Identifying the Heterogeneous Impact of Highly Anticipated Events: Evidence from the Tax Cuts and Jobs Act *

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Abstract

We develop a method for estimating the stock market impact of aggregate events. Based on using data on both stock and options prices, our technique accounts for two important sources of bias present in traditional methods. First, our method takes into account market anticipation, without the need for information on specific firm characteristics. Many event studies only measure a fraction of an event's full value effect, so the measured market reaction at event resolution can be misleading, particularly in the case of a very high degree of market anticipation. Second, our method is robust to the possibility of the event being good news for some firms and bad for others, with prior specification of this heterogeneity.

We apply the method to the passage of the Tax Cuts and Jobs Act (TCJA), which exhibits both anticipation and heterogeneity. We estimate the market anticipated the probability of passage to be as high as 95% 30 days before the event. The full value impact of the TCJA is found to be 12.36%, compared to 0.68% when market anticipation is ignored. The firm-level impact of the TCJA is considerably heterogeneous, with large and innovative firms with high growth prospects being the largest winners.

Keywords: Event Study, Market Anticipation, Options, Tax Policy, Innovation.
JEL Classification: G13, G14, G18, H25, O34

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1 Introduction

How can we assess the true impact of highly anticipated events using stock market data? How can we reliably determine the relative winners and losers of such events? The market's reaction at event resolution can be misleading, particularly in the case of a very high degree of market anticipation (Huberman and Schwert, 1985; Bhattacharya et al., 2000). A high degree of anticipation by market participants means that prices impound much of the impact of the event before the event's actual occurrence. Thus, any remaining signal regarding the relative value effects for individual firms may be swamped by noise introduced into prices by liquidity trades. The challenge becomes even greater when the event has differential effects on individual firms.

In this paper, we begin with a quantitative investigation of how event anticipation biases traditional event study estimators. We then offer a new estimation framework that can overcome these challenges. It exploits stock and option price data to estimate the full value effect, which takes into account a high degree of market anticipation, as well as heterogeneity of the effects on individual firms. We apply this new methodology to the passage of the Tax Cuts and Jobs Act (TCJA) in December 2017, an event that was both highly anticipated and impactful in terms of firm valuation. We assess its true aggregate impact, as well as how firms with different characteristics were individually affected.

We start by using Monte Carlo simulations of a simple model that illustrates the underlying problems associated with using traditional event study methods when the event is highly anticipated. First, we show that event anticipation induces a sharp drop in the correlation between the true firm-specific impact of an event and its estimate using traditional event study methods. Second, the estimates of the aggregate impact of the event suffer from more downward bias the higher the event anticipation becomes, rendering the true impact unrecoverable unless the econometrician has a priori information on market expectations regarding the probability of the event.

We build our new estimation framework in two steps. We first build a model that defines the price process for an asset exposed to an upcoming binary event, and show how it can be used to estimate the probability of the event as well as firm-specific parameters that inform us regarding the true firm-specific impact of the said event. This model lets us use stock and option price information on any date, which makes it feasible to obtain firm-specific impact estimates on any given date, which exploit considerably more information than that used in traditional event study methods. The estimates obtained using this model have a much higher hope of recovering the true relative impact of highly anticipated events.

In the second step, we offer a more advanced estimation strategy that allows for a careful joint estimation of the probability of a highly anticipated event and its aggregate impact. Our strategy exploits the stock and options information of all firms in a sample, significantly improving the reliability of the estimates compared to firm-specific methods. This new estimator represents a methodological contribution compared to existing firm-specific methods through the imposition of a common event probability assumption across the firms. While our new method results in an estimator that is computationally much more demanding, we use the properties of our model to develop an efficient algorithm, thus improving computational feasibility.

We apply our new method to the passage of the Tax Cuts and Jobs Act (TCJA). We estimate the market anticipated the probability of the TCJA to be as high as 95% 30 trading days before the event occurred. While there are some fluctuations across the time period, the estimated probability always remains in a very tight band [0.93, 0.97]. Thus, much of the impact of the event was already priced in before its occurrence, consistent with the lackluster stock market reaction on the event day. We estimate the aggregate impact of the TCJA on stock prices to be 12.36% in our sample of firms, compared to a negligible 0.68% impact produced by traditional event study methods that ignore market anticipation. The large aggregate impact we find is in line with the considerable upside impact a decrease in the effective corporate tax rate would theoretically yield.

While a large decrease in the effective corporate tax rate was perhaps the most important component of the TCJA, the act was the culmination of a multidimensional tax reform effort that since the 2016 presidential election, had been expected to produce both winners and losers (Wagner et al., 2018). We use the estimated firm-level impact of the reform to investigate what firm characteristics predict higher benefits accruing from the TCJA. In other words, we analyze what kind of firms become the relative winners and relative losers of the passage of the TCJA. Beyond commonly used firm characteristics, we pay particular attention to how the gains are related to the various aspects of a firm's innovativeness, by incorporating rich and up-to-date micro-data on patents from the UVA Darden Global Corporate Patent Dataset (Bena et al., 2017).

We find notable heterogeneity in the firm-level impact of the TCJA, with large and innovative firms with high growth prospects turning out to be the largest winners. However, we find a negligible effect on small firms that produce a low number of high impact patents. In this regard, Ayerst (2020) finds that high innovation firms are clustered into two groups in terms of their innovation output: firms that produce a low number of high quality patents with high knowledge externalities, and firms that produce very large numbers of comparatively mediocre patents with lower spillovers. Our results indicate that the impact of the TCJA on the latter group was larger, this implying encouragement of innovation with fewer spillovers. However, as a group, innovative firms are found to be relative winners compared to less innovative firms with low growth potential. Thus, the TCJA likely resulted in reallocating resources in a way that contributes to long-run productivity growth, albeit with some increased misallocation within innovative firms.

The value of expected event probabilities in correctly assessing market reactions has been long recognized in works that improve event studies by including firm characteristics such as Malatesta and Thompson (1985), Brennan (1990), Eckbo et al. (1990), Acharya (1993), Chaplinsky and Hansen (1993), Prabhala (1997), Song and Walkling (2000), Bhagat et al. (2005), and Cai et al. (2011). The limitation to these characteristic-based studies is that data on characteristics related to firm-specific events may be limited. More importantly, these characteristics must be identified ex-ante for each type of event, as certain firm characteristics may matter more for certain firm-specific events. Furthermore, firm characteristic data are not suitable for macroeconomic events such as policy changes that are likely to be exogenous to the characteristics of any individual firm.

Our work contributes to this literature in two dimensions. First, we use options price data to estimate anticipatory effects, thus obviating the need for firm characteristic data. Second, we extend the estimation of anticipation effects to aggregate events. While related work by Snowberg et al. (2007), Wolfers and Zitzewitz (2009), and Snowberg et al. (2011) has also looked at anticipation effects in aggregate events, their work is limited because they borrow event probabilities from predictive markets, which offer directly observable event probabilities. Thus their method, while innovative, is only is only applicable to certain events.

Our work also builds upon a small literature on investor expectations recovery that does not rely on firm characteristics or predictive markets instead leverages stock and options data to address both firm-specific events such as mergers (Subramanian, 2004; Barraclough et al., 2013; Borochin, 2014), as well as exogenous economy-wide events like the Obamacare healthcare regulation (Borochin and Golec, 2016). These methods rely on data from public markets, which are deeper and more liquid, and therefore do not require other less widely available firm characteristic data and are likely to be more informative than predictive markets.

We build upon this work in one important dimension by developing a method that can recover heterogeneous effects of aggregate events. In particular, in contrast to this previous work, we do not need to specify a known ordering of state-contingent payoffs. For example, in the case of merger negotiations, the target firm always gains more in the state in which the deal succeeds. In contrast, considerable heterogeneity in the effect of the TCJA on individual firms is likely, given the law's changes to the tax implications of investment in intellectual property, overseas operations, and deferred tax assets and liabilities. It is impossible to estimate this heterogeneity using prior work (e.g. Borochin, 2014) because application of this sort of methodology violates the identification constraints set forth in Stephens (2000) or Jasra et al. (2005). Estimation thus requires the more general approach that we develop in this study.

Our study follows a prior investigation of the potential future implications of a TCJA-like policy by Wagner et al. (2018), which relies on the unanticipated outcome of the 2016 presidential election to circumvent the challenge of anticipation in event studies. We believe the market's expectations about the effects of the TCJA are worth revisiting in data that fully incorporates the details of the proposed tax reform, as reliance on an election outcome for identification limits the external validity of any results to the details of the winning party's platform.

The paper is organized as follows. In Section 2, we present a simple model to illustrate the shortcomings of traditional event study methods in estimating anticipation effects and in ranking firms according to their benefits and costs they accrue from an event. In Section 3, we propose an alternative method to estimate the full value effect of an event using information of stock and options prices that is robust to high degrees of anticipation as well as heterogeneous effects on individual firms in the sample. In Section 4, we estimate the probability of the passage of the TCJA and its actual impact on firm value. In Section 5, we further study the effects of the TCJA passage on the state-contingent payoffs of our sample firms. Section 6 concludes.

2 Challenges in Estimating the Impact of Highly Anticipated Events

Since its introduction in Fama et al. (1969), event study methodology has been widely used in finance and economics to elicit the impact of certain events on the valuation of publicly traded companies. The magnitude of abnormal stock price performance at the time of the event can be used to back out the unanticipated impact of said event. However, as the degree of anticipation increases, the traditional event study methodology becomes increasingly unreliable in the inference of the complete ("true") effect of an event, both in the aggregate (e.g. the effect of a policy change on all publicly traded firms), as well as in the cross-section (e.g. the relative impact of a policy change on different firms). In this section, we lay out a simple model, the simulation of which illustrates the underlying problems associated with using traditional event study methods when the event is highly anticipated and realizes.[1] These problems motivate the use of the alternative methodologies we propose in Sections 3 and 4, which overcome the limitations of the event study methodology through the explicit estimation of the probability of the event, and simultaneously allow us to rely on richer data to estimate the firm-specific and aggregate effects of the event.

2.1 Environment

Consider an economy populated by by N publicly traded firms, indexed by $i \in \{1, ..., N\}$. The stock price of firm i at time t is denoted by $P_{i,t}$. An event will either realize or fail to realize at time $T+1$. The successful realization of the event is a Bernoulli random variable, denoted by $\mathbb{I}$. If the event realizes, $\mathbb{I}$ takes the value one, and is zero otherwise. The probability of event realization is given by $q \in [0, 1]$. This probability q is common knowledge among the market participants, but unknown to the econometrician.

If the event does not realize ($\mathbb{I} = 0$), the fair value of the stock of firm i at time $T+1$ is given by $x_i \epsilon_i$, where ϵ_i is an i.i.d. random variable with mean $\mu_\epsilon = 1$. x_i is a firm-specific scalar, and is common knowledge at time T. ϵ_i is a noise term that represents the fluctuation in the firm's value independent of the event. Therefore, $\mathbb{E}_T[x_i \epsilon_i | x_i] = x_i \mathbb{E}[\epsilon_i] = x_i$, so

[1] Naturally, the same issues arise when a "lowly anticipated" event fails to realize; e.g. when a vote that is highly anticipated to fail ends up failing. While we focus on the realization of highly anticipated events in the remainder of the paper, it should be noted that our results equally apply to such cases as well. In other words, the same problems are encountered whenever the event's outcome is "unsurprising" in the sense that the highly expected outcome materializes.

x_i represents the expected value of the stock of the firm at time T conditional on the non-realization of the event.

If the event realizes, it has a heterogeneous impact on firms $i \in \{1, ..., N\}$. The effect of the event on firm i is a random variable denoted by s_i, which is drawn from the distribution S with mean $\mu_s > 0$. The firm-specific effect s_i is known to the market participants even before the realization of the event, but is unknown to the econometrician. Contingent on this definition, the fair value of the stock of firm i at time $T+1$ conditional on the realization of the event ($\mathbb{I} = 1$) is given by $s_i x_i \epsilon_i$. The expected value of the stock of the firm at time T conditional on the realization of the event is given as $\mathbb{E}_T[s_i x_i \epsilon_i | s_i, x_i] = s_i x_i \mathbb{E}[\epsilon_i] = s_i x_i$. Therefore, s_i corresponds to the ratio of the expected value of the stock of the firm at time T conditional on realization divided by that conditional on non-realization.

2.2 Prices and the Traditional Event Study Estimators

Given the described environment, we can derive the implied stock prices. The stock price of firm i at time $T+1$ contingent on the realization of the event is written as:

$$P_{i,T+1} = \begin{cases} s_i x_i \epsilon_i & \text{if } \mathbb{I} = 1 \\ x_i \epsilon_i, & \text{if } \mathbb{I} = 0 \end{cases} \tag{1}$$

At time T, s_i and x_i are known to the market participants, but the noise term ϵ_i and the realization of the event $\mathbb{I}$ are not. Therefore, the stock price of firm i at time T is calculated as:

$$\begin{aligned} P_{i,T} &= \mathbb{E}_T[\mathbb{I}(s_i x_i \epsilon_i) + (1 - \mathbb{I})(x_i \epsilon_i) | s_i, x_i] \\ &= q s_i x_i \mathbb{E}[\epsilon_i] + (1 - q) x_i \mathbb{E}[\epsilon_i] \\ &= (q s_i + (1 - q)) x_i \end{aligned} \tag{2}$$

Consider the case in which the event realizes. Suppose the econometrician is interested in the aggregate effect of the event, which requires the estimation of μ_s, and the relative impact of the event on different firms, which requires the estimation of s_i for each firm i. The traditional event study estimator for the net firm-specific impact of the event, $s_i - 1$, would then be the change in the stock price of the firm between $T+1$ and T. Given $\mathbb{I} = 1$, this is calculated as:

$$\begin{aligned} \frac{P_{i,T+1} - P_{i,T}}{P_{i,T}} &= \frac{s_i x_i \epsilon_i - (q s_i + (1-q)) x_i}{(q s_i + (1-q)) x_i} \\ &= \frac{s_i \epsilon_i - (q s_i + (1-q))}{(q s_i + (1-q))} \end{aligned} \tag{3}$$

If the event was completely unanticipated, the traditional event study estimator would be a very reasonable one, since plugging in $q = 0$ yields:

$$\frac{P_{i,T+1} - P_{i,T}}{P_{i,T}} = s_i \epsilon_i - 1 \tag{4}$$

However, when the event is not completely unanticipated ($q > 0$), the traditional estimator captures only the unanticipated impact instead of the true impact $s_i - 1$. Still, if one is interested solely in the relative impact on the firms (e.g. figuring out the winners and the losers), the fact that it is positively correlated with the true impact $s_i - 1$ means that it may serve as a reasonable proxy. We quantitatively investigate its performance in the next subsection.

To estimate the net aggregate impact of the event $\mu_s - 1$, the traditional event study methodology would suggest taking the average of the individual estimates of $s_i - 1$, that is:

$$\frac{1}{N} \sum_{i=1}^{N} \frac{P_{i,T+1} - P_{i,T}}{P_{i,T}} = \frac{1}{N} \sum_{i=1}^{N} \frac{s_i \epsilon_i - (q s_i + (1-q))}{(q s_i + (1-q))} \tag{5}$$

Again, if the event was completely unanticipated ($q = 0$), this would be a reasonable estimator, since:

$$\mathbb{E}\left[\frac{1}{N}\sum_{i=1}^{N}\frac{P_{i,T+1}-P_{i,T}}{P_{i,T}}\right] \;=\; \frac{1}{N}\sum_{i=1}^{N}\left(\mathbb{E}[s_i]-1\right)=\mu_s-1 \tag{6}$$

However, for positive values of q, this estimator would only capture the unanticipated fraction of the aggregate impact of the event. Given that q is unknown to the econometrician, this would make it impossible to conclude whether a low estimate is obtained because of a low true impact (low μ_s) or high anticipation (high q).

2.3 Performance of the Traditional Event Study Estimators as a Function of Anticipation

As shown in the previous section, the performance of the traditional event study estimators hinge on the parameter values, and in particular, the anticipation of the event's realization, q. To quantitatively study their reliability, we conduct Monte Carlo simulations. To do so, we need some distributional assumptions. Assume that the idiosyncratic i.i.d. noise ϵ_i is drawn from the distribution $Lognormal(-\frac{\sigma_\epsilon}{2}, \sigma_\epsilon)$. Further assume that the distribution S from which the firm-specific s_i are drawn is normally distributed as $\mathbb{N}(\mu_s, \sigma_s)$. We do not need to make any assumptions regarding the distribution of x_i. For our baseline illustration, we pick the parameter values as $\mu_s = 1.1236, \sigma_s = 0.0952, \sigma_\epsilon = 0.0400$, and $N = 100$.[2] We conduct $T = 10,000$ simulations for each parameter set corresponding to a different value of the event anticipation q, and use bootstrapping to obtain 10% upper and lower bounds.

First, we assess the reliability of the traditional event study estimator in eliciting the relative impact of the event on different firms. Even if the estimator does not capture the true firm level impact $s_i - 1$, we would like it to at least be a reasonable proxy that captures

[2] These are not arbitrary values. μ_s and σ_s are obtained from the distribution of s_i we estimate in Section 4 where we study the impact of Tax Cuts and Jobs Act of 2017. σ_ϵ is obtained from the daily stock price volatility in our sample of firms. We set $N = 100$ since our sample consists of 100 firms.

the relative ranking of the firms to a sufficient degree. To evaluate the performance among this dimension, we compute the correlation between $(P_{i,T+1} - P_{i,T})/P_{i,T}$ and $s_i - 1$. Figure 1 presents the mean correlation we obtain across T = 10,000 simulations as a function of the event anticipation q, which ranges from 1% to 99%. When the anticipation is very low at $q = 1\%$, the correlation is quite strong at 89%, in which case the traditional event study estimator performs reasonably well. However, as the anticipation of the realized event increases, the reliability declines in a steep fashion. At $q = 80\%$, the correlation is already down to 44%. At $q = 96\%$ (which corresponds to the estimated probability of the Tax Cuts and Jobs Act of 2017 one day before its passage), the correlation is only 20%, and the 10% lower bound is 8.7%. As this example illustrates, for highly anticipated events, the traditional event study estimator cannot be relied upon even to assess the relative impact of the event across firms, let alone estimating the true impact at the firm level.

Next, we assess the reliability of the traditional event study estimator in calculating the aggregate impact of the event. Figure 2 displays the true aggregate impact of the event, along with the mean aggregate impact the traditional estimator delivers across T = 10,000 simulations as a function of the event anticipation q. This time, the performance is even worse. The estimated impact is biased downwards. The bias is increasing in q, since the increase in anticipation is mistakenly attributed to a lower true impact $\mu_s - 1$. At $q = 96\%$, the mean aggregate impact is a measly 0.29%, although the true impact is 12.4%, which is 42 times larger. This makes it clear that the traditional event study methodology cannot deliver any meaningful estimate of the aggregate impact of highly anticipated events.

2.4 Robustness of the Performance Results

To demonstrate that our results do not hinge on specific parameter values, and to offer further insight on how the performance of the traditional event study estimators is related to the parameters, we conduct some robustness checks. Figure 3 illustrates the results.

We first investigate the effects of changing the net aggregate impact of the event $\mu_s - 1$ to 50% and 150% of its value. The top-left subfigure repeats the exercise in Figure 1. It is seen that the mean correlation is slightly higher when the net aggregate impact $\mu_s - 1$ is lower, but not by a significant amount. The top-right subfigure repeats the exercise in Figure 2. Naturally, changing the net aggregate impact $\mu_s - 1$ scales its estimate up and down by the same amount. However, the relative downward bias compared to its true value as a function of the event anticipation q remains the same. Therefore, the magnitude of the true aggregate impact of the event is irrelevant for the downward bias ignoring event anticipation causes.

We next investigate the effects of changing the standard deviation parameters σ_s and σ_ϵ to 50% and 150% of their values. A higher value of σ_s implies more heterogeneity in the firm-specific impact s_i across firms. A higher value of σ_ϵ implies more volatile stock price fluctuations in firm value (independent of the event). The bottom-left and bottom-right subfigures repeat the exercise in Figure 1 for different values of σ_s and σ_ϵ, respectively. It is seen that the mean correlation is higher when σ_s is higher and σ_ϵ is lower. The intuition for these results is straightforward: When the firm-specific effect is more varied, it is easier to distinguish the winners from losers despite the presence of random noise ϵ_t. Likewise, when the random noise is more limited, even small differences in s_i can more reliably be estimated, as less noise means the relative ordering of firms according to the traditional event study estimator is less contaminated. These results show that the traditional event study estimator performs better when the heterogeneous impact across firms has a higher variance compared to the variance owing to the daily stock price fluctuations. On the other hand, note that the mean correlation is still quite low at high values of event anticipation ($q > 0.90$). This means the traditional event study estimator is still a poor proxy for estimating the relative firm-specific impact of highly anticipated events, such as the Tax Cuts and Jobs Act of 2017.

3 Estimating the Option-Implied Firm-Level Impact of the TCJA

The model in Section 2 predicts that market reaction can be insufficient to accurately rank firms relative to each other according to their benefits and costs due to a high-probability event, even after the event has occurred. We propose an alternative empirical measure of the value effect of an event that compares the firm's expected value to an expected counterfactual. Prior work on less-certain events has demonstrated that options data can be used to identify counterfactual firm values in the M&A setting (Barraclough et al., 2013; Borochin, 2014) as well as in proposed regulation for an industry sector (Borochin and Golec, 2016). The ability to jointly infer the two state-contingent values of the firm in both possible outcomes, even when the event is almost fully anticipated.

We build on the model of Subramanian (2004), defining the price process for an asset exposed to an upcoming binary event as one that converges to one of two possible geometric brownian motions at the event date with risk-neutral probability q and instantaneous risk-free rate r:

$$\frac{1}{r}dS = \begin{cases} S_u + \sigma_u S_u dz & \text{if event occurs with probability } q \\ S_d + \sigma_d S_d dz & \text{otherwise} \end{cases} \tag{7}$$

Here we assume $S_u \neq S_d$ and $\sigma_u \neq \sigma_d$ without loss of generality, with instantaneous expected returns in both states equal to r under the risk-neutral measure. Under the assumption that σ_u and σ_d are investor expectations of the true state-contingent volatility of the underlying asset that do not vary across option moneyness, we can express the values of the stock and options on it as functions of five unknown parameters: the risk-neutral probabilty of the event q, and the state-contingent values S_u and S_d and volatilities σ_u and σ_d of the stock. For a firm i given the current prices of the stock $S_{i,t}$ and N options with unique strike prices K_j and a common remaining time to maturity τ that ends after the event, on any day prior to the resolution of the binary event we can characterize the prices of the $N+1$ assets as follows:

$$\begin{aligned}
S_{i,t} =& E_t(q) \cdot E_t(S_{i,u}) + (1 - E_t(q)) \cdot E_t(S_{i,d}) \\
c_{i,1,t} =& E_t(q) \cdot C(E_t(S_{i,u}), E_t(\sigma_{i,u}), K_1, \tau) + (1 - E_t(q)) \cdot C(E_t(S_{i,d}), E_t(\sigma_{i,d}), K_1, \tau) \\
& \cdots \\
c_{i,N,t} =& E_t(q) \cdot C(E_t(S_{i,u}), E_t(\sigma_{i,u}), K_N, \tau) + (1 - E_t(q)) \cdot C(E_t(S_{i,d}), E_t(\sigma_{i,d}), K_N, \tau)
\end{aligned} \tag{8}$$

The pricing equations for the $N+1$ assets that derive their value from the time-t expectations of q, S_u, S_d, σ_u and σ_d provide identifying restrictions on these variables. This allows us to identify their values for any set of securities where $N+1 > 5$, and where the optimal choice of N trades off additional signal from overidentification for additional noise from the use of less-liquid and therefore less-accurate option prices. We focus the analysis on call options, consistent with related work by Barraclough et al. (2013), Borochin (2014), and Borochin and Golec (2016). Although put options could also be used, their prices are more likely to be distorted due to short-sale constraints around special events such as the TCJA passage for particularly sensitive firms. Furthermore, the equity put option market is generally less liquid than that for calls: during the fourth quarter of 2017, as the TCJA was being debated, an average of 8,154,592 equity call option contracts were traded each day in the OptionMetrics universe, whereas only 6,577,204 put contracts were traded. The total daily trading volume in put options is thus 20% lower than than for call options, which is particularly notable since the average daily total equity open interest was comparable between the two option types at 139,904,761 call contracts and 146,416,666 put contracts. Figure 4 presents the time series of option trading volume for the firms in our sample, with increases in option volume when the TCJA bill is introduced in the House of Representatives on November 9 and around the time of the Senate vote on the pre-conference version of the bill on December 2. We can observe that these volume increases were driven primarily by call option trading, consistent with their primacy in capturing investor beliefs about the

TCJA passage event relative to put options.

3.1 Data and Sample Characteristics

We require that the firms in our analysis have stock price data from CRSP, fundamentals data from Compustat, and at least six option contracts with non-zero open interest and highest volume during the 30 trading days between November 10, 2017, the first trading day after the TCJA bill was introduced in the Senate, and December 22, 2017, when the final reconciled bill was signed into law. We focus our analysis on the 100 firms with the most liquid options, as a tradeoff between representativeness of the sample relative to the universe, and the informativeness of option data from the included firms due to diminishing liquidity. Table 1 lists these firms, their average daily call option volume during the fourth quarter of 2017, their market capitalization at the beginning of the quarter, and their SIC2 industry sectors.

Setting an appropriate cutoff for the number of firms used in the study is an important consideration, as the decrease in option market depth across firms is stark: The firm with the most liquid option market in our sample, Apple Inc, has an average daily call option volume of 261,788 contracts in our sample period. Compared with this, the sample firm with the least liquid option data, Caesars Entertainment Corporation, has an average daily call volume of only 6,758 contracts. This decline in daily volume of 97.4% illustrates the cost of including additional firms: an increasing use of zero-volume (though positive open interest) contracts, which implies an increasing reliance on uninformative and stale option prices. Although our sample is only a subset of the universe of optionable stocks containing only the most liquid, it can be considered representative: over the fourth quarter of 2017 our sample firms account for between 27% and 42% of the total daily equity option volume in the OptionMetrics universe, and between 29% and 50% of its total daily call volume.

Sorting on option liquidity captures some of the largest public firms from the universe of available data spanning 31 distinct SIC2 industry sectors. The 100 firms in our sample have an average market capitalization of 95.84 billion USD, and an average book asset value of 166.44 billion USD. During the same time period, the average firm in the Compustat universe has a market capitalization of 5.72 and a book asset value of 14.67 billion USD, whereas the subset of S&P 500 firms has an average market capitalization of 45.90 billion and a book asset value of 69.06 billion USD. While the size bias in our sample introduced by maximizing option liquidity limits the generalizability of the magnitudes of our findings to smaller firms, it simultaneously makes it more representative of the whole domestic market which was affected by the TCJA: the market capitalization of the 100 firms in our sample is 22.45% of the Compustat universe. In other settings with high degrees of market anticipation of more narrowly defined events our method can be applied more selectively.

In addition to estimating the option-implied payoffs of TCJA passage $S_{i,u}$ and $S_{i,d}$, we consider their relationship with firm characteristics described in B. We focus on variables related to innovation, specifically R&D intensity, the number of patents granted and citations received, the originality and generality of patents similar to Hall et al. (2001), the tangibility of the firm's assets, and sales, asset, and employment growth as outcomes of successful innovation. Furthermore, we consider more general characteristics of firm performance that may drive the market's assessment of its sensitivity to the changes in the tax rules under the TCJA: the firm's effective tax rate, the amount of indefinitely reinvested foreign earnings and net tax assets existing prior to TCJA passage, the amount of cash held by the firm, its market-to-book ratio and size, the firm's leverage, financial constraint, and maturity of its assets, the fraction of assets in PP&E and advertising expenditures, and the firm's performance measures in terms of profitability, ROA, and ROE.

We construct updated measures of firm innovation by extending the methods found in Hall et al. (2001) and Acemoglu et al. (2020) to deal with the complications introduced by the new patent classification system adopted by the United States Patent and Trademark

Office (USPTO).[3]

3.2 Identification

We estimate investor expectations about the firms in our sample during the period of November 10, 2017 through December 22, 2017 in two mutually exclusive, collectively exhaustive states: one in which the Tax Cuts and Jobs Act is passed in both the House and Senate and signed into law, and one in which it is not. Without loss of generality, we assign the variables $S_{i,u}$ and $\sigma_{i,u}$ to represent the value and volatility of firm i if TCJA is passed, and $S_{i,d}$ and $\sigma_{i,d}$ if it is not.

Prior studies of option-implied beliefs around mergers and acquisitions (Barraclough et al., 2013; Borochin, 2014) and the Obamacare regulation (Borochin and Golec, 2016) allowed an intuitive identification restriction of $S_{i,u} > S_{i,d}$ since one state would undoubtedly lead to a higher value for the firm than another. The state in which an acquisition attempt succeeds leads to a gain for the target, consistent with an acquisition premium. Similarly, the passage of the Obamacare was expected to benefit hospital administrators and insurers by increasing coverage rates. The ability to impose this restriction on the firm's state-contingent values is important due its ability to resolve the problem of label switching in mixture models (Stephens, 2000; Jasra et al., 2005) analogous to the probability-weighted payoffs described in Eq. (8). The label switching phenomenon occurs because the states that the $S_{i,u}$ and $S_{i,d}$ variables represent can be exchanged arbitrarily, preventing the identification of either variable. Unlike these prior studies, this identifying restriction cannot be applied to an event like the TCJA passage, which cannot be expected to be uniformly beneficial: while the reduction in the corporate tax rate provides a benefit in terms of reducing present

[3] On January 1, 2013, the USPTO moved from using the United States Patent Classification (USPC) system to the Cooperative Patent Classification (CPC) system, a jointly developed system with the European Patent Office (EPO). Unlike the older USPC system, under CPC, patents are not assigned a unique primary technology class, but a large distribution of multiple classes. This change requires the development of new methods to account for technology class citation bias and to generate measures like originality and generality that capture the dispersion of inbound and outgoing citations in the technology space.

and future tax liabilities, it also imposes a cost on firms by reducing tax assets (Wagner et al. (2018)). Similarly, the benefits from the low rate for repatriation of foreign cash holdings must be weighed against increases in taxes on future foreign earnings due to the BEAT provision.

In this study we develop a more general approach to identify the state-contingent payoffs $S_{i,u}$ and $S_{i,d}$ for a set of firms with heterogeneous expected outcomes from an event, including both winners (such that $S_{i,u} \geq S_{i,d}$) and losers (such that $S_{i,u} < S_{i,d}$) simultaneously. We do this by exploring the risk-neutral probability space $q \in [0, 1]$ in increments of 1%, and for each candidate value of q minimizing the difference between observed security prices and their implied values as functions of q and the other model variables $\theta = \{S_{i,u}, S_{i,d}, \sigma_{i,u}, \sigma_{i,d}\}$ as described in Eq. (8). We do this for two independent scenarios for each firm i at each date t, a "winner" scenario where $S_{i,u} \geq S_{i,d}$ and a "loser" scenario where $S_{i,u} < S_{i,d}$, computing the absolute distance $V_{i,t}$ between the vector of observed stock and option prices as functions of model parameters under each scenario:

$$\begin{aligned} V_{i,t,winner}(q, \theta) &= \min_{\theta} |P_{i,t} - \hat{P}_{i,t}(q, \theta)| \;\; s.t.\; S_{i,u} \geq S_{i,d} \\ V_{i,t,loser}(q, \theta) &= \min_{\theta} |P_{i,t} - \hat{P}_{i,t}(q, \theta)| \;\; s.t.\; S_{i,u} < S_{i,d} \end{aligned} \tag{9}$$

For each firm i and date t, we observe whether the "winner" or "loser" scenario minimizes the distance between observed and model-implied stock and option prices across all possible values of q in the probability space. We classify the firm as a "winner" if the $S_{i,u} \geq S_{i,d}$ restriction results in a better fit more than half of the time over the 30-day period from November 10 to December 2, 2017, during which the TCJA was discussed in Congress, and as a "loser" otherwise. In other words, we let the data tell us which identifying restriction is more appropriate for each firm, allowing us to identify $S_{i,u}$ and $S_{i,d}$ regardless of whether the firm is expected to gain or lose from TCJA passage. Once this has been established, we repeat the optimization with the appropriate restriction in place:

$$V_{i,t}(q,\theta) = \begin{cases} \min\limits_{\theta} |P_{i,t} - \hat{P}_{i,t}(q,\theta)| \;\; s.t. \; S_{i,u} \geq S_{i,d} & \text{if firm } i \text{ is a ``winner''} \\ \min\limits_{\theta} |P_{i,t} - \hat{P}_{i,t}(q,\theta)| \;\; s.t. \; S_{i,u} < S_{i,d} & \text{otherwise} \end{cases} \tag{10}$$

Since q corresponds to the probability of $S_{i,u}$ occurring, we can be sure we have properly identified the state-contingent payoff by considering the value of q that corresponds to the minimum absolute price distance $V_{i,t}(q,\theta)$. Since the expected probability of TCJA was particularly high, if the lowest absolute distance in $V_{i,t}$ corresponds to a high q, that means that $S_{i,u}$ correctly represents the state in which TCJA is passed. On the other hand, if the lowest absolute distance corresponds to a low q, we would take that to mean that the labels were indeed switched, and that the low-probability state $S_{i,u}$ instead represents the payoff when TCJA is rejected. If our model is correctly specified, we should not expect to see an optimal q in the middle of the $[0,1]$ range since that would not be consistent with market expectations.

It should be noted that since a risk-neutral probability can be expressed as the product of a physical probability and the pricing kernel or stochastic discount factor, we can claim that our variable q can be interpreted as a true, rather than a risk-neutral, probability. This is because the analysis focuses on a relatively narrow 30-day window and is unlikely to represent a priced risk. If our approach were to be extended to long-run events that are more likely to be related to an equity risk premium reflected in the pricing kernel, the risk-neutral probability q would understate the physical probability p.

4 Estimating the Probability of TCJA Passage and Its Aggregate Impact

In Section 2, we demonstrate that using the standard event study methodology to estimate the aggregate impact of highly anticipated events delivers results that suffer from excessive amounts of downward bias. In this section, we offer a new methodology that builds upon the firm-level model presented in Section 3 to estimate the probability and aggregate impact of highly anticipated events. We then apply this methodology to the specific case of the passage of TCJA, and discuss the results.

4.1 Methodology

As demonstrated in Figure 2, the probability of the anticipated event q plays an extremely important role in the determination of the aggregate impact. Slight differences in the estimated q can yield substantial differences in the estimated aggregate impact when q is high. For instance, the same measured market reaction would imply roughly double the estimated impact with $q = 0.95$ compared to $q = 0.90$. It is, therefore, crucial to obtain a reliable estimate of the event realization probability q.

In the firm-level model presented in Section 3, we allow the event realization probability q to differ across firms and time, consistent with earlier studies. Allowing for heterogeneity in q across firms helps accommodate potential differences in subjective beliefs of the investors regarding the event. While this is a desirable property when the object of focus is the relative impact of the event on firms, a stronger assumption regarding investor beliefs would help deliver a much more reliable estimate of q, and therefore, the aggregate impact. In this section, we develop a new estimator in which we assume that there is a single event probability q shared across all investors of all firms. This assumption allows us to use the data from all firms in the estimation of q, instead of relying on the data from a single firm.

Define the absolute normalized distance of firm i at time t given event probability q and firm-specific parameters $\theta_i = \{S_{i,u}, S_{i,d}, \sigma_{i,u}, \sigma_{i,d}\}$ as follows:

$$W_{i,t}(q, \theta_i) = \begin{cases} |1 - \hat{P}_{i,t}(q, \theta_i)/P_{i,t}| \;\; s.t. \; S_{i,u} \geq S_{i,d} & \text{if firm } i \text{ is a “winner”} \\ |1 - \hat{P}_{i,t}(q, \theta_i)/P_{i,t}| \;\; s.t. \; S_{i,u} < S_{i,d} & \text{otherwise} \end{cases} \tag{11}$$

Then the estimator is given by

$$\left(q_t, \{\theta_{i,t}\}_{i=1}^M\right) = \underset{q,\{\theta_i\}_{i=1}^M}{\arg\min} \left\{ \sum_{i=1}^{M} W_{i,t}(q, \theta_i) \right\} \tag{12}$$

As is clear from the equation, a single common event probability q_t is estimated for each time period t, and the firm-specific parameters $\{\theta_{i,t}\}_{i=1}^M$ are consequently also jointly estimated. The advantage is easy to notice: instead of using N call options (6 in our application), the new estimator uses $M \times N$ call options (600 in our application) to estimate the event probability q_t in each time period. The cost is a much more demanding estimation in terms of computation power, where $4M + 1$ parameters must be jointly estimated.

The property that makes the exercise computationally feasible is the fact that the estimation of the firm-specific parameters $\{\theta_{i,t}\}_{i=1}^M$ depends on the results from other firms only through the common event probability q. Using this property, we develop an efficient algorithm in which we first divide the range $q \in [0, 1]$ into a discrete grid Q. Then, for each firm i, on each date t, and for every $q \in Q$, we estimate $\theta_{q,i,t}$ which minimizes $W_{i,t}(q, \theta_i)$ given q. Then q_t can be calculated as:

$$q_t = \underset{q}{\arg\min} \left\{ \sum_{i=1}^{M} W_{i,t}(q, \theta_{q,i,t}) \right\} \tag{13}$$

The resulting estimation algorithm is still much more demanding than existing methodologies with firm-specific q, multiplying the computational resources required by the cardinality of Q. However, each individual minimization problem is relatively simple (solving for 4 unknowns given N call option targets), which makes the estimation of firm-specific parameters as robust as existing methods.

4.2 Results

We employ the described algorithm to study the option-price implied probability the market attached to the passage of TCJA before its realization, and its aggregate impact on firm value. The number of firms is $M = 100$, and the number of call option targets is $N = 6$. We discretize the range $q \in [0, 1]$ into the uniform discrete grid $Q \in \{0.01, 0.02, ..., 1\}$ with 100 grid points. As discussed earlier, the passage of TCJA cannot be expected to be uniformly beneficial for all firms, so we need to determine whether each firm is a winner ($S_{i,u} \geq S_{i,d}$) or a loser ($S_{i,u} < S_{i,d}$). For each firm i, on each date t, and for every $q \in Q$, we estimate $\theta^w_{q,i,t}$ and $\theta^l_{q,i,t}$ which minimizes $W_{i,t}(q, \theta_i)$ given q and one of the identifying assumptions, where the superscript w corresponds to the "winner" assumption, and l corresponds to the "loser" assumption. After determining for each firm whether they are winners or losers, we estimate a common event probability q_t and the associated firm-specific parameters $\{\theta_{i,t}\}_{i=1}^M$ for the 30 trading days between November 10, 2017 and December 22, 2017 following the steps described in the previous section.

The estimation methodology we propose is a new one, and complex enough to make the algebraic derivation of confidence intervals unfeasible. We therefore use bootstrapping to come up with confidence intervals. We construct 1000 simulated samples for each day in the period, and for each simulation, draw 100 firms with replacement. Using the bootstrap sample, we construct 10% upper and lower bounds that define an 80% confidence interval, as well as a 90% confidence interval using the bootstrap sample standard deviation ($\pm 1.645\sigma$).

The estimation results are shown in Figure 5. The horizontal axis corresponds to the number of trading days between the event (December 22, 2017) and the data date t. For both subfigures, the solid blue line depicts the estimated event probability q_t before the passage of TCJA, and only data from that particular day is used in its estimation. The solid red line is the fitted value of estimated event probability using smoothing spline interpolation, which aggregates information across days. The dashed blue lines in the top subfigure display the top and bottom 10th percentiles using the bootstrap sample. The dashed blue lines in the bottom subfigure delineate the 90% confidence interval obtained using the bootstrap sample standard deviation.

As clearly seen in the Figure 5, the market had already anticipated the probability of the passage of TCJA to be as high as 95% even 30 trading days before it happened, and although there are some fluctuations, the estimated probability always remains in a very tight band $[0.93, 0.97]$. This implies that a very large fraction of the impact of the event was already priced in before its occurrence, consistent with the lackluster stock market reaction on the event day. As discussed earlier in Section 2, this means the traditional event study methodology becomes very unreliable, demonstrating the need to use a methodology such as ours that backs out the event anticipation q if one wishes to reliably estimate the aggregate as well as the relative impact of TCJA on firm stock values compared to our finding.

Using our estimates, we also calculate the aggregate impact of TCJA passage on the firms in our sample. The results are shown in Table 2. The first column corresponds to the mean of the estimated net firm-specific impacts $S_u/S_d - 1$ across our sample, which is found to be a 12.36% increase in stock price. The remaining columns report several measures traditionally used in event studies, such as the mean holding period return on the event date (RET), and the mean cumulative abnormal returns on firm stock prices using windows of 3, 5, 7, and 10 trading days. The observed numbers are consistent with the estimated value of q prior to the event date: these traditional estimators severely understate the impact of the passage of TCJA.

Table 3 presents the correlation between the estimated net firm-specific impacts $S_u/S_d - 1$ and the traditional firm-level estimators considered in Table 2. As can be seen, the correlation between these measures and our estimated firm-level impact is uniformly positive, but quite low, ranging between 13.3 and 23.3%. Since the event is highly anticipated, the relative value effects for individual firms are swamped by the noise introduced into the prices by unrelated idiosyncratic fluctuations. Given that our Monte Carlo simulations in Section 2 predicted a mean correlation of 20% between the true firm-level impact and the traditional event study estimators, these results lie well within the expected range, once again demonstrating the need to use our methodology if one wishes to reliably estimate the relative impact of TCJA on different firms.

How should one interpret the 12.36% number we estimate as the aggregate impact of TCJA on stock prices? While one might be tempted to extrapolate this finding to stand for the aggregate impact of TCJA on all firms in the United States, the caveats we mentioned earlier should be kept in mind: Our sample consists of the 100 firms listed in Compustat with the most liquid options. This is a highly selected sample, and the average market capitalization of the firms in our sample is roughly 10 times the average Compustat firm.[4] In this sense, we would be hesitant to extrapolate our estimated aggregate impact to all publicly-traded firms in the US, let alone private firms. At the same time, the large size of the firms in our sample does mean that our estimated impact is relevant. The market capitalization of the 100 firms in our sample is 22.45% of the Compustat universe. Therefore, we can confidently claim that the effect we estimate applies to around one quarter of all publicly-traded firms weighted by market capitalization, which constitute a significant portion of US GDP.

5 Empirical Analysis of the Relative Winners and Losers of the Tax Cuts and Jobs Act

In this section we consider the cross-sectional relation between firm characteristics and implied expected payoffs from TCJA passage. These expected payoffs are estimated over the final month of TCJA negotiations, and thus are likely to capture the full information

[4]As discussed earlier in Section 3, we focus our analysis on the 100 firms with the most liquid options, as a tradeoff between representativeness of the sample relative to the universe, and the informativeness of option data from the included firms due to diminishing liquidity.

set available to market participants about the potential implications of TCJA passage or failure despite a high degree of anticipation. This enables us to directly test the effects of TCJA passage on firm value. Prior studies of the TCJA have focused on tax rates (Dyreng et al., 2020; Wagner et al., 2020), market reactions without explicitly accounting for investor anticipation (Kalcheva et al., 2020), and corporate policies such as stock repurchases and leverage (Bennett et al., 2019; Carrizosa et al., 2020), payouts (Hanlon et al., 2019), executive compensation (Luna et al., 2019; De Simone et al., 2020), IPO valuations (Edwards and Hutchens, 2020), and uses of repatriated cash (Atwood et al., 2020; Beyer et al., 2019; Albertus et al., 2019; Olson, 2019). In contrast to these studies, we are able to get market-based measures of relative winners and losers from TCJA passage unbiased by anticipation, and to related these market expectations to firm characteristics.

We consider the effects of the TCJA passage on the state-contingent payoffs of our sample firms in two complementary ways. First, we create a test of the characteristics drive the market's expectations for the relative gain from TCJA passage in terms of the implied payoff ratio $\frac{S_u}{S_d}$ by splitting our sample into high- and low-gain subsamples about the median of the payoff ratio and testing the differences in firm characteristics between the two samples. Second, we split the sample of firms into high- and low-level subsamples about the median of each individual characteristic, and test the differences in the implied payoff ratio. The higher the S_u/S_d ratio, the more the options market expects the firm to benefit from the passage of TCJA (in which case the firm will receive the S_u state-contingent payoff) relative to its failure (in which case the firm will receive the S_d payoff).

5.1 Innovation

The TCJA introduced expensing of investment expenses in intellectual property and innovation (Auerbach, 2018). We therefore examing the relation between firm characteristics related to innovation and expected firm-specific payoffs from TCJA passage relative to its failure, summarized as the implied payoff ratio $\frac{S_u}{S_d}$. The first part of Table 4 presents t-test results of firm characteristic means between the high and low subsamples of the payoff ratio $\frac{S_u}{S_d}$ formed about its median. The higher the payoff ratio, the greater the benefit to the firm from TCJA passage relative to its defeat.

For the set of variables tied to innovation, we see consistent evidence that the options market associated greater innovative activity within firms with greater benefits from TCJA passage. Those firms with above-median option-implied payoff ratios that were expected to benefit more from TCJA relative to those with below-median option-implied payoff ratios had higher R&D intensity, patent and citation counts, and higher total originality and generality of patents. They also had a greater investment in intangible capital, as evidenced by a lower tangibility ratio. These firms were also reaping more benefits of past innovation and competitive strategy as evidenced by their higher sales and asset growth. Notably, however, they had lower average originality and generality per patent, consistent with a larger amount of patenting overall, all at the 1% statistical significance level. These differences in market expectations are consistent with the expectation of more favorable tax treatment of intellectual property expenses if TCJA were to pass, but consistent with an approach that favors quantity over quality in innovation. Since investment expenses for a less impactful innovation are not necessarily lower than those for a more impactful one, and since the addition of a tax shield reduces the marginal cost of innovation, this policy's effects on the greater production of more mediocre innovation are consistent with expectations.

5.2 Overseas Operations

The move toward territorial taxation in the TCJA did not mean that world-wide income was previously fully taxed by the US at the corporate level, since firms with overseas operations were able to defer US corporate taxes by reinvesting profits overseas. We measure the degree to which each firm took advantage of this tax deferral option using indefinitely reinvested foreign earnings, which were not taxed until they were repatriated to the USA. Since the TCJA passage would render this tax shelter obsolete, we expect the reform to favor those firms that took less advantage of it. Indeed, in Table 4 we see that firms expected to benefit more from TCJA had fewer tax shelters in place in terms of lower indefinitely reinvested foreign earnings and net tax assets relative to firm size, statistically significant at the 1% level. This is consistent with the devaluation of this tax shelter through TCJA passage. Further consistent with this view, firms that benefited from TCJA passage more had weakly lower cash holdings, significant at the 10% level. This is consistent with the predictions for greater earnings repatriation post-TCJA (Auerbach, 2018), as well as greater post-TCJA payouts (Bennett et al., 2019; Kalcheva et al., 2020; Hanlon et al., 2019).

5.3 Tax Rates

The TCJA proposed to lower the corporate tax rate from 35% to 21%, a first-order effect producing a greater expected benefit for higher-taxed firms as market reactions around the 2016 election showed (Wagner et al. (2018)). Notably, around the passage of TCJA itself we find the opposite outcome, with the highest payoff ratio firms having a substantially lower effective tax rate, significant at the 1% level. The net tax assets are no longer significantly related to the firm's payoff ratio either. This is consistent with market expectations already incorporating the first-order benefits from TCJA passage, leaving second-order effects like tax mitigation strategies to drive market reactions around the TCJA event itself.

5.4 Other Characteristics

Furthermore, we find that sorts on the payoff ratio correspond to other statistically significant firm characteristic differences. Beneficiary firms are larger in terms total assets, suggesting that the overall size of the firm correlates with its ability to capture benefits from the tax reform potentially driven by a greater likelihood of overseas operations and greater freedom to minimize tax exposure (Rego, 2003). Furthermore, beneficiary firms are less financially constrained as measured by the Whited and Wu (2006) financial constraint index and have lower leverage, consistent with the TCJA provisions on the limitation of interest payment deductions to 30% of firm EBIT after 2021. This is also consistent with the ex-post findings of Bennett et al. (2019) and Carrizosa et al. (2020) on observed leverage reductions post-TCJA.

In addition to the greater gains from TCJA passage to firms with lower tangibility, we find that relative beneficiaries had lower asset maturity and lower PP&E investments, consistent with the potential for a higher marginal value of future investments possible after the TCJA reduction of the marginal cost of investing. This is also consistent with the findings on post-TCJA investment by Bennett et al. (2019), but contrary to the absence of an effect on investment found by Kalcheva et al. (2020). Our analysis also shows that TCJA winners had lower advertising expenses and overall worse performance as measured by profitability, ROA, and ROE. These findings have not been previously documented in studies of the TCJA reform, illustrating the value of using a market-based measure of firm value to get a clearer measure of its implications. Furthermore, it is important to note that our ex-ante results are predictive and obtained using price and fundamentals data at the time of the TCJA passage, whereas the ex-post studies of individual firm characteristics require a substantial window of time after the event to be possible and can only be applied in a forensic, rather than a predictive, setting.

5.5 Firm Characteristic Sorts and Economic Significance

To test the robustness of these findings, and to quantify their economic value, we also consider the reverse of the relation between higher expected benefits from TCJA with firm characteristic levels. We do this by comparing the expected benefits from TCJA passage as measured by the option-implied S_u/S_d payoff ratio across subsamples of above- and below-median levels of firm characteristics in Table 5. The differences in the option-implied payoff ratio quantify the economic value of a firm moving from below- to above-median levels in each individual characteristic. The average net impact of TCJA passage, measured by $\frac{S_u}{S_d} - 1$ to take into account the effects of investor anticipation, is 12.36% as described in Table 2, meaning that the individual characteristic-level differences which are on the order of 2.00% account for a meaningful fraction of the total.

We observe consistent results with those in Table 4, finding that firms with higher R&D intensity, patent and citation counts, and total patent originality and generality all have higher expected payoff ratios from TCJA passage relative to those with lower levels of innovation characteristics, with values ranging between 3.6% and 2.0%. Given the average pre-TCJA market capitalizations of $123,219 MM for the firms in our sample, this means that moving from below- to above-median levels in any of these characteristics adds between $4,435 MM and $2,464 MM of value to the average firm. Furthermore, we find that firms with higher asset and sales growth as a consequence of superior competitive ability have higher expected payoff ratios ranging between 2.0 and 1.2 percent with statistical significance at the 1% and 5% levels respectively, with an average economic value of between $2,464 MM and $1,478 MM. Consistent with the expected payoff difference results in Table 4, firms that have greater average originality and generality, consistent with fewer but more impactful patents, have lower expected payoff ratios of -3.4% and -1.7% respectively. This translates to a -$4,189 MM and -$2,094 MM value effect for the average firm respectively.

Consistent with our results from Table 4 the firms with a higher effective tax rate and higher tax shields from indefinitely reinvested foreign earnings as a fraction of total assets have 2.1 percent lower payoff ratios, statistically significant at the 1% level. This translates to a relative loss of $2587 MM for a firm that moves from above-median cash ETR or indefinitely reinvested foreign earnings to below-median levels of either characteristic, enabling us to more precisely quantify the value effect of these characteristics on the individual firm than prior work by Wagner et al. (2018).

The relation between above-median cash holdings and lower payoff ratios is stronger in this setting, with a -2.2% reduction statistically significant at the 1% level. This results in a $2,710 MM loss for the average firm, providing additional insight into the economic value of foreign cash post-TCJA whether it is used to conduct repurchases (Beyer et al., 2019), acquisitions (Atwood et al., 2020), or domestic investment (Albertus et al., 2019).

Consistent with our characteristic difference results, firms with above-median size have payoff ratios that are 1.9% greater, statistically significant at the 1% level. This enables us to quantify the value of multinational operations and greater ability to avoid taxation (Rego, 2003) for the average-sized firm at $2,341 MM. Furthermore, firms with above-median advertising expenditure have 1.5 percent lower expected payoff ratios from TCJA passage at the 5% significance level, equating to an expected increase of $1,848 MM in value for an average-sized firm moving to below-median advertising expenses post-TCJA. Firms with greater financial constraint as well as higher ROA and ROE have lower expected payoff ratios ranging from 3.1 to 1.7 percent, significant at the 1% level. The effect on the average firm moving from above- to below-median in these characteristics therefore ranges from $3,819 MM to $2,094 MM. Taken together, these findings suggest that option market participants expected the TCJA tax code changes to benefit large firms with prolific but less impactful innovation. Furthermore, these tax changes produce meaningful quantifiable benefits for firms with lower tax shields and lower operating performance.

6 Conclusion

This paper develops a method to estimate ex-ante event probabilities for highly anticipated events, which is also robust to firm-level heterogeneity in the impact of the event. The incorporation of expected event probabilities is critical in properly evaluating the market value of an anticipated event, particularly for events with either very high degrees of anticipation such as the 2017 Tax Cuts and Jobs Act (TCJA) which had an anticipated probability of passage of well over 90%. This means that the true value effect on individual firms is more than 10 times that of the actual observed market reaction at the resolution of uncertainty. Indeed, we estimate the average value effect of the TCJA to be a gain of 12.36% across a sample of the 100 largest firms, compared to an average of 0.68% when market anticipation is ignored.

We provide theoretical insight on the role of anticipation on the correct measurement of the firm-specific effects of an event, as well as the existence of a downward bias about the aggregate impact of the event across multiple firms. These biases can be corrected for by ex-ante knowledge of the expected probability of the event, or the knowledge of whether the firm will be a winner or a loser. However, this ex-ante knowledge is difficult or impossible to obtain due to the illiquidity or absence of other predictive markets, and the challenge of inferring winner versus loser status from anticipation-biased market reactions.

Prior studies have developed methods to calculate option-implied probabilities that could correct for anticipation, but these rely on identifying assumptions about the preference ranking of the possible outcomes which do not apply in cases where the same event has different effects on different firms. The TCJA thus serves not only as an example of a highly anticipated event, but also of one with both winners and losers driven by firm characteristics such as innovation strategies, tax exposure, and operating characteristics. Our methodological innovation is to allow the data to tell us whether the event is a positive or negative one for each individual firm independently of its effects on others. Our approach allows us to generate expected event probabilities from a set of firms with liquid options data regardless of the proportion of winners and losers with respect to the event in question.

Applying this methodology to the TCJA, we find that large firms with high patent counts and growth prospects are the greatest relative winners from this policy change. Notably, small firms with a low number of high-impact patents are among the greatest relative losers. This is consistent with prior findings about two distinct innovation strategies: the production of a few high-quality patents with knowledge externalities versus the production of a larger number of more mediocre patents. Our results suggest that the TCJA tax policy change encourages more innovation but with lower impact and fewer knowledge spillovers.

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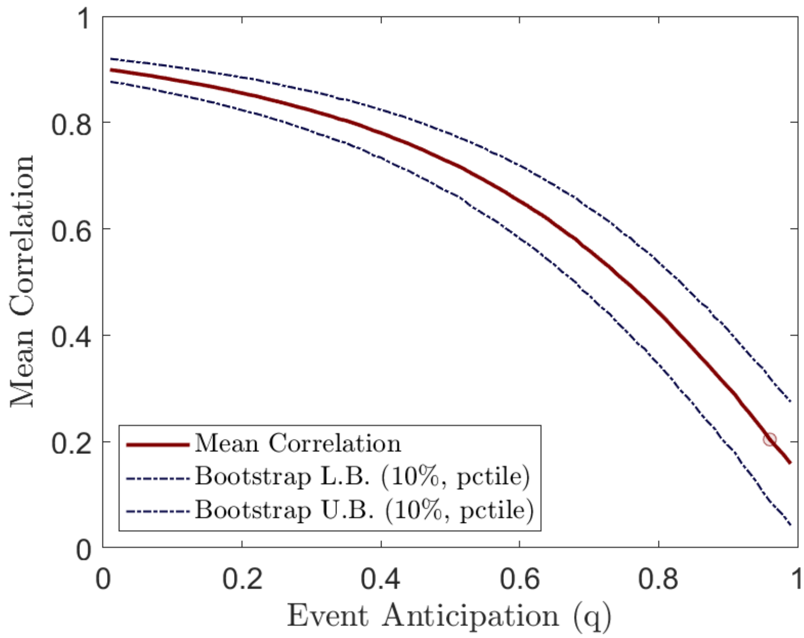
Appendix

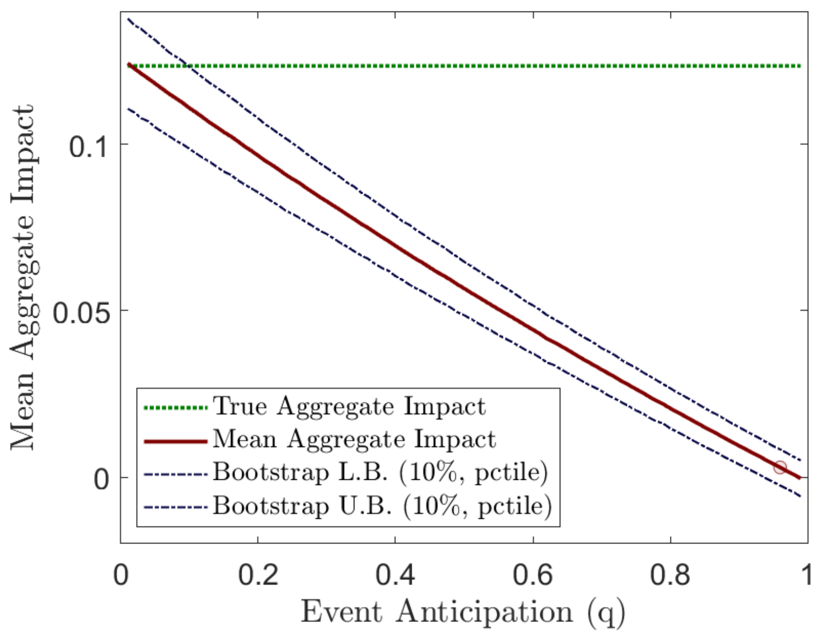
A Figures and Tables

FIGURE 1: THE CORRELATION BETWEEN $(P_{i,T+1} - P_{i,T})/P_{i,T}$ AND $s_i - 1$



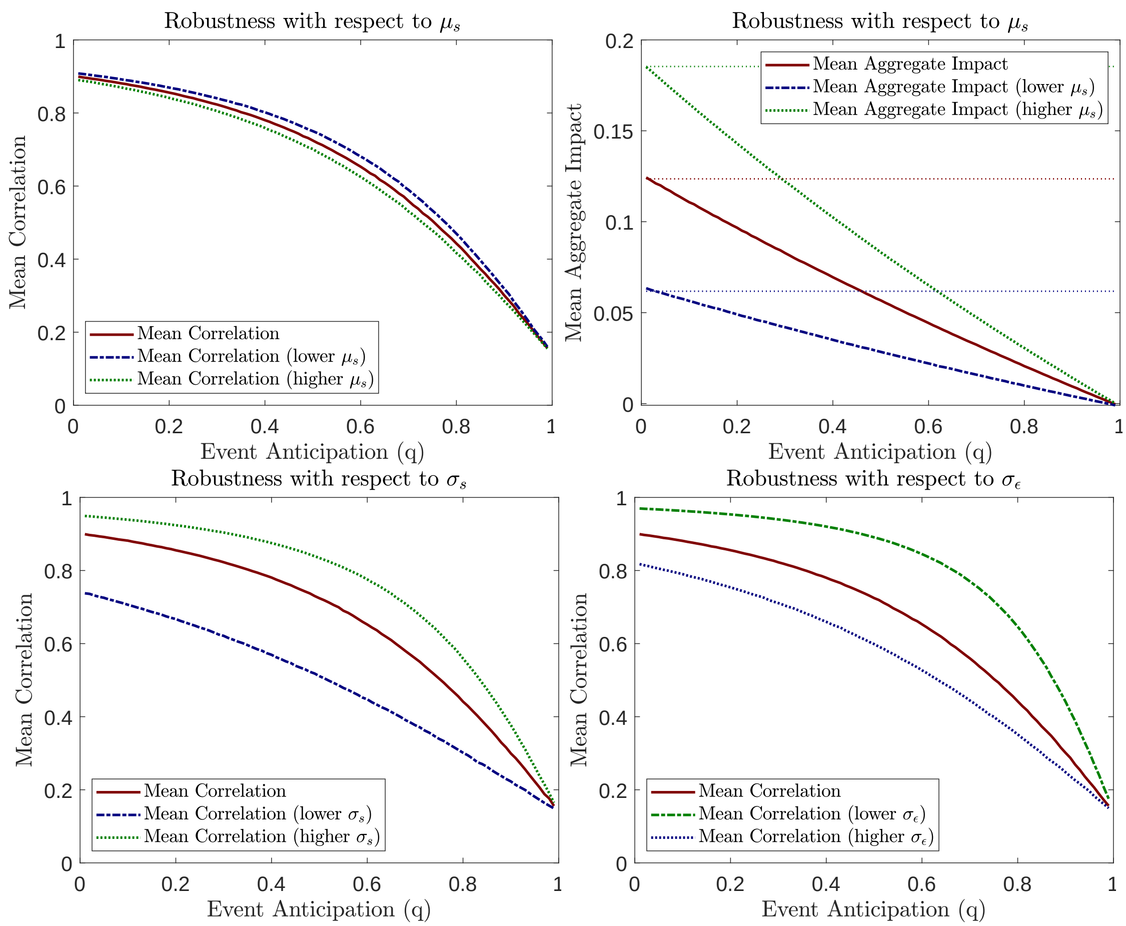
Notes: We pick the parameter values as $\mu_s = 1.1236, \sigma_s = 0.0952, \sigma_\epsilon = 0.0400$, and $N = 100$. We conduct $T = 10,000$ simulations for each parameter set corresponding to a different value of the event anticipation q, and use bootstrapping to obtain 10% upper and lower bounds. Figure 1 presents the mean correlation we obtain across T = 10,000 simulations as a function of the event anticipation q, which ranges from 1% to 99%.

FIGURE 2: THE TRUE AND ESTIMATED NET AGGREGATE IMPACT $\mu_s - 1$



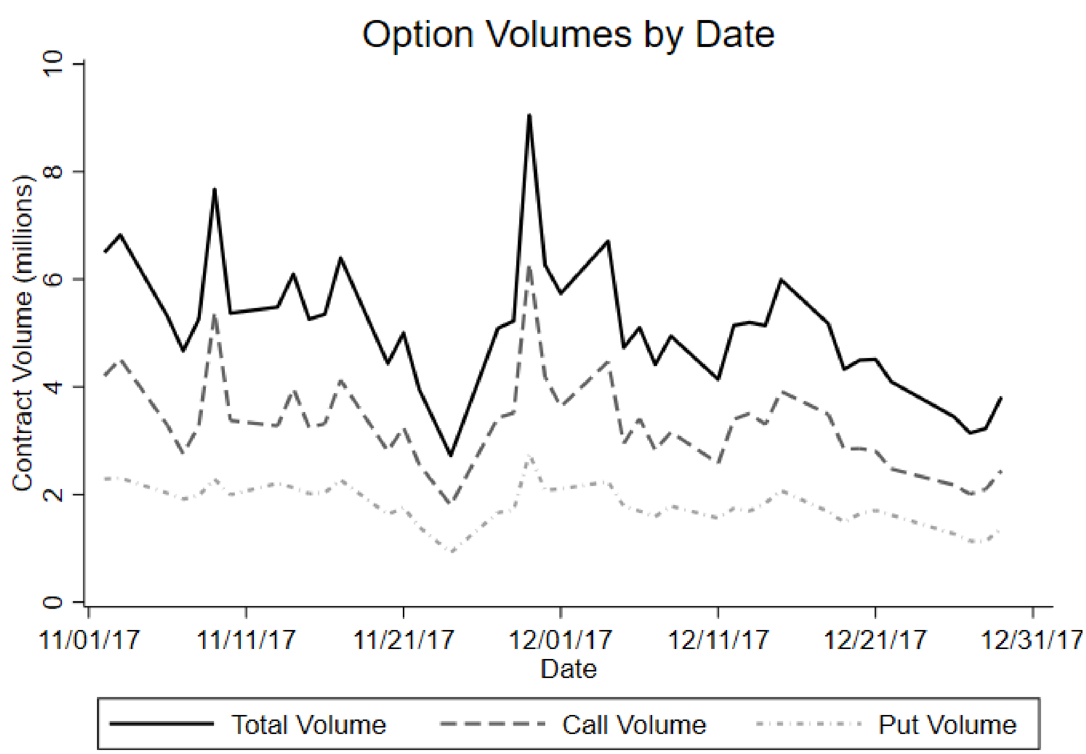
Notes: We pick the parameter values as $\mu_s = 1.1236, \sigma_s = 0.0952, \sigma_\epsilon = 0.0400$, and $N = 100$. We conduct $T = 10,000$ simulations for each parameter set corresponding to a different value of the event anticipation q, and use bootstrapping to obtain 10% upper and lower bounds. Figure 2 displays the true aggregate impact of the event, along with the mean aggregate impact the traditional estimator delivers across T = 10,000 simulations as a function of the event anticipation q.

FIGURE 3: ROBUSTNESS CHECKS



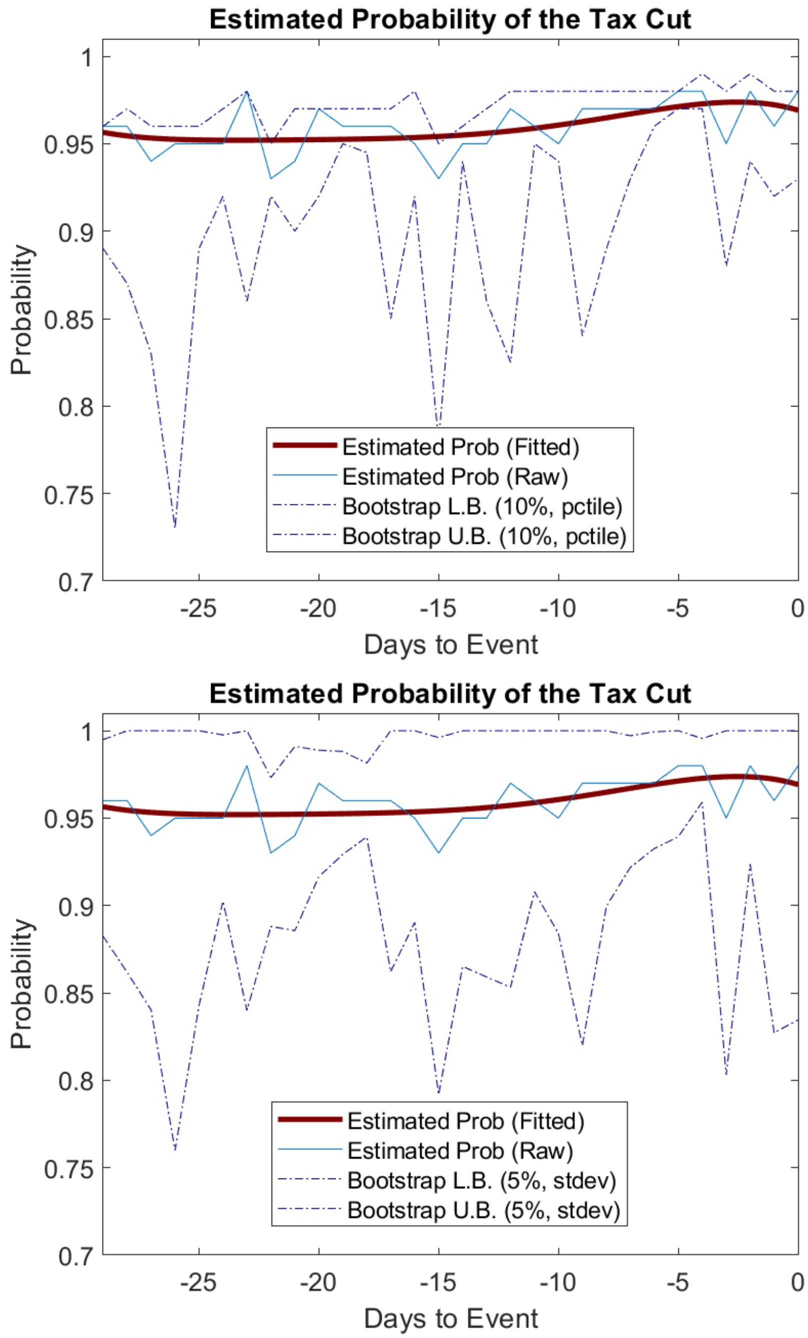
Notes: Figure 3 illustrates the results for the robustness checks. We first investigate the effects of changing the net aggregate impact of the event $\mu_s - 1$ to 50% and 150% of its value. The top-left subfigure repeats the exercise in Figure 1. The top-right subfigure repeats the exercise in Figure 2. We also investigate the effects of changing the standard deviation parameters σ_s and σ_ϵ to 50% and 150% of their values. A higher value of σ_s implies more heterogeneity in the firm-specific impact s_i across firms. A higher value of σ_ϵ implies more volatile stock price fluctuations in firm value (independent of the event). The bottom-left and bottom-right subfigures repeat the exercise in Figure 1 for different values of σ_s and σ_ϵ, respectively.

FIGURE 4: DAILY OPTION VOLUME FOR SAMPLE FIRMS



Notes: This figure depicts the daily option volume for all options for all firms in our sample. The solid line represents total daily trading volume for all options for all firms in our sample. The dashed line represents the call option volume, while the dot-dashed line represents the put option volume. Option trade data is from the OptionMetrics database.

FIGURE 5: THE ESTIMATED PROBABILITY OF TCJA PASSAGE



Notes: Figure 5 shows the estimated probability of TCJA passage. The horizontal axis corresponds to the number of trading days between the event (December 22, 2017) and the data date t. For both subfigures, the solid blue line depicts the estimated event probability q_t before the passage of TCJA, and only data from that particular day is used in its estimation. The solid red line is the fitted value of estimated event probability using smoothing spline interpolation, which aggregates information across days. The dashed blue lines in the top subfigure display the top and bottom 10th percentiles using the bootstrap sample. The dashed blue lines in the bottom subfigure delineate the 90% confidence interval obtained using the bootstrap sample standard deviation.

Table 1: List of sample firms with market capitalization, call option volume, and industry group

Name	Average daily call volume	Market cap ($MM)	SIC2 group
APPLE INC	261788.30	790050.13	Electronic & Other Electric Equipment
BANK OF AMERICA CORP	227064.60	303681.16	Depository Institutions
MICRON TECHNOLOGY INC	151133.80	35550.64	Electronic & Other Electric Equipment
GENERAL ELECTRIC CO	134709.80	151475.97	Conglomerate
FACEBOOK INC	130835.90	512792.75	Business Services
ADVANCED MICRO DEVICES INC	9940.76	2071.92	Electronic & Other Electric Equipment
A T & T INC	95675.03	238700.84	Communications
NVIDIA CORP	71702.85	148954.80	Electronic & Other Electric Equipment
INTEL CORP	70861.27	216351.92	Electronic & Other Electric Equipment
TESLA INC	67707.01	52554.95	Transportation Equipment
MICROSOFT CORP	62581.75	531312.44	Business Services
NETFLIX INC	62356.93	83194.12	Motion Pictures
TWITTER INC	58536.18	17933.12	Business Services
CITIGROUP INC	52913.8	191226.92	Nondepository Institutions
QUALCOMM INC	51401.65	76412.16	Electronic & Other Electric Equipment
AMAZON.COM INC	50022.58	566023.50	Miscellaneous Retail
BAUSCH HEALTH COMPANIES INC	47908.05	7246.17	Chemical & Allied Products
GENERAL MOTORS CO	45226.69	57386.00	Transportation Equipment
JPMORGAN CHASE & CO	43622.73	366301.59	Depository Institutions
FREEPORT MCMORAN INC	43530.30	27454.08	Metal Mining
TEVA PHARMACEUTICALS	40405.23	19272.15	Chemical & Allied Products
WALMART INC	36441.19	314683.19	General Merchandise Stores
CISCO SYSTEMS INC	35655.68	156715.34	Industrial Machinery & Equipment
WELLS FARGO & CO	35181.57	296774.41	Depository Institutions
SQUARE INC	32631.31	13701.38	Business Services
C B S CORP	31366.14	22597.00	Communications
COMCAST CORP	29656.43	186012.55	Communications
MACYS INC	27328.83	7908.65	General Merchandise Stores
GILEAD SCIENCES INC	26517.76	93705.117	Chemical & Allied Products
UNITED STATES STEEL CORP NEW	25735.71	6166.03	Primary Metal Industries
VERIZON COMMUNICATIONS INC	25576.61	215926.67	Communications
TIME WARNER INC NEW	23795.57	71346.60	Communications
DISNEY WALT CO	21265.29	149530.69	Communications
APPLIED MATERIALS INC	21029.74	59815.80	Industrial Machinery & Equipment
ORACLE CORP	20978.34	186739.84	Business Services
UNION PACIFIC CORP	20808.68	104721.10	Railroad Transportation
CELGENE CORP	19270.86	79240.55	Chemical & Allied Products
CHESAPEAKE ENERGY CORP	19169.32	3589.7083	Oil & Gas Extraction
HOME DEPOT INC	18810.10	232642.2	Building Materials & Gardening Supplies
INTERNATIONAL BUSINESS MACHS CORP	18485.36	141480.7	Business Services
GOLDMAN SACHS GROUP INC	18471.11	99076.164	Security & Commodity Brokers
EXXON MOBIL CORP	18442.48	354549.97	Petroleum & Coal Products
PFIZER INC	17279.66	216559.38	Chemical & Allied Products
VISA INC	16858.28	239315.77	Depository Institutions
STARBUCKS CORP	16359.45	239315.77	Eating & Drinking Places
BARRICK GOLD CORP	16170.36	16880.37	Metal Mining
UNITED CONTINENTAL HOLDINGS INC	16082.52	19341.98	Transportation by Air
DELTA AIR LINES INC	15626.81	39603.09	Transportation by Air
BOEING CO	15018.13	174303.31	Transportation Equipment

Name	Average daily call volume	Market cap ($MM)	SIC2 group
NIKE INC	14807.01	114951.80	Rubber & Miscellaneous Plastics Products
CATERPILLAR INC	14547.30	94173.91	Industrial Machinery & Equipment
J C PENNEY CO	14527.58	1157.52	General Merchandise Stores
COCA COLA CO	14227.10	195402.92	Food & Kindred Products
MERCK & CO	14107.95	151738.36	Chemical & Allied Products
AMERICAN AIRLINES GROUP INC	14003.07	24740.68	Transportation by Air
ALPHABET INC	13827.38	731884.44	Business Services
CENTURYLINK INC	13193.02	17833.74	Communications
MARATHON OIL CORP	13126.21	14390.50	Oil & Gas Extraction
RITE AID CORP	12780.18	2102.62	Miscellaneous Retail
BLACKBERRY LTD	12553.10	6515.96	Electronic & Other Electric Equipment
SALESFORCE.COM INC	12152.13	83137.56	Business Services
ELECTRONIC ARTS INC	11902.96	37144.30	Business Services
CHIPOTLE MEXICAN GRILL INC	11861.91	8100.36	Eating & Drinking Places
WESTERN DIGITAL CORP	11809.77	26048.40	Industrial Machinery & Equipment
M G M RESORTS INTERNATIONAL	11653.05	18907.96	Amusement & Recreation Services
SCHLUMBERGER LTD	11391.93	93263.24	Oil & Gas Extraction
SPRINT CORP NEW	11371.16	19544.40	Communications
HALLIBURTON CO	11330.84	42663.51	Oil & Gas Extraction
JOHNSON & JOHNSON	11237.08	374802.41	Chemical & Allied Products
MORGAN STANLEY	11166.05	93820.92	Security & Commodity Brokers
KROGER COMPANY	11097.44	26413.20	Food Stores
WEATHERFORD INTL PLC	10890.79	4140.81	Oil & Gas Extraction
LOWE'S COS INC	10615.52	86925.90	Building Materials & Gardening Supplies
MCDONALD'S CORP	10481.8	136680.50	Eating & Drinking Places
ACTIVISION BLIZZARD INC	10467.48	47965.21	Business Services
BRISTOL-MYERS SQUIBB CO	10229.38	100070.20	Chemical & Allied Products
ABBVIE INC	10006.11	153975.00	Chemical & Allied Products
TRANSOCEAN LTD	9972.15	4178.41	Oil & Gas Extraction
EBAY INC	9672.068	38834.46	Business Services
CHEVRON	9414.29	238449.60	Petroleum & Coal Products
ALTRIA GROUP	9314.74	135768.90	Tobacco Products
OVERSTOCK.COM INC	9057.30	1757.06	Miscellaneous Retail
BRITISH PETROLEUM PLC	8959.34	138820.40	Petroleum & Coal Products
WYNN RESORTS LTD	8928.98	17365.78	Amusement & Recreation Services
UNITED PARCEL SERVICE INC	8841.19	102349.90	Trucking & Warehousing
BLACKSTONE GROUP L P	8826.52	20149.99	Security & Commodity Brokers
SEAGATE TECHNOLOGY PLC	8837.90	11307.25	Industrial Machinery & Equipment
WALGREENS BOOTS ALLIANCE INC	8528.18	83443.70	Miscellaneous Retail
MACERICH CO	8376.49	9260.49	Holding & Other Investment Offices
C S X CORP	8280.11	48950.70	Railroad Transportation
ANADARKO PETROLEUM CORP	8113.05	28472.11	Oil & Gas Extraction
ADOBE INC	8087.35	89149.31	Business Services
MONDELEZ INTERNATIONAL INC	7942.79	63692.22	Food & Kindred Products
ALLERGAN PLC	7777.47	54014.12	Chemical & Allied Products
KINDER MORGAN INC	7671.50	40063.18	Electric, Gas, & Sanitary Services
MASTERCARD INC	7288.50	159533.40	Depository Institutions
PEPSICO INC	7142.62	170286.40	Food & Kindred Products
SHOPIFY INC	6934.33	10087.68	Business Services
M B I A INC	6854.60	669.66	Insurance Carriers
CAESARS ENTERTAINMENT CORP	6758.14	8652.60	Amusement & Recreation Services

Notes: Firms are sorted based on their average call option volume during the fourth quarter of 2017. We also provide their size measured by market capitalization, and industry classification according to the SIC.

TABLE 2: THE IMPACT OF TCJA PASSAGE

$S_u/S_d - 1$	RET	CAR[-3,0]	CAR[-5,0]	CAR[-7,0]	CAR[-10,0]
12.36%	0.68%	0.96%	0.89%	1.09%	2.29%

Notes: In this table, we report the estimated average impact of TCJA passage on firm stock return using our model and traditional event study methods. RET is the holding period return on the event date. CAR[-x,0] is the average of the cumulative abnormal returns of firm stock prices within the window of [-x, 0], where $x = 3, 5, 7, 10$. The cumulative abormal returns are computed based on Fama-French three factor models where abnormal returns are computed as the excess return on the stock minus the sum of its factor exposures times the factor returns, and the factor exposures are computed on daily market excess return, size, and value factor returns.

TABLE 3: THE CORRELATION BETWEEN THE ESTIMATED AVERAGE IMPACT BASED ON OUR MODEL AND TRADITIONAL METHODS

$S_u/S_d - 1$	RET	CAR[-3,0]	CAR[-5,0]	CAR[-7,0]	CAR[-10,0]
1.000	0.135	0.183	0.133	0.197	0.233

Notes: In this table, we report the correlation between the estimated average impact of TCJA passage on firm stock return using our model and traditional event study methods. RET is the holding period return on the event date. CAR[-x,0] is the average of the cumulative abnormal returns of firm stock prices within the window of [-x, 0], where $x = 3, 5, 7, 10$. The cumulative abormal returns are computed based on Fama-French three factor models where abnormal returns are computed as the excess return on the stock minus the sum of its factor exposures times the factor returns, and the factor exposures are computed on daily market excess return, size, and value factor returns.

TABLE 4: TESTING DIFFERENCES IN FIRM CHARACTERISTICS

Firm Attributes	Differences	t-statistics
R&D Intensity	0.021***	(4.05)
Patent Count	0.498***	(5.37)
Total Citations	0.489***	(4.86)
Total Originality	0.345***	(4.53)
Total Generality	0.201***	(4.09)
Average Citations	-0.014	(-0.86)
Average Originality	-0.018***	(-3.41)
Average Generality	-0.009**	(-2.16)
Tangibility	-0.029***	(-2.98)
Sales Growth	0.040***	(6.44)
Asset Growth	0.022***	(3.39)
Employment Growth	0.011**	(2.51)
Cash Effective Tax Rate	-1.616***	(-3.59)
Indefinitely Reinvested Foreign Earnings/Assets	-0.048***	(-5.14)
Net Tax Assets/Assets	-0.023***	(-4.50)
Cash/Asset	-0.006*	(-1.76)
Market to Book Ratio	-0.088	(-1.64)
Size (log(assets))	0.232***	(3.56)
Leverage	-0.012*	(-1.95)
Asset Maturity	-0.727***	(-4.13)
Property Plant and Equipment/Assets	-0.029***	(-2.98)
Profitability	-0.014***	(-3.95)
Return on Assets (ROA)	-0.015***	(-4.97)
Return on Equity (ROE)	-0.057***	(-3.48)
Whited-Wu Index	-0.011***	(-3.01)
Advertising Expenses	-0.007***	(-5.54)

Notes: In this table, we split the sample into two using the S_u/S_d ratio, and check whether characteristics are significantly different across the two groups. $***p < 0.01, **p < 0.05, *p < 0.1$.

TABLE 5: TESTING DIFFERENCES IN S_u/S_d PAYOFF RATIOS

S_u/S_d ratio	Differences	t-statistics
R&D Intensity	0.026***	(3.74)
Patent Count	0.036***	(6.52)
Total Citations	0.036***	(6.52)
Total Originality	0.027***	(4.83)
Total Generality	0.020***	(3.55)
Average Citations	0.005	(0.86)
Average Originality	-0.034***	(-6.09)
Average Generality	-0.017***	(-3.00)
Tangibility	-0.006	(-1.07)
Sales Growth	0.020***	(3.67)
Asset Growth	0.012**	(2.19)
Employment Growth	0.002	(0.37)
Cash Effective Tax Rate	-0.021***	(-3.71)
Indefinitely Reinvested Foreign Earnings/Assets	-0.021***	(-3.42)
Net Tax Assets/Assets	-0.006	(-1.11)
Cash/Asset	-0.022***	(-4.03)
Market to Book Ratio	-0.011*	(-1.94)
Size (log(assets))	0.019***	(3.46)
Leverage	-0.004	(-0.79)
Asset Maturity	-0.004	(-0.66)
Property Plant and Equipment/Assets	-0.006	(-1.07)
Profitability	-0.008	(-1.37)
Return on Assets (ROA)	-0.031***	(-5.58)
Return on Equity (ROE)	-0.017***	(-3.10)
Whited-Wu Index	-0.017***	(-3.10)
Advertising Expenses	-0.015**	(-2.24)

Notes: In this table, we split the sample into two using the median of firm characteristics themselves, and check whether the S_u/S_d ratio is significantly different across the two groups. $***p < 0.01, **p < 0.05, *p < 0.1$.

B Data Construction

We detail the construction of our variables below.

R&D Intensity
The R&D to Sales ratio averaged over the preceding five years, 2012 to 2016

Patent Count
The number of patents granted to the firm averaged over the preceding five years, 2012 to 2016

Total Citations
The number of citations received by the firm's patents averaged over the preceding five years, 2012 to 2016

Total Originality
The total dispersion of the patents cited by the patent across technology sectors following Hall et al. (2001) averaged over the preceding five years, 2012 to 2016

Total Generality
The total dispersion of the patents citing the patent across technology sectors following Hall et al. (2001) averaged over the preceding five years, 2012 to 2016

Average Citations
The average citations per patent received by the firm's patents averaged over the preceding five years, 2012 to 2016

Average Originality
The average originality per patent of the firm's patents averaged over the preceding five years, 2012 to 2016

Average Generality
The average generality per patent of the firm's patents averaged over the preceding five years, 2012 to 2016

Tangibility
The ratio of the firm's tangible to total assets averaged over the preceding five years, 2012 to 2016

Sales Growth
The year-on-year growth in sales averaged over the preceding five years, 2012 to 2016

Asset Growth
The year-on-year growth in assets averaged over the preceding five years, 2012 to 2016

Employment Growth
: The year-on-year growth in the number of employees averaged over the preceding five years, 2012 to 2016

Cash Effective Tax Rate
: The ratio of the firm's tax to its net income averaged over the preceding five years, 2012 to 2016

Indefinitely Reinvested Foreign Earnings / Assets
: The ratio of indefinitely reinvested foreign earnings as listed by the firm in its tax filing averaged over the preceding five years, 2012 to 2016

Net Tax Assets / Assets
: The ratio of net tax assets to book assets averaged over the preceding five years, 2012 to 2016

Cash / Assets
: The ratio of cash holdings to book assets averaged over the preceding five years, 2012 to 2016

Market / Book
: The ratio of the firm's market value to book value averaged over the preceding five years, 2012 to 2016

Firm Size
: The log of firm book assets averaged over the preceding five years, 2012 to 2016

Leverage
: The ratio of total debt to total assets averaged over the preceding five years, 2012 to 2016

Asset Maturity
: The average maturity of short-term and long-term assets weighted by their proportion of total assets following Benmelech (2006) and averaged over the preceding five years, 2012 to 2016

Property, Plant, and Equipment / Assets
: The firm's property, plant and equipment normalized by total assets averaged over the preceding five years, 2012 to 2016

Profitability
: The net income of the firm averaged over the preceding five years, 2012 to 2016

ROA
: The firm's return on assets averaged over the preceding five years, 2012 to 2016

ROE
: The firm's return on equity averaged over the preceding five years, 2012 to 2016

Whited-Wu Index

The Whited and Wu (2006) index of financial constraint averaged over the preceding five years, 2012 to 2016

Advertising Expenses

The firm's advertising expenditure normalized by sales averaged over the preceding five years, 2012 to 2016