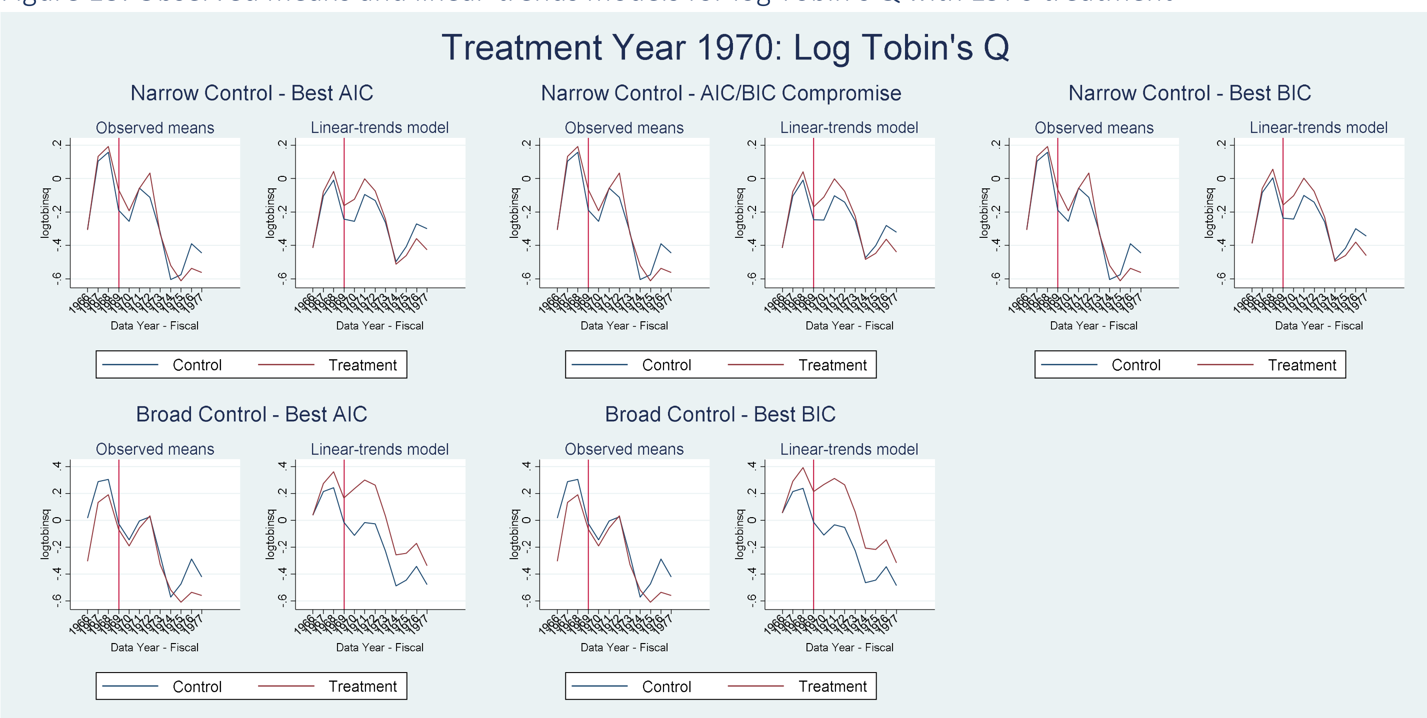


Figure 14: Observed means and linear-trends models for log Tobin's Q with 1969 treatment

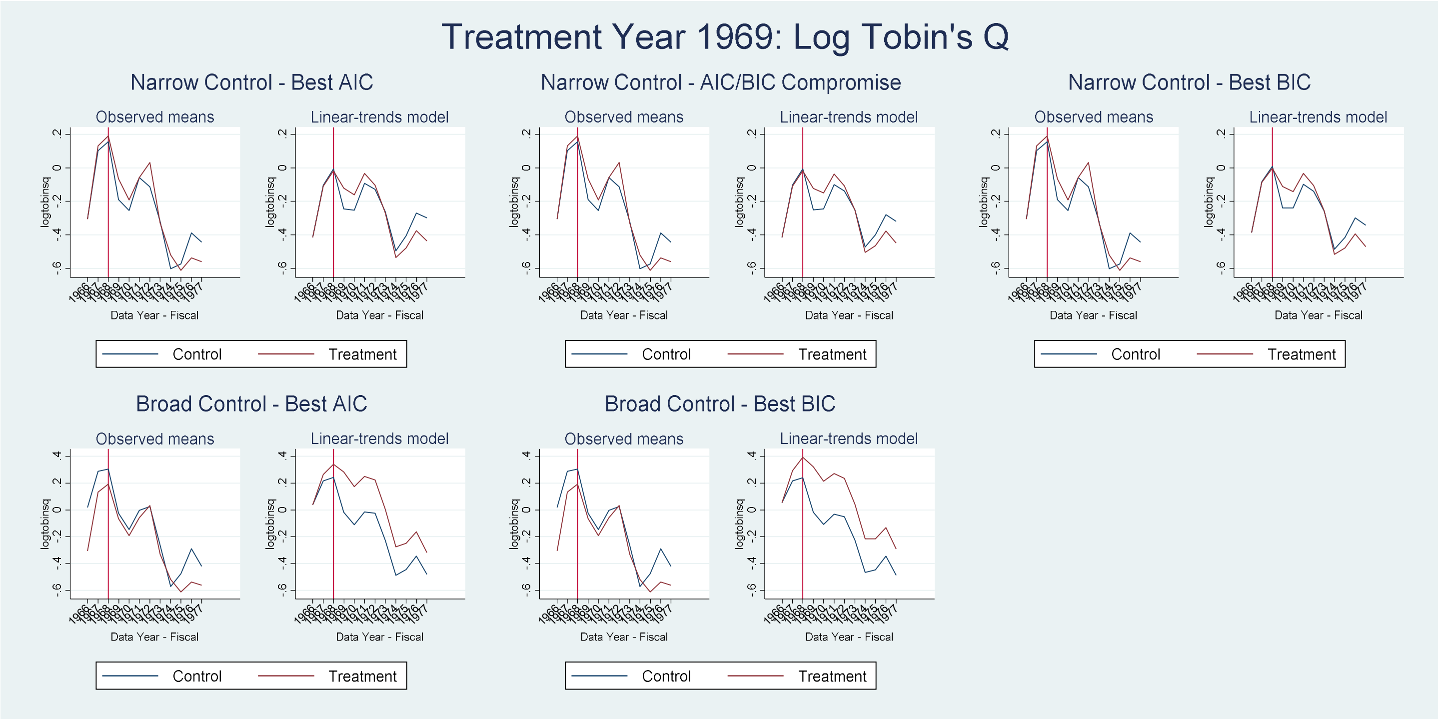


Figure 15: Observed means and linear-trends models for operating margin with 1974 treatment

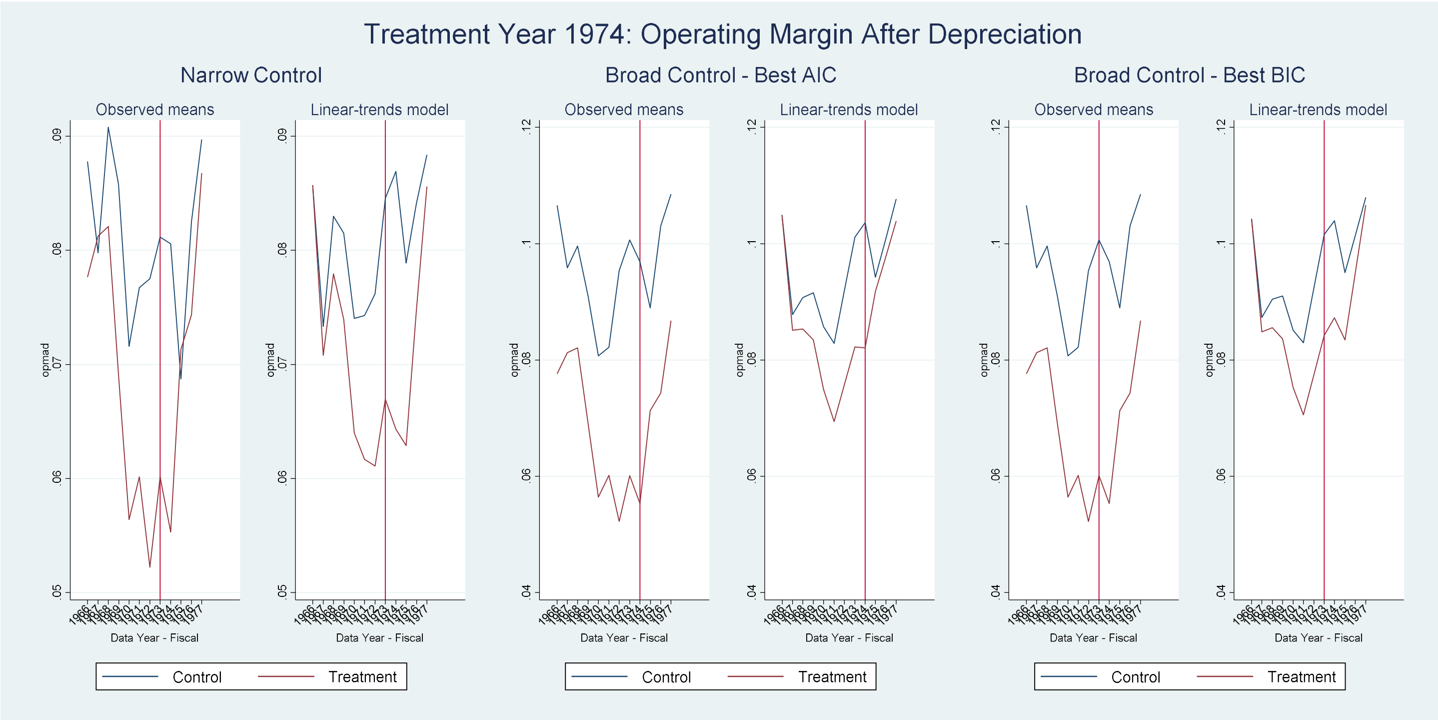


Figure 16: Observed means and linear-trends models for operating margin with 1973 treatment

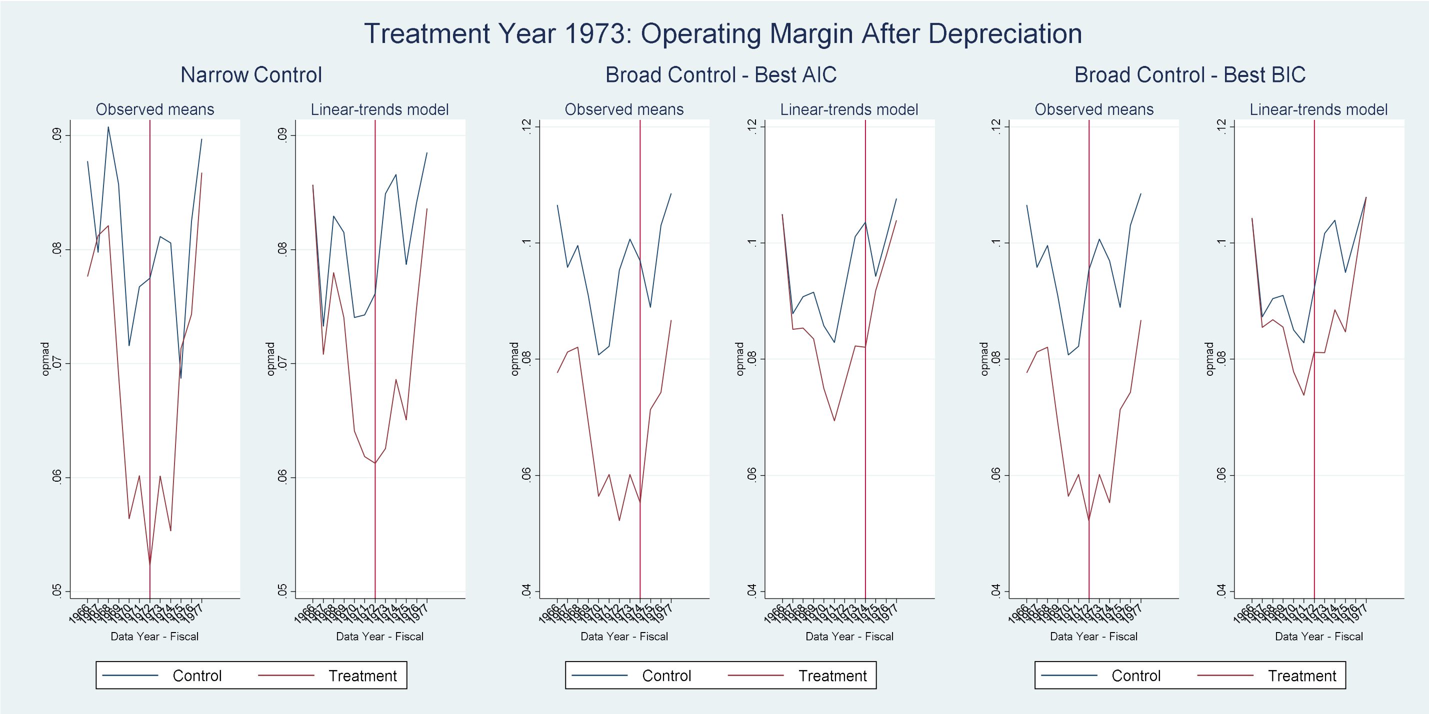


Figure 17: Observed means and linear-trends models for operating margin with 1972 treatment

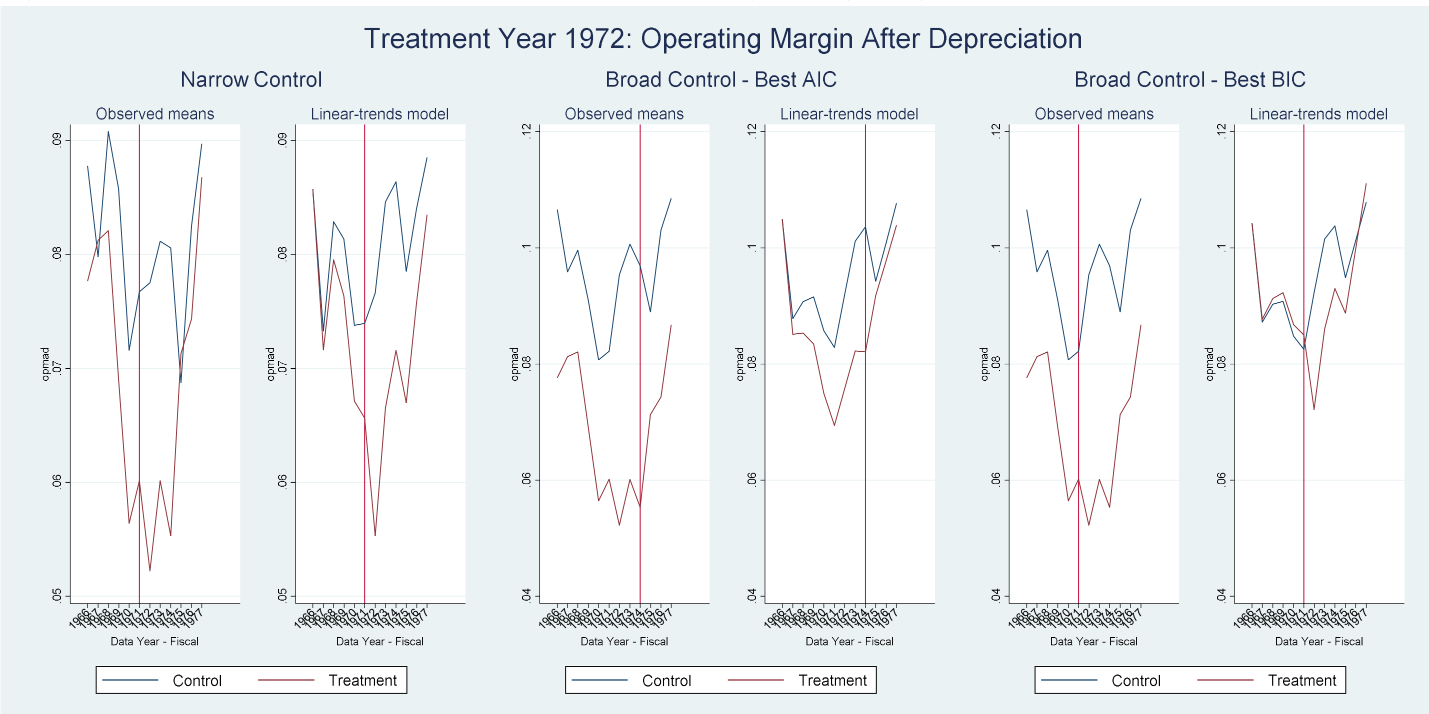


Figure 18: Observed means and linear-trends models for operating margin with 1971 treatment

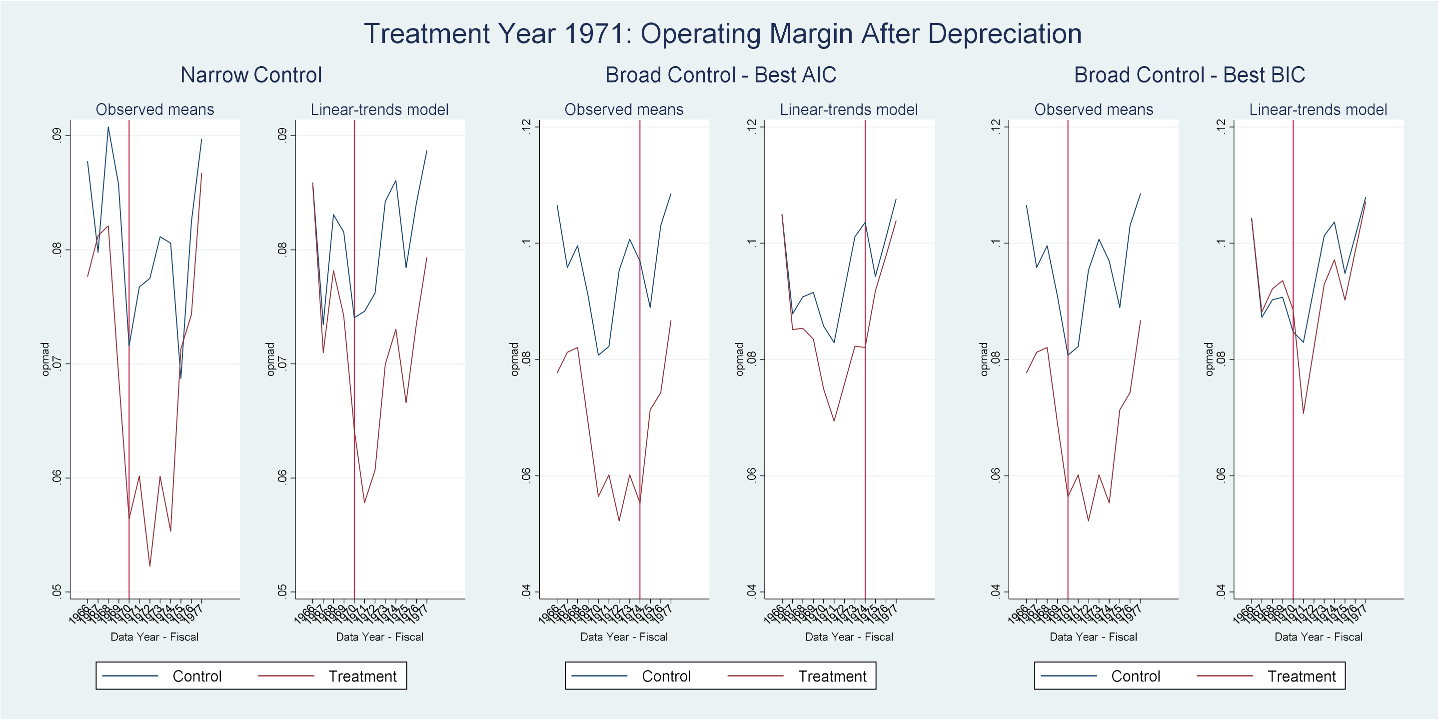


Figure 19: Observed means and linear-trends models for operating margin with 1970 treatment

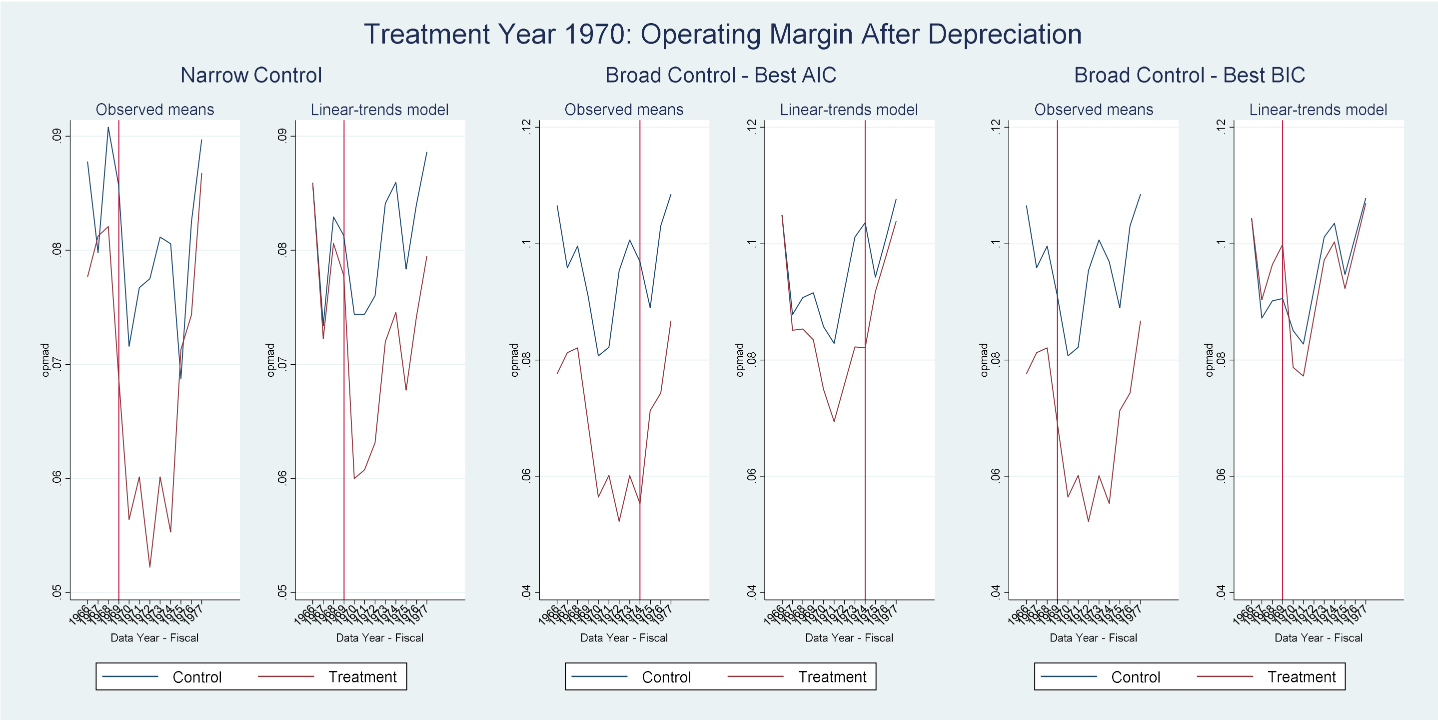
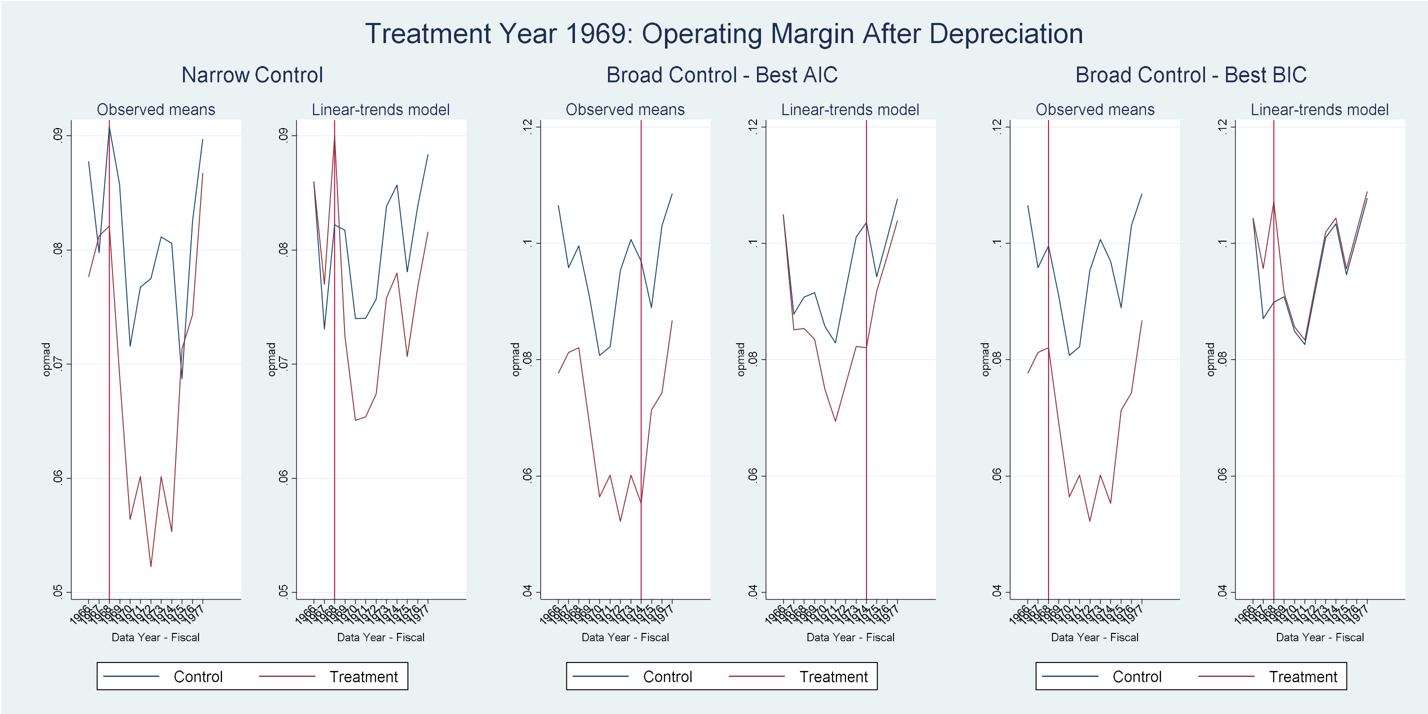


Figure 20: Observed means and linear-trends models for operating margin with 1969 treatment



Appendix 5: Additional SIC Codes Used for the Broad Control and Donor Pool

3812 SEARCH, DETECTION, NAVAGATION, GUIDANCE, AERONAUTICAL SYS

3721 AIRCRAFT

4833 TELEVISION BROADCASTING STATIONS

3724 AIRCRAFT ENGINES & ENGINE PARTS

3841 SURGICAL & MEDICAL INSTRUMENTS & APPARATUS

3630 HOUSEHOLD APPLIANCES

1389 OIL & GAS FIELD SERVICES, NEC

2821 PLASTIC MATERIALS, SYNTH RESINS & NONVULCAN ELASTOMERS

2810 INDUSTRIAL INORGANIC CHEMICALS

1040 GOLD AND SILVER ORES

3585 AIR-COND & WARM AIR HEATG EQUIP & COMM & INDL REFRIG EQUIP

3562 BALL & ROLLER BEARINGS