Trump, Regulation and Stock Returns

Santanu Kundu[1]

Abstract

This study explores the link between asset prices and regulatory policy changes. Using 2016 US Presidential election as an exogenous shock to expectations about future regulatory policy, I find that stocks returns in the most regulated industries reacted positively. These stocks earned approximately 2.4% cumulative abnormal returns more than other stocks during 10 trading days post the election results were declared. The results are robust to controlling for tax rates and other firm specific characteristics. Furthermore, I find that firms with higher growth opportunities reacted more positively. These results provides evidence confirming a causal link between government regulatory policies and asset prices.

[This Version: April 25, 2018
First Version: March 19, 2018]

[1]I would like to thank Alexandra Niessen-Ruenzi, Alison Schulz, Chiayi Yen, Christian Westheide, Clemens Mueller, Hala Jada, Hamed Davari, Michael Weber, Stefan Ruenzi, Tobias Etzel and Seminar participants at the GESS Research Day at the University of Mannheim and Seminar participants at Luxembourg School of Finance for their helpful comments. I would also like to thank the German Research Foundation (DFG) for providing financial support. Email: santanu.kundu@gess.uni-mannheim.de

Electronic copy available at: https://ssrn.com/abstract=3143454

1. Introduction

Government policies play central role in how our economy works. Among other things, governments decide on taxes, currency regime, fiscal and monetary policies and control many other important aspects of the economy through rules and regulations. Indeed, as noted in Pastor and Veronesi (2012), "rules of the game" are set by the government.

The various rules and regulations that governments impose impact broader economic outcomes. For example, Besley and Burgess (2004) studies labor regulation reform in India and finds a decline in employment, investment and productivity in manufacturing. Blanchard and Giavazzi (2003), in the context of explaining macroeconomic evolutions in Europe, finds that product market deregulation leads to higher real wages and lower unemployment in the long run but the opposite effects in the short run. Labor market deregulation is negative for the workers. Hall and Jones (1999) studying 127 countries finds that the "social infrastructure" i.e., the quality of the institutions and government policies have a significant effect on productivity of workers. In the US, Denison (2011) provides some evidence on the negative relation of regulation and economic growth. Dawson and Seater (2013) also reports similar findings. Other studies such as Jorgenson and Wilcoxen (1990) estimates the cost of environmental regulation for the US economy. On a more micro-level, Averch and Johnson (1962) provide theoretical foundation to the behaviour of a firm in a regulatory constrained industry. More recently, Ryan (2012) models the Portland Cement industry with regards to the 1990 Amendments to the Clean Air Act and finds that the increased regulation has substantially increased sunk cost and reduced overall welfare.

However, little is known about how capital markets react to regulatory changes. The effect of regulation on the cross-section of stock returns has not been well established empirically. This paper attempts to bridge this gap. As pointed out by Schwert (1981), under the efficient market hypothesis, if regulation impacts asset values, then the market valuation adjusts to this new information with regulatory changes when they are first anticipated. For example, if more regulation leads to higher costs for the corporates, deregulation should alleviate these costs and this in turn should lead to positive reaction to the stock prices. However, Binder (1985) exploring twenty major changes in regulations

Electronic copy available at: https://ssrn.com/abstract=3143454

since 1887 finds no relationship between regulation changes and stock returns due to its well anticipated nature. Another reason being the exact date when market prices in the effect of regulatory change is not clear. In most cases, regulations are publicly debated over a long period of time and the outcome of the debate are generally anticipated. This makes regulatory event studies ineffective. In this paper, I use a natural experiment, the 2016 US Presidential election results, as an exogenous shock to the expectation of deregulation in the United States to overcome these issues. As in Pastor and Veronesi (2012), the central hypothesis in this paper is the 2016 Presidential election outcome led investors to update their beliefs about future government regulatory policies and this leads to the reaction in the stock prices.

Using the 2016 US Presidential election as an exogenous shock to the expectation change of regulation in the US has two advantages in this context. First, as noted in Wagner et al. (2018a), the election results came as a surprise to most. Hence, the nature of surprise of the event provides an ideal setting where it can be argued that the event day for change of expectation of markets is identifiable. Second, one of the major points of difference between the two Presidential candidates was regulation. Donald Trump favored de-regulation and was quoted saying "I would say 70% of the regulation can go" at a Town Hall event just one month before the election[1]. Furthermore, in his "Contract with the American Voter" published on October 23, 2016, focus on de-regulation was clearly stated with an objective of cutting two existing regulations for one regulation his administration would impose if he was elected. Given the focus of the new President on de-regulation, many policy institutes have come up with their research agenda on regulation. For example, Brookings Institution, developed a tracker to monitor different regulation activity undertaken by the Trump administration. Hence, given this backdrop and the unexpected nature of the election outcome and a clear point of difference between the two presidential candidates helps to overcome the difficulties faced in regulatory event studies.

I use the RegData database provided by George Mason University and as developed

[1]See: The Reuters Link

Electronic copy available at: https://ssrn.com/abstract=3143454

in Al-Ubaydli and McLaughlin (2017) to allocate firms to different regulatory restricted industries. The method developed in Al-Ubaydli and McLaughlin (2017) calculates, for each year, industry specific measure of regulation by using the North American Industrial Classification System (NAICS) description of industries and the text used in the Code of Federal Regulations (CFR). Based on this measure, I group different industries into quartiles of regulation in order to minimize measurement errors. Firms are allocated to industries based on their three digit NAICS code. Accordingly, these firms are grouped as falling into one of these quartiles of regulation.

I find that the firms in highly regulated industries earn economically and statistically significant positive cumulative abnormal stock returns (adjusted by the Fama-French five factors and the momentum factor) around the day of the election results compared to the firms in less regulated industries. Firms in the most regulated industries, on an average earned approximately 1.4% more cumulative returns than other firms on the first trading day after the election results were announced (event date). Overall, during the 10 trading days after the event date, stock prices of firms in the most regulated industries gained in market value by approximately 2.4%. The results are robust to controlling for firm characteristics (market capitalization, Amihud (2002) illiquidity measure, capital structure and size) and Fama-French three factors[2]. I also control for tax rates as Wagner et al. (2018a) and Wagner et al. (2018b) show that expectation of lower tax rates also played a major role in the stock price movement of companies. Indeed the tax rate was cut from 35% to 21% through the Tax Cut and Jobs Act signed into law by President Donald Trump on December 22, 2017. The extent of out-performance of the firms in most regulated regulated industries remain unchanged and it is over and above the positive reaction due to anticipated tax cuts. Thus my results shows that the expected lowering of government regulations in highly regulated industries was perceived positively by the investors. This is the primary finding of this study. Furthermore, I document no significant reaction when any of the de-regulatory measures were implemented by the Trump administration thus confirming the finding of Binder (1985) and emphasizing the

[2]I note here that propensity-score matching might not be appropriate in this case as the firms are inherently different since they are from different industries

importance of capturing the actual date of anticipated regulatory change in the capital markets to measure its impact correctly.

Are these results a chance occurrence? In order to test the robustness of the results, I perform falsification test. It is possible that the results may be driven by some unobserved variables which might generate economically and statistically significant more returns for firms identified here as falling in the most regulated industries on any given day. To test if this is the case, I generate 252 random dates in between 2013 and November 8, 2016 and carry out the same empirical analysis around these dates. I find that the likelihood that these can be obtained on any given day is zero.

Having established the validity of the results, I explore whether expected de-regulation is perceived as a positive event across different firm characteristics. In particular, I examine whether the results are robust to excluding foreign incorporated firms and excluding finance and utilities companies. The results do not change across these sub-samples. The results also remain qualitatively similar if I include deferred tax assets from net operating losses carry forward and (net) deferred tax liabilities.

Third, I provide an economic channel through which these positive reactions can be explained. To the extent that de-regulation would help firms to grow, it might be expected that firms with higher growth opportunities would have a more positive stock price reaction. I find evidence confirming this channel. Specifically, I find that the positive returns of the firms in the most regulated industries are driven by firms having ex-ante higher growth opportunities as measured by Tobin's Q. The positive reaction of firms in the most regulated industry seems to stem from the firms with higher Tobin's Q. This is also in line with the differential reaction of firms in regulated and non-regulated industries as found in McConnell and Muscarella (1985). Additionally, I find that the stocks with higher returns had positive analyst forecast revisions ex-post, consistent with the argument that firms in the most regulated industries were expected to perform better than the other firms.

This paper is related to various strands of literature. First, this study provides a causal evidence of regulation on security prices in the cross-section by employing a natural experiment and using a novel measure of industry-specific regulation. Thus this

study extends the work of Schwert (1981), Binder (1985) among many others. Second, this study is related to the strand of literature examining the impact of government policies on asset prices. Pastor and Veronesi (2012) provides a theoretical framework on how government policy uncertainties can impact asset prices. Santa-Clara and Valkanov (2003) emphasizes the importance of studying specific government policies and in particular regulatory policies. Belo et al. (2013) documents how asset prices differ across different presidencies in the United States and identifies an economic channel. This study thus complements this growing strand of literature by looking at a particular policy, namely the regulatory policies, can have a first-order impact on asset prices. This study is an initial step in that direction. Studies most related to the present study are Wagner et al. (2018a) and Hachenberg et al. (2017) where the authors examine the expectation of tax-cuts and the repeal of reforms in financial services sector on a small set of firms respectively. I complement these studies in providing strong and robust evidence that the expected federal government deregulation played a major part in the abnormal returns of the stock returns on a broad sample of stocks.

The rest of the paper is organized as follows. Section 2 provides a brief description of the industry level regulation data used in the analysis along with other variables, Section 3 provides the main empirical results, Section 4 provides robustness checks of the main results, Section 5 provides evidence on the growth opportunities as a channel for the stock price reaction and Section 6 concludes.

2. Data

2.1. Regulation Data and Measurement

Measurement of regulation is in itself a complicated exercise. Research in this field have measured regulation using page count of the Code of Federal Regulations (hereafter CFR) as in Dawson and Seater (2013)[3]. Similarly, Mulligan and Shleifer (2005) use file size data of legislation in the United States as the measure of regulation. Becker and Mulligan (1999) uses different measures of regulation such as committee size, regulatory

[3]CFR contains the most recent regulations that are applicable and is updated each year in four waves.

costs as a percentage of GNP and population, among others, More recently, Al-Ubaydli and McLaughlin (2017) proposed an industry specific measure of regulation using the textual analysis of CFR. I use this measure for the present study. More specifically, the data comes from the RegData project of Mercatus Center of George Mason University.

In Al-Ubaydli and McLaughlin (2017), the authors first calculate the frequency of occurrence of the words indicating binding constraints such as "shall", "must", "may not", "prohibited" and "required" for each division of the CFR, say R_{py}, where p is the divisions in the CFR (having total P divisions) and y is the year. Then for each 3-digit NAICS code, i, a search string is created from the industry description of the NAICS code and calculates the occurrence of the strings in that particular division of CFR, say I_{pyi}. Then, to create an industry relevant count of regulations for the year y, the occurrence of the search strings, I_{pyi}, is multiplied with the occurrence of the restrictive words in that division, R_{py}. The resulting measure is then summed up across all division to give an aggregate count of regulation. Formally, the aggregate count of regulation in industry i for year y can be written as:

$$RRI_{iy} = \sum_{p=1}^{p=P} R_{py} I_{pyi} \tag{1}$$

Equation 1 gives the measure of regulation used here. As with any other textual analysis method, this method is not perfect. One of the key issues being measurement error[4]. To overcome this I follow two strategies. First, as suggested in Al-Ubaydli and McLaughlin (2017), I form industry quartiles based on the quantitative score received from equation (1) and assign firms to each of these quartiles based on their NAICS code. Second, as recommended in Al-Ubaydli and McLaughlin (2017), I use the three-digit NAICS code as this gives the most accurate count of the regulatory restrictions. I use the rankings of the three digit industries based on 2015. The rankings are virtually same in 2016 (correlation between the two rankings being 0.99). Then, I assign each firm to one of the quartiles of regulation based on their three-digit NAICS code. Table 1 provides example of industries in each quartile.

[4]Please see Al-Ubaydli and McLaughlin (2017) for a discussion on the limitations

[Insert Table 1 here]

The above table shows that the Al-Ubaydli and McLaughlin (2017) method has largely aligned the industries according to their regulation index as we would expect ex-ante. For example, most of the industries in the top quartile can be expected to have higher regulation than the others. This distribution of industries gives sufficient confidence in the method to be applied for further analysis. It is important to note here that the I do not expect each of the industry in fourth quartile to have higher regulation than each of the industry in the other three quartiles. Rather, the key assumption here is that the group of industries in the fourth quartile is expected to have higher regulation on average than the group of industries in the other quartiles.

2.2. Other Financial Data

Daily stock returns data is from the Center for Research in Security Prices (CRSP) and the accounting variables are taken from COMPUSTAT. I take the Fama and French (1993), the Fama and French (2015) and the momentum factor from Kenneth French's website. The industry definitions of NAICS are taken from the United States Census Bureau website. As control variables, I use variables that have been previously found to predict stock returns. Amihud (2002) shows that the measure is related to stock returns through the illiquidity premium. As discussed in Amihud (2002), I also control for firm size by taking the logarithm of total assets and market capitalization. Furthermore, Bhandari (1988) and Welch (2004) find that stock returns are related to the capital structure as reflected in the debt-equity ratio. Hence, I also control for each firm's debt-equity ratio in the empirical set-up. In order to control for any confounding effect, I control for the expected cash tax rates as it has been shown to be an important driver of stock returns around this event in Wagner et al. (2018a).

RegData provides regulation restriction scores for 54 NAICS 3-digit industries. Hence, I drop firms those are not in these 54 industries. Of these 54 industries, 3 industries do not have any firms in the CRSP database. Additionally, I exclude firms belonging to NAICS three digit code 525 (funds, trusts, and other financial vehicles) and 35 firms that have changed their NAICS code during the year. This leaves the sample size of 1,901

firms which are finally used in the regressions having data for all of the variables in the baseline model. This sample represents 61.5% of the total CRSP market capitalization as of November 8, 2016.

Before presenting some descriptive statistics, I provide some details on how some of these variables are calculated. The daily Amihud (2002) illiquidity measure is calculated using the absolute return scaled with the total dollar volume of shares traded on that day. The market capitalization, *MCAP*, is calculated by multiplying the closing price of each share to the number of shares outstanding on each day. It is measured in million dollars. *ASSET* is the logarithm of the total book assets of the firm as of fiscal year ending 2015. *DE* is the ratio of book-debt to total equity as of year ending 2015. For most firms, I get the data for the fiscal year ending 2015 from Compustat. I calculate one-year effective cash tax rates *ECTR* as given in equation (1).

$$CASH\_ETR_i = CashTaxpaid_i/(PreTaxIncomce_i - SpecialItems_i) \tag{2}$$

Alternative proxy for the expected cash tax rate can be the ten-year average cash tax rate as developed in Dyreng et al. (2008). This is given by equation (2)

$$CASH\_ETR_i = \sum_{t=1}^{10} CashTaxpaid_{it} / \sum_{t=1}^{10} (PreTaxIncomce_{it} - SpecialItems_{it}) \tag{3}$$

I use the one-year effective cash tax rates as an proxy for the future tax rates, This is for two reasons. First, as shown in Wagner et al. (2018a), during the period, one-year tax rates is a better predictor for the future tax rates. I also arrive at similar conclusion for my sample. Second, since this variable is not present for many firms over the past ten-year period, I lose significant number of observations in many of my empirical tests. However, as I show later, main results of the study do not alter if I use the long term average cash tax rates as a proxy for expected effective tax rates.

Table 2 presents a brief overview of how the financial variables are distributed across

different regulation quartiles[5]. As can be seen, the regulated firms in the fourth quartile tend to have higher illiquidity. There is no apparent difference in the size, debt-equity ratio and cash tax rates. In addition, it can be noted that the average gross returns of the firms in the fourth quartile is also higher compared to other quartiles. This gives an initial indication that the firms in the fourth quartile had a more positive price reaction compared to the other firms.

[Insert Table 2 here]

2.3. Empirical Strategy

I employ event study methodology for this analysis. I take November 9th as the first day after the event when the market starts. For each firm in my sample, I take a 60-day estimation window which ends at 30 days prior to the event. I calculate the Fama-French five factors (and three factors) and momentum adjusted cumulative abnormal returns (CARs) for each firm over the event window which starts on 9th November. I use multiple definitions of event window, specifically, 1, 5 and 10 trading days after the event. I look at short term (10 trading days) for two reasons. First, as mentioned in Fama (1998), the "bad-model problem" is limited in shorter horizons with the change in expected returns. For example, as we increase the time horizon different expected stock returns might change according to changes in macro-economic conditions. Second, as noted in Wagner et al. (2018a), reaction of stock prices to policy changes becomes increasingly difficult to measure in longer horizon due to the inherent difficulties as mentioned in Schwert (1981). In addition, I employ industry fixed-effects to absorb any unobserved industry-specific heterogeneity that might drive the stock returns during this short period of time. Thus, for each definition of event window, I calculate each firm's CAR and regress them on the dummy variable identifying the quartile of regulation that the firm is in controlling for other firm characteristics. The empirical specification can be formulated as below:

$$CAR_{id} = \alpha + \sum_{i=2}^{4} \beta \times R_i + \gamma \times \mathbf{X}_i + \varepsilon_i + \nu_i \tag{4}$$

[5]These quartiles are formed based on the initial list of 54 firms before I apply any data filter. This avoids any possible sample selection bias in defining the regulatory restrictions quartiles

In the above equation, α is the intercept. R is a dummy variable which takes the value of one to four indication least to most regulated industry quartiles. In the basic empirical setup, R_1 is taken as the reference category. $\boldsymbol{X}$ is the vector of control variables as discussed previously for each firm. ε_i is the industry fixed effect and ν_i is the error term. CAR_{id} denoted the cumulative abnormal return for firm i till day d after the event. In this case d takes the values 1, 5 and 10 as mentioned before.

3. Empirical Results

This section investigates the cross-section of stock price responses after the election outcome. As mentioned earlier, I look at short event windows to prevent any biases from confounding events. The results are presented at different time horizons, specifically after 1, 5 and 10 trading days after the event. I first present the results of the analysis without controlling for cash tax rates in order to get an estimate of the baseline effects of the expectation of deregulation across the cross section. Next, I control for cash tax rates.

3.1. Regulation and Stock Returns

Many deregulation initiatives have been taken since President Donald Trump has taken office. It can be seen from publicly available database, created by Brookings Institution to track all the deregulation initiatives taken under President Donald Trump[6], many of these initiatives are related to environmental protection and safety. However, notably, these initiatives span across different sectors.

[Insert Figure 1 here]

Figure 1 presents the difference in value-weighted cumulative abnormal returns of the firms in quartile four (most regulated) and quartile one (least regulated) around the event window, i.e., November 8, 2016. As is apparent from the figure, there is a clear jump in abnormal returns on November 9, 2016 for this "long-short" portfolio. Firms in the most regulated industries gained approximately 3% in market value on the very first day after the election outcome was announced. This effect seemed to have persisted thereafter.

[6]See: https://www.brookings.edu/interactives/tracking-deregulation-in-the-trump-era/

Hence, Figure 1 provides some initial evidence of the effect of expected deregulation on stock prices.

Next, I look analyze the returns more formally. Table 3 presents the results of regressing individual stock cumulative abnormal returns (CARs) on *QUTILE* (representing which quartile of regulated industries the firm belongs to, 1 being the lowest and 4 being the highest) and other control variables. This table implements the specification of equation (4).

[Insert Table 3 here]

Columns (1), (2)and (3) shows the result of regressing 1-day, 5-day and 10-day CARs of the firms on a dummy variable *QUTILEN* (where N = 1,2,3,4) which represents the respective regulatory quartile where the firm is placed based on its industry and other control variables respectively. The asymmetric price reaction is evident in the table. Only the firms in the highest quartile of deregulation experienced approximately 2.4% positive cumulative abnormal returns during this period. The positive reaction on the day of the election was around 1.5% for these firms and it gradually reached 2.4% by the end of the 10th trading day. The other control variables are not found to be statistically significant except for *MCAP* for the 10-day CAR indicating the small size premium. However, this too is marginally significant. The specification can explain approximately 9% to 12% of the variation in cumulative abnormal stock returns during this period for the sample of 1,901 firms as represented by the R^2. Thus we see that the expected deregulation has a strong impact on the valuation of the firms that are in the most regulated industries. This results shows that markets expected the firms in the most regulated industries to benefit more from the government deregulation. However, as noted earlier, the above results do not control for expected tax rates. The next section presents the results of the analysis controlling for tax rates.

3.2. Regulation, Taxes and Stock Returns

As documented in Wagner et al. (2018a), expectation of tax cuts played a big role in explaining abnormal returns across the cross section of stocks. Dyreng et al. (2008) show that the expected tax rate can be calculated by computing the long-run cash tax paid by

the firm. However, Wagner et al. (2018a) notes that during present period, the one-year cash tax rate is a better predictor of the future tax rate. Hence, I use both the tax rates as a control variable in separate regressions. The results are shown in Table 4. First three columns of Table 4 presents the analysis based on one year cash tax rates as a proxy for expected tax rate and the last three columns presents the results by taking the long term (10-year) average cash tax rate as an estimate for the expected tax rate.

[Insert Table 4 here]

First, it can be seen from Table 4 that the economic magnitudes of the stock returns for firms in the fourth quartile of regulation are very similar to that reported in Table 3. The firms in fourth quartile of regulation earned a positive abnormal returns of approximately 2.3% during the 10-day post event period after controlling for the expected one year cash tax rates. Using the long-term average cash tax rates as a proxy for expected tax rates decreases the sample size considerably to 1,223 firms. However, in this case also the effects are largely identical.

Second, we see that the coefficient of one year cash tax rates are positive and statistically significant for 1-day and 5-day event window indicating a positive relationship between expected cash tax rates and abnormal returns. The standard deviation of the effective cash tax rate is approximately 16%. By Table 4, this means that, on average, stock with one standard deviation higher effective tax rate earned approximately 40 basis points more abnormal returns by the end of 5-day event window. In terms of economic magnitude, sensitivity of stock returns to the expected tax rate is in line with what has been reported in Wagner et al. (2018a). The inclusion of the tax-rates do not help in explaining more variation of the cumulative abnormal returns as we see that the R^2 hardly change. The conclusion is similar based on the the 10-year average cash tax rates as shown in the last three columns of Table 4. These results imply that, ceteris paribus, the stocks returns were higher in regulated industries and this effect remains after controlling for expected tax rates. As before, the control variables do not explain the abnormal returns during this period.

4. Falsification Test

Are these results by chance? Since, the study is based on only one event, it might be possible that the firms in the top quartile are most likely to generate such abnormal positive returns on any random date due to some unobserved characteristics that are not absorbed by industry fixed effects or any other omitted variables. In order to address these concerns, I employ a falsification test. First, during the three-year period, I randomly take 252 trading days and run the similar event-study around each day. If there is any bias in the regression analysis before, I should find a large fraction of these randomly selected 252 days displaying a statistically significant and economically similar positive reaction that I documented before.

Panel A of Figure 2 shows the distribution of regression t-statistics and Panel B shows the distribution of coefficients of running the specification of Table 4 pertaining to *QUARTILE 4* of regulatory ranks of industries for 252 randomly generated dates for 1-day CAR. As can be seen, the likelihood of observing a positive and statistically significant returns for an average firm in the top quartile of regulation is zero. None of the regression coefficients are significant at 5% level and the economic magnitudes are also very small compared to what has been reported before. Put differently, on any given year (consisting of approximately 252 trading days), the likelihood of any random day generating a abnormal return for the firms in the topmost quartile of regulation is zero.

[Insert Figure 2 here]

Thus, we can rule out the possibility that the positive cumulative abnormal returns documented in Tables 3 and 4 for the firms in the most regulated industries are not driven by any some mechanical construction of the data that generates such returns or driven by some unobserved characteristics that are most likely to generate such returns on any given day.

5. Robustness Tests

This section presents the results of the previous analyses by taking alternative specifications, sub-samples and additional control variables.

5.1. Controlling for Foreign Operations

The focus of the Trump campaign being on "Make America Great Again" with emphasis on giving advantage to firms that are more domestically oriented might affect the valuations of such firms differently. There are number of dimensions on which the campaign promises made by Trump might be costly to internationally oriented firms. For example, any regulatory restrictions on trade or employability of highly skilled foreign workers might effect firms that depend on them. Furthermore, with Trump's plan of expansionary fiscal policies may lead the Fed to hike interest rates and thus may strengthen the dollar in the short run which in turn may hurt exports (Wagner et al. (2018a)). Though such a channel may not be directly related to regulation but it emphasizes the importance of controlling for such an effect in the empirical analysis[7]. However, it is difficult to identify through which channel the markets would react in the short run. Hence, I collect all the possible data on firms in relation to foreign operations from COMPUSTAT (namely, foreign assets and sales from COMPUSTAT segment files, pretax income foreign, deferred taxes foreign, income taxes foreign) and create a dummy variable *Foreign* which takes the value of 1 when there is any foreign operation indicated in these variables and zero otherwise. The advantage of this approach is that one does not have to consider about any non-linear relationship of foreign operations and can combine multiple dimensions of foreign operations into one variable. However, I lose many valuable and potentially interesting aspects to look at in this case. But, this being not the primary focus of the study is left for future research. Furthermore, I also carry out the analysis on a sub-sample of firms that are incorporated in the US.

[Insert Table 5 here]

Table 5 presents the results of this analysis. As can be seen from Columns (1) to (3), the point estimates and their statistical significance remain primarily unchanged running the specification of Table 4 after controlling for foreign operations. The coefficient

[7]As mentioned in Wagner et al. (2018a), though it is not possible to come up with a theoretical argument as to how the direction of the reaction of the stock prices should be, they find a negative reaction

on foreign operations itself is negative as is expected but the effect is not statistically significant in this sample. I lose 16 firms in this analysis as they do not have any of the data points considered for this analysis. Furthermore, columns (4) to (6) presents the result of the analysis after excluding foreign incorporated firms. This leads to dropping 204 firms from the original sample of 1,901 firms as reported in the first three columns of Table 4. In this sample, we see that the economic magnitudes of the coefficients are largely similar to those in Table 4 suggesting that the foreign operations do not change the market reaction of the firms in the most regulated industries. We also see that the inclusion of foreign operations dummy and the exclusion of foreign incorporated firms do not significantly help in explaining greater variation in the abnormal stock returns during the period as indicated by the R^2. Since the coefficient of *Foreign* is not significantly different from zero and also the R^2 are not different from what has been reported in Table 4, I exclude this variable from the further analysis.

5.2. Using DTA and DTL

Deferred tax assets and liabilities are inherently related to the cash flows available to the firms in the future and the expected tax rates in the future. If firms have deferred tax assets from net operating losses carry forward (NOL), a lower tax rate in the future reduces the present value of such expected tax savings and hence negatively related to firm value. However, as discussed in Wagner et al. (2018a), the tax plan of the House Republicans may have a positive effect on firm value if the addition of interest to NOL is allowed. On the other hand, limits on utilization of NOL for this purpose may be negative to the firm value. Thus, it is not apparent which way the stocks would react, i.e., if the negatives of statutory tax rate cut and utilization limits will be dwarfed by the addition of interest to the NOL. On a similar note, firms with net deferred tax liabilities may be expected to gain in market value as the present value of the tax expenses decrease with lower tax rates in the future. Even though these variables are not related to regulation directly, it is essential to control for stock price variation due to such tax-related expectations to make the estimate of the regulation dummies free from the bias of possible confounding effects. I include these variables to the main regression specification of Table 4.

I follow Wagner et al. (2018a) and collect the data of deferred tax assets from net operating losses carry forward for the firms in my sample from Bloomberg. Out of the sample of 1901 firms, Bloomberg do not any have data for 138 firms. Bloomberg provides deferred tax assets from net operating losses (DTA NOL) carry forward for 465 of the remaining firms. Next, for the remaining firms I employ the screening technique as mentioned in Lillian F. Mills and Novack (2003) to overcome data errors in Compustat. For the firms that are left with missing values, I replace them as having zero deferred tax assets from net operating losses carry forward. In the same regression, I also control for net deferred tax liabilities (DTLs) as the firms with net DTLs should have a positive reaction as the reduction in tax rates drops the future taxes payable by the firms.

[Insert Table 6 here]

Table 6 shows the results of the analysis. The point estimates for the fourth quartile of regulation are marginally higher for all event windows. For 5-day and 10-day event window we also see a positive and significant CAR for the firms in the third quartile of regulation. However, their economic magnitudes are almost 50% lower compared to the economic magnitudes of the returns for an average firm in the fourth quartile. However, the firms with higher DTA NOL have a significantly negative stock price reaction during the 5-day and 10-day event windows suggesting that the effect of tax cuts dwarfed any positive benefits markets expected from allowing interest to be added back to NOL. This is also in line with the findings of Wagner et al. (2018a). However, I do not find any significant relationship with net DTLs. However, it must be noted here that the measures of DTA NOLs and net DTLs are prone to errors due to data entry and most of the firms have missing values for DTA NOLs. Hence, I exclude these variables in my further analysis to take advantage of the maximum observations possible.

5.3. Excluding Finance and Utilities

Are these returns driven by finance and utilities? Since in most studies finance and utilities are considered to be most regulated, it might be possible that the results are driven by these firms. Furthermore most studies drops firms belonging to these industries due to their regulatory structure. In addition, as shown in Hachenberg et al. (2017),

firms in financial services sector also experienced positive abnormal returns. Hence, it is important to examine if the results are solely driven by a specific group of firms in the cross section.

In order to conduct this analysis, I exclude firms having the NAICS two-digit codes 52 (finance and insurance) and 22 (utilities) and conduct the regression analysis as per the specification of Table 4. Table 7 shows the results of the analysis. Columns (1) to (3) of Table 7 includes the one-year cash tax rates as the proxy for expected tax rates. The exclusion of firms in the finance and insurance and utilities leads to dropping 598 firms from the cross section. However, it can be seen that the magnitudes of the coefficients are economically higher marginally. The same conclusion is valid for columns (4) to (6) where I only use the firms that have the long-term average cash tax rates and are not in finance and utilities industry. Even though the sample size reduces significantly in this case, the similar positive effect is observable for this sub-sample of firms as well. Thus, Table 7 shows that the results are not driven by finance and utility companies alone.

[Insert Table 7 here]

6. Heterogeneous Effects

Having shown that the results of the analysis are robust to numerous specifications and controls, I now explore specific economic channels through which the positive stock price reactions of firms in the most regulated industries can be attributed to. I look at both ex-ante and ex-post measure of growth opportunities.

6.1. Regulation and Growth Opportunities – Ex-ante

One of the major ways through which regulation impacts firms is by defining their investment opportunity set. McConnell and Muscarella (1985) documents unequal responses of stock prices to announcement of capital expenditure changes for firms in industrial and regulated industries. The authors show that market valuation of firms in the regulated industries do not change when announcement of new investments are made. The authors argue that regulation hinders firms to take on projects that would earn higher than market required rate of return. Hence, announcements of new projects do not add

to the firm value for regulated firms. The implication of this finding to the present study is that the firms might react differently to growth opportunities as per their regulatory environment. Thus, stock prices might react differently to firms having similar regulatory restrictions but different growth opportunities and vice versa. In line with the argument of McConnell and Muscarella (1985), if the growth opportunities can be exploited by the firms in regulated industries due to expected lowering of regulation, then the price reaction may be driven by the firms having better growth opportunities given the firms are in the same quartile of regulation. Alternatively, firms having same growth opportunities but in different regulatory environments may react differently.

To explore this possibility, I control for investment opportunity (as measured by Tobin's Q) in Table 8. However, as noted in Laeven and Levine (2007), the conventional way of calculating Tobin's Q for banks may be problematic. Hence, as in Laeven and Levine (2007), for the financial firms in the sample, I replace Tobin's Q as the ratio of ratio of operating income (earnings before interest and taxes) to total assets. For all other firms, Tobin's Q is calculated as the ratio of the sum market capitalization and total assets minus book equity minus deferred tax liability to total assets. As with other accounting variables, I take the data for calculating Tobin's Q as of fiscal year 2015. Not all firms have the data available to compute Tobin's Q. Hence, the sample size in these regressions differ from the earlier tables.

[Insert Table 8 here]

Columns (1) to (3) show the specification of the respective columns of Table 4 adding Q as an additional control variable. Table 8 shows that the CARs of firms in the fourth quartile continues to be positive and the magnitude of the returns being similar to the ones reported in Table 4. Further, Q do not seem to explain additional variation in the abnormal returns. Columns (4) to (6) implements an interaction term between each quartile and Q. As can be seen, the interaction between the *QUARTILE 4* and Q is positive and significant except on the first day. I can report that the coefficient is significant from the second day onwards with economic significance qualitatively similar to the ones documented in columns (5) and (6) of Table 8. The coefficient on Q is not significant. As

previously, we also see that positive effects of tax continues to be persistent. The positive return abnormal reactions for the firms in most regulated industries is driven by growth opportunities as identified by Tobin's Q. It is evident from the results of Table 8 that firms having higher growth opportunities *and* conditional on being present in the most regulated quartile reacted positively after the event. In terms of economic magnitude of the returns, one standard deviation increase in Q for firms in the most regulated industries lead to an approximately 1.7% more positive abnormal returns during the event window. We also see that there is a positive relationship between Q and stock price reaction for firms in the third quartile of regulation at the end of the event window as shown in column (6). However, in this case, to be noted that the coefficient on the third quartile is itself negative. Combined together, it can be said that approximately 95% of the firms in quartile three of regulation do not have positive stock returns as a median firm in the fourth quartile. In other words, the sensitivity of firms' stock price reaction to growth opportunities differs according to their regulatory environment and a statistically significant and positive reaction is observed for firms in the most regulated industries.

[Insert Table 9 here]

6.2. Regulation and Growth Expectations – Ex-post

In this section, I further investigate whether the stock price reaction was accompanied by subsequent revision of analyst forecasts of earnings per share (EPS) from IBES. Da and Warachka (2011) finds that there is a slow incorporation of information in long term forecasts compared to short term forecasts. However, there are other studies such as Copeland et al. (2004) and Jung et al. (2012) who show that long term analyst forecasts also contains relevant information. Hence, I look at both short term and long term analyst forecast. For short term, I take one year ahead forecast and for long term, I look at the long term forecasts wherever present, else, I take the 5-year, 4-year or 3-year ahead forecasts in the order of importance wherever they are present[8]. As the baseline forecast, I take the most recent median forecast present for a firm during the past one

[8]Da and Warachka (2011) notes that analyst long term forecasts are done with a three to five year horizon

year before the election result for a particular forecasting period from the summary file of IBES. I then calculate the percentage forecast revision for each firm for each month for both short term and long term forecasts. To be noted, that the original long term forecasts are in annual percentage growth whereas forecasts for particular forecasting period is in EPS. Hence for the long term, I convert each of the 3-year, 4-year and 5-year forecasts into their implied average annual percentage growth in EPS. I also calculate the short term EPS growth rate. As in Da and Warachka (2011), since these variables have large outliers, I also take the decile ranks of for each firm based on these growth rates. These short term (STG)and long term (LTG) growth rates and their respective deciles (STG_DEC and LTG_DEC) are the variables used for the subsequent analysis. I conduct the analysis excluding the financial services (two-digit NAICS code as 52) as Morgan (2002) shows that banks and insurance companies are most opaque and given the diversity of the operations of these financial services companies (Laeven and Levine (2007)) may be difficult to value.

Table 9 and 10 presents the result of this analysis using analyst forecast revision after three months from the election result, i.e., February 2017[9]. Table 9 uses the decile ranks and Table 10 uses the original values.

Inference from Table 9 is similar to what is documented in Table 8. I see that the stocks with significant positive reaction was later associated with an increase in analyst short term earnings expectations. However, there is no relationship with long term forecast revisions. This is in line with slow incorporation of information in long term forecasts as noted in Da and Warachka (2011). Table 10, using the actual forecast growth also provides a similar picture.

[9]Results are similar when using 0-month (IBES revision date of November 17, 2016), 1-month, and 2-month revisions as well. For the 0-month revision, I see positive reaction in all the quartiles but this effect do not persist afterwards. For the "full sample" analysis including financial services industry, the result is similar for the 3-month revision but I do not see any significant change before that consistent with the argument that analyst may not be able to fully incorporate the effect of deregulation on these firms quickly.

7. Conclusion

I provide evidence that the election of Donald Trump as the President of United States provided investors with expectations of lower regulations along with lower tax cuts. This study finds evidence that the cross-section of stock returns after the after the election results reflected the expectation of a significant de-regulation only in highly regulated industries. The results are not driven by commonly assumed regulated industries like finance and utilities. The price reaction is significant after controlling for expected tax rates and various other firm characteristics. Furthermore, the positive effects is driven by firms with ex-ante higher growth opportunities that are operating in most regulated industries. In line with this finding, it is also seen that the firms in the most regulated industries which reacted positively during the event window also subsequently experienced a more positive revision in earnings expectations by the analysts compared to the firms in less regulated industries. Thus this paper complements the existing literature in asset pricing that investigates the effect of government policies on asset prices by looking at a particular policy, namely the regulatory policy and its impact on the cross section of stock returns. The effect seems to be concentrated in highly regulated industries.

References

Agrawal, A. and C. R. Knoeber (1996). Firm performance and mechanisms to control agency problems between managers and shareholders. *Journal of Financial and Quantitative Analysis 31*(3), 377–397.

Al-Ubaydli, O. and P. A. McLaughlin (2017). Regdata: A numerical database on industry-specific regulations for all united states industries and federal regulations, 1997–2012. *Quarterly Journal of Economics 11*(1), 109–123.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Averch, H. and L. L. Johnson (1962). Behavior of the firm under regulatory constraint. *American Economic Review 52*(5), 1052–1069.

Becker, G. S. and C. Mulligan (1999). Accounting for government growth.

Belo, F., V. D. Gala, and J. Li (2013). Government spending, political cycles, and the cross section of stock returns. *Journal of Financial Economics 107*(2), 305–324.

Besley, T. and R. Burgess (2004). Can labor regulation hinder economic performance? evidence from india. *Quarterly Journal of Economics 119*(1), 91–134.

Bhandari, L. C. (1988). Capital structure and stock returns. *Journal of Political Economy 43*(2), 507–528.

Binder, J. J. (1985). Measuring the effects of regulation with stock price data. *RAND Journal of Economics 16*(2), 167–183.

Blanchard, O. and F. Giavazzi (2003). Macroeconomic effects of regulation and deregulation in goods and labor markets. *Quarterly Journal of Economics 118*(3), 879–907.

Copeland, T., A. Dolgoff, and A. Moel (2004). The role of expectations in explaining the cross-section of stock returns. *Review of Accounting Studies 9*(2-3), 149–188.

Da, Z. and M. Warachka (2011). The disparity between long-term and short-term forecasted earnings growth. *Journal of Financial Economics 100*(2), 424–442.

Dawson, J. W. and J. J. Seater (2013). Federal regulation and aggregate economic growth. *Journal of Economic Growth 18*(2), 137–177.

Demsetz, H. and K. Lehn (2002). The structure of corporate ownership: Causes and consequences. *Journal of Political Economy 93*(6), 1155–1177.

Denison, E. F. (2011). *Trends in American Economic Growth*. The Brookings Institution.

Dyreng, S., M. Hanlon, and E. L. Maydew (2008). Long-run corporate tax avoidance. *The Accounting Review 83*(1), 61–82.

Fama, E. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics 49*(3), 283–306.

Fama, E. and K. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Fama, E. and K. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*(1), 1–22.

Hachenberg, B., F. Kiesel, S. Kolaric, and D. Schiereck (2017). The impact of expected regulatory changes: The case of banks following the 2016 u.s. election. *Finance Research Letters 22*, 268–273.

Hall, R. E. and C. I. Jones (1999). Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics 114*(1), 83–116.

Jorgenson, D. W. and P. J. Wilcoxen (1990). Environmental regulation and u.s. economic growth. *RAND Journal of Economics 21*(2), 314–340.

Jung, B., P. B. Shaneb, and Y. S. Yang (2012). Do financial analysts' long-term growth forecasts matter? evidence from stock recommendations and career outcomes. *Journal of Accounting and Economics 53*(1-2), 55–76.

Laeven, L. and R. Levine (2007). Is there a diversification discount in financial conglomerates? *Journal of Financial Economics 85*(2), 331–367.

Lang, L. H. P. and R. M. Stulz (1994). Tobin's q, corporate diversification, and firm performance. *Journal of Political Economy 102*(6), 1248–1280.

Lillian F. Mills, K. J. N. and G. F. Novack (2003). How well do compustat nol data identify firms with u.s. tax return loss carryovers? *Journal of the American Taxation Association 25*(2), 1–17.

McConnell, J. J. and C. J. Muscarella (1985). Corporate capital expenditure decisions and the market value of the firm. *Journal of Financial Economics 14*(3), 399–422.

Morgan, D. P. (2002). Rating banks: Risk and uncertainty in an opaque industry. *American Economic Review 92*(4), 874–888.

Mulligan, C. and A. Shleifer (2005). The extent of the market and the supply of regulation. *Quarterly Journal of Economics 120*(4), 1445–1473.

Pastor, L. and P. Veronesi (2012). Uncertainty about government policy and stock prices. *Journal of Finance 67*(4), 1219–1264.

Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica 80*(3), 1019–1061.

Santa-Clara, P. and R. Valkanov (2003). The presidential puzzle: Political cycles and the stock market. *Journal of Finance 58*(5), 1841–1872.

Schwert, G. W. (1981). Using financial data to measure effects of regulation. *Journal of Law & Economics 24*(1), 121–158.

Wagner, A. F., R. J. Zeckhauser, and A. Ziegler (2018a). Company stock price reactions to the 2016 election shock: Trump, taxes and trade. *Journal of Financial Economics Forthcoming*.

Wagner, A. F., R. J. Zeckhauser, and A. Ziegler (2018b). Unequal rewards to firms: Stock market responses to the trump election and the 2017 corporate tax reform. *American Economic Association Papers and Proceedings Forthcoming*.

Welch, I. (2004). Capital structure and stock returns. *Journal of Political Economy 112*(1), 106–132.

Figure 1 – Difference in Value-Weighted cumulative abnormal returns of firms in Quartile 4 and Quatile 1 (Q4 - Q1) of regulation

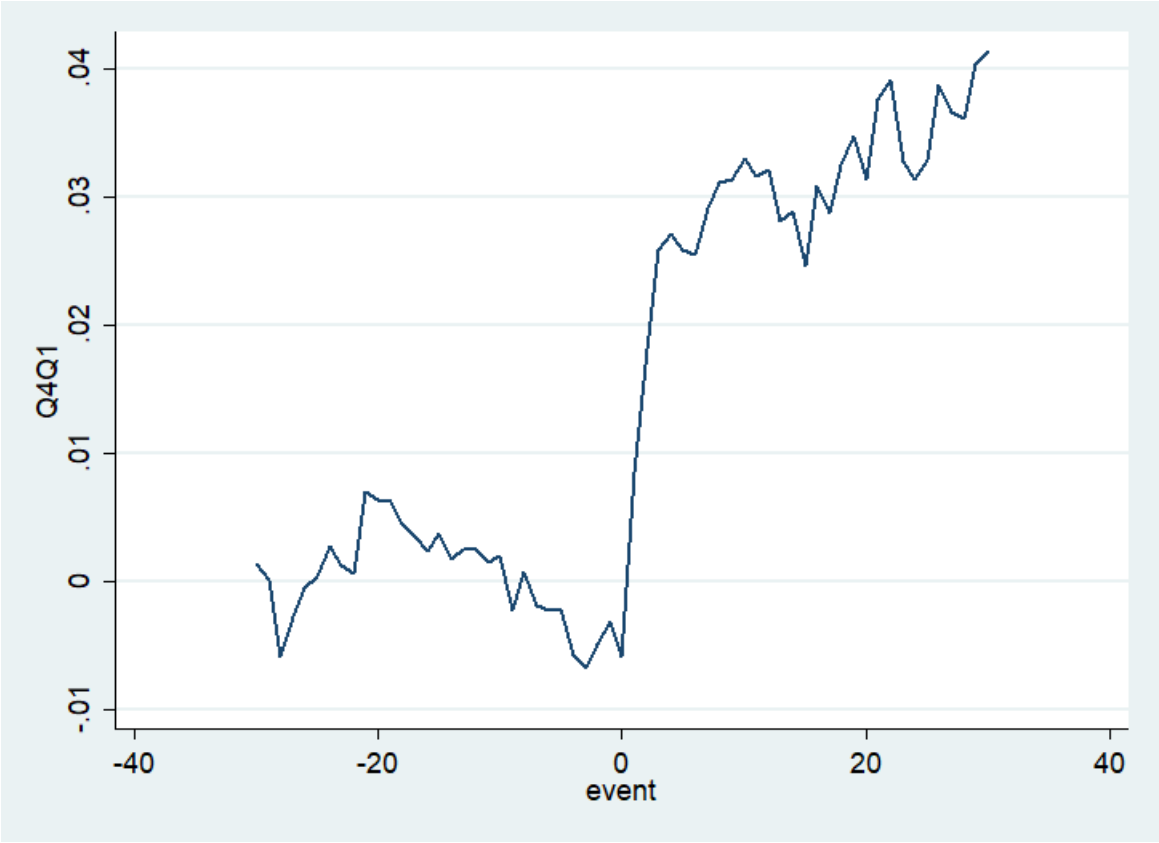

Figure 2 – Frequency distribution of t-statistics (Panel A) and coefficient corresponding to the dummy variable indication *QUARTILE 4* of regulation (Panel B) for randomly generated 250 days between 2013 and November 8, 2016

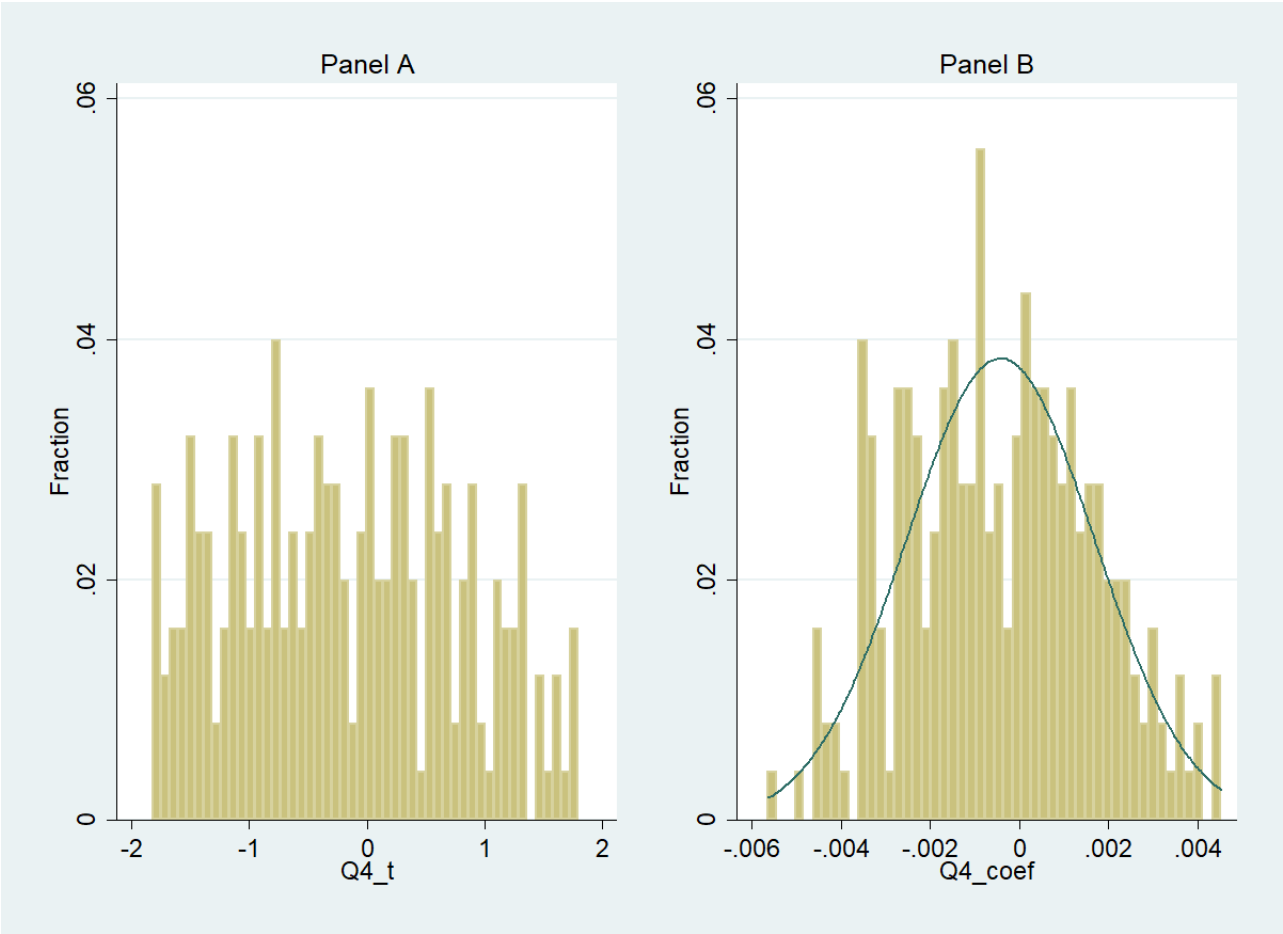

Table 1 – Example of Industries in each Quartile
This Table presents a list of three digit NAICS industries that form the top 10 in each regulated industry quartile. The industry definitions are taken from United States Census Bureau website.

Quartile	NAICS	Name of the Industries
4	325	Chemical Manufacturing
	324	Petroleum and Coal Products Manufacturing
	515	Broadcasting (except Internet)
	522	Credit Intermediation and Related Activities
	611	Educational Services
	562	Waste Management and Remediation Services
	481	Air Transportation
	221	Utilities
	541	Professional, Scientific, and Technical Services
	523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities
3	336	Transportation Equipment Manufacturing
	112	Animal Production and Aquaculture
	624	Social Assistance
	327	Nonmetallic Mineral Product Manufacturing
	524	Insurance Carriers and Related Activities
	621	Ambulatory Health Care Services
	111	Crop Production
	312	Beverage and Tobacco Product Manufacturing
	512	Motion Picture and Sound Recording Industries
	212	Mining (except Oil and Gas)
2	331	Primary Metal Manufacturing
	445	Food and Beverage Stores
	517	Telecommunications
	483	Water Transportation
	486	Pipeline Transportation
	211	Oil and Gas Extraction
	311	Food Manufacturing
	424	Merchant Wholesalers, Nondurable Goods
	454	Nonstore Retailers
	423	Merchant Wholesalers, Durable Goods
1	335	Electrical Equipment, Appliance, and Component Manufacturing
	213	Support Activities for Mining
	425	Wholesale Electronic Markets and Agents and Brokers
	236	Construction of Buildings
	519	Other Information Services
	333	Machinery Manufacturing
	521	Monetary Authorities-Central Bank
	334	Computer and Electronic Product Manufacturing
	115	Support Activities for Agriculture and Forestry
	326	Plastics and Rubber Products Manufacturing

Table 2 – Summary Statistics

This table presents the summary stats of the six variables. *QUTILE* is variable indicating the quartile of regulation, with 1 being the lowest and 4 being the most regulated industry quartile. *N* presents number of firms in each quartile during the event window from the day of the election (November 9, 2016) to next 10 trading days. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015, *ECTR* is the cash tax rate of the firm for the fiscal year ending 2015. *RET* is the average daily gross returns of the firms during the 10-day post event window. The variables *DE*, *ECTR* and *RET* have been winsorized at 1 and 99 percentiles.

QUTILE	ILLIQ	MCAP	ASSET	DE	ECTR	RET	N
1	0.19	14.08	7.24	0.66	0.18	0.78%	541
2	0.04	14.48	7.72	0.86	0.21	0.66%	218
3	0.20	14.77	8.24	0.72	0.23	0.75%	247
4	0.34	14.07	7.82	0.77	0.21	1.01%	895

Table 3 – Baseline Results – Regulation and Stock Returns
This table presents the results of implementing the baseline specification of Equation (4) without including cash tax rates. *QUTILEN* is variable indicating the quartile of regulation, with 1 being the lowest and 4 being the most regulated industries. In the regression *QUTILE1* is the reference category. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015 and winsorized at 1 and 99 percentiles. *N* presents number of firms in the regression. The regressions are with 2-digit NAICS industry fixed effects.

	CAR_01	CAR_05	CAR_10
QUTILE2	0.004	-0.004	-0.004
	(0.78)	(-0.42)	(-0.32)
QUTILE3	0.008*	0.013*	0.004
	(1.82)	(1.78)	(0.45)
QUTILE4	0.015***	0.026***	0.024**
	(3.52)	(3.40)	(2.52)
ILLIQ	-0.017	-0.004	-0.004
	(-0.21)	(-0.95)	(-0.09)
MCAP	-0.001	-0.003	-0.006**
	(-0.98)	(-1.55)	(-2.22)
ASSET	0.000	-0.001	-0.001
	(0.28)	(-0.34)	(-0.39)
DE	-0.000	0.000	-0.000
	(-0.17)	(0.05)	(-0.00)
R^2	0.10	0.09	0.12
N	1,901	1,901	1,901
IndustryFE	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4 – Main Results – Regulation, Taxes and Stock Returns
This table presents the results of implementing the baseline specification of Equation (4) including cash tax rates. *QUTILEN* is variable indicating the quartile of regulation, with 1 being the lowest and 4 being the most regulated industries. In the regression *QUTILE1* is the reference category. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015. *ECTR* in Columns (1) to (3) is the cash tax rate of the firm for the fiscal year ending 2015. *ECTR* in Columns (1) to (3) is the 10-year average cash tax rate of firms as of the fiscal year ending 2015.*DE* and *ECTR* have been winsorized at 1 and 99 percentiles. *N* presents number of firms in the regression. The regressions are with 2-digit NAICS industry fixed effects.

	CAR_01	CAR_05	CAR_10	CAR_01	CAR_05	CAR_10
QUTILE2	0.004	-0.004	-0.003	0.006	-0.000	-0.006
	(0.88)	(-0.35)	(-0.28)	(0.90)	(-0.04)	(-0.43)
QUTILE3	0.007*	0.012	0.003	0.006	0.009	0.006
	(1.71)	(1.64)	(0.35)	(1.23)	(1.04)	(0.64)
QUTILE4	0.014***	0.025***	0.023**	0.018***	0.025***	0.028**
	(3.41)	(3.26)	(2.42)	(3.53)	(2.74)	(2.58)
ILLIQ	-0.012	-0.004	-0.005	0.004	-0.048	0.073***
	(-0.15)	(-0.86)	(-0.10)	(0.05)	(-0.39)	(2.67)
MCAP	-0.001	-0.004*	-0.006**	0.000	-0.001	-0.003
	(-1.09)	(-1.66)	(-2.31)	(0.16)	(-0.48)	(-1.07)
ASSET	0.000	-0.001	-0.001	-0.001	-0.003	-0.005
	(0.38)	(-0.24)	(-0.32)	(-0.48)	(-1.11)	(-1.29)
DE	-0.000	0.000	-0.000	0.000	0.002	0.003*
	(-0.18)	(0.04)	(-0.01)	(0.11)	(1.51)	(1.66)
ECTR	0.014**	0.025**	0.023	0.010	0.018	0.013
	(2.16)	(2.00)	(1.54)	(1.28)	(1.18)	(0.75)
R^2	0.10	0.09	0.12	0.12	0.12	0.15
N	1,901	1,901	1,901	1,223	1,223	1,223
IndustryFE	Y	Y	Y	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5 – Considering Foreign Operations

This table presents the results of implementing the baseline specification of Equation (4) including cash tax rates. Columns (1) to (3) include a dummy variable *Foreign* which takes the value of 1 when the firms has any of foreign assets, foreign sales, foreign income, deferred taxes foreign and income taxes foreign identified from COMPUSTAT. Columns (4) to (6) exclude foreign incorporated firms as identified from CRSP. *QUTILEN* is variable indicating the quartile of regulation based on the random rank assignment, with 1 being the lowest and 4 being the most regulated industries. In the regression *QUTILE1* is the reference category. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015. *ECTR* is the 1-year cash tax rate of the firm for the fiscal year ending 2015. *DE* and *ECTR* have been winsorized at 1 and 99 percentiles. *N* presents number of firms in the regression. The regressions are with 2-digit NAICS industry fixed effects.

	CAR_01	CAR_05	CAR_10	CAR_01	CAR_05	CAR_10
QUTILE2	0.004	-0.006	-0.007	0.006	-0.005	-0.005
	(0.89)	(-0.61)	(-0.56)	(1.14)	(-0.43)	(-0.42)
QUTILE3	0.007*	0.011	0.002	0.006	0.013*	0.011
	(1.72)	(1.48)	(0.23)	(1.42)	(1.80)	(1.31)
QUTILE4	0.013***	0.021**	0.018*	0.013***	0.024***	0.026***
	(3.11)	(2.57)	(1.84)	(2.84)	(2.99)	(2.66)
ILLIQ	-0.009	-0.001	-0.043*	0.007	-0.001	-0.038
	(-0.12)	(-0.66)	(-1.78)	(0.10)	(-0.62)	(-1.55)
MCAP	-0.001	-0.003	-0.006*	-0.002	-0.004	-0.005*
	(-0.64)	(-1.04)	(-1.92)	(-1.58)	(-1.51)	(-1.90)
ASSET	0.000	-0.002	-0.002	0.002	-0.000	-0.002
	(0.04)	(-0.66)	(-0.49)	(1.46)	(-0.03)	(-0.56)
DE	-0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(-0.55)	(0.03)	(-0.14)	(-0.68)	(-0.09)	(-0.27)
ECTR	0.014**	0.025**	0.021	0.014*	0.025*	0.021
	(2.20)	(1.97)	(1.43)	(1.95)	(1.86)	(1.38)
Foreign	-0.004	-0.011*	-0.010			
	(-1.49)	(-1.79)	(-1.42)			
R^2	0.10	0.10	0.12	0.10	0.09	0.12
N	1,875	1,875	1,875	1,697	1,697	1,697
IndustryFE	Y	Y	Y	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6 – Including DTA NOLs and DTLs

This table presents the results of implementing the baseline specification of Equation (4) including cash tax rates, deferred tax assets from net operating losses carry forward (*DTANOL*) and net deferred tax liabilities (*(net)DTL*). *QUTILEN* is variable indicating the quartile of regulation based on the random rank assignment, with 1 being the lowest and 4 being the most regulated industries. In the regression *QUTILE1* is the reference category. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015. *ECTR* is the 1-year cash tax rate of the firm for the fiscal year ending 2015. *DE* and *ECTR* have been winsorized at 1 and 99 percentiles. *N* presents number of firms in the regression. The regressions are with 2-digit NAICS industry fixed effects.

	CAR_01	CAR_05	CAR_10
QUTILE2	0.007	0.007	0.007
	(1.30)	(0.71)	(0.59)
QUTILE3	0.009**	0.015*	0.013
	(2.03)	(1.93)	(1.38)
QUTILE4	0.013***	0.032***	0.032***
	(2.77)	(3.57)	(2.98)
ILLIQ	-0.002	-0.003	-0.003
	(-0.02)	(-0.82)	(-0.06)
MCAP	-0.002	-0.004	-0.005*
	(-1.55)	(-1.52)	(-1.77)
ASSET	0.002	-0.000	-0.002
	(1.08)	(-0.16)	(-0.65)
DE	-0.000	-0.000	-0.001
	(-0.39)	(-0.20)	(-0.42)
ECTR	0.012*	0.017	0.017
	(1.66)	(1.22)	(1.06)
DTANOL	0.002	-0.083**	-0.115***
	(0.14)	(-2.17)	(-2.61)
netDTL	0.015	-0.016	0.004
	(1.23)	(-0.68)	(0.15)
R^2	0.10	0.11	0.14
N	1,558	1,558	1,558
IndustryFE	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7 – Excluding Finance and Utilities

This table presents the results of implementing the baseline specification of Table 4 but excluding finance and utilities firms pertaining to two digit NAICS code 52 and 22 respectively. *QUTILEN* is variable indicating the quartile of regulation based on the random rank assignment, with 1 being the lowest and 4 being the most regulated industries. In the regression *QUTILE1* is the reference category. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015.*ECTR* in Columns (1) to (3) is the 1-year cash tax rate of the firm for the fiscal year ending 2015. *ECTR* in Columns (1) to (3) is the 10-year average cash tax rate of firms as of the fiscal year ending 2015. *DE* and *ECTR* have been winsorized at 1 and 99 percentiles. *N* presents number of firms in the regression. The regressions are with 2-digit NAICS industry fixed effects.

	CAR_01	CAR_05	CAR_10	CAR_01	CAR_05	CAR_10
QUTILE2	0.007	0.003	-0.000	0.009	0.006	-0.003
	(1.48)	(0.27)	(-0.03)	(1.38)	(0.53)	(-0.25)
QUTILE3	0.009*	0.010	0.003	0.010*	0.012	0.013
	(1.89)	(1.27)	(0.34)	(1.78)	(1.29)	(1.24)
QUTILE4	0.016***	0.037***	0.030**	0.016***	0.029**	0.024
	(3.18)	(3.53)	(2.39)	(2.65)	(2.30)	(1.62)
ILLIQ	-0.120	-0.003	0.009	0.042	-0.016	0.099***
	(-0.46)	(-0.88)	(0.18)	(0.17)	(-0.13)	(3.73)
MCAP	-0.000	0.000	-0.002	0.001	0.002	0.001
	(-0.30)	(0.09)	(-0.52)	(0.28)	(0.64)	(0.23)
ASSET	-0.001	-0.005*	-0.005	-0.002	-0.007**	-0.009*
	(-0.90)	(-1.81)	(-1.29)	(-0.88)	(-2.05)	(-1.87)
DE	-0.000	-0.000	0.000	-0.000	0.001	0.002
	(-0.43)	(-0.26)	(0.07)	(-0.78)	(0.83)	(1.01)
ECTR	0.012	0.022	0.016	0.006	0.013	-0.001
	(1.42)	(1.35)	(0.86)	(0.65)	(0.68)	(-0.06)
R^2	0.08	0.08	0.08	0.07	0.08	0.09
N	1,303	1,303	1,303	832	832	832
IndustryFE	Y	Y	Y	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 8 – Growth Opportunities and Regulations

This table presents the results of implementing the baseline specification of Equation (4) including cash tax rates and interaction between Tobin's Q and each regulatory quartile. *QUTILEN* is variable indicating the quartile of regulation based on the random rank assignment, with 1 being the lowest and 4 being the most regulated industries. In the regression *QUTILE1* is the reference category. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015. *ECTR* is the 1-year cash tax rate of the firm for the fiscal year ending 2015. *Q* is the Tobin's Q for firms based on the financial statements of fiscal year ending 2015. *DE*, *ECTR* and *Q* have been winsorized at 1 and 99 percentiles. *N* presents number of firms in the regression. The regressions are with 2-digit NAICS industry fixed effects.

	CAR_01	CAR_05	CAR_10	CAR_01	CAR_05	CAR_10
QUTILE2	0.006	-0.002	-0.002	0.011	-0.001	0.002
	(1.16)	(-0.18)	(-0.16)	(1.43)	(-0.05)	(0.12)
QUTILE3	0.005	0.009	0.002	0.001	-0.009	-0.031*
	(1.26)	(1.22)	(0.24)	(0.18)	(-0.64)	(-1.86)
QUTILE4	0.015***	0.028***	0.028***	0.009	0.006	-0.004
	(3.45)	(3.44)	(2.87)	(1.33)	(0.43)	(-0.24)
ILLIQ	-0.015	-0.004	-0.000	-0.010	-0.003	0.003
	(-0.19)	(-0.90)	(-0.00)	(-0.12)	(-0.66)	(0.07)
MCAP	-0.001	-0.001	-0.004	-0.000	-0.001	-0.003
	(-0.40)	(-0.49)	(-0.97)	(-0.26)	(-0.30)	(-0.69)
ASSET	-0.000	-0.003	-0.004	-0.000	-0.003	-0.005
	(-0.06)	(-0.91)	(-0.97)	(-0.22)	(-1.12)	(-1.24)
DE	0.000	-0.000	0.000	0.000	0.000	0.000
	(0.11)	(-0.00)	(0.04)	(0.32)	(0.16)	(0.23)
ECTR	0.013**	0.021	0.019	0.014**	0.023*	0.020
	(1.97)	(1.61)	(1.27)	(2.08)	(1.74)	(1.35)
Q	0.000	0.000	-0.000	-0.002	-0.008	-0.010*
	(0.03)	(0.02)	(-0.01)	(-0.79)	(-1.47)	(-1.65)
QUTILE2#Q				-0.004	-0.003	-0.005
				(-1.26)	(-0.36)	(-0.53)
QUTILE3#Q				0.001	0.008	0.017**
				(0.51)	(1.12)	(2.14)
QUTILE4#Q				0.004	0.014**	0.016**
				(1.56)	(2.48)	(2.57)
R^2	0.10	0.10	0.12	0.11	0.11	0.13
N	1,785	1,785	1,785	1,785	1,785	1,785
IndustryFE	Y	Y	Y	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 9 – Analyst Forecast Revisions and Regulations

This table presents the results of implementing the baseline specification of Equation (4) including cash tax rates and interaction analyst forecast revisions as of February 2017 (with respect to the most recent forecast before the election) and each regulatory quartile. *QUTILEN* is variable indicating the quartile of regulation based on the random rank assignment, with 1 being the lowest and 4 being the most regulated industries. In the regression *QUTILE1* is the reference category. The control variables are *ILLIQ*, *MCAP*, *ASSET*, *DE* and *ECTR*. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015. *ECTR* is the 1-year cash tax rate of the firm for the fiscal year ending 2015. *STG_DEC* is the decile of short term forecast revisions with 1 being the lowest and 10 being the highest. *LTG_DEC* is the decile of short term forecast revisions with 1 being the lowest and 10 being the highest. *Q* is the Tobin's Q for firms based on the financial statements of fiscal year ending 2015. *DE*, *ECTR* and *Q* have been winsorized at 1 and 99 percentiles. *N* presents number of firms in the regression. The regressions are with 2-digit NAICS industry fixed effects.

	CAR_01	CAR_01	CAR_05	CAR_05	CAR_10	CAR_10
QUTILE2	-0.004	0.002	-0.028	-0.010	-0.033	-0.010
	(-0.47)	(0.21)	(-1.50)	(-0.64)	(-1.38)	(-0.48)
QUTILE3	-0.003	0.010	-0.006	0.020	-0.005	0.016
	(-0.45)	(1.26)	(-0.42)	(1.36)	(-0.31)	(0.91)
QUTILE4	0.002	0.016**	0.000	0.031**	0.002	0.029*
	(0.29)	(2.20)	(0.02)	(2.20)	(0.11)	(1.79)
STG_DEC	-0.002***		-0.004***		-0.003*	
	(-2.80)		(-2.69)		(-1.84)	
QUTILE2#STG_DEC	0.001		0.004		0.004	
	(1.10)		(1.15)		(0.96)	
QUTILE3#STG_DEC	0.002		0.004*		0.004	
	(1.32)		(1.70)		(1.33)	
QUTILE4#STG_DEC	0.002**		0.005***		0.005**	
	(2.53)		(2.78)		(2.37)	
LTG3_DEC		0.000		0.001		0.002
		(0.65)		(0.61)		(0.95)
QUTILE2#LTG_DEC		0.001		0.001		0.000
		(1.18)		(0.34)		(0.13)
QUTILE3#LTG_DEC		-0.000		-0.000		-0.000
		(-0.37)		(-0.20)		(-0.14)
QUTILE4#LTG_DEC		0.000		-0.000		-0.001
		(0.36)		(-0.26)		(-0.37)
R^2	0.13	0.12	0.12	0.11	0.14	0.12
N	1,480	1,222	1,481	1,222	1,481	1,222
IndustryFE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10 – Analyst Forecast Revisions Using Actual Values and Regulations
This table presents the results of implementing the baseline specification of Equation (4) including cash tax rates and interaction between analyst forecast revisions as of February 2017 (with respect to the most recent forecast before the election) and each regulatory quartile. *QUTILEN* is variable indicating the quartile of regulation based on the random rank assignment, with 1 being the lowest and 4 being the most regulated industries. In the regression *QUTILE1* is the reference category. The control variables are *ILLIQ*, *MCAP*, *ASSET*, *DE* and *ECTR*. *ILLIQ* is the average Amihud illiquidity measure during the event window, *MCAP* is the average market capitalization of the stocks during the event window, *ASSET* is the average of the logarithm of book assets of the firm as per the financial statement of fiscal year 2015, *DE* is the average debt-equity ratio of firms calculated using the the financial statement of fiscal year 2015. *ECTR* is the 1-year cash tax rate of the firm for the fiscal year ending 2015. *Q* is the Tobin's Q for firms based on the financial statements of fiscal year ending 2015. *STG* is the short term growth forecast and *LTG* is the implied annualized long term growth forecast. *DE*, *ECTR*, *Q*, *LTG* and *LTG* have been winsorized at 1 and 99 percentiles. *N* presents number of firms in the regression. The regressions are with 2-digit NAICS industry fixed effects.

	CAR_01	CAR_01	CAR_05	CAR_05	CAR_10	CAR_10
QUTILE2	0.002	0.009	-0.012	-0.006	-0.017	-0.008
	(0.44)	(1.49)	(-1.06)	(-0.50)	(-1.19)	(-0.55)
QUTILE3	0.004	0.008*	0.012	0.018**	0.011	0.014
	(0.81)	(1.65)	(1.54)	(2.05)	(1.19)	(1.42)
QUTILE4	0.014***	0.017***	0.025***	0.028***	0.026**	0.025**
	(2.83)	(3.43)	(2.83)	(3.02)	(2.54)	(2.32)
STG	-0.000**		-0.001**		-0.001*	
	(-2.21)		(-2.37)		(-1.87)	
QUTILE2#STG	0.000		0.001		0.001	
	(1.31)		(1.40)		(1.18)	
QUTILE3#STG	0.000		0.000		0.000	
	(1.14)		(1.31)		(1.18)	
QUTILE4#STG	0.000*		0.001**		0.001**	
	(1.84)		(2.32)		(2.24)	
LTG		0.001		0.001		0.001
		(1.27)		(0.52)		(0.73)
QUTILE2#LTG		0.001		0.000		0.000
		(0.92)		(0.16)		(0.02)
QUTILE3#LTG		-0.001		-0.001		-0.000
		(-0.71)		(-0.48)		(-0.23)
QUTILE4#LTG		0.000		-0.000		-0.000
		(0.05)		(-0.12)		(-0.27)
R^2	0.12	0.12	0.12	0.11	0.14	0.12
N	1,480	1,222	1,481	1,222	1,481	1,222
IndustryFE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$