The impact of UK elections on Business Tendency Survey data: Evidence from the CBI.

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Abstract

This report is an introductory work and examines a rather complex issue that is the impact of elections on survey data and whether firms respond differently to Business Tendency Surveys during election periods. The purpose of Business Tendency Surveys is to obtain qualitative information from firms for use in tracking the current business situation and for the short-term economic forecasting of variables such as output, inflation, unemployment etc. Their effectiveness in this regard is reliant upon the quality of firms' perceptions of their own company's performance and plans. Events which are surrounded by heightened uncertainty (which may be both before and after the event) have the potential to distort or disrupt these perceptions, potentially weakening the quality of survey data as an early indicator of official data.

This analysis will examine the link between political uncertainty due to elections and business survey data involving a number of elections over the years in UK, with an application to the CBI's Industrial Trends Survey. The link between political and economic uncertainty and survey data will be addressed firstly. Secondly, a detailed overview of the dataset along descriptive statistics is summarised. The third part is the empirical methodology, where we address the reasoning behind our modelling approach by including lagged terms of the dependent variable on the right hand side of the regression. The model specification and an application on the Industrial Trends Survey are also outlined. The fourth part involves the dynamic regression results where issues such as the correlation between firm perceptions of UK business conditions and expectations of output, investment intentions, employment rates, business confidence etc. are compared between pre and post-election periods. We also included a another type of quantitative variables which is the predictive power of firms expectations on output, employment, total new orders and tracking the manufacturing output growth. Regressions and hypothesis testing have been carried out in order to investigate election period effects on survey data (positive or negative, temporary or long lasting, stable or changing over the period of the election-related uncertainty). We conclude with a summary and a general discussion of our results as well as future research proposal and advice on how better measure election uncertainty directly from the questionnaire.

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1. Introduction

There is an extensive literature (see Nardo 2003) focused on extracting valuable qualitative information from Business and Consumer surveys for mainly two reasons. First to understand agents' behaviour in response to changes in the state of the economy and the other to create survey-derived economic indicators in order to track what will actually happen to the economy in the near future.

However, economic indicators derived from Business & Consumer opinion Surveys can be severely biased and over or underestimate the actual movements of the macroeconomic quantity in question. This may occur particularly under conditions of high uncertainty where incomplete information or finite information processing capacity within firms leads agents to positively or negatively overreact to news, thus leading them to misjudge their current and/or future situation, which will potentially lead to biased survey based indicators.

In our study, we will investigate what happens to the quality of survey-based indicators using data from the CBI's Industrial Trends Survey (ITS) during UK national elections. Our analysis involved univariate and multivariate hypothesis testing, dynamic regressions and graphical representations in order to understand and try to uncover any effect that electoral cycles may have on the survey data. Looking at the **Table B4** half of the questions examined show a statistically significant effect attributed to the post election period.

The rest of the report is structured as follows:

In section **1**, we motivate the link between electoral/political uncertainty and firms' perceptions and in addition give a summary of the political background to the UK elections from 1958 until 2017[1] . In section **2**, we give a detailed description of the dataset as well as the descriptive statistics. In section **3**, we motivate, describe the framework and provide an application of our empirical method more specifically the LDV model. We end with section **4** and a summary of our findings followed by the conclusion, which is a discussion as well as a recap of the empirical results. Finally we consider improvements to survey data by capturing the election impact directly from the questionnaire and conclude with reflections on future research.

[1] The UK – general elections of 2017 are excluded.

1.1 Political uncertainty and firms' perceptions

There are many important reasons for examining factors which may influence the quality of business survey data. Such surveys are used to provide early economic indicators for various economic quantities before the quantitative official data are at agents' disposal. Another benefit is that all these survey-based indicators can be used to compare the economies between countries on unemployment, production, business confidence, investments and exports and other micro and macro-economic quantities. Furthermore, they are frequently used by central banks to estimate inflation rates and inform short-term economic forecasts. Various scholars-economists (Buthe & Lindt 2002, Kuziakiv 2006, et al.) suggested that during periods of high political uncertainty and more specifically during election events, firms' "business as usual" situation is rattled.

From both a theoretical and a practical stand point, we know that economic conditions can be affected by non-economic factors such as uncertainty. And elections usually involve a degree of uncertainty. Political uncertainty can disrupt business' investment plans, particularly for large projects that have a big sunk cost or where the returns are realised over a longer time horizon. Uncertainty may be particularly elevated when firms believe that a certain election outcome would result in a marked change in the political climate. When the election race is close between two major parties with differing policy priorities, uncertainty is likely to be heightened. Even once the election has taken place and the outcome is known, uncertainty may persist. Consider the situation where there is a change of power: uncertainty may persist if firms are unable to judge the degree to which pre-election promises will be adhered to. This may occur, for example, if the new governing party has not been in power for a prolonged period of time, where the nature of the party's ideology has changed significantly since they were last in government or where the party has a track record of unpredictability in the implementation of policy. Political uncertainty can also weigh on plans for investment and other strategic decisions. High levels of policy uncertainty shown to have negative effects especially for firms having large not-easily reversible investments (see Abberger et al. 2016). Also Bernanke (1983) works out a "wait and see" approach on investments for firms facing high uncertainty. Political and policy uncertainty are closely related with Electoral uncertainty (Buthe 2002). Uncertainty created by elections mainly has negative effects (see also Buthe and Kuziakiv) to the economy, as firms' business confidence will take a downward trend which could result in cutting down investments and hiring new people. Companies with a large global presence may look to expand elsewhere in the world, or hold back on increasing their exposure to the UK.

Buthe (2002) suggest that even though firms have knowledge that general elections are coming up (before they get announced) next year or in next *x* quarters that does not necessary mean they take into account this information when answering the surveys. Usually if there is an extensive media coverage of the elections, then it is more likely that firms will take notice *x* quarters before when assessing their short or long term planning.

Measuring uncertainty in elections

Uncertainty is inherently hard to quantify. And political uncertainty and electoral uncertainty are very closely related and sometimes difficult to separate. Quantified proxies for political risk can be estimated by calculating the dispersion in answers from a business tendency survey. Other approaches may include the calculation of a policy uncertainty index, for example, measuring the difference in polls against the margin of error, capturing newspaper sentiment etc. We are only interested in electoral uncertainty in a broader sense basically looking deviations from normal times due to elections. Therefore, we have chosen to use a set of dummy variables that take the value of 1 if we are 0-6 quarters before or after an election and 0 otherwise. Also we introduce a time related variable to allow each month or quarter to have a different effect as we are coming closer or further away from an election. These two time effect variables one for pre and one for the post-election period increase sequentially as we are moving closer to or further away from an election. We chose to procced with this set of dummies in an attempt to capture all the information that theoretically would be election-related uncertainty.

Correlation vs causation

The objective is to discover whether there is a systematic pattern in the aggregate level of firms' perceptions when we are relatively close to an election event. However, by taking an indirect measure of electoral uncertainty and using electoral cycles to identify the timing of systematic patterns in firms' responses, we can only identify an association with electoral uncertainty, but will not be able to refer to a casual effect. A causal effect is more complicated and requires strong assumptions see **Section 3**. We instead use asymptotic results for our findings, while noticing when the sample size increases, the number of elections also increase, then as we move forward in time and gather more data we would be able to infer with more certainty a causal effect between electoral uncertainty and firms perceptions.

1.2 Political Background in the UK

In the UK, general elections are mandated to occur every five years – this timetable has been in effect since 2011; prior to that time, the government was free to call a general election at any time. However, the government of the day may place a vote before Parliament to call an election outside of this timetable and if Parliament votes in favour, then an election can be called – this was the case for the 2017 general election. The next general election is theoretically scheduled to take place in 2022, but in effect could be called at any time. So the timing of an election remains essentially uncertain. Once an election has been called, the degree to which it disrupts firm perceptions ahead of the election result will depend upon prevailing political conditions – namely, the relative performance of the major parties during their respective election campaigns and related trends in the polls (which themselves have become less informative over time). The election result itself may or may not be unexpected and, if unexpected, may be associated with heightened and/or prolonged uncertainty or caution with regards to the policy priorities of the successful parties and their economic implications. In the event of a hung parliament (which occurs when no one party succeeds in achieving an outright majority, as was the case in 2017), uncertainty after the election result may become especially elevated and will last as long as it takes a party (usually, but not necessarily, the one with the largest share of the vote) to succeed in negotiating a coalition or other form of agreed support with one or more minority parties. This indicates a reason where firms could be highly uncertain in the first few months ex-post an election.

2 Data and Descriptive Statistics.

The Industrial Trends Survey (ITS), conducted by the Confederation of British Industry, is the longest running survey on UK manufacturing, having began in 1958, and continues to be an accurate and timely bellwether for UK manufacturing sector and the wider economy. In a recent paper from Goldman Sachs (July 2017 Andrew Benito), the ITS is identified from a pool of many other indicators as a highly informative predictor (probability score >80%) for real UK GDP. The ITS asks manufacturing firms key questions on the *past* (nowcast) and *future* (forecast) regarding movements in domestic and export orders, capacity, output, employment, investment etc. Firms have three responses available to reflect trends in their e.g. output y_t: *"Up", "Same"* and *"Down"*.

An example of some of the questions chosen as phrased in the quarterly Industrial Trends Survey are:

Question (**1**)*: "Are you more, or less, optimistic than you were* ***three months ago*** *about the* ***general business situation*** *in your industry?*

1. *"Less"*
2. *"Same"*
3. *"More"*

Question (**8a**)*: "Excluding seasonal variations, what has been the trend over the* ***past three*** *months, with regard to the* ***volume of output****?"*

1. *"Down"*
2. *"Same"*
3. *"Up"*

Question (**8b**)*: "Excluding seasonal variations, what are the* ***expected*** *trends over the* ***next three*** *months, with regard to the* ***volume of output****?"*

1. *"Down"*
2. *"Same"*
3. *"Up"*

Questions (**1**), (**8a**) refers to respondents' retrospective views (nowcast) and (**8b**) to their prospective views (forecast).

In **Appendix A** we provide all the questions used in this analysis. Taking advantage of the 60 year-old historical time series of the ITS, we also decided to go as far as possible in terms of historical elections.

By looking at **Appendix A** in the section on UK national elections **Table A2,** we consider all the elections that happen from October 1958 to April 2017[2]. Our dataset consists of both quarterly and monthly time series on the aggregated balances of the variable in question[3] see **Table A1**.We tried to switch on the monthly time series with the hope to increase the sample size thus by having more data to estimate the models and reduce the standard error of the parameters of interest (election dummies). We concluded that this would only be useful in the case of the volume of output over the next three months because it is the only monthly question of interest that dates back as far as April 1975[4]. All other monthly questions start from October 1995 which means a total sample of 259 observations but only 5 elections to work with. The ITS quarterly dataset has a total sample of 223 observations and a total of 14 elections. A drawback of the quarterly dataset is that the questions about the volume of output in the past and next three months started on April 1975 – prior to that, the question was about the value of output instead of the volume. Another issue, is our monthly data for the volume of output of past three months do not start from 1975 but from 1995. However, the month on three month expectations of firms' manufacturing output is a time series which contains a total sample size of 505 observations and a total of 9 elections.

Table 2.1 provides a short summary of potential sample size benefits arising from a switch between monthly and quarterly data sets. The monthly data give one extra observation for each quarter away from an election, which means that if we are considering the pre-election period to be 6 months before an election, then by using the ITS Q time series we get 28 observations which we assign to a pre-election period and 28 to a post-election. If we switch to the ITS M time series we get 30 an excess of 2 observations[5]. However, this small win is overwhelmed by the loss of a considerable number of elections (- 9) from the sample. As a result, we decide to work mostly with the quarterly dataset and only study the volume of output monthly.

Table 2.1	Pre and Post election sample size quarters away from the election					
Datasets	Total Sample	Elections[6]	$\mp Q1$	$\mp Q2$	$\mp Q3$	$\mp Q4$
ITS Q data [1958Q2, 2017Q2]	223	14	14	28	42	56
ITS M data [1995M10, 2017M04]	259	5	15	30	45	60
Output NEXT 3M [1975M04, 2017M04]	505	9	27	54	81	108
Outturn M data [1975M04, 2017M04]	505	9	27	54	81	108
Outturn Q data [1958Q2, 2017Q2]	223	14	14	28	42	56

[2] We do not take into consideration the "snap" elections of June 2017 for this stage of the analysis. Thus the year 2017 is considered as a "normal" year. Also because our only focus is the effect of national elections we did not take into account famous referendums such as the EU referendum in June 2016 or the Scottish referendum in September 2013 or United Kingdom European Communities membership referendum in June 1975.

[3] Note only the volume of output and numbers employed are also asked on a monthly basis.

[4] Of course all monthly time series counted from their beginning are a superset of their relevant quarterly time series.

[5] The numbers 28 and 30 for ITSQ and ITSM respectively is the product (number of Q's before or after an election) × (number of elections in the sample). Therefore for ITSQ we have $2\ (Quarters\ ) * 14\ (Elections) = 28$ and in case of ITSM $6\ (Months\ ) * 5\ (Elections) = 30$.

[6] For estimation and simplicity purposes we only use one election from the year 1974 which is the 10 October 1974. On 28 February 1974 an election was called. In the January 1974 ITS survey we observe very high negative values

The descriptive statistics of the datasets used can be found in **Appendix B Table B1**.

Looking at Table B1 during the whole sample period [1958Q2, 2017Q2] the variables Business Confidence, Investment Plans in Machinery, Employment and Total New Orders have the highest variability according to highest values of standard deviation, range and mean (negative). All variables have negative overall means which indicates that firms overall are more pessimistic on where the direction of the economy is going. Business Confidence seems to have the largest negative value (-75) this event correlates to 1974 January Industrial Trends Survey. During that period the Conservative government introduced a policy measure called "*three-day week"* where commercial users of electricity could only use it for three consecutive days specified by the government. This was an attempt from the current government to conserve electricity which was severely restricted because of the industrial action by coal miners. In fact that period is where we also see a -108% and -194% decrease in Investment Plans in Machinery and Buildings for next 12 months respectively. By categorizing the time series to different periods using 14 elections and taking a pre, post-election periods of 1-2 quarters each we see that the post-election period has a negative overall impact in most of the variables studied. The mean and median is lower in post-election than in normal or pre-election periods in the majority of cases. Same pattern can be found when we are looking only at election where the government changed. It remains to examine if these patterns are statistically significant.

Moving on to the other part of our dataset which consists of variables we named "predictive powers" that as the title suggests attempt to capture the ability of firms to predict their own future answers. For that we consider the difference between the aggregate expectations of firms in the survey at (t) for $(t+1)$ against their aggregate assessment in the survey $(t+1)$ for what has happened in period (t). Next we describe the process of how such a variable is calculated.

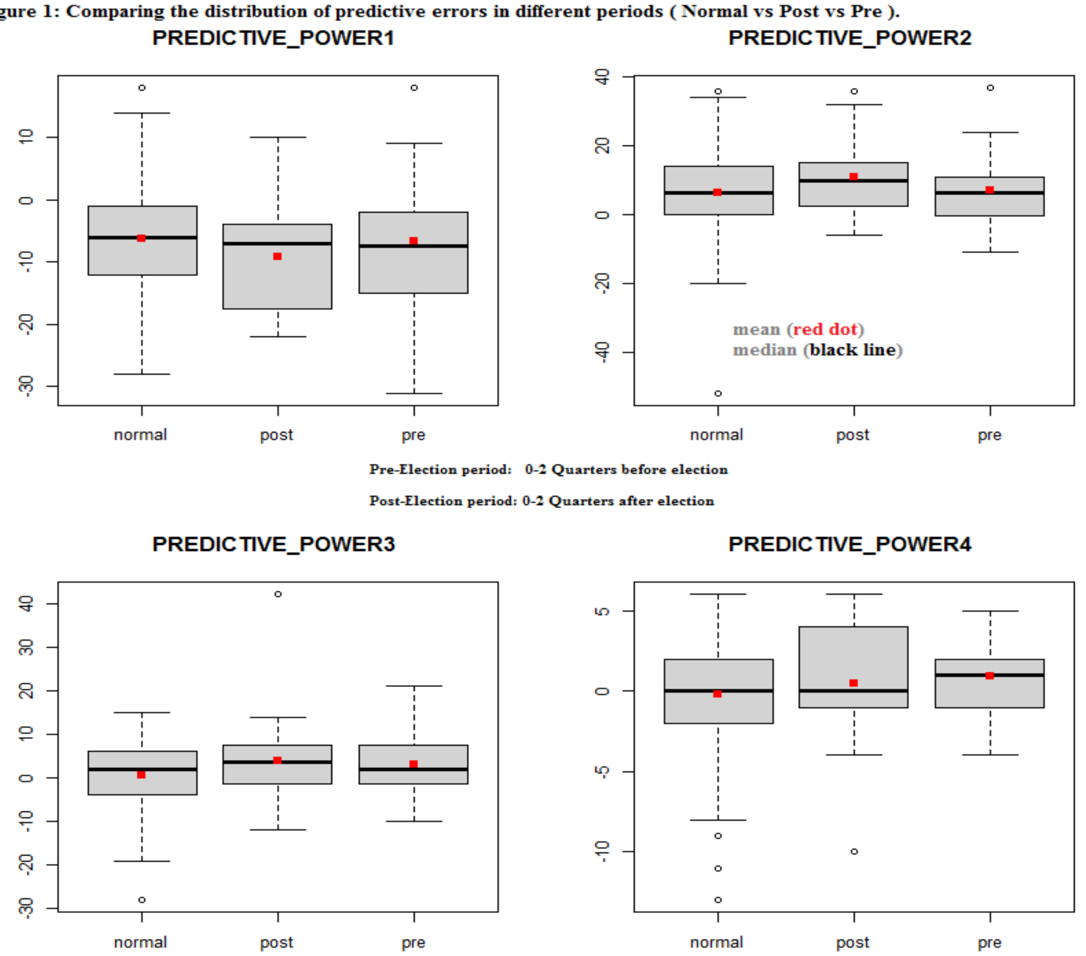
Consider for example the question on the volume of output over the next 3 months. The answer is the expectation of each firm (${}_{t}U^{e}_{i,(t+1)}$, ${}_{t}D^{e}_{i,(t+1)}$, ${}_{t}S^{e}_{i,(t+1)}$) where i indicates each firm on the sample at (t). On aggregate yields a percentage (" ${}_{t}U^{e}_{(t+1)}$, ${}_{t}D^{e}_{(t+1)}$, ${}_{t}S^{e}_{(t+1)}$). Then if we take balance statistic of that percentage we get ${}^{OutNext}_{t}B^{e}_{t+1} \coloneqq {}_{t}U^{e}_{t+1} - {}_{t}D^{e}_{t+1}$. This is the aggregate expectation formed at t for the next period $t+1$ on the volume of output. Now we need to go to the next survey $t+1$ and look what at the aggregate perception of firms over the past 3 months ${}^{OutPast}_{t+1}B_{t}$. Finally in order to measure their "predictive power" on their volume of output we need $y = {}^{OutNext}_{t}B^{e}_{t+1} - {}^{OutPast}_{t+1}B_{t}$. We follow the same procedure for the volume of total new orders and for employment, ending up with three new variables. By taking these differences we are aiming to investigate whether the aggregate predictive error of firms' future perceptions increases during election periods.

Last but not least, another dependent variable is created which reflects the aggregate predictive power of firms on the manufacturing outturn. This was achieved in two stages: first we took expectations of the volume of output and constructed an indicator (scaled balanced statistic) and second we used as the outturn the time series of official manufacturing output 3 month on 3 month a year ago growth downloaded directly from the Office of National Statistics website. Finally we measured firms' predictive power on output growth as the difference between firms' qualitative predictions against the corresponding quantitative official data.

Table 2.2 Time series	Predictive power time series
Predictive Power 1 [1975Q1, 2017Q2]	$\boldsymbol{PP_1\ (t)} = {}_{t}Output_{Past3M}(t) \quad - {}_{t-1}Output_{Next3M}(t)$
Predictive Power 2 [1958Q2, 2017Q2]	$\boldsymbol{PP_2(t)} = {}_{t}Total\ new\ orders_{Past3M}(t) \quad - {}_{t-1}Total\ new\ orders_{Next3M}(t)$
Predictive Power 3 [1958Q2, 2017Q2]	$\boldsymbol{PP_3(t)} = {}_{t}Employment_{Past3M}(t) \quad - {}_{t-1}Employment_{Next3M}(t)$
Predictive Power 4 Q [1975Q1, 2017Q2]	$\boldsymbol{PP_4(t)} = {}_{t-1}Outturn(t) \quad - \hat{\lambda} * {}_{t-1}Output_{Next3M}(t)$
Predictive Power 4 M [1975M04, 2017M04]	$\boldsymbol{PPM_4(t)} = {}_{t-3}Outturn(t) \quad - \hat{\lambda} * {}_{t-3}Output_{Next3M}(t)$
Note: where λ is the scaling parameter from Carlson & Parkin (1975) method	

Looking at **Figure 1** below, we do not observe any severe level changes on the predictive error distribution across periods. However we observe a shift in both the mean and the median level on the **Predictive Power 2 ($\boldsymbol{PP_2}$)** during the post-election period. The firms seem to increase the size of their error estimates when predicting their new total orders for the next 3 months, 0-6 months after an election.

Figure 1: Comparing the distribution of predictive errors in different periods (Normal vs Post vs Pre).



The **Predictive Power 4** ($\boldsymbol{PP_4}$) indicates that firms' predictive power on the official data increases (the closer to zero the better) 0-6 months after an election and in a normal period is were firms perform at their best on aggregate. We notice that in $\boldsymbol{PP_1}$ and $\boldsymbol{PP_4}$ which are a byproduct of output expectations, the error is a bit higher in the pre-election period and then it comes down in the post-election period. Whereas in the $\boldsymbol{PP_2}$ (orders) and $\boldsymbol{PP_3}$ (employment) the predictive error always increases in the post-election period. Finally we notice some outliers on the data. The majority of them locate in normal periods which will probably be related with some kind of a crisis event. By not including these events as part of the pre and post-election period will be mostly beneficial. The reason is that these unexpected crisis events would be the main driver of increased uncertainty rather than elections. Therefore, in the model estimation procedure we will probably end up overestimating the effect of elections. In general, uncertainty could be high in elections but not nearly as high as in other major unexpected events such as electricity crisis, terrorist attacks, 2008 financial crisis etc. these events create extremely high uncertainty and their effects last way longer than usual. Including these events in pre and post-election periods will not be beneficial when trying to isolate the effect of elections. So the more we expand the election period from 0-3 to 0-6 or from 0-6 from 0-12 we risk the accuracy of the results. On the other hand when using quarterly data we cannot use only 1 observation for pre and 1 for the post-election period for every election because the sample size will be very small. Thus we need to do find the middle point and 0-6 months or 2 quarters seems like a good choice.

Next stop we continue with **Section 3** and a discussion around empirical methods used to assess the effect between UK general elections and the survey data given in **Tables 2.1** and **2.2.**

3 Empirical Method

Brief Strategy

Uncertainty that is created in the context of elections can be measured in various ways. One is via the vote margin between the two leading parties which will indicate how certain the outcome of an election is. In this analysis, we use a dummy variable to capture election created uncertainty. By doing, this we aim to measure the effects of election driven events during electoral cycles that could be causing a systematic pattern in the time series survey data. We start by examining the differences in firms' historical perceptions 0-6 months before and after an election took place.

We employ a form of dynamic models called lagged dependent variable or distributed lag models. This is an attempt to avoid the problem of omitted variable bias while trying to isolate the impact of elections and assess the effect. One might ask "why is it difficult to assess the causal relationship between elections and survey data?" The answer is simple: because we do not have a control group. In studies that assess the causal effects of a treatment (in our case an election) before and after the event or "intervention", they often employ mostly controlled randomized experiments. They key point here is that the control group is not exposed to the intervention: only the treatment group. But in the case of elections, we do not have a control group to compare with and assess the impact of an election. We also do not have hard quantitative variables to control for all other factors that affect firms' perceptions and also could affect our results and lead us to false conclusions.

That's where the lagged dependent variable comes into play, as it enables us to essentially control of these factors. Statistically this approach is not perfect but it performs better than many other estimators such as GLS and classic OLS when the dynamic form of the data is evident (see Keele & Kely 2005). Next, we recap some of the key problems we faced leading up to the implementation of LDV models and the CausalImpact algorithm.

3.1 Motivation

In this Section we outline the reasoning behind our choice to estimate the effect of elections on the business survey data via a dynamic Lagged Dependent Variable model. In statistical analysis, we often need to find a model (usually starting with a linear regression) that fits the data well, then test for any violations of the hypothesis of the model and if we are satisfied from the test results proceed to inferential statistics. If however model violations are apparent, they warrant further investigation. Often an analyst will attempt to correct for these using techniques such as other estimators for the model parameters, transformations on the data or even a completely different modelling approach. No matter what the approach, the key point in statistics is, in order to make strong inferences, one has to make strong assumptions first. If and only if those model based assumptions hold, can one go ahead and trust the findings and make useful statistical inferences about the outcome.

Coming back to our case-study, we need to assess the impact of elections on survey data. The impact naturally implies a casual effect. In other words, based on what we have observed in the past we need to investigate the following two statements. First “when elections are coming up, do firms’ perceptions actually behave differently compared to a period without elections?” and second, “Are elections causing the change in the performance of firms’ perceptions”.

The latter is the causal effect of elections and should apply to all firms, independent of individual firm differences or other events happening in that period. If in fact the causal effect is present, then all firms will always be responding somewhat differently on the survey questionnaire only because we are during an election period.

To have a better understanding of why it is important to isolate the election-driven effect from the noise here is an example. On 28 February 1974, an election was called. In the “January 1974” Industrial Trends Survey, we observe significantly negative values for Business Confidence (-75%) as well as a -150% decrease for Total new orders and Investment Plans compared to the “October 1973” ITS. Since the election is held on 28 February and we define our pre-election period to be from 0-2 quarters before, we ought to include “October 1973” and “January 1974” surveys in the pre-election period. Therefore, these high negative values will be treated a result caused by the elections, which is not actually the case. The effect is in fact likely to have been caused by a combination of a necessary government policy and the coal miners’ strike. The coal miners’ strike in fact led the Prime Minister Edward Heath to call for an election. Thus, by including these two surveys “October 1973” and “January 1974” in the pre-election period, we risk inflating the type I error (false-positive).

In order for the causality to be true, all variables that may have an effect on firms' perceptions have to be eliminated. In order to identify exactly whether an election is the cause of any changes in variables, we need to control for all these unobserved variables which we not only do not know, but even if we did know, may not be able to measure.

If we have no control group we have no baseline for comparison. This leads us with two options. First, involves controlling for as many variables as possible to avoid the omitted variable bias. The second option is to create an artificial control called synthetic control and estimate what would happen to that synthetic control group if no elections were happening. Both methods have their potential drawbacks and their difficulties to implement in terms of modelling complexity.

In this study we chose to take the road guided by the first option[7]. The first option is also quite challenging due to the fact that is difficult to get rid of the all the nuisance factors. However there may still be a way to get the results we need. Remember the problem of not controlling for unobserved variables in a linear regression is called omitted variable bias and statistically translates to regression residuals being auto-correlated which violates the strict exogeneity assumption one of the (Gaussian Markov conditions) and as a result the OLS estimators will be inconsistent which implies that we cannot trust the p-values from the t-tests, therefore we cannot conclude whether the effect (value of the coefficient) is significantly different from zero. There are many ways one can attempt to correct the autocorrelation in the regression residuals. Our approach involves including a lagged term of the dependent variable in our regression model. These models are called Lagged Dependent Variable (LDV) models, and are a special case of Autoregressive Distributed Lag (ADL) models.

[7] The second option involves the CausalImpact algorithm approach published by Google in 2015 see Kay H. Brodersen (2015).

3.2 Lagged Dependent Variable Model: Specification and Application

Road leading up to an LDV model

The first step is to create a categorical variable with three categories a "pre-election", "post-election" and a "normal" period. Hence we need to create two dummy variables a pre-election with the value of 1 when we are from 0 up to 2 quarters before an election and 0 otherwise. We also need a post-election dummy which takes the value of 1 when we are from 0 up to 2 quarters after an election and zero otherwise. This will leave the normal period as our baseline category.

Then one can go ahead and estimate with the naïve linear regression model the effect of elections as:

(1) $B_i = c + b_1 PRE_i + b_2 POST_i + u_i$

This model suffers from many problems, but the most obvious one here is treating the time series feature as one big cross-section. In this regression the time feature of the data is not really captured by the model even if you naively replace $i = t$ (as we have done) is still the same. This model is a static model. In the case of time series data, it is often the case that the past has relevance when predicting the future e.g. B_{t+1} depends on B_t or/and B_{t-1} etc. If this is the case, then fitting a static model when in fact the Data Generating Process (DGP) is dynamic in nature, our estimations will perform poorly see (Keele & Kelly 2005).

LDV Model Specification

Another problem with this model is we do not control for other variables meaning that the model suffers from omitted variable bias and is likely to fail. One simple approach to avoid these two problems is to include a dependent variable into the right hand side (RHS) of the equation (1).

(2) $y_t = c + \ a y_{t-1} + b_1 PRE_t + b_2 POST_t + u_t$[8]

Then y_{t-1} is a lagged variable of the first order which will make our model an ADL(1,0) or LDV(1). The extra AR(1) coefficient a basically says how much the dependent variable correlates with past values of itself. Lagged term(s) of the response on the RHS serves to capture information on the state of the economy until today. In a sense by including an LDV on the RHS is like controlling for all these unobserved factors we do not have measurements for.

[8] Re-writing (1) by replacing B with y for convenience and replacing i with t to note the order of time.

Hence there are two main reasons to include a lagged dependent variable in the model: the first reason is to capture the dynamic features of our data and the second is to reduce the omitted variable bias. Theoretically, by including the lagged term of the dependent variable, we are indirectly controlling for all these unobserved factors without having them on the RHS of the equation as individual independent variables. In theory, all their information is incorporated within the LDV. This procedure of course is not perfect but is better than nothing. In fact by reviewing the literature Keele & Kale (2005) stress the conditions on where is appropriate to use LDVs. They also use Monte Carlo experiments to test the bias and asymptotic results between OLS with Newey-West, fGLS, ARMA and OLS with LDV estimators. One of the conclusions was if the data display dynamic properties then OLS with LDV is superior to OLS and GLS without an LDV.

The general framework for a simple LDV model.

(3) $y_t = c + ay_{t-1} + bx_t + u_t$

(4) $x_t = \rho x_{t-1} + e_{1t}$

(5) $u_t = \phi u_{t-1} + e_{1t}$

Equations (3), (4) and (5) consist of an LDV(1) or an ADL(1,0). If one adds a lagged term of the independent variable x_{t-1} then the model is an ADL(1,1) (see Hendry 1995).

There are a number of conditions that an LDV (3)(4)(5) [9] model has to satisfy in order to be appropriate.

Achen (2000) points out that when $a = 0$, the DGP is static instead of dynamic and the implication of incorrectly incorporating an LDV in a common factor concept is that the estimations will be biased and inconsistent. Achen goes ahead and recommends OLS without LDV, but using Newey-West standard errors in order to correct for residual autocorrelation and provide meaningful inferences.

LVDs are appropriate to use **under certain conditions:**

1. y is stationary (or weakly)
2. y and x should not be cointegrated.
3. Eq(3) to be stationarity for that to happen we need $|a + \phi| < 1$.
4. No residual autocorrelation
5. $a \neq 0$

Some additional findings from Keele & Kale (2005) Monte Carlo experiments.

- LDV models perform well for $a > 0.5$. This also indicates the data GDP is strongly dynamic.
- Even if process is weakly dynamic, OLS without LDV as well as GLS perform poorly.
- LDVs when residual autocorrelation is present perform poorly.

[9] In our case, for explanatory variable(s) x_t we can use a balance statistic from another question (not highly correlated with y_{t-1} to avoid colllinearity) or just the dummy variable. When the only x_t is a dummy variable then to an AR model with structural breaks.

- If variables on the LHS and RHS are not stationary or cointegrated LDV is probably inappropriate.
- If the past matters to the current values, then LDV is probably the best choice.

For our survey time series dataset the past matters significantly. In testing for autoregressive properties we found that the past matters for all questions we used. The variables were also tested for unit roots and indicate stationary (**Table A3)**.

For the majority of our analysis, we used LDV based models or a similar form of a simple dynamic model. The reasons we chose this approach over other forms of static regression are:

- Dynamic form of the data ↔ past matters.
- Account for omitted variable bias and remove residual autocorrelation.
- Dependent variables found to be stationary with no unit root.
- The majority of dynamic regressions passed all the diagnostic tests.
- The estimators are consistent.

The models were estimated with a mix of a lagged dependent variable, independent variables (sometimes no independent), seasonal dummies and structural breaks on the RHS using Ordinary Least Squares (OLS) estimators.

LDV application with ITS time series data

As a first stage, we start by looking for a significant effect of elections on different ITS questions using both quarterly and monthly data (see Appendix **Table B1**). To measure the change in behaviour of firms' expectations as well as predictive powers, we tried to identify changes in the mean level for the pre and post-election periods against a normal period. An election period is measured in relation to its distance away from an election event. Every survey that happened in the 6 months prior to an election is considered a pre-election survey (and the period 6 months after is the post-election period), i.e. in our quarterly dataset, this gives us 2 quarterly surveys; the monthly dataset, gives us 6 surveys.[10]

This pre-post period specification is based on the assumption that all elections have the same effect, i.e. the 1974 election is similar to the 2005 election. There is an extra assumption within this specification which treats 1, 2..., k months or quarters before or after elections as having the same constant effect on the dependent variable over time. We relax this assumption to allow for a different effect inside the pre and post-election periods. To do that, we introduce two time index variables on for each period that take values $i = 1, 2..k,$ quarters or months away from elections. Then we add the interaction term between the dummy variables and the time indexes into the model. This will capture the magnitude of the effect

[10] Because the CBI usually closes surveys around the 10th of each month, if an election happened before or on the day, the survey is considered as a pre-election survey. There is a potential issue there because some firms may respond to the same survey knowing the outcome when others do not. A number of elections have occurred in May, which affects the monthly time series: the 2005, 2010, and 2015 elections all happened on 7th of May.

from month to month or quarter to quarter. If one quarter after ($i = 1$) an election, firms are always more optimistic regarding their output compared to when we are two quarters ($i = 2$) ahead, we would expect a positive sign on the coefficient of the interaction term meaning that the effect of "two quarters" away on y_t is γ_2 larger than "one quarter" away. The dynamic linear model described above looks like this:

(6) $y_t = c + ay_{t-1} + b_1 PRE + \gamma_1 PRE * t_{pre,i} + b_2 POST + \gamma_2 POST * t_{post,i} + u_t$

Here y_t represents the time series of balance static of an ITS question e.g. volume of output or business confidence, etc. y_{t-1} is the 1-time point lagged time series of y_t. The constant c represent the average change of y_t during a "*normal*" period.

- Normal period: $PRE = 0$ & $POST = 0$

$$E[y_t|X] = c + ay_{t-1}$$

- Pre-election: $PRE = 1$ & $POST = 0$

$$E[y_t|X] = c + ay_{t-1} + b_1 + \gamma_1 * t_{pre,i}$$

Here $t_{pre,i} = i - k$ and $i = 0,1,..,k$ where k is the election time. The election time is $t_e \coloneqq t_k$. If $k = 2$ then the coefficient γ_1 gives the instantaneous effect of the pre-election period $t_{pre,i} = -2$ quarters away from elections. Similar for the post-election equation.

- Post-election: $PRE = 0$ & $POST = 1$

$$E[y_t|X] = c + ay_{t-1} + b_2 + \gamma_2 * t_{pre,i}$$

From (6) our main interest is to find significance in the coefficients $b_1, \gamma_1, b_2, \gamma_2$.

If there is a pre-election effect, we would expect $b_1$and γ_1 to be statistically significant, and to test for no difference between a "normal" period and a "pre-election" period, we can test the null hypothesis $b_1 = \gamma_1 = 0$.

In the LDV model above we could also add additional explanatory variables or trend and seasonal effects then (6) becomes:

(7) $y_t = c + ay_{t-1} + b_1 x_t + b_2 x_{t-1} + b_3 PRE + \gamma_1 PRE * t_{pre,i} + b_3 POST + \gamma_2 POST * t_{post,i} + \gamma_3 t + \gamma_4 Year_j + u_t$

The more complicated the model becomes the more difficult is to interpret the parameters. Even considering model (6) is very difficult to derive and interpret the long run effects. At this stage we are mainly more concerned finding a significant effect rather than pure parameter interpretation and complex derivations of the long run solution and the persistent future effects of PRE and $POST$. In the chapter 4 in the dynamic regression results we open a more detailed discussion on the matter.

4. Empirical results

4.1 Analysis overview

Our main goal with this analysis is to identify any statistically significant effect of elections on survey data. For the regression analysis, we defined the pre and post-election dummies to be 0-6 months prior and 0-6 months after an election. Figures **B2** and **B3** where summary statistics for all variables are depicted together in a graph, suggest a significant effect on the Employment, Output, Investment Plans and Business Confidence. The predictive powers also indicate a “significant” impact.

Before carrying out the dynamic regressions (OLS with LDVs), we start our analysis with multiple tests for a unit root in all of our dependent variables the results in **Table B2** where all the variables pass both the Phillips-Perron and the Augmented Dickey Fuller test at level of significance $a = 5\%$. Thus we can proceed and run the dynamic regressions (see chapter 3) for each dependent variable. Because we have many variables, dummies and other seasonal effects, the regression analysis involves a trial and error procedure. Our approach is similar to “forward elimination”. We start with the restricted model basically an AR(1) (OLS estimator) and then we add explanatory variables, including the dummy for the election period. When we insert a variable into the model, we run the diagnostic tests (see **Tables B.7.1-3 validation checks**), look at the r^2 of the model, look at how well the model fits the response time series via plotting them together, then add and remove other variables and repeat the procedure.

When deciding if we are to add or remove an explanatory variable, we use an ANOVA F-test for nested models. Remember our final goal is to assess whether there is a systematic pattern in the survey responses or their predictive powers (errors) during election periods. Since we have three categories for the election variable (pre-post-normal) we need two dummies one for pre and one for post-election. As mentioned earlier in Section 3**,** this dummy specification allows us to compare pre and post against a normal period.

4.2 Analysis procedure & Regression results

To demonstrate our approach, take for example as the dependent variable Investment Plans in Machinery over the Next 12 months (see **Appendix A Table A1**). In addition the regression results are given in **Table B.7.2** (column four). We are going to demonstrate how we arrived in the final model for Investment Plans in Machinery.

Let's start with the *restricted* model for y_t ≔ITSQ: Investment Plans for Machinery Next 12M

Model 1: $y_t = a * y_{t-1} + u_t$,

where u_t is the idiosyncratic error and it holds that $u_t \sim iid\ with\ E[u_t] = 0, V[u_t] = s.$

The restricted model could simply be the intercept, but since the data show a dynamic characteristic, we start with an AR(1) no intercept and then decide whether adding an intercept into the model adds significant explanatory power.

Model 2: $y_t = \boldsymbol{c} + a * y_{t-1} + u_t$

To do that, we use an F-test (Model 1, Model 2). If the $p - value$ of that test is less 0.05, it means that we reject the Null Hypothesis $H_0: c = 0$ given that y_{t-1} is in the model.

We carried out the test which gave a $p - value < 0.05$ indicating significant explanatory power gained by adding the intercept.

Moving on to the elections explanatory variable which is the one we are actually interested in, we estimate the following dynamic model.

Model 3: $y_t = c + a * y_{t-1} + \beta_1 * D_{pre} + \beta_2 * D_{post} + u_t$

Running this model we look at the individual coefficients β_1 and β_2 to see if their $p - value < 0.05$ which indicates their individual effect to be significant. In this case, only one of them β_2 was found to be significant. The coefficient β_2 gives us the instantaneous effect of the post-election period. We want to test the *total effect* of elections (pre & post) because we want to know whether during an election period we get significant explanatory power in predicting firms' answers. Therefore we use an F-test between Model 1 and Model 3.

Model 1: $y_t = c + a * y_{t-1} + u_t$

Vs

Model 3: $y_t = c + a * y_{t-1} + \beta_1 * D_{pre} + \beta_2 * D_{post} + u_t$

The results from the F-test (Model 1, Model 3) give a $p - value = 0.085$ under 0.10 and relative close to 0.05 threshold but not under it.

Therefore, we cannot say we have enough evidence to reject the $H_0: \beta_1 = \beta_2 = 0.$

Before we move forward, let's try to add some seasonal effect and a deterministic time trend.

Model 4: $y_t = c + a * y_{t-1} + u_t + \lambda_1 * t + \lambda_2 * year + u_t$

Model 4 coefficients λ_1 and λ_2 are not statistically significant (*t-test p-values* >5%) from zero. We also perform an F-test (Model 1, Model 4) which gives a $p - value$ more than 5% (and 10%) meaning we cannot reject the $H_0: \lambda_1 = \lambda_2 = 0$.

Let's try including the interaction term between election dummies and "time to election". This allows the model to add a different (time) effect on the response the closer we are to an election.

Model 5: $y_t = a * y_{t-1} + \beta_1 * D_{pre} + \beta_2 * D_{post} + \boldsymbol{\gamma_1} * D_{pre} * t_{pre} + \boldsymbol{\gamma_2} * D_{post} * t_{post} + u_t$

The interaction coefficients γ_1 and γ_2 indicate the extra effect added each time (quarter) we are coming closer to elections γ_1 or getting further away γ_2.

The variables $t_{pre} = \begin{cases} 1, \ if \ t = t_e - 2 \\ 2, \ if \ t = t_e - 1 \\ \quad 0 \ otherwise \end{cases}$, $t_{post} = \begin{cases} 1, \ if \ t = t_e - 1 \\ 2, \ if \ t = t_e - 2 \\ \quad 0 \ otherwise \end{cases}$, where t_e is the time of election[11].

Running **Model 5**, we get only coefficient $\boldsymbol{\gamma_2}$ to be statistically significant at 5%. From the regression output we get:

$$\hat{\gamma}_2 = -6.25, \ se(\hat{\gamma}_2) = 2.93, \ t - statistic \ = \frac{\hat{\gamma}_2}{se(\hat{\gamma}_2)} = -2.13, \ p - value = \mathbf{0.034} < a = 0.05 \text{ '}*\text{'}$$

In order to assess the inclusion of the interaction term on the total effect of elections, we need to compare again with our restricted model.

Model 1: $y_t = c + a * y_{t-1} + u_t$

Vs

Model 5: $y_t = c + a * y_{t-1} + \boldsymbol{\beta_1} * D_{pre} + \boldsymbol{\beta_2} * D_{post} + \boldsymbol{\gamma_1} * D_{pre} * t_{pre} + \boldsymbol{\gamma_2} * D_{post} * t_{post} + u_t$

Here we are testing the total effect hypothesis $H_0: \boldsymbol{\beta_1} = \boldsymbol{\beta_2} = \boldsymbol{\gamma_1} = \boldsymbol{\gamma_2} = \mathbf{0}$[12].

The F-test (Model 1, Model 5) gives a $p - value = 0.055$ which indicates the effect of elections on the response to be borderline statistically significant at level of 5%.

Note the effect of elections here is both the main effect $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ and the interaction effect $\boldsymbol{\gamma_1}$ and $\boldsymbol{\gamma_2}$.

From column four of **Table B.7.2,** we can get the coefficient values as estimated by the dynamic regression depicted in **Model 5**. We can then we go ahead and re-write the following model by putting the values of the coefficients into the equation.

Model 5

$$y_t = \quad \boldsymbol{c} \quad + \quad \boldsymbol{a} * y_{t-1} + \quad \boldsymbol{\beta_1} * D_{pre} + \boldsymbol{\beta_2} * D_{post} + \boldsymbol{\gamma_1} * D_{pre} * t_{pre} + \boldsymbol{\gamma_2} * D_{post} * t_{post} + u_t \leftrightarrow$$

$$y_t = \mathbf{-3.1} + \mathbf{0.80} * y_{t-1} + \mathbf{2.65} * D_{pre} + \mathbf{8} * D_{post} - \mathbf{1.7} * D_{pre} * t_{pre} - \mathbf{6.2} * D_{post} * t_{post} + u_t$$

According to our regression results, the coefficient of the interaction term (red) was found statistically significant at 5%. The main effect coefficient of post-election (blue) was not found significant at 5% but at 10%. All the other election related coefficients were found to be insignificant. The overall effect of elections was (borderline) statistically significant at 5% according to the F-test (p.value = 0.055).

[11] It really does not matter if t_{pre} for example takes the value of 1 when we are 1 quarter away and 2 when we are 2 quarters away as it is effectively the exact same model and only the coefficients will change.

[12] In order to test just the interaction term we need compare Model 3 vs Model 5.

Now **Model 5** can be re-written to address the effect of the interaction term for each time period.

Normal: $D_{pre} = D_{post} = 0$

$$\textbf{(A)}\, y_t = -3.1 + 0.80 * y_{t-1} + u_t$$

Pre-Election: $D_{pre} = 1 \ \& \ D_{post} = 0$

$$\textbf{(B)}\ y_t = -0.45 + 0.80 * \boldsymbol{y_{t-1}} - 1.7 * \boldsymbol{t_{pre}} + u_t$$

The equation **B** when we are **two quarters** before $t_e - 1 < t \leq \boldsymbol{t_e - 2}$ elections becomes:

$$\textbf{(B1)}\ y_t = -2.15 + 0.80 * y_{t-1} + u_t$$

and when we are **up to one quarter** $t_e < t \leq \boldsymbol{t_e - 1}$ before elections:

$$\textbf{(B2)}\ y_t = -3.85 + 0.80 * y_{t-1} + u_t$$

By comparing equations **A**, **B1**, **B2** it is evident that the closer we get to an election the equation **B** becomes almost the same as **A**. This shows why the pre-election effect was not found to be statistically significant in the first place (see **Table B.7.2 column four**).

Post-Election: $D_{pre} = 0 \ \& \ D_{post} = 1$

$$\textbf{(C)}\ y_t = 4.9 + 0.80 * y_{t-1} - 6.2 * t_{post} + u_t$$

Then equation **C** when we are **one quarter** after elections $t_e \geq t < \boldsymbol{t_e + 1}$ becomes:

$$\textbf{(C1)}\ y_t = -1.3 + 0.80 * y_{t-1} + u_t$$

and when we are **two quarters** after $\boldsymbol{t_e + 1} \geq t < \boldsymbol{t_e + 2}$ elections:

$$\textbf{(C2)}\ y_t = -7.5 + 0.80 * y_{t-1} + u_t$$

Comparing between **A**, **C1**, **C2** we can see that the further away we move from an election the more negative the impact is. The coefficient on the post-election interaction is that negative effect $\boldsymbol{\gamma_2 = -6.2}$. It can be viewed as the instantaneous effect every time we move a quarter forward inside the post-election period. Then for every quarter passed, firms become instantaneously more pessimistic by an extra $\boldsymbol{-6.2}$ points in their estimates concerning Investment Plans in Machinery over the next 12 months.[13]

Moving from the pre-election to the post-election period, firms gain confidence immediately after an election (instantaneous effect $\beta_2 = 8$), but soon afterwards the confidence balance drops back down again by a magnitude of $(\boldsymbol{-6.2})$ and after 3 to 6 months (2nd quarter) the negative impact of elections on firms' investments is evident.

[13] Remember due to the dynamics of the model the instantaneous effects $\beta_1, \beta_2, \gamma_1, \gamma_2$ do not disappear but they continue to exist to infinity. The rate of decay if based on a. Therefore the exact interpretation of the Model 5 parameters is difficult. Only the instantaneous effect is clear at this point.

We need to also check for violations in the model assumptions. The hypothesis we need to check are:

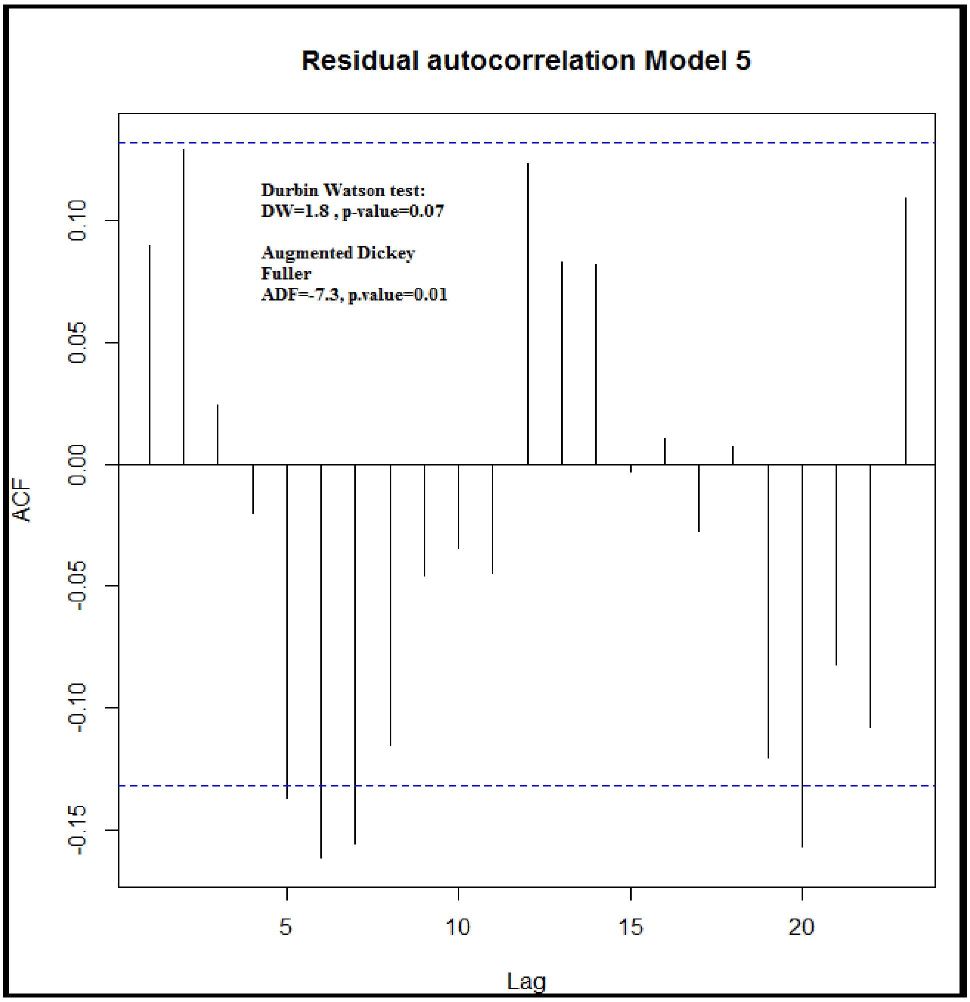
I. Stationarity condition for an OLS model with LDV where $|\, a + \phi| < 1$ (see Model Spec p16)

From the regression results we have $\hat{a} = 0.8$ and now we need to estimate ϕ. To do that we fit an AR(1) on the Model 5 residuals. Then the estimation for ϕ will be the AR(1) coefficient.

$u_t = u_{t-1} * \hat{\phi} + e_t$.

Running the AR(1) on u_t we get value $\hat{\phi} = 0.09$ and $|\, 0.8 + 0.09 \,| = 0.89 < 1$

II. Signs of Autocorrelation on u_t



Looking at the Figure above the graph ACF show no severe violations of residual autocorrelation. The Durbin Watson statistic and the Augmented Dickey Fuller confirm no violations.

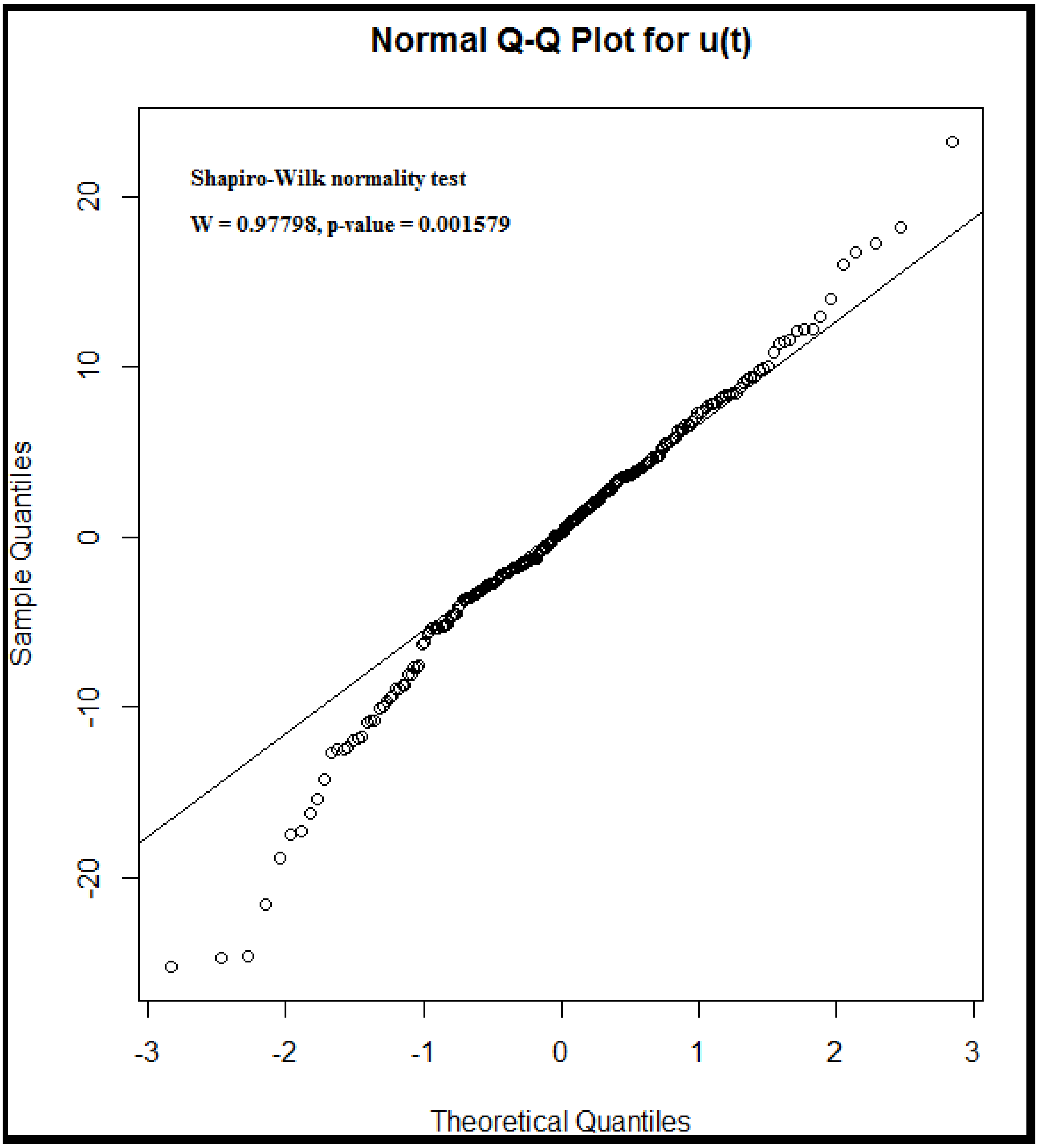
III. Signs of Heteroscedasticity on u_t

To test for heteroscedasticity we perform the studentized Breusch-Pagan test which gives us no evidence to reject the hypothesis for homoscedasticity.

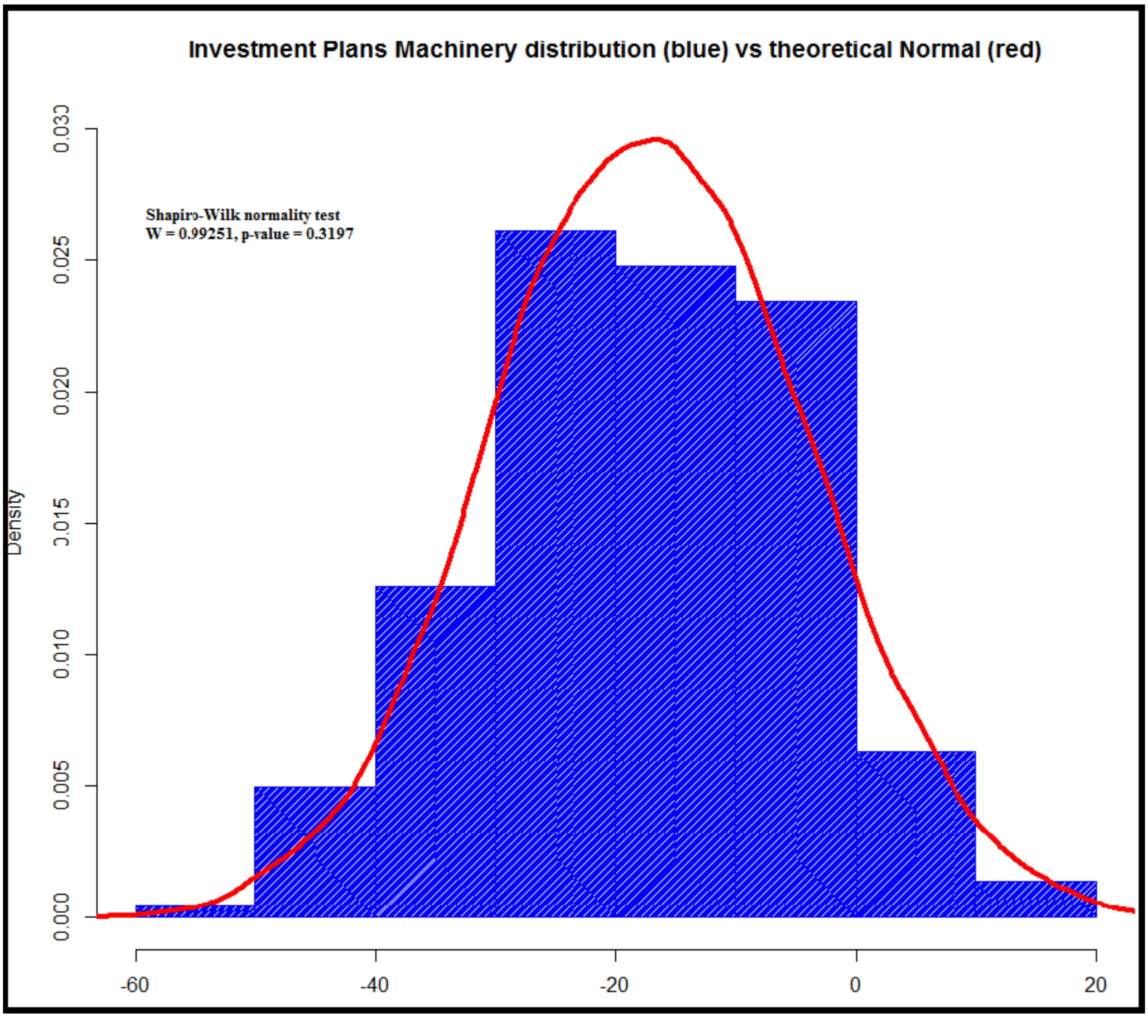
Breusch-Pagan: BP = 4.5545, df = 5, p-value = 0.4726

IV. Normality of u_t

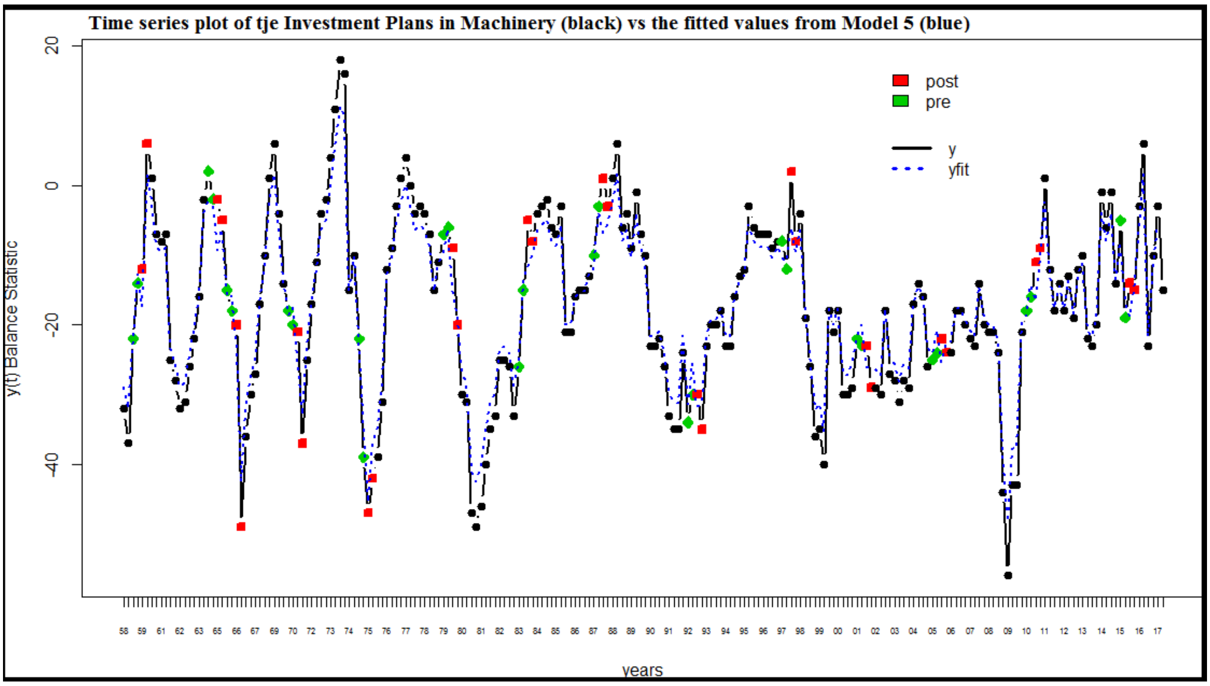
For the normality, test we use the Shapiro-Wilk's test and the normal quantile plot on the residuals u_t to look for non-normality characteristics. The Figure below shows a substantial deviation from normality as both the graph and the normality test reject the normality hypothesis. This is due to the fact that we have many outliers thus the error distribution has heavier tails than a normal one. Maybe student distribution is a better fit for the residual distribution.



We also conducted a normality test on our dependent variable: Investment Plans in Machinery. The histogram below as well as the Shapiro – Wilk test validate that Investment Plans in Machinery is normally distributed. This results is fortunate because F-tests are very sensitive to non-normality.



We should also be checking at how well Model 5 fitted the time series of Investment Plans in Plant and Machinery via the following plot.



The blue-dotted line is the fitted values from Model 5. The fit is quite good, with $r^2 = 64.5\%$ suggesting that the model explains a high percentage of the variability in Investment Plans Machinery. The explanatory power Model 1 gained when the election effect (main and interaction) was added into the model

(Model 5) is a bit less than 0.5% the p-value of the F-test is 0.055 therefore we cannot really say that the total effect overall is significant.

Furthermore, we check for multicollinearity by calculating the Generalised Variance Inflation Factors

Explanatory Variables	$GVIF^{\frac{1}{2*df}}$
y_t	1.00
D	2.96
$D_{pre} * t_{pre}$	2.97
$D_{post} * t_{post}$	2.97

We use the rule of thumb and consider values of GVIF less than 5 to be acceptable. The value of GVIF[14] indicates that the standard error for D would 2.96 times larger than it would be if D was uncorrelated with the other predictors. Adding and removing other quantitative explanatory variables does not change the GVIFs much. Also the coefficient γ_2 is always statistically significant by itself, whereas the coefficient β_2 is always significant at 10% level never at 5%.

The example demonstrated here is not the smoothest one, in the sense that the overall election effect is borderline significant (0.055 F-test p-value). In fact the actual output in **R** is depicted in the figure below.

Model 5: Dynamic Regression output

```
Residuals:
     Min       1Q   Median       3Q      Max
-25.2932  -3.5491   0.2553   4.6438  23.2716

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
Intercept          -3.12311    0.92477  -3.377 0.000869 ***
Y(t-1)              0.80441    0.04006  20.082  < 2e-16 ***
Dpre                2.64904    4.68600   0.565 0.572454
Dpost               8.00775    4.68620   1.709 0.088932 .
Dpre*tpre          -1.76249    2.93905  -0.600 0.549350
Dpost*tpost        -6.25167    2.93974  -2.127 0.034593 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.775 on 215 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.6538,    Adjusted R-squared:  0.6457
F-statistic: 81.19 on 5 and 215 DF,  p-value: < 2.2e-16
```

The interaction coefficient γ_2 is statistically significant with p-value = 0.034593 and the next closest one is β_2 where is significant only at a=10%. The F-test for the total effect almost rejects the joint hypothesis $H_0: \beta_1 = \beta_2 = \gamma_1 = \gamma_2 = 0$. The results above show the post-election period to be the main driver of the election effect, more evidence is required.

A similar procedure to what we have described in detail above we follow for all the other dependent variables (monthly and quarterly) including the predictive powers. The final dynamic regression results are summarised in the **Tables B.7.1-3**.

[14] For more information regarding GVIF see Fox, J. and Monette, G. (1992) and Fox, J. (1997)

4.3 Results Discussion

Somehow we did not find any pre-election coefficient to be statistically significant in any of the dependent variables or in any regression we tried. This is kind of questionable because by looking at **Figure B3** we would think that in some cases such as the output the pre-election period has some noticeable differences. On the other hand our regression results on Output past 3m show the post-election main effect and the interaction term to be statistically significant at 5% and 1% respectively. Therefore we turn our attention to the overall effect of election rather than distinguishing between a pre or post effect.

From the **Tables B.7.1-3** we should be quite confident[15] that we uncovered a correlation between firms' perceptions and electoral cycles[16]. This correlation seems to be mostly attributed to the post-election period (see also **Table B8**). The nature of the post-election effect is negative in all variables except the predictive power 2 (firms' ability to predict their total new orders). We count the Investment Plans in Machinery and Buildings as one case we call Investment Intentions. The regression results in **Tables B.7.2** for the Investment Plans in Buildings show that the total election effect is statistically significant at 5% (F-test PASS '*') but none of the election dummy coefficients are individually statistically significant. On the other hand the Investment in Plants and Machinery gives a statistically significant coefficient on the post-election interaction term but the total effect is not found to be significant at 5%, only at 10% (F-test FAIL '.'). In both cases we found elections to slightly predicting the sentiment of firms' Investment Plans. The results are quite robust to adding and removing other quantitative explanatory variables such as and seasonality trends. When we considered only the elections where government changed we did not find a significant effect. This discrepancy could be due to the low sample size of the observations belonging to the pre and post-election periods.

However, statistically significant effects at 1% were found in Business Confidence, Total new orders and Employment over the next 3 months. The total effect was found to be significant at 1% in all three cases. For the Employment Next 3M we used Model 5 (without intercept), for Business Confidence and Total New Orders the model is the very similar to Model 3.

The results from Business Confidence and Total new orders are similar, the post-election coefficients are large, negative ($\hat{\beta}_{2,BC} = -9.3, \hat{\beta}_{2,ORD} = -7$) and significant at 1%.

The coefficients show the instantaneous change of firms when entering a post-election period. The large negative sign indicates that firms react badly in the post-election period regarding their employment and business confidence. From **Table B.7.2** and **B.7.3** Investment Plans in Buildings over the next twelve months and the volume of Output over past three months show the total effect of elections to be statistically significant effect at the 5% level. When studying the Investment Plans in Plant and Machinery the total effect was not found to be statistically significant but the post-election interaction effect was. In addition, the total effect of Output over the next three months, Employment over the past three months

[15] All the models pass the validation checks thus we do not have good reason at the moment to doubt the findings.
[16] By electoral cycle we consider the state of the economy from two quarters before until two quarters after an election.

and Total new order over the past three months, was insignificant.

Before we move on to the predictive powers. Let's consider for a moment only the case of Total New Orders over the past the months. Although the coefficient $\beta_2 \cong \hat{\beta}_{2,ORD}$ is showing the instantaneous change in the post-election period on the firms' expected new orders. Things do not stop here. The post-election effect also influences the answers of the next survey on expected Total new orders y_{t+1} but this time $(t+1)$ the effect is $a * \beta_2$. We carry on with the influence on y_{t+2} which is $a^2 * \beta_2$ then for the k survey y_{t+k} is $a^k * \beta_2$ and so on, until infinity. Because y_t is stationary $\hat{a}_{ORD} = 0.76 < 1$ the effect will eventually decay to zero in time.

- At $t = 0$ (instant) the effect is $\hat{\beta}_{2,ORD} = -7$
- At $t = 1$ $0.76 \ * (-7) = -5.32$ on y_{t+1}
- At $t = 2$ $0.76^2 * (-7) = -4.04$ on y_{t+2}
- At $t = 3$ $0.76^3 * (-7) = -3.07$ on y_{t+3}
- ……
- At $t = 8$ $0.76^8 * (-7) = -0.342$ on y_{t+8}

We can see eight periods after the effect would be almost zero. Keep also in mind that the scale of all our dependent variables is from $[-100, 100]$ therefore as we move forward in time the effect becomes very small almost neglectable.

There is a problem with the logic behind this interpretation because it does not make sense to go forward into the future assuming we are always in a post-election period. The only effects we should be interested in are from $t = 0$ to $t = 3$ where y_{t+3} will be in the normal period once again[17], but will carry on the last post-election effect from y_{t+2}. Interpreting the models where the interaction was included e.g. in Investment Plans Machinery, Output past and Employment Next is difficult. The interaction term shows the extra instantaneous negative impact (if negative sign) on firms' perceptions for every quarter away from the elections.

Looking at **Table.7.3.1** only firms' predictive power on their future total new orders (PP_2) appeared to have a significant effect with elections at 5%. The post-election coefficient is significant at 5% and the total effect (via F-test vs restricted model) is borderline significant at 5% and significant at 10%. The equation of the model estimated for PP_2 is:

- $y_t = 3.65 + 0.39 * y_{t-1} + 0.45 * D_{pre} + 4.7 * D_{post} + u_t$

Adding the interaction term, a seasonal dummy or a time trend found to be insignificant. Although when we added the Manufacturing Index as a control variable the significance of the total effect deviated further away from 5% but the post-election coefficient was still significant at the 5% level. Looking at the equation for PP_2 we can see that on average firms overestimate their future Total new orders by 4.7 immediately after the post-election period. The effect of the first quarter is $0.39 * 4.7 = 1.833$ and the

[17] The post-election period ends 2 quarters after an election. If an election takes place at t=0 then t=1 and t=2 are considered post-election.

effect on the second quarter is $0.39^2 * 4.7 = 0.71$. As we move away from an election the equation return back to a normal period. In the pre-election period the instantaneous effect on the predictive power is very small (0.39). This is an indicator that the pre-election period does not affect the way firms predict their future total new orders. Finally we have some extra results from the multivariate hypothesis testing. We analysed all the predictive powers together and looked at differences on their joint mean levels. **Tables B.3** and **B.5** show the $T^2 - Hotelling$ and the MANOVA results whereas **Table B.4** show the descriptive multivariate statistics. The results indicate no evidence of an election effect on the predictive powers. Last but not least, we did make the switch to monthly data for the Output and found the post-election interaction term to be statistically significant at 5% in both Output past and next three months. The main effect and the total effect failed to be significant though. The post-election interaction term on the Output over the next three months was found to be more significant when considering only those elections were government changed. Even though the total effect was not significant the post-election period seems to be important on how well firms predict their own future output. As far as firm's ability to predict the manufacturing output over the next 3 months (PP_4) is concerned, we had a difficult time finding an appropriate model. The dynamic regression did not seem to be the right model for Predictive Power 4 therefore we also tried OLS with Newey-West standard errors (see also footnote 18). Adding a control variable in the regression and using the Heteroscedasticity Autocorrelation Consistent standard errors we found the post –election period to be statistically significant at 1% whereas the pre-election period was once again insignificant. However this result failed to be robust when adding and removing control variables the significance of the post-election coefficient changed dramatically. In addition when considered only the election where government changed the significance disappeared. The only robust result that remained during all this was the sign of the pre and post coefficients which shows a similar pattern to the other variables we studied. Even though we report this result we require more evidence to conclude for a significant effect. Anyway the Heteroscedasticity & Autocorrelation correction procedure show the effect of the post-election period to be $\hat{\beta}_2 = 1.04$ with the HAC standard error $se[\hat{\beta}_2] = 0.37$ (**Table B.7.4 column 3**). We treat this result carefully and keep only the positive sign of the coefficient $\hat{\beta}_2$ which can also be interpreted as follows: When firms have underestimated the outturn therefore $PP_4 > 0$ then the post-election period will add (instantaneously) to that underestimation 1 point. If however firms have overestimated the outturn before the elections therefore $PP_4 < 0$ then when entering the post-election period their estimates on average will get better by 1 point.

5. Conclusion

To conclude our preliminary study around the impact of elections on the business tendency survey data, we have gathered some of the most interesting results from the dynamic regressions described in the previous sections. Out of the 13 variables we studied we did not find anyone were the pre-election effect was statistically significant. This leads us to believe that all the explanatory power falls into the post-election period. The regression results of the post-election estimated coefficients are shown in the **Summary Table** below. In 8 out of 10 variables the sign was negative indicating the instantaneous post-election effect is in fact negative. It seems that firms' first reaction immediately after the election result becomes public, is more pessimistic than it was supposed to be in a normal period. The interaction effect when included in the model always had a negative sign indicating the drop in the confidence level of firms, as we move a quarter (or month) forward away from an election. Due to the model dynamics this effect decays (in the power) in time depending on the LDV coefficient a **see Section 3&4**. The normal and the pre-election period (as we defined it) seem to have no difference whatsoever. This could be explained because in UK the actual pre-election period *(purdah)* starts after the elections are officially announced which is usually about a six weeks before the event.

Summary Table:

Post-election effect	Quarterly: Main effect value	Quarterly: Main effect sign. level	Quarterly: Interaction effect value	Quarterly: Interaction effect sign. level	Quarterly: F-test	Monthly: Main effect value	Monthly: Main effect sign. level	Monthly: Interaction effect value	Monthly: Interaction effect sign. level	Monthly: F-test
Business Confidence	-9.3	**	-	-	**					
Investment Buildings	-6.9	‘.’	-2.6		*					
Investment Machinery	8	‘.’	-6.2	*	‘.’					
Total new orders Next	-7	**	-	-	**					
Total new orders Past	-2.4		-	-	‘.’					
Output Next	-2.9		-0.18			0.82		-1.03	*	‘.’
Output Past	16.3	*	-12.1	**	*	6.04	‘.’	-1.68	*	‘.’
Employment Next	5.1		-7	*	**					
Employment Past	10.7		-8.8	*						
Predicting Power 1	-3.4		-3.07							
Predicting Power 2	4.7	*	-	-	‘.’					
Predicting Power 3	5.12		-3.17							
Predicting Power 4	-1.15		1.01			1.04	* *			

Significance codes for different critical values: ‘*’ 0.1%, ‘**’ 1%, ‘*’ 5%, ‘.’ 10%**

Highlighted in red are the variables were both the main effect and the total election effect was significant (both PRE, POST and their interactions if they were estimated). The highlighted in yellow are the coefficients where the sign was negative. The highlighted in blue are the variables were main effect was not significant, the interaction term was significant and the F-test for the overall election effect succeed.

The variables Business Confidence, Total new orders next three months and Output past three months show strong evidence of correlation with the election period. Their post-election main effect and interaction terms (when included) are always statistically significant at least below the 5% level. The total election effect was also significant at the 5% level or less. The Employment over the next three months is another special case were the total effect was found to be significant at 1% level but none of the main effects were. The only term that was significant was the interaction term at 5%. If you would take out the interaction term then none of the main effects either pre or post are significant and the F-test fails. This leads us to believe that the post-election effect on Employment next three months is not constant inside the post-election period. However we require more evidence since the results are not robust enough. We also do not have strong evidence to conclude that the Investment Plans in both Buildings and Machinery (Investment Intentions) are effected by the election period. Although we have an indication that Investment intentions are possibly negatively correlated with elections and especially with the post-election period we require more evidence to validate that claim. Their post-election main effect coefficients are statistically significant at 10% (see **Summary Table**). A 10% type I error is not acceptable because we inflate the chances to report an effect when there isn't actually one. Since all the models passed the diagnostic tests we do not have any reason to doubt the variables highlighted in red. Another good supplemental evidence of robustness comes by looking at the monthly series of the Output past three months the coefficients have the same sign as in the quarterly series and the post-election interaction term is significant at 5%. The F-test for the overall effect fails but the post-election effect is significant (main effect at 10% and interaction at 5%). These numbers are associated with the standard error of their respective coefficients therefore they can easily be more accurate by increasing the sample size related to elections. To increase the sample size we either increase the number of elections or the window of the pre to post election period. The latter is a risk, because of potentially including other events not relevant with elections but highly correlated with firms' perceptions.

The monthly series on the Output past three months start 20 years after the quarterly series. Which means we do not account for 6 elections. However the results between monthly and quarterly indicate similar patterns. Therefore one could conclude that firms when assessing their output immediately after elections are 16.3 points more confident than they would be during a normal period according to the quarterly data and 6 points according to the monthly. However that confidence drops dramatically when we reach the first quarter by -12.1 and by -1.68 in the first month. Then the negative effect decays as we move away from elections and the assessments of firms eventually return back to normal. One reason that the coefficients using quarterly data are $(\beta_1 = 16.3, \beta_2 = -12.1)$ and for monthly are $(\beta_1 = 6.4, \beta_2 = -1.68)$ could be because two monthly surveys precede a quarterly. Therefore the effect is very similar between the two series. This is strong evidence to infer a correlation between the Output and the post-election period.

Generally, I would speculate that quarterly data overestimate the magnitude of the election effects since the last quarterly pre-election survey could be 2 months away from an election. For example if the election is in June the last quarterly pre-election ITS survey is ITS April, but it is ITS May if you take the monthly. It could even be June if the survey is closed before the election result goes public. This suggests the monthly data would be more accurate. Although to account for that we have chosen the pre and post-election periods such that the effect between months (or quarters) is fixed (time-invariant) and is given by one parameter for each β_1 for pre and β_2 for post. The interaction terms γ_1 and γ_2 are the ones that allow an extra effect to be added for each month we move closer or away. Considering the dynamic feature of the model the interpretation becomes very complicated especially when the interaction term is included. The difficulty arises because the coefficients $\beta_1, \beta_2, \gamma_1, \gamma_2$ do not only have an effect on y_t but also effect y_{t+1}, y_{t+2} ..until infinity, with a decaying rate.

Business confidence and Total new orders have also shown strong evidence of correlation. The post-election shocks are large and negative and decay relative slow over time. (see **Table B.7.2** coefficient of y_{t-1} is above 0.5).

Finally, the systematic pattern that was found mainly during the post-election period in Output past three months does not compromise the predictive power of firms neither on their own output (PP_1) or on the outturn (PP_4).[18] On the other hand firms' predictive power on their future Total new orders indicate some evidence for a correlation with the election period. Actually the post-election main effect is significant and positive at 5%. The F-test does not allow us to reject the hypothesis (at 5% level). This means the total effect of elections on the Predictive Power 2 could actually be a "fugazi". The positive sign of firms' predictive error on their future total new orders can be interpreted as follows: If firms have overestimated their Total new orders just before the elections, then immediately after in the post-election period they will increase their predictive error by another 4.7 points. Hence, firms will tend to be overconfident right after an election. Also if before the election they have underestimated their total new orders entering the post-election period they will gain a confidence boost of 4.7 points which will push their predictive error towards the zero mark and basically act as a correction on their predictions. Therefore, if firms overestimated their Total new orders three months prior then they will become even more confident after an election which will lead them to even worse (upward) predictions. This result does not actually imply increase or decrease in uncertainty on firms' perceptions but it certainly implies an upward trend on their predictions immediately after elections. Increase in uncertainty does not show up in firms' predictive powers but it shows up in the post-election period through the majority of the independent variable where the negative signs of the coefficients rule (see **Summary Table, Tables B7.3.1-3**).

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[18] Variable PP_4 caused many problems see also p.29. The dynamic regression model for $PP_4$with LDV(1) was autocorrelated. We tried adding another LDV y_{t-2} as well as lags of Business Confidence as an extra control variable. At this point the model was very complicated but pass all the validation checks. Slight problem with Heteroscedasticity p-value which was very close to 5%. Adding the election dummy did not turn out to be significant. When we included the interaction the result was similar. The individual main effect coefficient for the post election period was significant but at '.'10%.

Last but not least, I would like to add some points regarding the second stage of this analysis and a future work to have a better understating and gather more evidence on how elections could impact the survey data. Starting with the issues we faced with the sample size. This could be solved by instead of taking the aggregate balances work with the qualitative answers directly. Unfortunately at the moment our firm-level data go back to 2000. But we have the archives and tools to go very far back. This is a process we are currently working on. When we have this data the sample size will be a couple of million answers in total then could try ordinal logistic regression models in an unbalanced panel dataset with both random and fixed effects in order to assess the election effect by also taking into account all these nuisance factors (firm-specific and external). Another more simplistic way to look at the problem is to take a panel data treating each survey as a repeated measure and the panel will be ITS, SSS and DTS (our three main surveys). There we could look each variable as we did in this preliminary study and see differences between and within surveys. The problem with this approach is that the “common” questions between ITS, SSS and DTS start from 2003. We currently use these time series to construct the CBI growth indicator. Hence we would need more observed elections for accurate estimations. Although we could just merge the firm-level data of these three surveys and work only with 2005-2010-2015 and the recent 2017 elections. The most accurate approach would be if we were to take firm-level survey data for the same questions but from another country where there was no election during the same periods. Therefore we would use this dataset as a control group and our dataset as a treatment-group and we will examine the differences between them. Of course this sounds easier than it actually is because there many between and within country factors as well as firms’ individual differences or other major events which will probably compromise the outcome and therefore we would have to increase the complexity of the model to capture all these nuisance effects. As a second stage study we would be interested in implementing a multivariate approach joining all the surveys together and work on the balance statistics or using the firm-level data from 2000. A greater emphasis will be given in methods to distinguish between election-created events from other events in order to assess the causal relationship with the survey data.

To conclude this study, we found some evidence on correlation between the post-election period and firms’ perceptions with many ITS questions both assessments (Business Confidence, Output Past 3M) and expectations (Total New Orders next 3M). Nonetheless, this correlation did not leave its’ mark on how well firms predict the future movements of the underlying economic variables. There is a way to measure the bias introduced by elections before we collect the data. This can be done by introducing an election related question and ask firms directly how an election will impact their finances “positive”, “negative” or “neutral”. As a final thought one could also add the “election” as an option on a question like “What factors are likely to limit (wholly or partly) your capital expenditure authorisations over the next twelve months?”. By implementing this approach we will be able to measure directly the effect attributed to elections and once we have a better idea, then we decide how to handle survey data during elections.

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Appendix A

TABLE A1 **Industrial Trends Survey questions used for data analysis.**

Business Confi-dence

Are you more, or less, optimistic than you were three months ago about the general business situation in your industry?

More	Same	Less
☐	☐	☐

Invest-ment Plans

Do you expect to authorise more or less capital expenditure in the next twelve months than you authorised in the past twelve months on:

	More	Same	Less	n/a
a) Buildings	☐	☐	☐	☐
b) Plant and machinery	☐	☐	☐	☐

Employ-ment

Excluding seasonal variations, what has been the trend over the past three months and what are the expected trends for the next three months, with regard to:

	Trend over past three months				Expected trend over next three months			
	Up	Same	Down	n/a	Up	Same	Down	n/a
Numbers employed	☐	☐	☐	☐	☐	☐	☐	☐
Total new orders Volume of total new orders	☐	☐	☐	☐	☐	☐	☐	☐
Volume of output Volume of output (ie production)	☐	☐	☐	☐	☐	☐	☐	☐

A2	United Kingdom's National Elections from 1959 to 2017		
ELECTION YEAR	**ELECTION DATE**	**ELECTED PRIME MINIS-TER**	**ELECTED WINNING PARTY**
1959 (MPs)	08-Oct-59	Harold Macmillan	Conservative
1964 (MPs)	15-Oct-64	Harold Wilson	Labour
1966 (MPs)	31-Mar-66	Harold Wilson	Labour
1970 (MPs)	18-Jun-70	Edward Heath	Conservative
1974 (MPs)	28-Feb-74	Harold Wilson	Labour (minority government)
1974 (MPs)	10-Oct-74	Harold Wilson James Callaghan	Labour
1979 (MPs)	03-May-79	Margaret Thatcher	Conservative
1983 (MPs)	09-Jun-83	Margaret Thatcher	Conservative
1987 (MPs)	11-Jun-87	Margaret Thatcher John Major	Conservative
1992 (MPs)	09-Apr-92	John Major	Conservative
1997 (MPs)	01-May-97	Tony Blair	Labour
2001 (MPs)	07-Jun-01	Tony Blair	Labour
2005 (MPs)	05-May-05	Tony Blair Gordon Brown	Labour
2010 (MPs)	06-May-10	David Cameron	Conservative (formed coalition with Liberal Democrats)
2015 (MPs)	07-May-15	David Cameron Theresa May	Conservative
2017	08-Jun-17	Theresa May	Conservative (minority government)

Appendix B

	TABLE B1: DESCRIPTIVE STATISTICS ITS-Q, ITS-M	N	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
	BUSINESS CONFIDENCE	222	-3.4	24.0	-2.0	-2.3	20.8	-75	55	130	-0.4	0.3	1.6
	INVESTMENT PLANS: MACHINERY	222	-2.1	17.7	-1.0	-1.5	19.3	-57	39	96	-0.3	-0.3	1.2
	INVESTMENT PLANS: BULDINGS	222	-17.2	13.1	-18.0	-16.8	14.1	-56	18	74	-0.2	-0.1	0.9
	OUTPUT PAST 3M	169	1.1	16.8	3.0	2.3	16.3	-53	36	89	-0.7	0.4	1.3
	OUTPUT NEXT 3M	169	7.9	14.3	11.0	9.4	11.9	-43	33	76	-1.1	1.3	1.1
	TOTAL NEW ORDERS NEXT 3M	222	9.6	17.7	12.0	10.4	14.8	-54	51	105	-0.5	1.0	1.2
	TOTAL NEW ORDERS PAST 3M	222	3.9	22.1	5.0	4.0	19.3	-61	64	125	0.0	0.3	1.5
	EMPLOYMENT NEXT 3M	222	-10.7	18.6	-11.0	-10.3	18.5	-65	33	98	-0.2	-0.2	1.3
	EMPLOYMENT PAST 3M	222	-11.9	20.2	-11.0	-10.8	20.8	-70	29	99	-0.5	-0.2	1.4
	Predictive Powers dataset	**N**	**mean**	**sd**	**median**	**trimmed**	**mad**	**min**	**max**	**range**	**skew**	**kurtosis**	**se**
	PREDICTIVE POWER1	169	-6.6	8.8	-7.0	-6.7	8.9	-31	18	49	0.1	0.1	0.7
	PREDICTIVE POWER2	222	7.1	11.1	7.0	7.1	8.9	-52	37	89	-0.4	2.9	0.7
	PREDICTIVE POWER3	222	1.4	7.9	2.0	1.5	7.4	-28	42	70	0.2	2.7	0.5
	PREDICTIVE POWER4	168	0.4	3.3	0.8	0.7	2.4	-13	6	19	-1.3	2.7	0.3
	ITS-Q dataset [1958Q3-2017Q2]	**N=222**	**mean**	**sd**	**median**	**trimmed**	**mad**	**min**	**max**	**range**	**skew**	**kurtosis**	**se**
"NORMAL"	BUSINESS CONFIDENCE	114	-3.9	23.5	-2.0	-2.5	20.0	-70.0	53.0	123.0	-0.5	0.2	2.2
"POST"	BUSINESS CONFIDENCE	52	-5.1	26.2	-4.5	-4.3	25.9	-64.0	48.0	112.0	-0.2	-0.4	3.6
"PRE"	BUSINESS CONFIDENCE	56	-1.0	23.2	0.0	-0.6	14.8	-75.0	55.0	130.0	-0.4	1.2	3.1
"NORMAL"	INVESTMENT PLANS MACHINERY	114	-1.8	19.2	-1.0	-1.1	20.0	-57.0	39.0	96.0	-0.3	-0.2	1.8
"POST"	INVESTMENT PLANS MACHINERY	52	-3.4	17.9	-5.5	-3.1	20.8	-41.0	32.0	73.0	-0.1	-1.0	2.5
"PRE"	INVESTMENT PLANS MACHINERY	56	-1.5	14.0	1.0	-0.4	14.8	-38.0	19.0	57.0	-0.7	-0.4	1.9
"NORMAL"	INVESTMENT PLANS BULDINGS	114	-17.1	13.6	-18.0	-16.7	13.3	-56.0	18.0	74.0	-0.2	0.1	1.3
"POST"	INVESTMENT PLANS BULDINGS	52	-17.4	14.4	-18.5	-16.9	17.0	-49.0	6.0	55.0	-0.2	-0.9	2.0
"PRE"	INVESTMENT PLANS BULDINGS	56	-17.4	10.7	-16.0	-17.0	11.9	-43.0	2.0	45.0	-0.3	-0.6	1.4
"NORMAL"	TOTAL NEW ORDERS NEXT 3M	114	10.1	19.9	12.5	11.0	14.8	-54	51	105	-0.6	0.9	1.9
"POST"	TOTAL NEW ORDERS NEXT 3M	52	6.6	16.3	8.5	7.5	13.3	-33	39	72	-0.5	-0.3	2.3
"PRE"	TOTAL NEW ORDERS NEXT 3M	56	11.4	13.7	12.0	11.8	13.3	-25	35	60	-0.3	-0.3	1.8
"NORMAL"	TOTAL NEW ORDERS PAST 3M	114	3.6	23.7	5.0	4.0	19.3	-61	64	125	-0.1	0.5	2.2
"POST"	TOTAL NEW ORDERS PAST 3M	52	1.8	18.9	1.0	1.4	22.2	-30	46	76	0.2	-0.8	2.6
"PRE"	TOTAL NEW ORDERS PAST 3M	56	6.4	21.4	7.0	6.7	18.5	-44	53	97	-0.1	-0.2	2.9
"NORMAL"	EMPLOYMENT NEXT 3M	114	-11.3	19.2	-11.0	-10.5	17.8	-65	33	98	-0.4	0.1	1.8
"POST"	EMPLOYMENT NEXT 3M	52	-12.7	18.0	-15.0	-13.4	20.8	-42	29	71	0.3	-0.7	2.5
"PRE"	EMPLOYMENT NEXT 3M	56	-7.7	18.1	-8.5	-6.9	17.8	-45	25	70	-0.3	-0.7	2.4
"NORMAL"	EMPLOYMENT PAST 3M	114	-12.1	19.9	-11.0	-10.3	19.3	-70	26	96	-0.8	0.5	1.9
"POST"	EMPLOYMENT PAST 3M	52	-13.5	20.8	-12.5	-14.2	27.4	-51	28	79	0.1	-1.0	2.9
"PRE"	EMPLOYMENT PAST 3M	56	-9.8	20.7	-10.5	-9.0	18.5	-52	29	81	-0.4	-0.5	2.8
	ITS-Q Output [1975Q3-2017Q2]	**N=169**	**mean**	**sd**	**median**	**trimmed**	**mad**	**min**	**max**	**range**	**skew**	**kurtosis**	**se**
"NORMAL"	OUTPUT PAST 3M	94	1.3	17.7	5.0	3.2	14.8	-53.0	33.0	86.0	-1.0	0.7	1.8
"POST"	OUTPUT PAST 3M	39	2.2	16.8	1.0	2.2	20.8	-28.0	36.0	64.0	0.0	-1.1	2.7
"PRE"	OUTPUT PAST 3M	36	-0.7	14.4	3.0	0.3	11.1	-36.0	24.0	60.0	-0.8	0.0	2.4
"NORMAL"	OUTPUT NEXT 3M	94	7.1	15.9	11.0	9.1	11.9	-43.0	33.0	76.0	-1.2	1.2	1.6
"POST"	OUTPUT NEXT 3M	39	7.9	13.1	9.0	8.5	11.9	-23.0	29.0	52.0	-0.5	-0.7	2.1
"PRE"	OUTPUT NEXT 3M	36	9.9	10.7	11.5	10.4	12.6	-14	26	40	-0.3	-1.0	1.8

	Only when Government changed	N=222	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
"NORMAL"	BUSINESS CONFIDENCE	174	-2.5	23.4	-2.0	-1.4	20.8	-70.0	55.0	125.0	-0.4	0.3	1.8
"POST"	BUSINESS CONFIDENCE	24	-14.2	23.1	-10.5	-14.3	21.5	-63.0	37.0	100.0	0.0	-0.5	4.7
"PRE"	BUSINESS CONFIDENCE	24	0.3	27.3	6.0	2.5	11.9	-75.0	50.0	125.0	-1.0	1.1	5.6
"NORMAL"	INVESTMENT PLANS MACHINERY	174	-2.6	18.2	-3.5	-2.2	20.0	-57.0	39.0	96.0	-0.2	-0.3	1.4
"POST"	INVESTMENT PLANS MACHINERY	24	-4.8	15.8	2.5	-3.8	14.1	-41.0	21.0	62.0	-0.5	-0.8	3.2
"PRE"	INVESTMENT PLANS MACHINERY	24	3.8	14.3	10.0	6.3	11.9	-38.0	19.0	57.0	-1.6	2.1	2.9
"NORMAL"	INVESTMENT PLANS BULDINGS	174	-17.5	13.3	-18.0	-17.3	14.8	-56.0	18.0	74.0	-0.1	-0.1	1.0
"POST"	INVESTMENT PLANS BULDINGS	24	-18.7	14.0	-17.5	-18.2	16.3	-47.0	2.0	49.0	-0.4	-1.0	2.9
"PRE"	INVESTMENT PLANS BULDINGS	24	-13.9	10.5	-13.0	-12.6	7.4	-43.0	2.0	45.0	-1.1	1.3	2.1
"NORMAL"	TOTAL NEW ORDERS NEXT 3M	174	9.7	17.8	11.0	10.4	13.3	-54.0	51.0	105.0	-0.6	1.3	1.4
"POST"	TOTAL NEW ORDERS NEXT 3M	24	4.3	17.2	4.5	4.3	15.6	-28.0	39.0	67.0	-0.1	-0.7	3.5
"PRE"	TOTAL NEW ORDERS NEXT 3M	24	14.5	16.0	16.0	16.0	14.1	-25.0	35.0	60.0	-0.8	-0.1	3.3
"NORMAL"	TOTAL NEW ORDERS PAST 3M	174	2.5	22.6	3.0	2.7	19.3	-61.0	64.0	125.0	0.0	0.3	1.7
"POST"	TOTAL NEW ORDERS PAST 3M	24	1.3	16.7	6.0	2.1	17.8	-30.0	26.0	56.0	-0.4	-1.1	3.4
"PRE"	TOTAL NEW ORDERS PAST 3M	24	16.3	20.0	12.0	16.4	17.0	-29.0	53.0	82.0	0.1	-0.4	4.1
"NORMAL"	EMPLOYMENT NEXT 3M	174	-11.7	18.9	-12.0	-11.3	19.3	-65.0	33.0	98.0	-0.2	-0.1	1.4
"POST"	EMPLOYMENT NEXT 3M	24	-12.1	17.7	-12.0	-11.8	23.0	-40.0	14.0	54.0	-0.2	-1.5	3.6
"PRE"	EMPLOYMENT NEXT 3M	24	-1.8	15.6	-6.5	-1.9	15.6	-32.0	25.0	57.0	0.1	-1.1	3.2
"NORMAL"	EMPLOYMENT PAST 3M	174	-12.8	20.4	-12.0	-11.7	20.8	-70.0	28.0	98.0	-0.5	-0.1	1.5
"POST"	EMPLOYMENT PAST 3M	24	-13.2	20.8	-6.0	-12.4	20.8	-51.0	15.0	66.0	-0.4	-1.4	4.2
"PRE"	EMPLOYMENT PAST 3M	24	-3.7	17.3	-5.0	-3.2	14.8	-42.0	29.0	71.0	-0.1	-0.4	3.5
	Only when Government changed	N=169											
"NORMAL"	OUTPUT PAST 3M	142	1.0	17.2	2.0	2.2	16.3	-53.0	36.0	89.0	-0.7	0.4	1.4
"POST"	OUTPUT PAST 3M	15	1.0	17.5	7.0	1.5	13.3	-28.0	24.0	52.0	-0.4	-1.5	4.5
"PRE"	OUTPUT PAST 3M	12	2.8	12.0	6.5	5.2	6.7	-31.0	12.0	43.0	-1.8	2.4	3.5
"NORMAL"	OUTPUT NEXT 3M	142	7.7	14.5	11.0	9.3	11.9	-43.0	33.0	76.0	-1.1	1.5	1.2
"POST"	OUTPUT NEXT 3M	15	4.7	13.2	4.0	5.0	20.8	-16.0	22.0	38.0	-0.2	-1.5	3.4
"PRE"	OUTPUT NEXT 3M	12	14.2	11.5	18.5	16.0	7.4	-14.0	24.0	38.0	-1.1	0.3	3.3
	ITS-Q Predictive Powers [1975Q3-2017Q2]	**n**	**mean**	**sd**	**median**	**trimmed**	**mad**	**min**	**max**	**range**	**skew**	**kurtosis**	**se**
"NORMAL"	PREDICTIVE_POWER1	142	-6.7	9.0	-7.0	-6.8	8.9	-31	18	49	0.1	0.1	0.8
"POST"	PREDICTIVE_POWER1	15	-5.9	7.9	-7.0	-5.9	7.4	-21	10	31	0.1	-0.5	2.0
"PRE"	PREDICTIVE_POWER1	12	-6.2	7.8	-8.5	-6.6	8.9	-15	7	22	0.4	-1.4	2.3
"NORMAL"	PREDICTIVE_POWER2	174	7.8	10.7	8.0	7.6	10.4	-20	37	57	0.2	-0.1	0.8
"POST"	PREDICTIVE_POWER2	24	6.7	9.8	8.0	6.5	8.2	-16	36	52	0.5	1.8	2.0
"PRE"	PREDICTIVE_POWER2	24	2.6	14.3	4.0	4.4	10.4	-52	19	71	-2.2	6.2	2.9
"NORMAL"	PREDICTIVE_POWER3	174	0.8	7.4	2.0	1.1	8.2	-28	15	43	-0.4	0.4	0.6
"POST"	PREDICTIVE_POWER3	24	4.5	11.4	5.5	3.9	5.9	-13	42	55	1.0	2.7	2.3
"PRE"	PREDICTIVE_POWER3	24	2.5	7.5	2.5	2.6	5.9	-15	21	36	-0.1	0.6	1.5
"NORMAL"	PREDICTIVE_POWER4	141	0.5	3.2	0.9	0.8	2.4	-13	6	19	-1.3	3.4	0.3
"POST"	PREDICTIVE_POWER4	15	-1.5	4.6	0.2	-1.4	3.1	-10	4	14	-0.7	-1.0	1.2
"PRE"	PREDICTIVE_POWER4	12	1.1	2.4	1.2	1.0	1.7	-3	6	9	0.1	-0.7	0.7
	Only when Government changed	**n**	**mean**	**sd**	**median**	**trimmed**	**mad**	**min**	**max**	**range**	**skew**	**kurtosis**	**se**
"NORMAL"	PREDICTIVE_POWER1	142	-6.7	9.0	-7.0	-6.8	8.9	-31	18	49	0.1	0.1	0.8
"POST"	PREDICTIVE_POWER1	15	-5.9	7.9	-7.0	-5.9	7.4	-21	10	31	0.1	-0.5	2.0
"PRE"	PREDICTIVE_POWER1	12	-6.2	7.8	-8.5	-6.6	8.9	-15	7	22	0.4	-1.4	2.3
"NORMAL"	PREDICTIVE_POWER2	174	7.8	10.7	8.0	7.6	10.4	-20	37	57	0.2	-0.1	0.8
"POST"	PREDICTIVE_POWER2	24	6.7	9.8	8.0	6.5	8.2	-16	36	52	0.5	1.8	2.0
"PRE"	PREDICTIVE_POWER2	24	2.6	14.3	4.0	4.4	10.4	-52	19	71	-2.2	6.2	2.9
"NORMAL"	PREDICTIVE_POWER3	174	0.8	7.4	2.0	1.1	8.2	-28	15	43	-0.4	0.4	0.6
"POST"	PREDICTIVE_POWER3	24	4.5	11.4	5.5	3.9	5.9	-13	42	55	1.0	2.7	2.3
"PRE"	PREDICTIVE_POWER3	24	2.5	7.5	2.5	2.6	5.9	-15	21	36	-0.1	0.6	1.5
"NORMAL"	PREDICTIVE_POWER4	141	0.5	3.2	0.9	0.8	2.4	-13	6	19	-1.3	3.4	0.3
"POST"	PREDICTIVE_POWER4	15	-1.5	4.6	0.2	-1.4	3.1	-10	4	14	-0.7	-1.0	1.2
"PRE"	PREDICTIVE_POWER4	12	1.1	2.4	1.2	1.0	1.7	-3	6	9	0.1	-0.7	0.7

ITS-M Output PAST+NEXT: [1995M01-2017M04]		n=259	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
"NORMAL"	OUTPUT PAST 3M	139	2.0	15.3	4.0	3.5	11.9	-53	29	82	-1.1	1.8	1.3
"POST"	OUTPUT PAST 3M	60	3.2	12.6	4.0	3.4	14.8	-23	24	47	-0.2	-1.2	1.6
"PRE"	OUTPUT PAST 3M	60	4.3	13.8	8.0	6.7	10.4	-45	23	68	-1.8	3.2	1.8
"NORMAL"	OUTPUT NEXT 3M	139	6.1	16.2	10.0	7.8	14.8	-48	36	84	-1.1	1.6	1.4
"POST"	OUTPUT NEXT 3M	60	7.2	11.5	10.0	8.3	10.4	-28	27	55	-1.0	0.8	1.5
"PRE"	OUTPUT NEXT 3M	60	10.8	11.6	12.5	11.3	12.6	-17	32	49	-0.4	-0.3	1.5
"NORMAL"	PREDICTIVE_POWER1	139	8.3	5.7	7.0	7.8	5.9	0	27	27	0.7	0.0	0.5
"POST"	PREDICTIVE_POWER1	60	7.9	5.7	7.0	7.6	5.9	0	21	21	0.4	-1.0	0.7
"PRE"	PREDICTIVE_POWER1	60	7.7	5.3	7.0	7.3	5.2	0	20	20	0.5	-0.6	0.7
"NORMAL"	PREDICTIVE_POWER4	139	-0.4	3.0	0.2	0.1	2.4	-12	3	15	-1.8	4.1	0.3
"POST"	PREDICTIVE_POWER4	60	0.6	2.5	0.7	0.5	2.2	-4	6	10	0.4	-0.3	0.3
"PRE"	PREDICTIVE_POWER4	60	0.2	2.8	0.8	0.6	1.5	-10	5	15	-2.0	4.7	0.4
Only when Government changed		**n=259**	**mean**	**sd**	**median**	**trimmed**	**mad**	**min**	**max**	**range**	**skew**	**kurtosis**	**se**
"NORMAL"	OUTPUT PAST 3M	211	1.8	13.9	3.0	2.9	11.9	-53	29	82	-1.0	1.9	1.0
"POST"	OUTPUT PAST 3M	24	15.3	5.0	14.0	15.2	4.4	7	24	17	0.2	-1.0	1.0
"PRE"	OUTPUT PAST 3M	24	-0.7	18.4	8.0	1.7	10.4	-45	16	61	-1.2	-0.1	3.8
"NORMAL"	OUTPUT NEXT 3M	211	6.5	15.0	9.0	7.9	11.9	-48	36	84	-1.1	1.8	1.0
"POST"	OUTPUT NEXT 3M	24	14.3	6.0	14.0	14.3	5.9	3	27	24	0.1	-0.7	1.2
"PRE"	OUTPUT NEXT 3M	24	8.3	13.0	12.5	9.3	12.6	-17	25	42	-0.6	-0.9	2.7
"NORMAL"	PREDICTIVE_POWER1	211	8.4	5.8	8.0	8.0	7.4	0	27	27	0.5	-0.3	0.4
"POST"	PREDICTIVE_POWER1	24	6.3	5.5	4.0	5.8	5.2	0	18	18	0.7	-0.9	1.1
"PRE"	PREDICTIVE_POWER1	24	6.7	4.0	6.5	6.4	3.7	1	16	15	0.6	-0.2	0.8
"NORMAL"	PREDICTIVE_POWER4	211	-0.3	2.6	0.2	0.1	2.0	-12	3	15	-1.9	5.5	0.2
"POST"	PREDICTIVE_POWER4	24	2.7	2.0	2.0	2.6	1.8	1	6	6	0.5	-1.6	0.4
"PRE"	PREDICTIVE_POWER4	24	-0.4	4.2	0.9	0.1	1.8	-10	5	15	-1.2	0.2	0.9
ITS-M Output: [1975M01-2017M04]		**n=505**	**mean**	**sd**	**median**	**trimmed**	**mad**	**min**	**max**	**range**	**skew**	**kurtosis**	**se**
"NORMAL"	OUTPUT NEXT 3M	289	7.6	17.4	12.0	9.6	14.8	-48	40	88	-1.1	1.0	1.0
"POST"	OUTPUT NEXT 3M	108	10.0	14.2	11.5	10.4	13.3	-28	38	66	-0.3	-0.3	1.4
"PRE"	OUTPUT NEXT 3M	108	10.2	12.6	12.0	10.4	13.3	-18	37	55	-0.2	-0.7	1.2
"NORMAL"	PREDICTIVE_POWER4	289	-0.4	3.7	0.3	0.1	2.5	-14	7	21	-1.3	2.1	0.2
"POST"	PREDICTIVE_POWER4	108	1.0	3.1	1.0	1.2	2.9	-10	6	16	-0.7	1.2	0.3
"PRE"	PREDICTIVE_POWER4	108	0.1	2.7	0.5	0.3	1.7	-10	5	15	-1.1	2.1	0.3
Only when Government changed		**n=505**	**mean**	**sd**	**median**	**trimmed**	**mad**	**min**	**max**	**range**	**skew**	**kurtosis**	**se**
"NORMAL"	OUTPUT NEXT 3M	457	8.4	16.3	11.0	9.7	14.8	-48	40	88	-0.9	1.0	0.8
"POST"	OUTPUT NEXT 3M	24	14.3	6.0	14.0	14.3	5.9	3	27	24	0.1	-0.7	1.2
"PRE"	OUTPUT NEXT 3M	24	8.3	13.0	12.5	9.3	12.6	-17	25	42	-0.6	-0.9	2.7
"NORMAL"	PREDICTIVE_POWER4	457	-0.1	3.4	0.4	0.3	2.4	-14	7	21	-1.3	2.5	0.2
"POST"	PREDICTIVE_POWER4	24	2.4	2.0	1.5	2.2	1.5	0	6	6	0.5	-1.5	0.4
"PRE"	PREDICTIVE_POWER4	24	-0.6	4.0	0.5	-0.2	1.6	-10	5	14	-1.1	0.1	0.8

TABLE B2: Unit root tests for stationarity.

H_0: *unit root*, $a = 5\%$	**Phillips-Perron test**		**Augmented Dickey-Fuller test**	
ITS Q time series				
	STATISTIC	P-VALUE	STATISTIC	P-VALUE
Business Confidence	-80	0.01	-6.0	0.01
Investment Plans Machinery	-50	0.01	-5.1	0.01
Investment Plans Buildings	-55	0.01	-5.2	0.01
Output Past 3M	-38	0.01	-3.8	0.02
Output Next 3M	-44	0.01	-4.1	0.01
Total New Orders Next 3M	-62	0.01	-4.9	0.01
Total New Orders Past 3M	-51	0.01	-4.8	0.01
Employment Next 3M	-32	0.01	-3.5	0.04
Employment Past 3M	-30	0.01	-3.5	0.04
Predictive Power 1	-144	0.01	-4.4	0.01
Predictive Power 2	-155	0.01	-5.2	0.01
Predictive Power 3	-247	0.01	-5.4	0.01
Predictive Power 4	-45	0.01	-3.8	0.017
ITS M time series				
Output Past 3M	-39	0.01	-4.7	0.01
Output Next 3M	-42	0.01	-4.3	0.01
Predictive Power 1	-221	0.01	-6.0	0.01
Predictive Power 4	-43	0.01	-4.4	0.01

Figure B1: Boxplot of absolute predictive error in +/- Quarters from elections

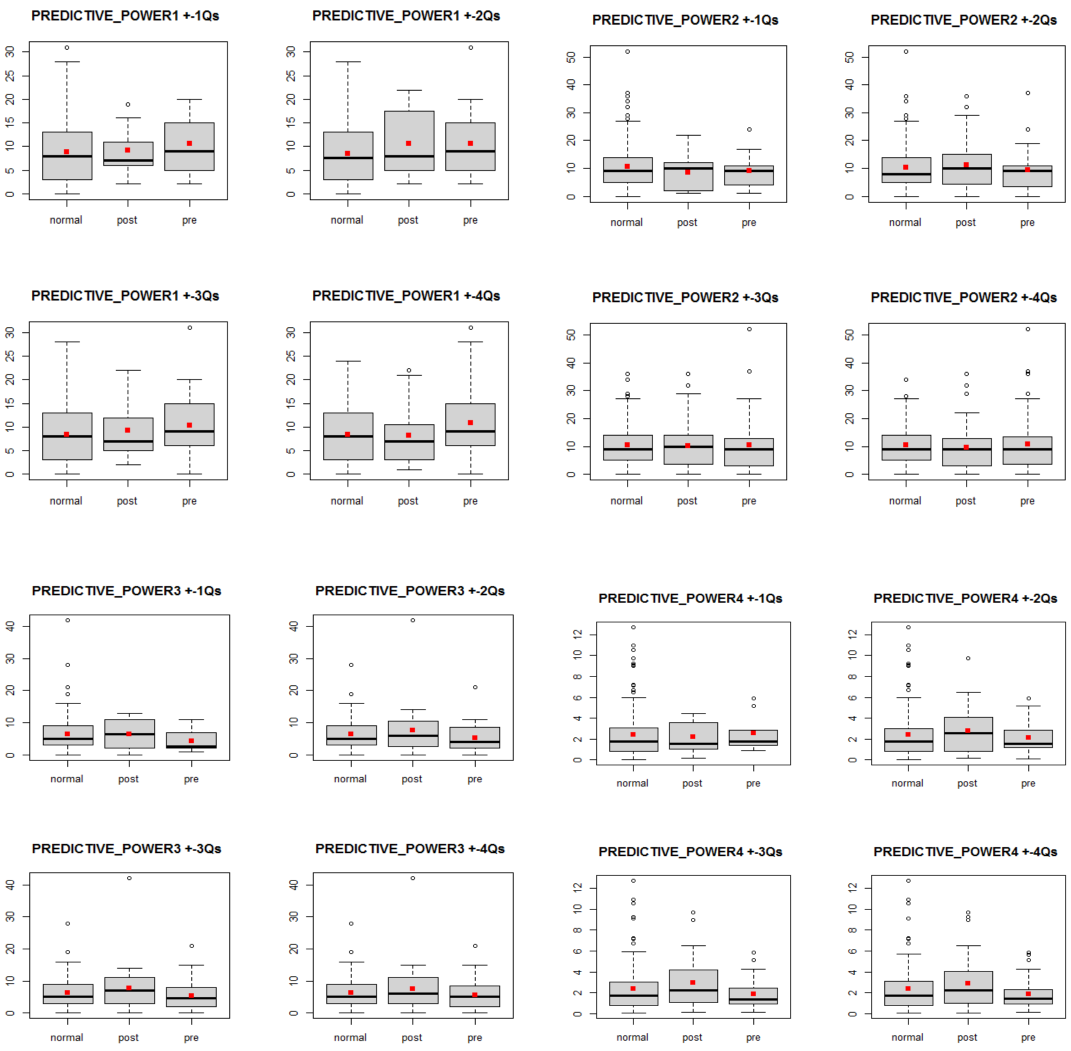

Figure B2: Comparing the means, medians and standard deviations of the Predictive Powers between pre-post-normal periods

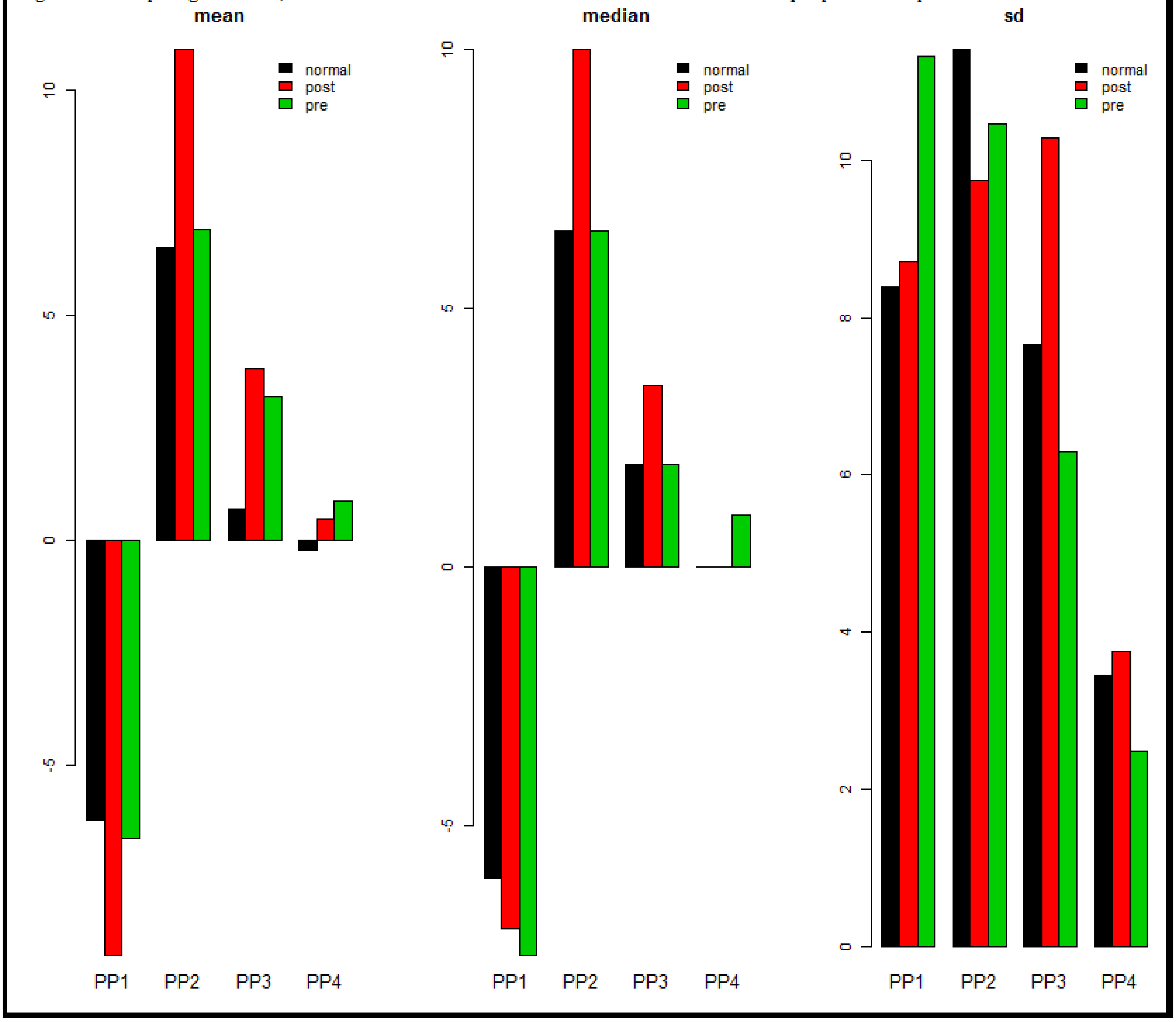

Figure B3: Comparing means, medians and standard deviations across different response variables between pre-post-normal periods

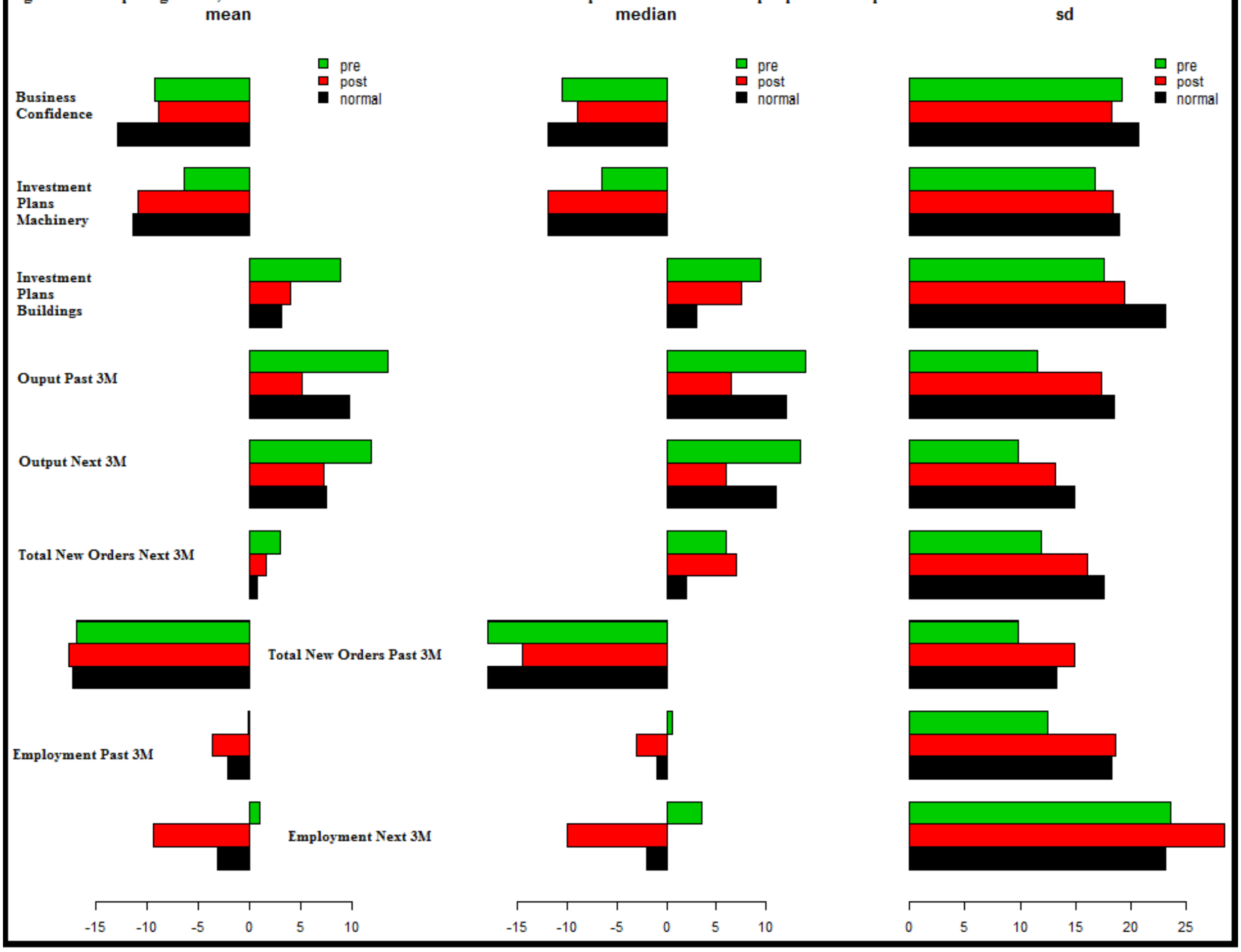

Table B.3: T^2 Hotelling multivariate tests for the Predictive Powers on PRE and POST election periods.

	PRE vs POST	POST vs NORMAL	PRE vs NORMAL
T^2 Hotelling Statistic	1.10	3.48	2.21
$p - value$	0.22	0.25	0.24
Sample size of group1	18	19	18
Sample size of group 2	19	131	131
Degrees of freedom	4, 32	4, 145	4, 144
Number of variables used (p)	4	4	4

Table B.4: Predictive Power Multivariate Statistics				
	Predictive 1	Predictive 2	Predictive 3	Predictive 4
$mean$	-6.6	7	-0.36	-0.02
$variance$	77.3	106	53	11
$skewness$	0.13	0.35	-0.4	-1.1
$kurtosis$	3.09	2.95	3.17	5.0

Note: The variable Predictive Power 4 is problematic in a sense that it shows signs of non-normally distributed. Normal distributed variables have skewness 0 and kurtosis 3. The joint distribution of the variables probably will not be a normal. We exclude Predictive Power 4 and re-run the results.

Table B.5: Predictive Powers (1-3) MANOVA				
$H_0: \begin{bmatrix} \bar{Y}_{1,PRE} \\ \bar{Y}_{2,PRE} \\ \bar{Y}_{3,PRE} \end{bmatrix} = \begin{bmatrix} \bar{Y}_{1,POST} \\ \bar{Y}_{2,POST} \\ \bar{Y}_{3,POST} \end{bmatrix} = \begin{bmatrix} \bar{Y}_{1,NORM} \\ \bar{Y}_{2,NORM} \\ \bar{Y}_{3,NORM} \end{bmatrix}$	Pillai	Wilks	Hotelling-Lawley	Roy
6-months period	Box's M test H_0: Homogeneity across periods $\chi^2 = 12.641, \quad df = 12, \quad p-value = 0.3956$			
$Statistic$	0.015	0.984	0.015	0.011
$p-value$	0.86	0.86	0.86	0.58
12-months period	Box's M test H_0: Homogeneity across periods $\chi^2 = 10.449, \quad df = 12, \quad p-value = 0.5766$			
$Statistic$	0.02	0.97	0.02	0.02
$p-value$	0.59	0.6	0.6	0.35

Note: The results from all multivariate tests are similar indicating no evidence to reject the H_0 therefore no significant differences is between these periods are observed. However the categories are unbalanced 18,19, 131 observations respectively. We tested for multivariate normality and homogeneity of variances and the tests indicate no evidence to conclude substantial deviations from these hypothesis.

Table B.7.1 Dynamic regression results for all predictive powers

dependent Y_t / explanatory	Predictive power 1	Predictive power 2	Predictive power 3	Predictive power 4
intercept	-23.5	3.65	8.11	NO
	(8.15) **	(0.91) ***	(1.56) ***	
Y_{t-1}	-0.01	0.39	-0.09	0.78
	(0.052)	(0.06) ***	(0.07)	(0.04) ***
Pre-election	4.64	0.45	-4.02	0.87
	(4.21)	(2.09)	(4.43)	(1.40)
Pre-election*Tpre	1.2	NO	3.61	-0.23
	(2.70)		(2.78)	(0.90)
Post-election	-3.4	**4.7 ***	5.12	-1.15
	(4.40)	**(2.09)**	(4.38)	(1.40)
Post-election*Tpost	-3.07	NO	-3.17	1.01
	(2.67)		(2.71)	(0.90)
control variables				
X_t	-0.6	NO	-0.3	NO
	(0.04) ***		(0.05) ***	
X_{t-1}	NO	NO	NO	NO
seasonality effects				
time trend	-1.3	NO	-0.07	NO
	(0.45) **		(0.01) ***	
year	5	NO	NO	NO
	(1.81) **			
Government Changed	NO	NO	NO	NO
other statistics				
R^2_{adj}	59%	16%	35%	66%
Degrees of freedom	159	216	161	162
Observations	168	222	222	168
Joint F-test H0: election coefficients are all zero.	FAIL	PASS ‘.’	FAIL	FAIL
validation checks				
$\lvert\hat{a}+\hat{\varphi}\rvert < 1$	PASS	PASS	PASS	PASS
Residuals acf	PASS	PASS	PASS	PASS
Unit root test	PASS	PASS	PASS	PASS
Durbin-Watson test	PASS	PASS	PASS	PASS
Breusch-Pagan test	PASS	PASS	PASS	PASS
Normality test	PASS	FAIL	PASS	PASS
Variance Inflation Factor	PASS	PASS	PASS	PASS

Signif. codes: ‘*’ 0.001 , ‘**’ 0.01, ‘*’ 0.05, ‘.’ 0.1, ‘ ’ 1**

F-test: H_0: $\hat{b}_1 = \hat{b}_2 = \hat{\gamma}_1 = \hat{\gamma}_2 = 0$ *vs* H_1: any unequal to zero. $\lvert\hat{a}+\hat{\varrho}\rvert < 1$ is a necessary condition for the dynamic process to be stationary.

Unit root test is the Augmented Dickey Fuller test for stationarity. PASS means the null hypothesis is rejected at 1% significance level.

Durbin-Watson is to test residuals for autocorrelations signs. PASS means the NULL was not rejected.

Breusch-Pagan is to test residuals for heteroscedasticity signs. PASS means the NULL hypothesis is not rejected.

Normality test we use Shapiro Wilks test. PASS indicates that the hypothesis was not rejected.

Variance Inflation Factor is a measure to check for collinearity amongst explanatory variables. We use the rule of thumb and for every continuous variable accept a squared VIF value less than 5.

The normality test fails in case of Predictive Power 2 because of the presence of outliers.

Table B.7.2 Dynamic regression results for Business Confidence, Investment Plans and Total new orders.

dependent Y_t / **explanatory**	Business Confidence	Investment Buildings Next 12 months	Investment Machinery Next 12 months	Total new orders Next 3 months	Total new orders Past 3 months
intercept	NO	NO	-3.1 (0.92) ***	3.1 (0.95)**	2.54 (0.61) ***
Y_{t-1}	0.67 (0.04) ***	0.83 (0.03) ***	0.80 (0.04) ***	0.76 (0.04) ***	0.72 (0.02) ***
Pre-election	1.03 (3.3)	3.9 (5.8)	2.65 (4.6)	0.56 (2.31)	2.04 (1.58)
Pre-election*Tpre	NO	-2.5 (3.67)	-1.7 (2.9)	NO	NO
Post-election	**-9.3 (3.3) ****	-6.9 (3.6) ‘.’	8 (4.6) ‘.’	**-7 (2.3) ****	-2.39 (1.58)
Post-election*Tpost	NO	-2.59 (1.15)	**-6.2 (2.9) ***	NO	NO
control variables					
X_t	NO	NO	NO	NO	YES
X_{t-1}	NO	NO	NO	NO	YES
seasonality effects					
time trend	NO	NO	NO	NO	NO
year	NO	NO	NO	NO	NO
Government Changed	YES	NO	NO	YES	NO
other statistics					
R^2_{adj}	47%	70%	65%	60%	87%
Degrees of freedom	218	216	215	217	216
Observations	222	222	222	222	222
Joint F-test H0: election coefficients are all zero.	PASS**	PASS*	PASS‘.’ **0.055**	PASS **	FAIL‘.’
validation checks					
$\lvert\hat{a} + \hat{\varphi}\rvert < 1$	PASS	PASS	PASS	PASS	PASS
Residuals acf	PASS	PASS	PASS	PASS	PASS
Unit root test	PASS	PASS	PASS	PASS	PASS
Durbin-Watson test	PASS	PASS	PASS	PASS	PASS
Breusch-Pagan test	PASS	PASS	PASS	PASS	PASS
Normality test	PASS	FAIL	FAIL	FAIL	FAIL
Variance Inflation Factor	PASS	PASS	PASS	PASS	PASS

Signif. codes: ‘*’ 0.001 , ‘**’ 0.01, ‘*’ 0.05, ‘.’ 0.1, ‘ ’ 1**

Table B.7.3 Dynamic regression results for **quarterly** manufacturing output and employment

dependent Y_t / **explanatory**	Output Next 3months	Output Past 3months	Employment Next 3 months	Employment Past 3 months
intercept	2.16	NO	NO	NO
	(0.87) *			
Y_{t-1}	0.76	0.82	0.89	0.90
	(0.05) ***	(0.04) ***	(0.028) ***	(0.02) ***
Pre-election	-7.52	4.9	-3.2	9.6
	(7)	(7.1)	(5.4)	(6.7)
Pre-election*Tpre	6.6	-0.98	2	-5.7
	(4.3)	(4.5)	(3.4)	(4.2)
Post-election	-2.9	**16.3**	5.1	10.7
	(7)	**(7.1) ***	(5.4)	(6.7)
Post-election*Tpost	-0.18	**-12.1**	**-7**	**-8.8**
	(4.3)	**(4.5) ** **	**(3.4) ***	**(4.25) ***
control variables				
X_t	YES	NO	NO	YES
X_{t-1}	YES	NO	NO	NO
seasonality effects				
time trend	NO	NO	NO	NO
year	NO	NO	NO	NO
Government Changed	NO	NO	NO	YES
other statistics				
R^2_{adj}	57%	67%	82%	90%
Degrees of freedom	162	163	216	215
Observations	168	168	222	222
Joint F-test H0: election coefficients are all zero.	FAIL	PASS *	PASS **	FAIL
validation checks				
$\lvert \hat{a} + \hat{\varphi} \rvert < 1$	PASS	PASS	PASS	FAIL
Residuals acf	PASS	PASS	PASS	PASS
Unit root test	PASS	PASS	PASS	PASS
Durbin-Watson test	PASS	PASS	PASS	PASS
Breusch-Pagan test	FAIL	PASS	PASS	FAIL
Normality test	FAIL	FAIL	FAIL	FAIL
Variance Inflation Factor	PASS	PASS	PASS	PASS

Table B.7.4 Dynamic regression results for **monthly** manufacturing Output and Predictive Power 4.

dependent Y_t / **explanatory**	Output Next 3months [1975M04-2017M04]	Output Past 3months [1995M10-2017M04]	Predictive Power 4 [1975M04-2017M04]
intercept	1 (0.4) **	NO	-0.31 (0.14) *
Y_{t-1}	0.87 (0.02) ***	0.84 (0.03) ***	NO
Pre-election	2.24 (1.29) ‘.’	5.66 (3.26) ‘.’	0.29 (0.28)
Pre-election*Tpre	-0.46 (0.47)	-1.42 (0.83) ‘.’	NO
Post-election	0.82 (1.3)	6.04 (3.25) ‘.’	**1.04 (0.27)*** **
Post-election*Tpost	**-1.03 (0.48) ***	**-1.68 (0.83) ***	NO
control variables			.
X_t	NO	NO	NO
X_{t-1}	NO	NO	NO
seasonality effects			
time trend	NO	NO	NO
year	NO	NO	NO
Government Changed	INTERACTION	NO	NO
other statistics			
R^2_{adj}	79%	71%	40%
Degrees of freedom	498	253	501
Observations	505	259	505
Joint F-test H0: election has no effect	FAIL ‘.’	FAIL ‘.’	-
validation checks			Not Robust: adding and removing control variables change the results significantly
$\lvert \hat{a} + \hat{\varphi} \rvert < 1$	PASS	PASS	-
Residuals acf	PASS	PASS	PASS
Unit root test	PASS	PASS	PASS
Durbin-Watson test	PASS	PASS	PASS
Breusch-Pagan test	PASS	PASS ‘.’	PASS
Normality test	PASS	PASS	-
Variance Inflation Factor	PASS	PASS	-

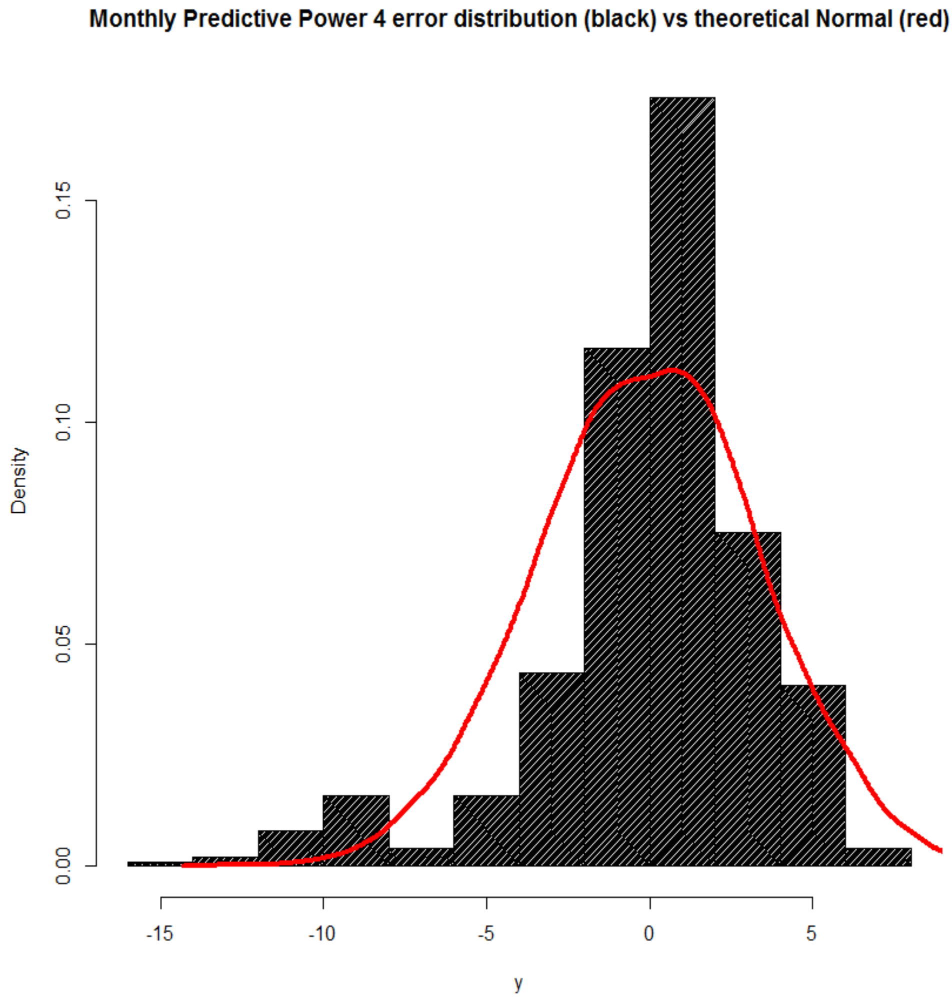
Monthly Predictive Power 4 error distribution (black) vs theoretical Normal (red)
Density
0.00
0.05
0.10
0.15
-15
-10
-5
0
5
y

Table B.8	Summary table of regression results:					
Table Description: Number of cases where the election effect was found to be statistically significant in the regressions. Considering both the main and interaction effects.	Quarterly Data			Monthly Data		
	EXPECTATIONS	ASSESSMENTS	TOTAL	EXPECTATIONS	ASSESSMENTS	TOTAL
VARIABLES EXAMINED	8	4	12	2	1	3
POST-ELECTION	1/8	3/4	4/12	0/2	0/1	1/3
PRE-ELECTION	0/8	0/4	0/12	0/2	0/1	0/3
ELECTION*TIME	2/8	2/4	4/12	2/2	1/1	2/3
EITHER	4/8	3/4	7/12	2/2	1/1	3/3
GOVERNMENT CHANGED	0/8	1/4	3/12	1/2	0/1	1/3
TOTAL EFFECT	4/8	2/4	6/12	1/2	0/1	1/3

Note: In 6/12 cases the total effect was found to be statistically significant when the test against the model without an election effect. The total effect is both the main effect and the interaction term if it is incorporated in the model.
The variables Business confidence, Output Past 3M, Employment Next 3M, Total New orders Next 3M, Investment Intentions Next 12M and Predictive Power 2 (Ability to predict their own employment) the total effect was found statistically significant. The total effect of elections also found to be statistically significant in the Output Past 3M and Predictive Power 4 (Ability to predict their own output).