The 283 Days of Stock Returns after the 2016 Election*

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Abstract

The stock market rose by 25% between the 2016 election and the day TCJA was signed into law. To determine how much the prospect of tax cuts contributed to this increase, we construct a human-based attribution by examining non-public Market Intelligence from FRBNY for each of the 283 days during this period. We find that the prospect of tax cuts had a net impact of less than 1%. Corroborating evidence is provided by a machine textual approach, cross-sectional regressions including a newly constructed optimally-weighted measure of tax exposure, market-based probability measures, and a Gordon growth model.

Keywords: Stock Market; Taxes; TCJA
JEL Classification: E00; E58; E60

***The analysis and conclusions set forth in this paper are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors of the Federal Reserve System**. **Also, this analysis was conducted independently of and separately from the Federal Reserve Bank of New York.** Diercks is corresponding author. E-mail: Anthony.M.Diercks@frb.gov Web: http://www.anthonydiercks.com/. Special thanks to Olivier Blanchard, Andrew Chen, Christine Dobridge, Raymond Fisman, Fabio Gaertner, Erin Henry, Jeffrey Hoopes, Oliver Levine, Karel Mertens, Dino Palazzo, Francisco Palomino, Nitish Sinha, Steve Sharpe, Tugkan Tuzun, Alexander Wagner, the Capital Markets section in the division of Research and Statistics, the Monetary and Financial Markets Analysis section in the division of Monetary Affairs, and the University of Wisconsin Finance department for helpful comments and suggestions.

1 Introduction

The Tax Cuts and Jobs Act of 2017 (TCJA), signed into law 283 trading days after the 2016 election, was the largest corporate tax cut ever, decreasing the statutory rate from 35% to 21%. Over these 283 days the stock market increased by 25%, much of which the financial press attributed to the expectations of tax reform.[1] Ex post, this narrative suggests an investor might have profited from a strategy that went long in high-tax firms and short in low-tax firms, all else equal.

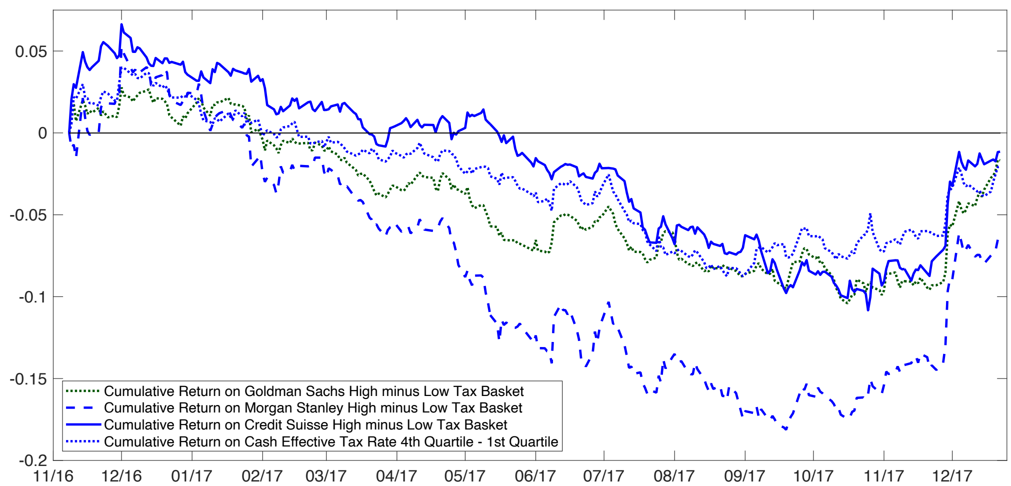


Figure 1: **High minus Low Tax Baskets: November 8, 2016 to December 22, 2017**

This figure shows High minus Low Tax Baskets as constructed by Goldman Sachs, Credit Suisse and Morgan Stanley. Also shown is a 4th minus 1st quartile return sorted on cash effective tax rates. Data descriptions are available in Internet Appendix E.

However, each of the portfolios plotted in Figure 1 ended up with a *negative* return by the time the bill was signed into law. Given such evidence of high-tax firms underperforming low-tax firms, to what extent did the promise of tax legislation contribute to the 25% return in the 283 days after the election? Additionally, what role might other administration policies, such as deregulation, have played in this increase? These questions have important ramifications for determining the expected effects of future changes in fiscal policy.

The relationship between fiscal policy and asset prices has been extensively studied. Bretscher, Hsu, and Tamoni (2020) empirically and theoretically show fiscal policy plays a key role for the determination of bond prices. Sialm (2005, 2006, 2009) provides a number of contributions by establishing that effective tax rates are negatively associated with stock valuations. Consistent with this finding, Croce, Kung, Nguyen, and Schmid (2012) finds that tax distortions reduce equity prices in a production-based general equilibrium framework. More recently, the TCJA has received

[1]For example, a CNBC article proclaimed on December 1, 2017 that, "(e)xpectations of lower corporate taxes have been a boon for US stocks since President Donald Trump got elected, helping the major indexes reach all-time highs." https://www.cnbc.com/2017/12/01/us-stock-futures-data-opec-tax-on-the-agenda

considerable attention. Wagner, Zeckhauser, and Ziegler (2018a) and Wagner, Zeckhauser, and Ziegler (2018b) document that the time-series variation in the cross-sectional sensitivity of stock returns to firm-level tax exposure is associated with aggregate daily returns. However, these studies leave open the first-order question of how much of the observed cumulative market return can be attributed to taxes.

We contribute to this literature by conducting a comprehensive analysis of the effects of the prospective tax legislation on the stock market's performance over the 283 days after the 2016 election. We employ a three-prong approach to estimate these effects. Our first approach uses non-public Market Intelligence provided by the Federal Reserve Bank of New York to determine key drivers on each of the 283 business days over this period.[2] This analysis enables us to identify news-worthy events that might have influenced the stock market, including expectations about tax policy. Our findings suggest that tax policy-related days account for 52 of the 283 days with a net contribution to the market return of 0.99%. Due to its subjective nature, we check the human daily attribution with a machine-based daily attribution based on relevant keywords in the Bloomberg News Trend database and find that tax-policy days contributed modestly more (2.5%) to the market return on net. Additionally, we also find that deregulation had close to double the net-effect of tax policy, contributing 4 to 6% on net to the market return.

Our second approach investigates the cross-sectional distribution of returns across firms during the 283 days. We estimate cross-sectional regressions of firm-level cumulative returns on various firm-specific characteristics (similar to Wagner, Zeckhauser, and Ziegler (2018a) and Wagner, Zeckhauser, and Ziegler (2018b)), including various measures of a firm's tax exposure. We find the one-year cash effective tax rate significantly explains variations of returns across firms immediately after the election, turns insignificant one year after the election, and regains significance prior to passage of the TCJA. However, Dyreng, Hanlon, and Maydew (2008) and Henry and Sansing (2018) note that the one-year cash effective tax rate may be a noisy measure of a firm's true tax exposure and a relatively poor predictor of future effective tax rates.

Therefore, we consider standard alternative measures of firm tax exposure in addition to formulating a new measure which optimally weights the history of past cash tax rates to predict future one-year ahead tax rates. Most of the various tax measures show an initial boost to high tax firms immediately after the election. However, the significance of taxes in explaining the cross-section of returns over longer horizons is highly dependent on the choice of the tax measure.

We also use these cross-sectional regressions to conduct another daily attribution and find that days in which the firm-level cash effective tax rate were most important explain approximately 3% of the overall market return. In contrast, the percentage of foreign revenues, which explain close to 10% of overall market returns, seems to be a stronger explanatory factor for the variation in

[2] See https://www.newyorkfed.org/markets/market-intelligence for more information about the Federal Reserve Bank of New York's Market Intelligence. We cross-check this data with publicly available sources. Specifically, we use the Wall Street Journal, Valueline.com, and Zack's Investment Services, which all provide detailed summaries of events surrounding market movements on a daily basis.

returns throughout the majority of the sample. We also consider the role of regulatory policy by constructing a novel metric based on a firm's self-reported risk factors. We find this regulatory measure explains a similar portion of the overall market returns to that attributed to tax exposure.

The third and final approach uses time series to analyze the relationship between stock market fluctuations and movements in prediction markets, building on the approaches of Wolfers and Zitzewitz (2004, 2006a,b, 2009, 2016). We begin by constructing a probability measure for the passage of tax legislation based on PredictIt market daily data. We show that there is an insignificant relationship at the daily frequency between the probability in the 2017 market (deadline for passage of tax cuts being the end of 2017) and the overall market return. However, because the betting market does not cover all potential timelines/outcomes, we combine a similar market measure, formed in October 2017 that framed the market with a 2018 deadline, with our 2017 measure. This restores a significant and positive relationship between this tax proxy and the overall market return. Similar to our human attribution and cross-sectional analyses, the estimated effect is relatively modest at approximately 2%.

For robustness, we also appeal to other proxies that might be affected by the prospects of tax policy, including (1) the spread between municipal and Treasury bonds – which to our knowledge, has not been studied for this period–, (2) the 5-year, 5-year forward inflation expectations, (3) the value of the dollar, and (4) the High minus Low tax baskets constructed by Goldman Sachs, Credit Suisse, and Morgan Stanley (shown in Figure 1). All of these measures convey a similar dynamic of "up, down, and up", consistent with our three main approaches. The aftermath of the election saw a rise in the probability of passage along with the rest of the corresponding proxies. However, this probability steadily declines until the last few months, where it again rises. Our daily attribution suggests notable events occurred in the summer of 2017 that seriously decreased the prospects of tax legislation, such as the failure to pass healthcare reform and the announcement of special prosecutor Mueller. We find that excluding this middle portion of the sample will lead to an upward bias on the estimated effects of the prospect of tax legislation on the market.

While a 1 to 3% attribution to the prospect of tax legislation may seem small, it is worth remembering, first, that effective tax rates were much lower to begin with than the statutory rates.[3] Second, the decrease in tax rates would be substantially smaller because it is offset by limits on net interest deductions and the repeal of other deductions.[4] And finally, an important discount rate channel offsets some of these positive cash flow effects via higher interest rates (the Fed's SEP in December 2016 upped the expected number of rate hikes in 2017).[5] To better formalize

[3] The actual tax rate paid by S&P 500 firms over the previous three years was already at a substantially lower rate of 25%.

[4] As pointed out in Blanchard, Collins, Jahan-Parvar, Pellet, and Wilson (2018), the Joint Committee on Taxation projected federal corporate tax revenues to fall by 16% over the next 10 years, which is a notable distance from the 40% implied by the change in statutory rates. On that note, Wagner, Zeckhauser, and Ziegler (2020) document that 30% of the firms had in fact higher cash effective tax rates the year after the TCJA was passed.

[5] Diercks and Waller (2017) emphasize this point and find some evidence for this offsetting discount rate

and quantify these arguments, we show through a standard Gordon growth calculation that the calculated estimated return can drop from 21% to 1.6% once we account for the modifications listed above.

If tax expectations only account for 1 to 3% of the aggregate return, then what explains the remainder of the stock market's rise over the 283 day sample? Both the human and machine-based attribution analyses suggest that the bulk of the 25% gain corresponded to days with positive economic data releases (53 days) and positive earnings (21 days), which contributed about 10% and 6%, respectively. We find that strong global growth, a weaker dollar, and an existing economic environment with relatively low unemployment likely played a key role in the positive economic data and strong earnings releases. More specifically, we find that global growth was significantly higher during this time period and may have been a more important driver as the Eurozone and China were experiencing some of their best economic performances in years. This is consistent with the outperformance of foreign stock indices such as FTSE and also the outperformance of high foreign revenue firms in our cross-sectional regressions. With 40% of revenues being foreign for S&P 500 firms, the strong global growth combined with the weaker dollar (which coincided with declines in the prospect for passage of tax legislation) boosted multinationals and manufacturers along with the overall market. Deregulation also likely played an important role. The daily human and machine-based attribution analyses both suggest that deregulation-related days may have had a larger net-effect on markets than the tax-policy days over the full sample. Both approaches imply most of this effect came in the first half of the sample, which is intuitive given that the administration implemented many of these changes either through executive order or through the legislature with the Congressional Review Authority. The human and machine-based analyses find a net-effect attributable to deregulation of between 4 to 6%, close to double the net-effect of tax policy.

The findings in this study should be viewed in light of some limitations. First, the human-audited daily attribution is subjective even though we provide numerous details and explanations for the vast majority of the days in the sample. Moreover, a machine-based textual analysis approach produces results that are roughly in line with our findings from the human attribution. Second, the aggregate market can be affected on a daily basis by multiple considerations so distilling these considerations into a primary driver may understate secondary drivers. We also track secondary drivers but for expositional purposes focus on results based on primary drivers.[6] Finally, it is possible that the prospect of tax legislation influenced the other categories on days in which tax news was not the most important. For instance, one might argue that the anticipated tax cuts helped drive stronger than expected positive US Data releases over the full sample. While we acknowledge this potential effect, we offer evidence that suggests otherwise. First, the historical evidence on

channel since 1980.

[6] Full descriptions of secondary drivers on any given day are available upon request. For days that we could not determine which category was the primary driver, we classified as Other. Considerations of secondary drivers are explored in Internet Appendix A.1.

the effects of anticipated tax legislation prior to enactment goes against this notion. Mertens and Ravn (2012) find no evidence of systematic effects on economic data prior to enactment.[7] Second, our cross-sectional analysis and other measures imply that markets were far from pricing in the prospect of tax cuts with certainty. Many of these measures were considerably lower in the middle of the year than they were on Election Day. Third, some may suggest the prospect of tax legislation had an effect on sentiment. To address this concern, we incorporate daily sentiment measures into our time-series analysis but find an insignificant relationship with respect to the aggregate market return.

Overall, the combination of these approaches and novel insights suggest that although tax policy had a positive effect over the 283 days, other factors likely played a notably larger role in the 25% increase in the market. In Section 2 we provide a deeper discussion of the related literature. Section 3 details the human-based daily attribution along with the machine attribution. Section 4 covers the firm-level regressions in addition to the optimally-weighted measure of firm tax exposure. Section 5 examines prediction markets and Section 6 goes deeper into explaining the aggregate market increase. Section 7 concludes.

2 Related Literature

The events surrounding the 2016 election and the passage of the Tax Cuts and Jobs Act at the end of 2017 have attracted considerable interest in the literature. Snowberg, Wolfers, and Zitzewitz (2008, 2011, 2007) and Wolfers and Zitzewitz (2004, 2006a,b, 2009, 2016) have extensively studied prediction markets and often their relationship to financial markets, with the latter study focused on events leading up to the 2016 election. Wagner, Zeckhauser, and Ziegler (2018a) provide extensive analysis of the aftermath of the 2016 election and find that high tax firms outperformed low tax firms in the five months after the election using firm-level regressions.[8] Likewise, Wagner, Zeckhauser, and Ziegler (2018b) has similar findings for the events near the end of 2017, when momentum started to pick up for the eventual passage of tax legislation. The latter study also looks into the full sample (Nov. 2016 to Dec. 2017) and determines that a one standard deviation greater sensitivity of stock returns to taxes on a given day is associated with 33 percent of a standard deviation increase in Russell 3000 returns. However, both of these studies leave open the important question of how much of the observed cumulative market return can be attributed to taxes. One study that tackles this question is Blanchard, Collins, Jahan-Parvar, Pellet, and Wilson (2018). They primarily rely on the PredictIt probability of tax legislation being passed and find the tax

[7] Their study finds that anticipated tax cuts give rise to contractions in output and investment, with insignificant effects on consumption. Only when the tax cut is implemented do they find significant and positive effects on the macroeconomy.

[8] It should be noted that Wagner, Zeckhauser, and Ziegler (2018a) also provides a closer look into some of the days during the few months after the election using methods similar to our machine-based textual analysis in Section 3.3, as shown in their online appendix.

package contributed between 2 to 6% to the overall return. Their findings suggest that the rest of the increase is due to a lower equity premium and higher realized and anticipated dividends. Other studies such as Fisman and Zitzewitz (2019) explore this time period using a long-short portfolio based on winners and losers on election day. Hanke, Stöckl, and Weissensteiner (2020) take a similar approach but account for betting odds prior to election day. Albertus, Glover, and Levine (2021) focus more on the territorial tax implications of the TCJA in terms of foreign investment. Borochin, Celik, Tian, and Whited (2021) leverage stock and options data for the 30 days leading up to passage to develop a novel technique that accounts for anticipation, finding the TCJA's full value impact to be close to 12.5%. In contrast to our study, they focus on the 100 firms with the most liquid options, representing 23% of the market capitalization of the Compustat universe.

Additional studies have looked extensively into the subperiod from September 2017 to December 2017. Gaertner, Hoopes, and Williams (2020) study international stock price reactions to TCJA on six event days and find significant heterogeneity in market responses by country and industry. Kalcheva, Plečnik, Tran, and Turkiela (2020) also study this time period with a greater focus on the effect for firm level decisions and the broader provisions of the TCJA. While our focus is on the 283 days between election and the signing of the TCJA, the latter study also examines firm behavior after this time period. Numerous other studies have looked at the effects of the TCJA after its passage, such as Wagner, Zeckhauser, and Ziegler (2020) and Dyreng, Gaertner, Hoopes, and Vernon (2020) to name just a few.

We expand upon each of these studies by taking a unique approach that yields a detailed analysis of this period. First, in contrast to the previous studies, we qualitatively examine the news for reports of potential market drivers on each of the 283 days over this time period. While time-consuming, this process allows us to identify news-worthy events that might have influenced the stock market, including expectations about tax policy, over the 283 days. Second, our machine-based textual analysis, with over 1,500 specifications, provides greater insights into which topics were most reported on a daily basis. The human-audit combined with the machine-based textual analysis allow us to assign primary and secondary drivers to each day across a number of relevant categories. Third, we extend the firm-level cross sectional regressions over the full 283 days and use various cash effective tax rate measures that have been used the literature. We find that under some tax measures, high tax firms did not significantly outperform low tax firms over the full sample. We find similar results when using Goldman Sachs constructed tax baskets and portfolios sorted on high minus low cash effective tax rates. To our knowledge, this evidence that high tax firms may have underperformed low tax firms over the full sample is novel and further calls into question the extent to which tax policy drove the overall market. In contrast, we show that high foreign revenue firms vastly outperformed low foreign revenue firms in both firm-level regressions and portfolios constructed by quartiles. Fourth, we construct a novel probability based on the PredictIt market using daily data (Blanchard, Collins, Jahan-Parvar, Pellet, and Wilson (2018) uses rolling weekly data and does not include measures of sentiment) that shows the probability of passage of tax cuts was associated with less than a 2% increase in the market. Fifth, to our knowledge, we are the first to examine muni-implied tax rates over this time period and show they follow a similar pattern to the rest of our tax proxies.

3 Daily News-Based Attribution

3.1 Methodology

To better understand the large stock market return in the 283 days after the election, we examine the news for reported potential drivers on each of the days. This qualitative approach offers a valuable check on the more objective tax proxies described in the sections that follow because it allows us to precisely identify key drivers of the markets. Previous studies have used newspapers to better understand stock market movements such as Niederhoffer (1971), Cutler, Poterba, and Summers (1989), Manela and Moreira (2017), and Baker, Bloom, Davis, and Kost (2019b). Our analysis is similar to Baker, Bloom, Davis, and Sammon (2019a), who use a team of human auditors to examine newspapers the day after major stock-market jumps dating back to 1900. Likewise, we use daily summaries of events and market movements provided by the Federal Reserve Bank of New York.[9]

Although non-public, these summaries provide guidance for identifying the most relevant news items on any given day. We cross-check and confirm these news items with multiple publicly available sources to ensure that our analysis is not based on non-public information. Specifically, we use detailed daily write-ups provided by the Wall Street Journal, Zack's Investment Research, and Value Line. We then make judgments as to which topical category was likely the central driver on any given day. These categories include news related to the Administration Tax Policy, US Data, Oil, Geopolitical Risks, FOMC, Earnings, Global Data/ECB, and a category defined as Other, in which we could not determine a clear primary driver. Each of these categories have been identified as playing important roles on various days throughout the time period. It is important to reiterate that this qualitative analysis is 100% independent of the Federal Reserve Bank of New York and strictly based on our own judgments.

3.2 Timeline of Human Attribution

Figure 2 shows the attribution of daily market returns for each news category. In what follows, we split the full 283 day sample into a beginning (the first two months), a middle (the next eight months), and end (last four months) and discuss the primary drivers of aggregate stock returns in each of these subperiods based on the daily human attribution method.

[9] See https://www.newyorkfed.org/markets/market-intelligence for more information about the Federal Reserve Bank of New York's Market Intelligence.

3.2.1 First few months: Election to end of 2016, Upward Trend

Table 1 and Figure 3 zoom-in to only the first few months of the daily attribution results. The daily attribution shows that the largest jump on tax-related news days came on November 9th, the day after the election. Over these first two months, we observe a 5.35% total market return and 4 days that we attributed to tax-related news (primarily the few days after the election).

The main driver of the positive return over this two-month time period were days in which there were important releases of economic data. This is interesting because these data releases are backward looking and based on periods observed prior to the election. In other words, this positive data was a reflection of an existing economic environment in which unemployment was near its historical lows and had nothing to do with the outcome of the election. For instance, October existing home sales and housing starts were the highest in nine years, while third quarter GDP growth was its highest value in two years.

Over these first few months, tax policy days contributed 1.65% of the 5.35% return. Other factors such as US Data and Global Data/ECB were judged to be the most important on 9 and 4 days, respectively. Interestingly, the days for both of these categories contributed more to the overall return than the tax policy days. The Other category was associated with the most negative net effect, with most of these days falling at the end of the year when profit-taking was cited. The FOMC category also contributed negatively, primarily due to the day when the SEP showed three rate hikes in the upcoming year compared to two rate hikes in the previous projections.

3.2.2 Next 8 months: Downward Trend

The full accounting of the daily attribution over the next 8 months is shown in Table 2 and Figure 4. While the aggregate market continued to increase over this period, it is evident that some of the largest declines in the market came on days that had implications for the prospect of tax policy. However, many of these days are associated with events indirectly related to potential tax legislation. For example, early in this 8 month subsample, the administration enacted an executive order that banned travelers from Muslim countries. While the connection of this event to tax legislation may be less than obvious, investors reportedly viewed this event as implying that the administration may be less business-friendly than previously expected. In other words, this potentially less business-friendly decision may have started the process in which investors questioned the administration's commitment to passing pro-business legislation, such as corporate tax cuts.

The daily attribution also shows that there were large market declines on multiple days in which healthcare legislation failed and Robert Mueller was announced as special counsel. Again, on the surface, the healthcare legislation failures could be viewed as unrelated to tax legislation. But as we will show later, the declines we observe in numerous tax-implied measures suggest otherwise. Investors interpreted these failures as adding additional uncertainty about Congress's ability to pass a tax cut or one that was as large as promised. Similarly, the appointment of Robert Mueller also added further clouds to the prospects of tax legislation. Lastly, news of the potential resignation of National Economics Director Gary Cohn was also reportedly viewed by investors as a negative signal, as Cohn was one of the largest proponents of tax cuts in the administration.

Earnings (13 days) and US Data (33 days) days contributed the most to the 8.47% return over these eight months. Corporate earnings were strong over this time period partially due to global growth and a weaker dollar. US Data continued to push the market higher over this time period, with some of the highest annual wage gains in over a decade. Many of these data releases were consistent with a late-cycle economic environment in which unemployment was not far from historical lows. FOMC days also contributed positively to the overall market during this subsample. This is consistent with the US Data attribution, which documents that there were five consecutive below-expectations inflation prints during this time period. These lower than expected inflation prints likely reduced the extent to which monetary policy felt the need to raise rates over this time period, providing further support to the overall market. The Other category was also important during this period. On occasion, these days may reflect some news about other administration policies, such as trade or regulation. However, the vast majority of these days receive the judgment of Other because little to nothing happened and there was no clear driver.

3.2.3 Last 4 months: Upward Trend

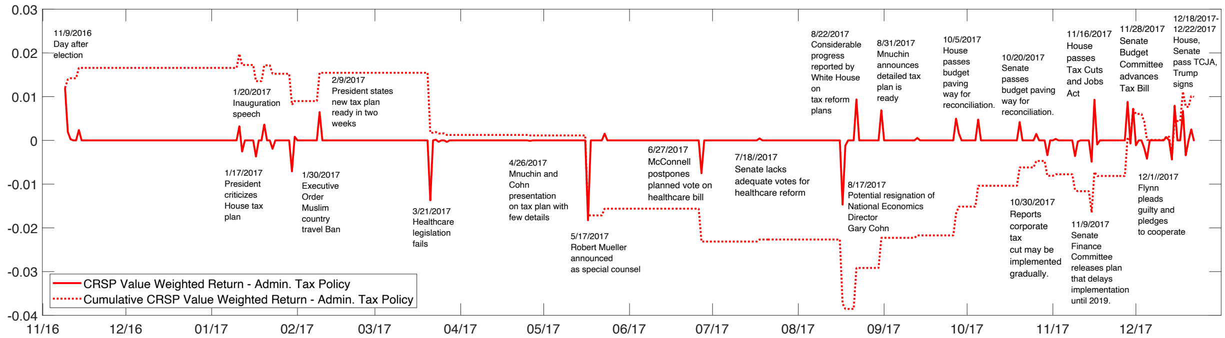
The last four months, from mid-August through the end of December, we see a similar theme to the first two months. Table 3 shows that 29 days were judged to be where tax policy was the primary driver. Close to half of the 10.5% return on the last 88 days came on these 29 tax policy days. Most of these days were associated with positive market returns, although some were not. For instance, reports that the tax plan might be implemented only gradually or with a delay were met with market declines. Continuing positive US Data also contributed about a third to the total return, with some of the highest manufacturer readings since 2011. A reduction in geopolitical risks also modestly contributed positively to the overall return during this time period. Figure 5 provides a visual daily breakdown for the last four months. One can see that most of the largest gains were attributed to days in which tax policy was the key driver.

3.2.4 Full Sample: 283 days of Up, Down, Up

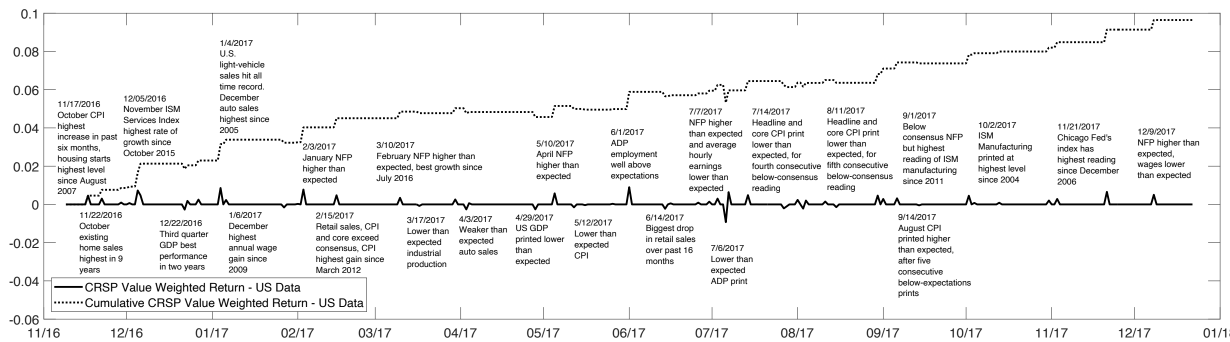
Table 4 along with Figure 6 provide the full breakdown for the daily attribution over the entire sample. Administration Tax Policy-related developments had 52 days in which they were judged to be the primary driver. Surprisingly, the net sum of market returns on these days was less than 1%. In contrast, US Data, which was judged to be the primary driver on 53 days, was associated with the largest return at 9.64%. Many of these US Data days were associated with strong manufacturing data releases, which benefited from strong global growth and a weaker dollar. Consistent with this narrative, the Earnings category had the second largest impact on the total return, contributing 5.52%. As can be seen in Figure 2 Panel (e), on many of these days, firms with large foreign exposure beat expectations, leading the market upward.

Figure 2: **Human Daily Attribution: Full Sample, Part 1 of 2**

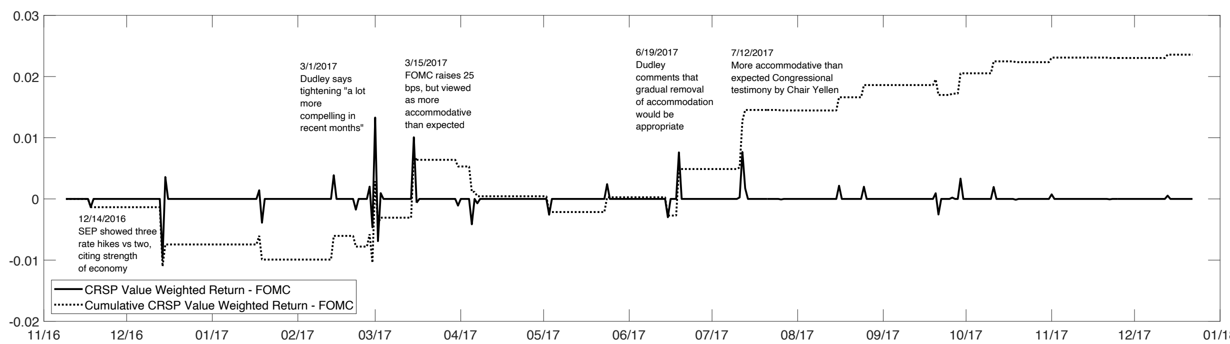
This figure shows the days attributed to each respective category based on the human-audited news approach for the full sample from November 9, 2016 to December 22, 2017. Text descriptions are given for particularly important dates. The vertical axis measures the daily CRSP value-weighted index returns and the implied cumulative returns for certain categories.



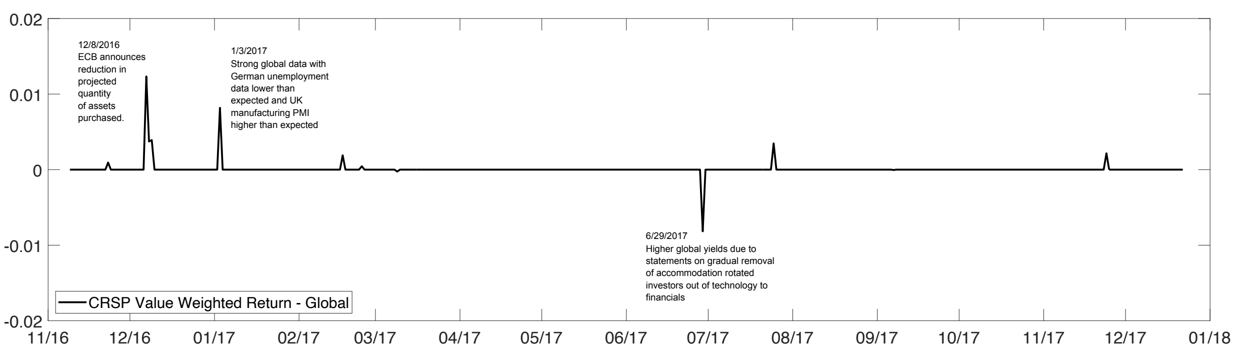
(a) Attribution: Tax Policy



(b) Attribution: US Data



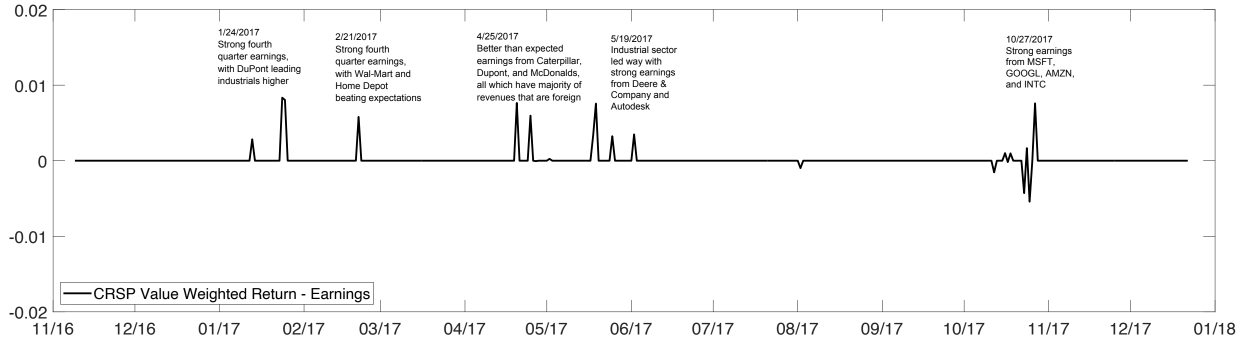
(c) Attribution: FOMC



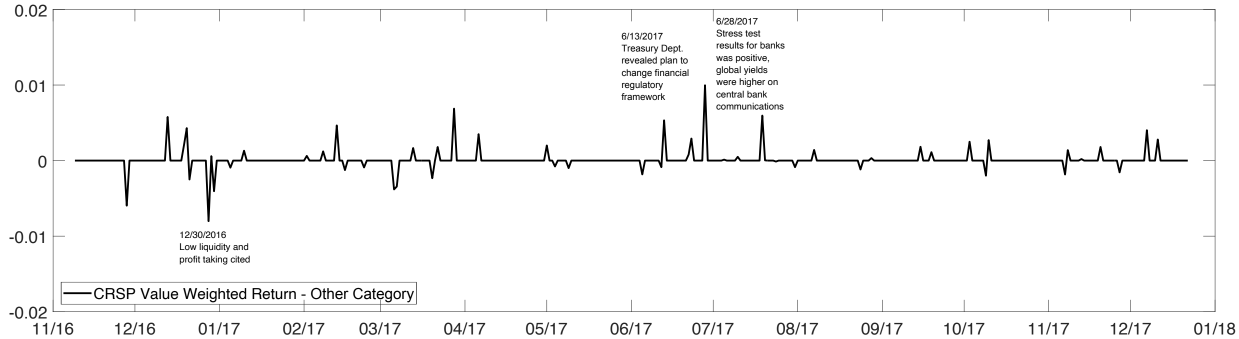
(d) Attribution: ECB and Global Data

Figure 2: **Human Daily Attribution: Full Sample, Part 2 of 2**

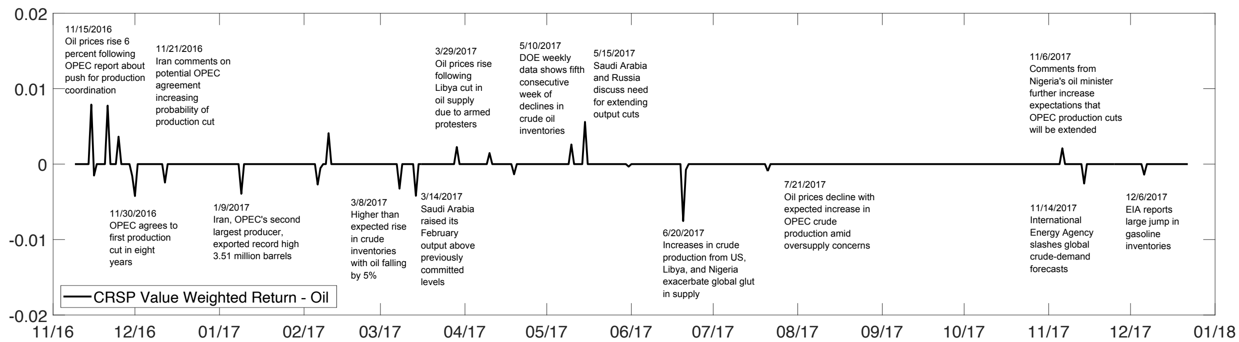
This figure shows the days attributed to each respective category based on the human-audited news approach for the full sample from November 9, 2016 to December 22, 2017. Text descriptions are given for particularly important dates. The vertical axis measures the daily CRSP value-weighted index returns and the implied cumulative returns for certain categories.



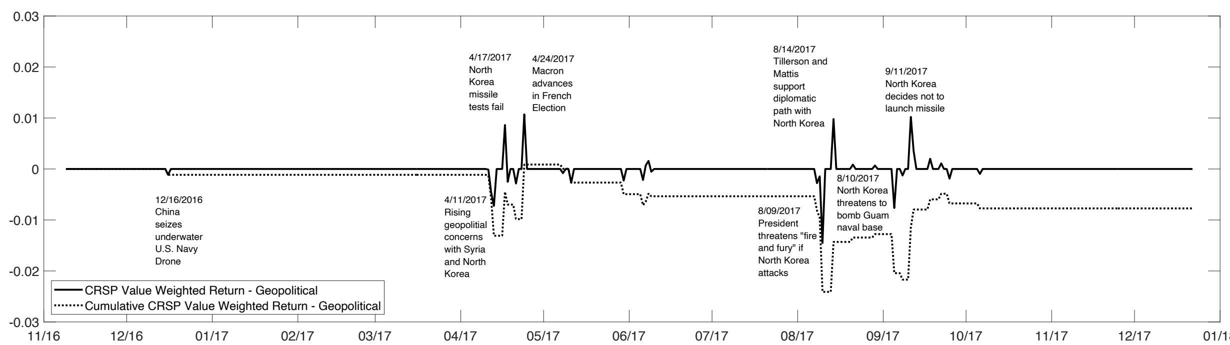
(e) Attribution: Earnings



(f) Attribution: Other



(g) Attribution: Oil



(h) Attribution: Geopolitical

Consistent with the positive global growth narrative, the Global Data/ECB category also played an important role, with close to a 3% contribution. Likewise, on days in which FOMC-related news was judged to be the primary driver (36 days), the net effect was 2.36%. The positive net effect is consistent with decisions that were often viewed as more accommodative than expected by investors [Figure 2 Panel (c)]. These decisions were likely partially driven by the five consecutive below expectations inflation prints that are documented in Figure 2 Panel (b). With inflation coming in below expectations, this potentially provided monetary policy with room to not respond as much as they otherwise would have to the relatively strong data releases and the prospect of future tax legislation.

The two categories that contributed negatively to the overall return were Geopolitical Risks (29 days) and Oil (25 days). Days on which Geopolitical Risks were judged to be the primary driver were often associated with headlines surrounding North Korea, as shown in Figure 2 Panel (h). Oil days also ended up contributing negatively to the total return, albeit modestly. Figure 2 Panel (g) shows that the energy sector was frequently beset by oversupply concerns.

The last category is classified as Other (55 days). As shown in Figure 2 Panel (f), most of these days are ones in which the market was little changed and/or it was difficult to identify a primary driver. A few of these days were associated with announcements regarding administration regulations or stress testing results. Overall, we find that the Other category contributed 3.9% to the total return.

The cumulative effects of each category are plotted with the cumulative market return (solid green line) in Figure 7. The legend is ordered based on the magnitude of the cumulative return for each category, with US Data contributing the most. We can see that Administrative Tax Policy (solid red line) was a key contributor at the beginning and end of sample, but declined significantly in between. In the middle of the sample, the overall market continued to climb as positive US Data and positive Earnings days seemed to dominate. Overall, Figure 7 shows that different categories played key roles in the steady rise in the overall market over this time period. More importantly, the figure suggests that tax-policy related days were not the main driver throughout the entire sample.

3.3 Machine Daily Attribution

To address concerns about biases and inconsistencies that could arise in the human-based attribution, we apply a machine technique that employs the Bloomberg News Trend Function. The Bloomberg News Trend Function allows for us to count the number of times a specific word or phrase has been used in various major news outlets on any given day. In an attempt to mitigate concerns about robustness, we consider over 1,500 specifications and provide a full discussion of the procedure in Internet Appendix A.

Table 5 summarizes the differences between the human attribution and the machine attribution across the 1,500 specifications. On average, the machine attributes 2.61% of the total return to taxes compared to 0.99% when using the human attribution. Figure 8 shows the cumulative return for the Tax category across all the specifications along with the mean on each day (blue), with the human attribution (green) plotted for comparison. There are two notable differences between the machine and human attributions across the entire sample. First, the machine on average attributes relatively fewer days in the initial months after the election to taxes compared to the human attribution. Interestingly, a number of these positive market days identified by taxes in the human attribution were attributed to deregulation by the machine. Second, the machine on average attributes relatively fewer days in the middle of the sample to taxes as well. As noted in Section 3.2.2, the human attributes multiple market decline days to taxes when the perceived likelihood of tax legislation fell due to the failure to pass healthcare reform and the appointment of Robert Mueller. A nontrivial amount of the machine specifications also attribute these days to taxes, consistent with observed declines in the prediction markets and the constructed tax baskets, but a considerable portion do not.

Despite these two differences, the exercise largely confirms the main finding from the human attribution that tax policy was not the primary driver of the aggregate market return over the 283 day sample. In fact, the most optimistic machine specification attributes only 7.12% of the overall return to tax news. Internet Appendix A provides a more extensive discussion that includes numerous robustness checks and a breakdown of the other key market factors.

4 Firm-Level Regressions

In this section, we move beyond the daily attribution and shift our focus to firm-level regressions. Firm-level regressions provide us with the ability to better disentangle the primary drivers of the cross-section of returns at various points over the full sample.

Before diving into the set of firm-level regressions, it is useful to look at the performance of the top and bottom quartiles of firms based on either (1) effective tax rates, or (2) dependence on foreign revenues. The red line of Figure 9 shows the difference in cumulative returns for the highest-taxed firms (i.e., firms in the fourth quartile of the cash effective tax rate) and the lowest-taxed firms (i.e., the first quartile).[10] Similar to the other approaches considered in the paper, the prospect of tax legislation at the beginning of the sample is reflected as high-tax firms outperform low-tax firms in the first three months. Across the full sample, low-tax firms outperform high-tax firms with most of these relative gains coming from March to November 2017. High-tax firms make a strong comeback in December of that year as the TCJA makes progress through Congress and is eventually signed into law, but never fully overcome the cumulative returns of the first quartile.

In contrast, firms with a relatively high degree of reliance on foreign revenues outperformed firms who were less exposed to the foreign sector. This finding is illustrated by the green line in Figure 9 which shows the difference in cumulative returns between firms in the highest quartile of

[10]See Internet Appendix E.4 for more details on the construction of this portfolio.

the percentage of foreign revenue and those firms in the lowest quartile. For the initial four months after the election, firms in the highest quartile of foreign revenues were outperformed by firms in the lowest quartile. However, the performance of foreign-exposed firms reversed course as the dollar became weaker and positive global growth news emerged throughout 2017. Ultimately, the portfolio consisting of firms with highest percentage of foreign revenues outperformed the portfolio with the lowest foreign revenues.

These comparisons between quartile portfolios suggest that higher dependency on foreign revenues, and not a high tax rate, explained the firms who relatively outperformed in the full sample. To investigate this further, we estimate cross-sectional regressions of cumulative returns for various time spans after the election on a number of firm-specific characteristics.[11] In our baseline regressions in Table 6 , we consider a firm's (i) cash effective tax rate, (ii) market value of equity, (iii) revenue growth, and (iv) profitability.[12] Internet Appendix B outlines the sources and specific data used in the cross-sectional regressions. The first column of Table 6 displays the coefficient estimates and the associated standard errors for the various firm characteristics in a regression with firm-specific returns on the day after the election (November 9, 2016). The cash effective tax rate is statistically significant, matching the aggregate results that the prospect of tax legislation drove returns early in the sample. Moving to the second column, the cash effective tax rate remains a significant explanatory factor of cumulative returns from the election to April 28, 100 days after the inauguration. The third columns illustrates the flailing prospects of tax legislation one-year after the election (November 8, 2017) as the tax rate is no longer significant. However, the cash effective tax rate regains significance in the run-up to the passage of the TCJA (December 22, 2017).

4.1 Alternative Measures of Tax Exposure

The literature suggests that the one-year cash effective tax rate may be an inappropriate measure of tax exposure (or, alternatively, the market's perception of a given firm's future tax exposure). Dyreng, Hanlon, and Maydew (2008) find that a firm's cash effective tax rate constructed over longer horizons is a better measure since the one-year tax rate rate may capture an anomalous year

[11] We use raw cumulative returns rather than CAPM or Fama-French abnormal returns because a number of our firm-specific tax measures (GAAP ETR, Δ, and CashETR10^{w}) as well as foreign revenues are significantly positively correlated with a firm's market beta. As pointed out by Wagner, Zeckhauser, and Ziegler (2018a), using adjusted returns in this scenario would potentially underestimate the effect of these variables of interest and lead to incorrect inference on the role of taxes or regulation in explaining the cross-section of returns.

[12] We report specifications that exclude industry-level fixed effects since they absorb the substantial between-industry variation in our primary variables of interest. This is particularly true for foreign revenues, as illustrated by an R-squared of 0.30 from a cross-sectional regression of foreign revenues on the Fama-French 38 industry fixed effects. The inclusion of other firm-level characteristics in the regressions should control for aspects of firm returns typically proxied for by industry effects. Insomuch as variation in firm returns maybe driven by industry factors that are not captured by these firm characteristics, this choice may affect inference. Therefore, we reestimate our main tests with industry-level fixed effects as a robustness check. Unless otherwise noted in the text, results that include these industry-level fixed effects, and thus focus on within-industry variation in our primary variables of interest, are qualitatively similar.

of tax data. Additionally, Henry and Sansing (2018) notes that the common practice of removing firms with negative pretax income or negative effective tax rates can lead to substantially different results when using CashETR as a measure of tax exposure. In order to check the robustness of our findings, Table 7 repeats the previous regressions using four alternative measures of tax exposure instead of the one-year cash effective tax rate.

The first alternative metric, GAAP ETR, is the ratio of a firm's total income taxes based on the Generally Accepted Accounting Principles (GAAP) to pretax income. GAAP ETR is a common alternative effective tax rate measure to CashETR, though it suffers from the same sample restrictions as pointed out by Henry and Sansing (2018). The regression results presented in the first panel of Table 7 using GAAP ETR shed some doubt on the significance of firm-level tax exposure explaining returns across the various horizons considered. Despite still being significant on the day after the election, tax exposure is no longer a significant explanatory factor at explaining positive returns in the cross-section. In fact, GAAP ETR suggests firms with relatively higher tax exposure experienced significantly lower returns. This result matches the finding from the other methodologies considered in this paper that the stock market began to drag as the likelihood of tax legislation began to diminish.

The second alternative measure of firm-level taxes comes from Henry and Sansing (2018) which they call Δ. The Δ measure is constructed as a firm's cash taxes paid after adjusting for tax refunds receivable minus its pretax income times the prevailing marginal corporate tax rate. Intuitively, Δ measures whether a firm pays more or less than the implied statutory amount, and therefore if they are a tax-favored or tax-disfavored firm. As suggested by Henry and Sansing (2018), we normalize Δ by the market value of assets (MVA). Similar to GAAP ETR, the regressions in the second panel of Table 7 using Δ find that high-tax firms outperformed on the day after the election but significantly underperform by April 28. In addition, Δ suggests that firms continued to significantly underperform one year after the election.

The tax measures previously considered may not accurately reflect a firm's future ETR. That is, the current CashETR, GAAP ETR, and/or Δ may not be good predictors of investors expectations of a firm's realized future tax rate. Using this logic, Wagner, Zeckhauser, and Ziegler (2018a) rely on the past one-year CashETR measure since it provides a more accurate fit of the current ETR than the firm's past ten-year CashETR. However, we find that neither of these two horizons (the one-year and ten-year ETRs) were the best predictor of a firm's current ETR. A trade-off exists between using a relatively short or long history of past ETRs in predicting the current ETR. A relatively short horizon may be noisy, whereas a very long horizon of tax history may contain past tax characteristics that are no longer relevant. To determine the optimal amount of past tax information, we regressed the current CashETR on each potential ETR history from one to ten years. We calculate a firm's past h-year CashETR by taking the sum of cash taxes paid over the past h years divided by the sum of pretax income over that same horizon:[13]

$$\text{CashETRh}_{t-1} = \frac{\sum_{j=1}^{h} TXP_{t-j}}{\sum_{j=1}^{h} PI_{t-j}}.$$

The sample included all firms in Compustat with ten consecutive non-missing year observations over the period 1987 to 2015. The first ten rows of Table 8 show the estimated coefficient for each historical ETR and its associated R-squared. Our results suggest the historical three-year CashETR (CashETR3) is actually the best predictor of a firm's current CashETR, so we will consider this as the third alternative to the one-year CashETR as a measure of tax exposure. Interestingly, the past one-year CashETR provided the worst fit of the histories considered.

Taking this idea further, one could calculate the optimal predictor of current CashETR using optimized weights of each past year's tax information. We find the optimal weights by solving the following problem:

$$\min_{w_1 \geq 0, \ldots, w_{10} \geq 0} \sum_t \sum_i \left(\text{CashETR}_{it} - \frac{\sum_{j=1}^{10} w_j TXP_{t-j}}{\sum_{j=1}^{10} w_j PI_{t-j}} \right)^2 . \tag{1}$$

The only restriction placed on the weights w_j are that they are non-negative, so the set of possible weightings includes the standard measures of a firm's historical ETR. Figure 10 plots the optimal weights (solid line) compared to the standard, flat weights (dashed line) of CashETR10 as outlined by Dyreng, Hanlon, and Maydew (2008). Compared to the standard weighting, the optimal measure places relatively more weight on the three most recent years and relatively less weight on the later seven years. This overweighting of the three recent years coincides with CashETR3 being the optimal predictor of standard historical ETR measures.[14] Using these optimal weights, we construct the optimal predictor CashETR10^w. The last row of Table 8 shows that, perhaps unsurprisingly, CashETR10^w dominates the standard, flat historical ETRs in predicting the current ETR.

The third and fourth panel of Table 7 display the regression results of using CashETR3 and CashETR10^w as the alternative measure of tax exposure, respectively. As with CashETR, GAAP ETR, and Δ, both of these alternatives reinforce the finding that higher-tax firms outperformed on the day after the election. However, taxes based on these two alternative measures fail to explain differences in firm-level cumulative returns at both of the intermediate horizons. Similar to the results using the one-year CashETR, both CashETR3 and CashETR10^w regain significant explanatory power in the last month leading up to the passage of tax legislation.

In summary, these cross-sectional results corroborate the findings of our other approaches. Taxes provided an initial boost to stock returns after the election, this effect dissipated in early to mid 2017, and reemerged in the last month before passage of the TCJA. All the various tax

[13] Pretax income is adjusted for special items as in Dyreng, Hanlon, and Maydew (2008) and Wagner, Zeckhauser, and Ziegler (2018a).

[14] We should note that although there is a downward trend of the weights, they do not decrease monotonically across the lag horizon. One potential explanation is that the weights are point estimates and standard errors might find no statistical difference of weights between some horizons.

measures show this “up, down, and up again” behavior in explaining the cross-section of cumulative returns.

4.2 Considering Foreign Growth and Regulation

The previous section considered only differences in firm-level tax exposure in trying to explain differences in cumulative returns. As illustrated by the other methods outlined in this paper, there exists two other important factors that might explain cross-sectional differences: strong global growth and potential changes in regulation policy. We measure an individual firm’s exposure to the foreign sector by the percent of revenues from foreign sources. Since there is not a well-accepted measure of firm-level exposure to regulation in the literature, we construct a novel metric based on a firm’s self-reported risk factors. Our proxy takes the ratio of the number of words which begin with either “regulat-” or “deregulat-” to the total number of words in Item 1A of the firm’s 2015 Form 10-K disclosure.[15]

Table 9 augments the previous regressions with foreign revenues and our novel regulation-exposure measure. Each horizon-specific regression includes one of the various tax measures considered in the previous section along with the other firm-specific controls. The “up, down, and up again” pattern of taxes explaining the cross-section of cumulative returns is retained even after controlling for exposure to foreign growth and regulation. For four of the five tax measures, high-tax firms experience significantly higher returns than relatively low-taxed firms on the day after the election. However, this relationship loses significance throughout the next year as the likelihood of tax legislation falls. Despite the point estimates increasing from November 9 to December 22 for all specifications, only the regression results using the one-year CashETR find that taxes are a significant explanatory factor for the cross-section of cumulative returns across the entire sample.

As seen in the second row of each panel in Table 9, the estimation results for the percent of revenues from foreign sources also match the findings of our other approaches. Early in the sample, there is no (robust) significant difference in performance between firms with relatively high- or low-exposure to the foreign sector. However, firms with large foreign revenues outperform their counterparts throughout the following year as the percent of revenues from foreign sources becomes statistically significant one-year out from the election and when the TCJA was signed into law.

The third row of each panel in Table 9 tell a similar story for regulation exposure explaining variation in returns. For all specifications, firms with a high-degree of regulatory risks outperform those with low regulatory risks on the day after the election as deregulation via executive orders became more likely. One year after the election, regulation exposure is again significant across the various tax measures. For three of the five tax measures, we find regulation remained a significant explanatory factor even up to the signing date of the TCJA.

These augmented regressions reinforce the findings of our other approaches. Taxes only played a

[15] We exclude the words ”a”, ”an”, ”the”, and ”and” in our count of total words.

marginal role in explaining stock returns across the 283 days. Rather, exposure to other important factors, such as foreign growth and regulatory changes, played a more substantial role in explaining differences in cross-sectional returns across the full sample.

4.3 Recursive Daily Regressions and Daily Attribution

For completeness, we estimate this same regression of cumulative returns since the election on one of the five tax measures, the percent of revenues from foreign sources, and the constructed regulation exposure measure for every single day in our sample. The t-stats for each of the key explanatory variables are shown in Figure 11 across specifications which differ only on the tax measure. The horizontal lines represent the 10% critical t-value.

The first subfigure of Figure 11 show the recursive t-stats for the various tax measures. The overall trends match well with the findings of the quartile portfolio comparison presented earlier in this section. In the aftermath of the election, higher tax rates were a significant, positive explanatory variable for the distribution of returns across firms. However, this relationship disappears in the summer and only reappears for the one-year CashETR as the TCJA passes through Congress and is eventually signed into law. Using GAAP ETR, Δ, or the optimal predictor CashETR10^w substantially mitigates these findings as these measures lose significance by March 2017 and none of these measures regain significance by December 22. Nevertheless, the estimation results for foreign revenue exposure are consistent across the five tax measures, as shown in the second subfigure of Figure 11. Early in the sample, foreign revenues actually have a significant negative relationship with firm-level cumulative returns. As the dollar weakens and global growth picks up, foreign revenues eventually become a positive significant factor for explaining cross-sectional returns. As illustrated by the last subfigure of Figure 11, the statistical significance of the regulation measure mimics the tax rate for the first half of the sample as it is highly significant early in the sample, and loses significance in early 2017. However, regulation regains significance in the middle of the summer and slowly mitigates late in 2017 as taxes regain some explanatory power. This finding suggests that expectations for tax policy were not a key driver for the stock market in the 283 days after the election; other policies, such as the presidential administration's regulation policy, could have played a more vital role.

Two of the approaches previously considered attribute daily aggregated returns based on either a human-audited news assessment or a machine-based specification. In spirit with those approaches, we attribute a given day's aggregate market return based on which variable (taxes, foreign revenues, or regulation) was most significant in explaining the cross-section of stock returns on that day. That is, we first regress daily firm-level returns on each of the tax measures, the percent of revenues from foreign sources, our novel regulation measure, and the other firm-level controls. A comparison is then made between the t-stats for the variables of interest for each day. Daily aggregate returns are attributed to taxes when the t-stat is largest for the tax rate (and matches the sign of the aggregate return for that day). Similarly, daily returns are attributed to foreign revenues or regulation when the t-stat for either respective variable is largest (and matches the sign of aggregate returns). If neither of our three variables of interest is statistically significant (or match the sign of that day's aggregate return), we attribute that day to other factors.

Figure 12 displays the cumulative returns from this regression-based daily attribution. Again, the results reinforce the findings of the human- and machine-based attributions. Taxes were important at the very beginning of the sample, but end up explaining a relatively low amount of the overall cumulative return in aggregate market over the full 283 days. Foreign revenues stand in stark contrast to the tax rate as it consistently rises over the sample and explains a substantial portion of the cumulative returns. Regulation exposure played a similar role to taxes according to a number of the tax measures based on this daily attribution method.

5 Analyzing Prediction Markets

PredictIt.org is a betting website that tracks market-implied probabilities for various events of interest. Immediately after the election, PredictIt constructed a market that paid out depending on whether or not a personal or corporate tax cut would be passed by the end of 2017. This market imposes betting limits of $850 and its liquidity, although limited, is similar to that observed in the federal funds futures market. For instance, the total volume over the period was over 800,000, which is close to 3,000 trades a day, a number that is not far off from the historical average volume of a 6-months out federal funds futures contract (approximately 4,500).[16]

Aside from potential liquidity concerns, the main issue with this tax proxy is that PredictIt placed an arbitrary deadline on the passage of legislation as the end of 2017. It wasn't until October 24, 2017 that PredictIt came out with a second betting market that asked the same question but changed the end date to 2018. On the day the new 2018 market was created, the probability of tax legislation being passed was 59% vs 22% for the 2017 market. This suggests that using the arbitrary deadline of the end-of-2017 created a tax proxy that was likely understating the chances that tax legislation would be passed unconditionally, which is how equity markets would be pricing in such an event.

To address this concern, we construct a novel measure of the probability by projecting the end of 2018 measure onto the 2017 measure when both were simultaneously available. We then use the predicted coefficients from this regression to backfill the 2018 measure using the dynamics of the 2017 measure. Plotted in Figure 13 is the end result, with our novel measure shown in red. Note, that this measure never falls below 0.5, in contrast to the 2017 measure, which falls below 0.2 in October and November of 2017.

We take this measure (in addition to the existing probabilities) and determine their relationships

[16]PredictIt.org shows that the total volume was 459,247 and 390,272 for the corporate and personal tax cut, respectively. Historical volume data for federal funds futures is from the CME Group via Quandl dating back to 1988.

with the aggregate market return in regressions at the daily frequency. We also include the MSCI World-excluding-US return as some sort of proxy for international developments (which, admittedly, may be influenced by domestic developments and vice versa). Additionally, one could argue that the PredictIt measures do not fully reflect consumers' and investors' increased optimism about the economy, which then drove increased market returns.[17] To control for any sentiment effects, we also include daily changes in the Gallup Economic Confidence Index.[18] Specifically, we regress the daily returns of the CRSP value-weighted market portfolio onto the daily changes in our variables of interest.

Table 10 shows the results and there are several takeaways. First, by themselves, the daily changes in the existing probability measures have an insignificant relationship with the daily market return. Only when we move to our novel construction do we find a positive and significant relationship. This relationship is relatively small, with a movement from zero to 1 for the probability of passage associated with a 1.72% return. Second, we do find significance for the 2017 corporate tax probability when we include the MSCI World-excluding US return but the probability's effect is less than 1% . With our measure, the effect is three times as large at 1.92% and also more significant. Third, the individual tax cut measure seems to have the opposite sign and is insignificant, indicating that individual tax cuts may have been less of a focus relative to the corporate tax cuts. Fourth, the regressions seem to want to attribute a much greater share to the international index. And lastly, economic confidence is not significant in any of the specifications.

A potential caveat to this analysis is that these probability measures began the day after the election, so that using changes would exclude this first day from the analysis. There was a relatively large increase in the market on this first day so it might be important not to miss this day. To address this concern, one could assume a 50% increase on the day after the election (which would indicate that the probability went from 30% to 80%). With this assumption in place, we find the implied effect of the corporate tax cut does increase and become more significant, but only rises modestly, with a movement from zero to 1 for the probability of passage associated with a 2.52% return.

6 Explaining the Aggregate Market Increase

6.1 The "Up-Down-Up" Effect of Taxes

In Section 3, the human daily attribution of news showed that taxes first put upward pressure on the stock market for the first few months of the sample, followed by eight months of downward

[17] In fact, Lewis, Makridis, and Mertens (2020) finds that over the period Feb. 2008 to Dec. 2017 the largest single day increase in economic confidence occurred on Nov. 9, 2016 (the day Clinton conceded) and the third largest occurred on Dec. 20, 2017 (the day the tax bill was passed by the Senate).

[18] We also considered two alternative measures of daily sentiment – the Rasmussen Consumer Confidence Index and Rasmussen Investor Confidence Index – and the results are nearly identical.

pressure, and upward again as the prospect of tax legislation became more likely. Cross-sectional firm regressions corroborated these findings, as well as our analysis of prediction markets. To further justify this "up-down-up" narrative, Figure 14 plots key metrics that reinforce this "up-down-up" narrrative.

The first panel compares the performance of the broad US stock market, as measured by the CRSP value-weighted index, to the European market measured by the FTSE. The second panel shows the cumulative return of two portfolios constructed on the cross-section of tax exposure: the Goldman Sachs High minus Low Tax Basket Portfolio and a portfolio based on quartiles of firms' cash effective tax rate.[19] The third panel shows the PredictIt implied probability of either a corporate or individual tax cut. The fourth panel shows an implied tax measure from the spread between municipal and Treasury bonds.[20] The final two panels plot two macroeconomic financial indicators: the value of the US dollar and long-term inflation expectations.[21]

In the first few months after the election, a number of factors drove the aggregate market as nearly all of the measures move in tandem in a positive direction. First, the CRSP value-weighted index jumped out to a 5 percent relative outperformance of the European FTSE index in the days after the election [red line, Panel (a)], indicating that domestic markets may benefit more from the outcome of the election than global markets. Second, in terms of the cross-section, we see in Panel (b) of Figure 14 that the high tax firms outperform low tax firms as constructed by Goldman Sachs and also based on our construction with the cash effective tax rate. Third, the PredictIt measure began on the day after the election with an 80% likelihood of passage for corporate and individual tax cuts in betting markets and remained elevated as shown in Panel (c). Fourth, the muni-implied expected future tax rate measure also declined over this time period [Panel (d)], consistent with the notion of increased likelihood of lower taxes. Finally, the macroeconomic financial indicators of 5-year, 5-year forward inflation compensation and the DXY US dollar index both rise and remain elevated in the two months after the election [Panels (e) and (f)]. The latter increases are consistent with investors pricing in positive fiscal stimulus amid late business-cycle dynamics with expectations of higher inflation and correspondingly higher nominal rates, which could push up the value of the dollar.

In contrast to the first two months, which saw consistent gains across all of our measures, the

[19] See Section E.1 in the Internet Appendix for more details.

[20] This approach has not been applied with respect to this time period in previous studies. Unlike Treasury bonds, municipal bonds are tax-free and thus can act as a proxy for implied future tax rates. We confront the potential liquidity and credit risks in these measures with a wide set of controls. For simplicity and expositional purposes, we focus on a five year maturity and discuss its construction and controls in the Internet Appendix (other maturities yield similar results).

[21] Both of these macro-financial variables were considered by market participants as indicators for the prospect of tax legislation. That's because the tax stimulus occurring near the end of a long expansion was expected to increase inflation, raise rates, and increase the value of the dollar. This sequence of events has frequently been cited as the "Trump trade." Wall street firms such as Goldman Sachs tracked these metrics and discussed their relationship to the prospect of tax legislation throughout 2017. (See Goldman Sachs US Daily, May 19, 2017.)

eight months that followed paint a different picture. These 8 months, starting in January 2017 and going through August 2018, show a very different relationship between our measures and the overall market return. Figure 14 Panel (a) shows that the CRSP-value weighted return was surpassed by the European FTSE index near the middle of the year. This is consistent with a global growth narrative in which the Eurozone growth hit a 10-year high in 2017, surpassing US growth. Panel (b) shows that the high tax firms start to underperform relative to the low tax firms. We also start to see the probability of a corporate tax cut based on the PredictIt measure start a downward trend over a similar time period [Panel (c)]. Likewise, the muni-implied measure of expected future tax rates [Panel (d)] rises back above where it was prior to the election, with a large jump up at the end of January.

We see similar dynamics with the inflation compensation and dollar index measures. The inflation compensation [Panel (e)] stops rising around the end of January and starts a downward trend. We also see further declines in the value of the dollar, as shown in Panel (f) of Figure 14. The decline in inflation compensation and the value of the dollar is consistent with investors exiting the trade in which tax cuts were expected to boost inflation, nominal rates, and the value of the dollar. This notion, combined with the outperformance of international growth, contributed to the decline in the value of the dollar to levels below that observed on the day of the election.

This decline in the value of the dollar played an important role in the surge in domestic industrials and the earnings releases of multinationals. For instance, over 40% of S&P 500 companies derive revenues from foreign sources, which would be boosted by a weaker dollar. This relative importance of foreign revenues and the global growth narrative will be further explored in Section 6.3.

Moving towards the last two months of the full sample, we see the CRSP value-weighted return make-up ground on the European FTSE index, with the CRSP return rising faster [Panel (a)]. The cross section measure also starts to rise in the last two months [Panel (b)] as well as the PredictIt probabilities [Panel (c)]. Likewise, Panel (d) shows that the muni-implied tax measure declines back to levels below the election day level. We also see rises in inflation compensation and the value of the dollar, as seen in Panels (e) and (f), respectively. Again, these moves are consistent with increased expectations of positive effects of future tax cuts.

Remarkably, over the full sample, we see that the cumulative returns in our cross-section measures imply that high tax firms underperformed low tax firms, on net [Figure 14, Panel (b)]. This provides evidence that while there were time periods in the beginning and the end of the sample that corresponded with high tax firms outperforming, tax policy was not the main driver of the large market return observed over the full sample. Crucially, this underperformance of high tax firms over the full 283 days would be missed by focusing only on the short time periods around the beginning and ending of the sample.

6.2 Gordon Growth Exercise

How could a 14% drop in the corporate tax rate only translate into a 1 - 2.5% aggregate market increase? In this section, we take a more mechanical approach to determining what investors might have expected to see based on a standard Gordon Growth discounted cashflow model. We start with the most basic scenario that some likely had in mind: A permanent reduction in the statutory tax rate that fully translates into higher cash flows. Under this benchmark scenario, the implied increase in the stock market is substantially larger than the moderate increase suggested by our various methods. We then adapt the model to consider sensible departures from this baseline, including (1) effective tax rates (based on taxes actually paid), (2) some elimination of loopholes (3) a reduction that is not permanent, and (4) a response by monetary policy.

6.2.1 Baseline Exercise

The baseline scenario is for a permanent reduction in statutory rates, no elimination of loopholes, and no response of monetary policy. We consider a Gordon-growth type model to analyze the implied market return from the tax cut:

$$P^{old} = \frac{(1-\tau^{old}) \cdot D}{r-g}$$

$$P^{new} = \frac{(1-\tau^{new}) \cdot D}{r-g}$$

$$Return = \frac{P^{new}}{P^{old}} = \frac{1-\tau^{new}}{1-\tau^{old}} = \frac{1-0.35}{1-0.21} = 21.5\%$$

Coincidentally, this calculation is fairly close to the overall observed return in the 283 days after the 2016 election of around 25% which appears to run counter to our moderate findings. But most firms do not pay the statutory tax rate. Due to the presence of loopholes and other distortions, the effective tax rate – the tax rate firms actually pay – is much lower.

6.2.2 Effective Tax Rate Scenario

Below, we conduct the same exercise but consider the cut in effective tax rates instead of statutory rates. To compute the new effective rate (while assuming no reduction in loopholes) we subtract the ratio of the old effective tax rate to the old statutory rate multiplied by the change in the statutory rates:

$$\tau^{eff-new} = \tau^{eff-old} - \frac{tax^{eff-old}}{tax^{stat-old}} \cdot \left(tax^{stat-old} - tax^{stat-new}\right) = 0.25 - \frac{0.21}{0.35}(0.35 - 0.21) = 15\%$$

$$Return = \frac{1-0.25}{1-0.15} = 13.3\%$$

This is still a fairly large return, making up more than half of the observed return over the time period. However, the legislation also included removal of loopholes in an attempt to broaden the base.

6.2.3 Effective Tax Rate With Removal of Loopholes Scenario

Instead of the effective rate falling to 15%, Blanchard, Collins, Jahan-Parvar, Pellet, and Wilson (2018) estimate that the effective rate would only fall 4%. The analysis of Wagner, Zeckhauser, and Ziegler (2020) suggests that the effective rate fell from 22% to 17%. If we use those values instead

$$Return = (1 - 0.22)/(1 - 0.17) = 6.4\%$$

By incorporating the estimated effects of the removal of loopholes, the estimated return declines by more than half.

6.2.4 Effective Tax Rate With Removal of Loopholes, 50 Years Scenario

What if we assume that the tax cut was transitory and not permanent? While a reasonable period might be considered 30 years, we assume for this calculation that the tax rate is changed for 50 years and then reverts back to its old effective rate. If this happens, the return drops to 4.9%.

$$P^{new-0-50} = \frac{1-\tau^{eff-new}}{1-\tau^{eff-old}} \cdot \left(1 - \left(\frac{1+g}{1+r}\right)^{50}\right) \frac{D}{r-g}$$

$$P^{new-50-\infty} = \left(\frac{1+g}{1+r}\right)^{50} \frac{D}{r-g}$$

$$P^{new} = P^{new-0-50} + P^{new-50-\infty}$$

$$Return = \frac{P^{new}}{P^{old}} = 4.9\%$$

6.2.5 Effective Tax Rate With Removal of Loopholes, 50 Years Scenario with Modest Response of Monetary Policy

What happens if interest rates go up? Note that the Federal Reserve unexpectedly increased its SEP projections in the meeting following the election by 25 basis points. Moreover, R-star measures (a proxy for the long-term interest rate at which the economy is neither expansionary nor contractionary) increased over the 283 days after the election by an average of about 10 basis points.[22] If we incorporate this into our calculations, it increases the denominator by 0.1% and the return can be shown to decline to 1.63%.

[22] See R-Star estimates for Laubach and Williams (2003) and Holston, Laubach, and Williams (2017).

Overall, the 21.5% return the model predicts under the baseline assumptions declines once we account for (1) differences in effective tax rates (to 13.3%), (2) removal of loopholes (to 6.4%), (3) possibly non-permanent change in taxes (to 4.9%), and (4) a very modest but persistent monetary policy response (to 1.6%). These exercises suggest the estimated effects from our other approaches (1 to 2.5%) are not too distant from what one would find in a Gordon growth exercise with sensible modifications.

6.3 The Synchronized Global Growth Narrative

The importance of global growth is a key theme for understanding the market over this time period. In this section, we summarize some of the evidence and leave a full discussion for Internet Appendix D. Specifically, we point to two key indicators: (1) the Citigroup Economic Surprise Indices and (2) foreign inflation.

The Citgroup Economic Surprise Index (CESI) captures the extent to which data releases were coming in higher than expected. As shown in Figure 15, the Global CESI was almost exclusively below zero for the entirety of 2015 and into the first half of 2016. The index crosses into positive territory in mid-2016 and then becomes relatively elevated for most of 2017. These elevated global readings can be explained by a few items: (1) Eurozone growth hit a 10-year high in 2017, surpassing US growth over this time period, (2) none of the Eurozone's 19 members had deflation for the first time in over a half-decade, and (3) 2017 was the first year since the crisis that no major economy was in contraction mode. As shown in Panel (d), inflation in the Eurozone and the UK jumped up dramatically in 2017, reaching multi-year highs. Most importantly, these increases started to occur prior to the election. Internet Appendix D provides a more extensive discussion along with additional supporting evidence on the importance of global growth over this time period.

7 Conclusion

How much did the promise of tax legislation contribute to the 25% return in the 283 days after the election? Our study tackles this challenging question using some novel approaches that yield a detailed and exhaustive forensic analysis of this time period, generating a number of contributions and insights.

First, we carefully read the news and make judgments about the drivers on each of the 283 days based on daily summaries of events and market movements provided by the Federal Reserve Bank of New York (which we cross-check with publicly available sources). This time-consuming process allows us to better identify key events and get a clearer sense of how important tax policy news was over the 283 days. We conclude that tax policy-related days account for 52 of the 283 days with a net market return of 0.99%. We document several key dates in the middle of the sample that had indirect but important negative implications for the prospects of passage of tax legislation. We corroborate this evidence with a machine-based textual analysis with over 1,500 specifications, which finds the estimated average total return on tax-related days to be 2.5%. Our findings suggest that future studies should be cautious about excluding this portion of the sample as it could lead to overstating the effects that the prospect of tax legislation had on the overall market.

Second, we investigate the cross-sectional distribution of returns across firms during the 283 days. We consider standard alternative measures of firm tax exposure in addition to formulating our own novel measure of firm tax exposure which is an optimally-weighted history of past cash effective tax rates. All the various tax measures show an initial boost to high tax firms after the election, which dissipates over the next year until the passage of the TCJA. We find similar results when using Goldman Sachs constructed tax baskets and portfolios sorted on high minus low cash effective tax rates. To our knowledge, this evidence that high tax firms may have underperformed low tax firms over the full sample is novel and further calls into question the extent to which tax policy drove the overall market.

We also use the cross-sectional regressions to conduct another daily attribution, and find that days in which the firm-level cash effective tax rate were most important explain approximately 3% of the overall market return. In contrast, the percentage of foreign revenues, which explain close to 10% of overall market returns, seems to be a stronger explanatory factor for the variation in returns throughout the majority of the sample. We also consider the role of regulatory policy by constructing a novel metric based on a firm's self-reported risk factors. Our proxy takes the ratio of the number of words which begin with either "regulat-" or "deregulat-" to the total number of words in Item 1A of the firm's 2015 Form 10-K disclosure. We find this regulatory measure explains a similar portion of the overall market returns to that attributed to tax exposure.

Third, we construct a novel probability based on the PredictIt market using daily data that shows the probability of passage of tax cuts was associated with less than a 2% increase in the market. Fifth, to our knowledge, we are the first to show that muni-implied tax rates over this time period follow a similar pattern to the rest of our tax proxies. Specifically, the up, down, and up again dynamics over the full sample.

Overall, the combination of these approaches and novel insights suggest that although tax policy could have had an important positive effect over the time period, other factors likely played a notably larger role in the 25% increase in the market. We provide evidence that global growth was significantly higher during this time period and may have been a more important driver as the Eurozone and China were having some of their best economic performances in years. This is consistent with the outperformance of foreign stock indices such as FTSE and also the outperformance of high foreign revenue firms in our cross-sectional regressions. With 40% of revenues being foreign for S&P 500 firms, the strong global growth combined with the weaker dollar (which coincided with declines in the prospect for passage of tax legislation) boosted multinationals and manufacturers along with the overall market.

The implications of our analysis will be relevant going forward. One potential implication is that if there exists the prospect for future tax increases, this will likely be associated with lower market returns. However, if future situations are anything like the 283 days after the 2016 election, our extensive analysis suggests the net effect is likely to be modest.[23] Other factors, such as US economic data, global economic data, changes in other policies, and the actions of monetary policy will likely play a relatively larger role in determining the performance of the overall stock market.

[23]Of course, this implication assumes the response of the stock market to prospective tax increases are symmetric to those of tax cuts.

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Category	# Days	Return	Category	# Days	Return
Administration Tax Policy	4	1.65%	Geopolitical Risks	1	-0.11%
US Data	9	2.29%	Global Data, ECB	4	2.09%
Earnings	0	0.00%	Oil	7	0.95%
FOMC	3	-0.74%	Other	8	-0.78%
			Total	**36**	**5.35%**

Table 1: **Human Daily Attribution: November 2016 through Dec 2016**

This table shows the number of days attributed to each category by the human-audited news approach. The cumulative CRSP-value-weighted index returns are also shown for the period November 9, 2016 to December 30, 2016, based on the human-audited daily attribution.

Category	# Days	Return	Category	# Days	Return
Administration Tax Policy	19	-5.51%	Geopolitical Risks	18	-1.31%
US Data	33	4.06%	Global Data, ECB	6	0.56%
Earnings	13	5.54%	Oil	15	-0.95%
FOMC	23	2.41%	Other	32	3.67%
			Total	**159**	**8.47%**

Table 2: **Human Daily Attribution: January 2017 through mid-August 2017**

This table shows the number of days attributed to each category by the human-audited news approach. The cumulative CRSP-value-weighted index returns are also shown for the period January 3, 2017 to August 18, 2017 based on the human-audited daily attribution.

Category	# Days	Return	Category	# Days	Return
Administration Tax Policy	29	4.85%	Geopolitical Risks	10	0.66%
US Data	11	3.29%	Global Data, ECB	2	0.22%
Earnings	8	-0.02%	Oil	3	-0.19%
FOMC	10	0.70%	Other	15	1.02%
			Total	**88**	**10.51%**

Table 3: **Human Daily Attribution: mid-August 2017 through December 2017**

This table shows the number of days attributed to each category by the human-audited news approach. The cumulative CRSP-value-weighted index returns are also shown for the period August 20, 2017 to December 22, 2017 based on the human-audited daily attribution.

Category	# Days	Return	Category	# Days	Return
Administration Tax Policy	52	0.99%	Geopolitical Risks	29	-0.77%
US Data	53	9.64%	Global Data, ECB	12	2.86%
Earnings	21	5.52%	Oil	25	-0.19%
FOMC	36	2.36%	Other	55	3.91%
			Total	**283**	**24.34%**

Table 4: **Human Daily Attribution: Full Sample**

This table shows the number of days attributed to each category by the human-audited news approach. The cumulative CRSP-value-weighted index returns are also shown for the period November 9, 2016 to December 22, 2017 based on the human-audited daily attribution.

	Number of Days							
Category	Taxes	US Data	Earnings	FOMC	Geopol.	Global	Oil	Other
Human Attrib.	52	53	21	36	29	12	25	55
Machine Avg.	42.6	58.6	28.4	31.2	33.5	26.1	19.2	44.4
25th-75th %	[26 57]	[51 66]	[25 32]	[25 37]	[28 39]	[20 33]	[15 23]	[33 62]
Min - Max	[18 80]	[41 85]	[18 44]	[16 54]	[19 52]	[12 45]	[10 36]	[0 91]

	Returns							
Category	Taxes	US Data	Earnings	FOMC	Geopol.	Global	Oil	Other
Human Attrib.	0.99	9.64	5.52	2.36	-0.77	2.86	-0.19	3.91
Machine Avg.	2.61	7.93	1.19	2.77	0.53	2.19	2.52	4.98
25th-75th %	[1.9 3.2]	[6.8 8.8]	[0.6 1.6]	[1.7 3.7]	[-0.2 1.2]	[0.5 3.8]	[1.8 3.0]	[1.8 7.7]
Min - Max	[-0.8 7.1]	[4.5 13.4]	[-0.2 3.5]	[-1.5 6.4]	[-1.8 3.8]	[-1.1 7.1]	[0.5 6.0]	[-2.2 11.7]

Table 5: **Comparison of Machine-Attribution Specifications to Human Attribution**

This table compares the daily attribution of the machine-based method to the human-audited daily attribution. The top panel compares the number of days across the entire sample (November 9, 2016 to December 22, 2017) associated with each category based on the human attribution to the average number of days associated with the machine-based specifications. The top panel also shows the interquartile range and full range for the number of days across the specifications. The bottom panel compares the cumulative CRSP value-weighted returns associated with each category based on the human attribution to the distribution of cumulative returns using the machine-based attribution method.

	(1)	(2)	(3)	(4)
	Nov 9	Nov 9 - Apr 28	Nov 9 - Nov 8	Nov 9 - Dec 22
CashETR	0.03***	0.07*	0.10	0.22***
	(0.01)	(0.04)	(0.07)	(0.08)
Log MVE	-0.52***	-1.27***	-0.84	-0.82
	(0.06)	(0.31)	(0.56)	(0.60)
Revenue Growth	-0.01	0.02	0.05	0.08
	(0.00)	(0.04)	(0.08)	(0.09)
Profitability	-0.02**	-0.23***	-0.12	0.02
	(0.01)	(0.07)	(0.12)	(0.13)
Constant	6.29***	27.42***	30.96***	32.88***
	(0.49)	(2.87)	(5.12)	(5.57)
Observations	1650	1628	1588	1578
R-squared	0.073	0.023	0.005	0.011

Table 6: **Regressions of Firm-Level Returns on CashETR**

This table shows regression results of cumulative firm-level returns on the one-year cash effective tax rate as well as other firm-level controls (the log of the market value of equity, revenue growth, and profitability). Each column displays the regression results using cumulative returns at various horizons since November 9, 2016. Our sample includes firms in the Russell 3000 on November 8, 2016 and a positive cash effective tax rate that is less than 100%. Return data comes from CRSP and the firm financial characteristics come from Compustat. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
	Nov 9	Nov 9 - Apr 28	Nov 9 - Nov 8	Nov 9 - Dec 22
GAAP ETR	0.02**	-0.09*	-0.13	0.06
	(0.01)	(0.05)	(0.09)	(0.09)
Observations	1632	1613	1567	1556
R-squared	0.059	0.025	0.007	0.006
Δ/MVA	0.16**	-1.05***	-2.02***	-0.86
	(0.06)	(0.36)	(0.63)	(0.73)
Observations	1828	1807	1754	1737
R-squared	0.069	0.010	0.009	0.007
CashETR3	0.04***	0.05	0.00	0.14*
	(0.01)	(0.04)	(0.08)	(0.08)
Observations	1634	1614	1575	1565
R-squared	0.088	0.023	0.002	0.006
CashETR10^w	0.05***	0.04	-0.04	0.22*
	(0.01)	(0.05)	(0.10)	(0.12)
Observations	1194	1176	1150	1144
R-squared	0.094	0.016	0.003	0.010
All panels:				
Constant and Controls	Yes	Yes	Yes	Yes

Table 7: **Regressions of Firm-Level Returns on Alternative Tax Measures**

This table shows regression results of cumulative firm-level returns on alternative measures of tax exposure as well as other firm-level controls (the log of the market value of equity, revenue growth, and profitability). Each column displays the regression results using cumulative returns at various horizons since November 9, 2016. Our sample includes firms in the Russell 3000 on November 8, 2016 and a positive cash effective tax rate that is less than 100%. Return data comes from CRSP and the firm financial characteristics come from Compustat. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Historical CashETR	Coeff	R-squared
CashETR$_{t-1}$	0.423	0.169
CashETR2$_{t-1}$	0.539	0.203
CashETR3$_{t-1}$	0.593	0.214
CashETR4$_{t-1}$	0.606	0.207
CashETR5$_{t-1}$	0.628	0.209
CashETR6$_{t-1}$	0.639	0.205
CashETR7$_{t-1}$	0.655	0.205
CashETR8$_{t-1}$	0.661	0.202
CashETR9$_{t-1}$	0.661	0.197
CashETR10$_{t-1}$	0.659	0.193
CashETR10$^{w}_{t-1}$	0.716	0.239

Table 8: **Regressions of CashETR$_t$ on Past CashETR Measures**

This table shows regression results of the current CashETR ($CashETR_t$) on past CashETR across different horizons. A firm's past h-year CashETR equals the sum of cash taxes paid over the past h years divided by the sum of pretax income paid over those h years. All data came from Compustat, and includes firms with ten consecutive non-missing years of tax information from 1987 to 2015. The top panel shows regression results from regressing the current CashETR on each of the tax histories. The bottom row shows the result from regressing the current CashETR on $CashETR10^{w}_{t-1}$, an optimally-weighted ten-year tax history based on equation (1).

	(1) Nov 9	(2) Nov 9 - Apr 28	(3) Nov 9 - Nov 8	(4) Nov 9 - Dec 22
CashETR	0.03***	0.05	0.08	0.21**
	(0.01)	(0.05)	(0.09)	(0.10)
Foreign Revenues	-0.00	0.03	0.20***	0.11*
	(0.00)	(0.03)	(0.06)	(0.06)
Regulation 10-K	1.92***	2.49	7.37**	6.62*
	(0.45)	(2.16)	(3.67)	(3.93)
Observations	1116	1112	1088	1082
R-squared	0.085	0.017	0.021	0.017
GAAPETR	0.02*	-0.10*	-0.06	0.13
	(0.01)	(0.06)	(0.11)	(0.12)
Foreign Revenues	-0.00	0.02	0.21***	0.12**
	(0.00)	(0.03)	(0.06)	(0.06)
Regulation 10-K	2.04***	4.65**	12.09***	11.80***
	(0.47)	(2.17)	(3.64)	(3.93)
Observations	1104	1101	1074	1068
R-squared	0.074	0.023	0.025	0.015
Δ/MVA	0.11	-1.35***	-1.93***	-0.68
	(0.07)	(0.42)	(0.73)	(0.86)
Foreign Revenues	0.00	0.06**	0.21***	0.16***
	(0.00)	(0.03)	(0.06)	(0.06)
Regulation 10-K	3.32***	4.49	8.82*	8.57
	(0.54)	(2.86)	(5.01)	(5.59)
Observations	1275	1270	1238	1227
R-squared	0.102	0.022	0.026	0.016
CashETR3	0.03***	0.04	-0.02	0.13
	(0.01)	(0.05)	(0.09)	(0.09)
Foreign Revenues	-0.00	0.05	0.21***	0.12**
	(0.00)	(0.03)	(0.05)	(0.06)
Regulation 10-K	1.94***	2.93	8.14**	7.26*
	(0.45)	(2.13)	(3.62)	(3.93)
Observations	1113	1108	1086	1080
R-squared	0.099	0.019	0.022	0.014
CashETR10^{w}	0.04***	-0.01	-0.07	0.24
	(0.01)	(0.07)	(0.12)	(0.15)
Foreign Revenues	-0.00	0.05*	0.23***	0.15**
	(0.00)	(0.03)	(0.06)	(0.06)
Regulation 10-K	1.76***	1.94	6.57*	5.39
	(0.52)	(2.39)	(3.73)	(4.03)
Observations	817	813	797	793
R-squared	0.105	0.020	0.030	0.023
All panels:				
Constant and Controls	Yes	Yes	Yes	Yes

Table 9: **Regressions of Firm-Level Returns on Various Tax Measures Plus Foreign Revenues and Regulation Exposure**

This table shows regression results of cumulative firm-level returns on the various measures of tax exposure, the percentage of foreign revenues from abroad, and the regulation exposure measure from Item 1A of Form 10-K (as well as other firm-level controls – the log of the market value of equity, revenue growth, and profitability). Each column displays the regression results using cumulative returns at various horizons since November 9, 2016. Our sample includes firms in the Russell 3000 on November 8, 2016 and a positive cash effective tax rate that is less than 100%. Return data comes from CRSP and the firm financial characteristics come from Compustat, besides the percentage of revenues from foreign sources which comes from Bloomberg. The regulation exposure variable measures the percentage of words in Item 1A of a firm's 10-K that mentions regulation. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			CRSP Value-weighted Returns			
Corporate Tax Cut 2017	0.0050			0.0060*		
	(0.0035)			(0.0032)		
Individual Tax Cut 2017		-0.0003			-0.0008	
		(0.0035)			(0.0032)	
Corporate Tax Cut 2018 Projection			0.0172*			0.0193**
			(0.0095)			(0.0086)
MSCI excluding US				0.3885***	0.3850***	0.3881***
				(0.0492)	(0.0495)	(0.0491)
Economic Confidence Index				-0.0001	-0.0001	-0.0001
				(0.0001)	(0.0001)	(0.0001)
Constant	0.0008***	0.0008***	0.0008***	0.0005**	0.0005**	0.0005**
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Observations	283	283	283	283	283	283
R-squared	0.007	0.000	0.012	0.190	0.180	0.194

Table 10: **Regressions of Market Return on Probability Measures**

This table shows a regression of daily CRSP value-weighted index returns onto (i) the PredictIt probability of a corporate tax cut by the end of 2017, (ii) the PredictIt probability of an individual tax cut by the end of 2017, (iii) the PredictIt probability of a corporate tax cut by the end of 2018, (iv) the daily returns on the MSCI World-excluding-US index, and (v) the daily change in the Gallup Economic Confidence Index. We backfill the PredictIt probability of a corporate tax cut by the end of 2018 before its initial market offering (October 24, 2017) by using its implied projections from the probability of a corporate tax cut by the end of 2017. The sample covers November 9, 2016 to December 22, 2017. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

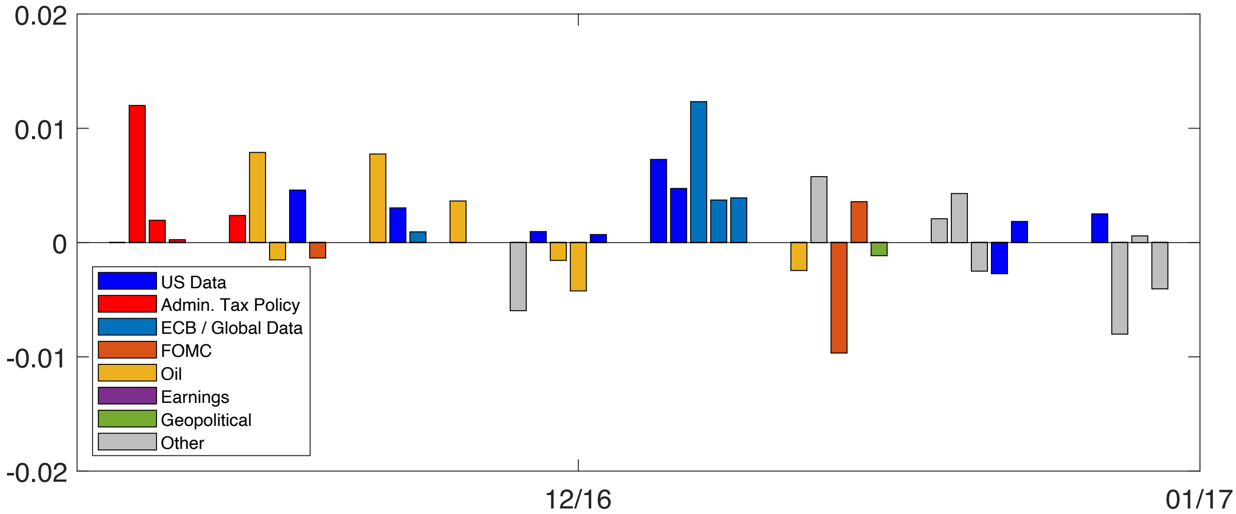


Figure 3: **Human Daily Attribution: November 2016 through Dec 2016**

This figure shows the category for which each day's return is attributed based on the human-audited news approach. The height of each bar shows the daily CRSP value-weighted index returns from November 9, 2016 to December 30, 2016.

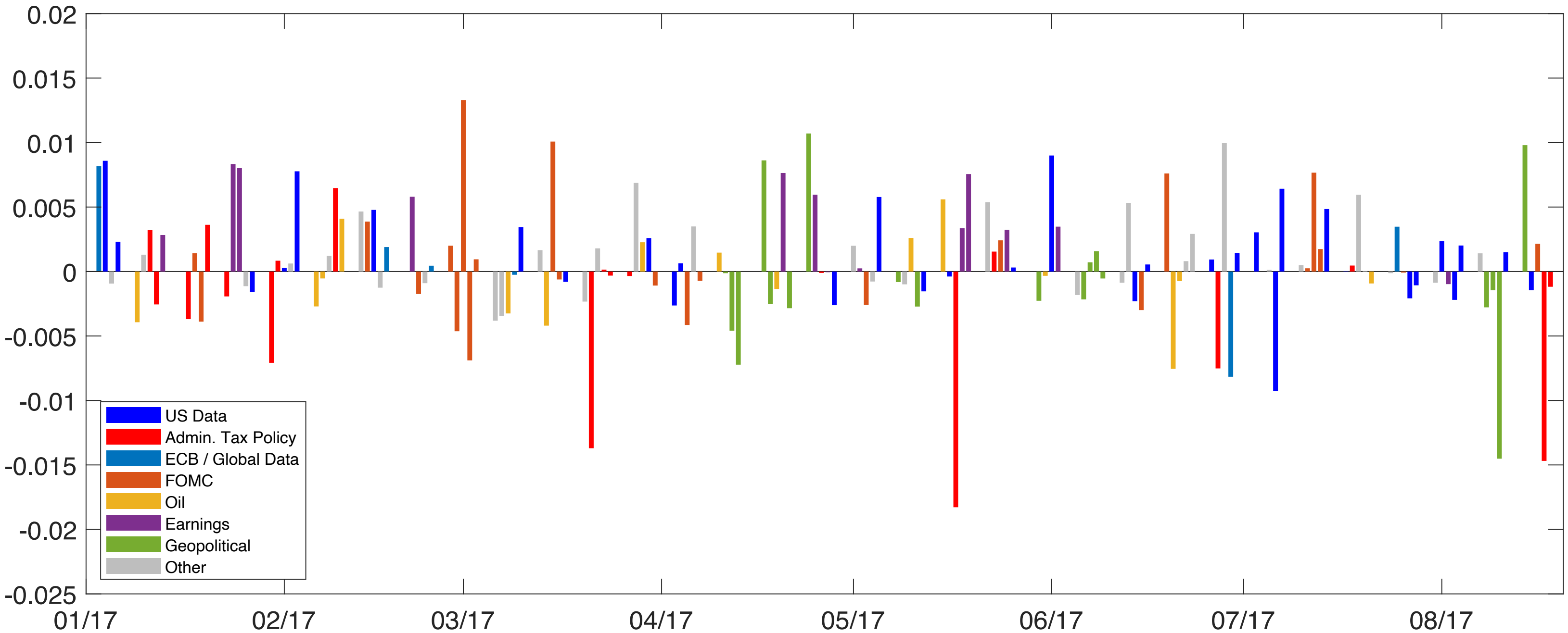


Figure 4: **Human Daily Attribution: January 2017 through mid-August 2017**

This figure shows the category for which each day's return is attributed based on the human-audited news approach. The height of each bar shows the daily CRSP value-weighted index returns from January 3, 2017 to August 18, 2017.

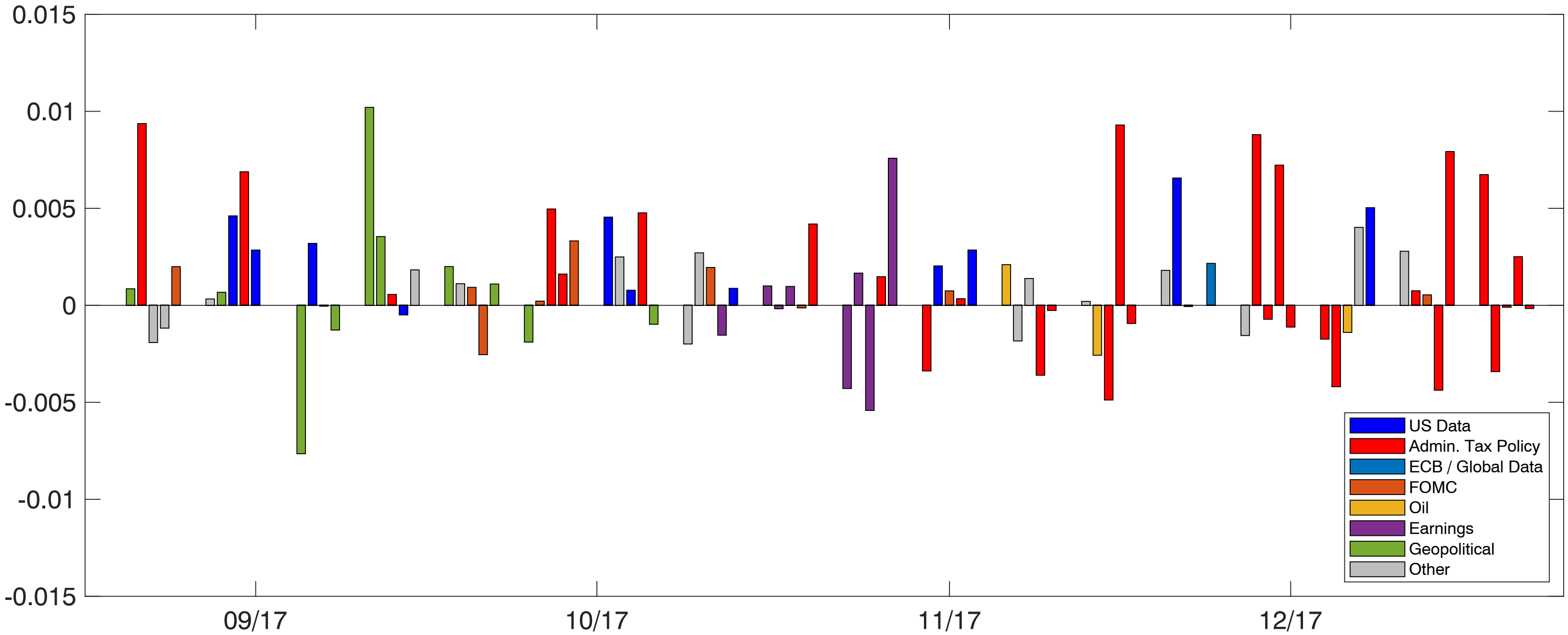


Figure 5: **Human Daily Attribution: mid-August 2017 through December 2017**

This figure shows the category for which each day's return is attributed based on the human-audited news approach. The height of each bar shows the daily CRSP value-weighted index returns from August 20, 2017 to December 22, 2017.

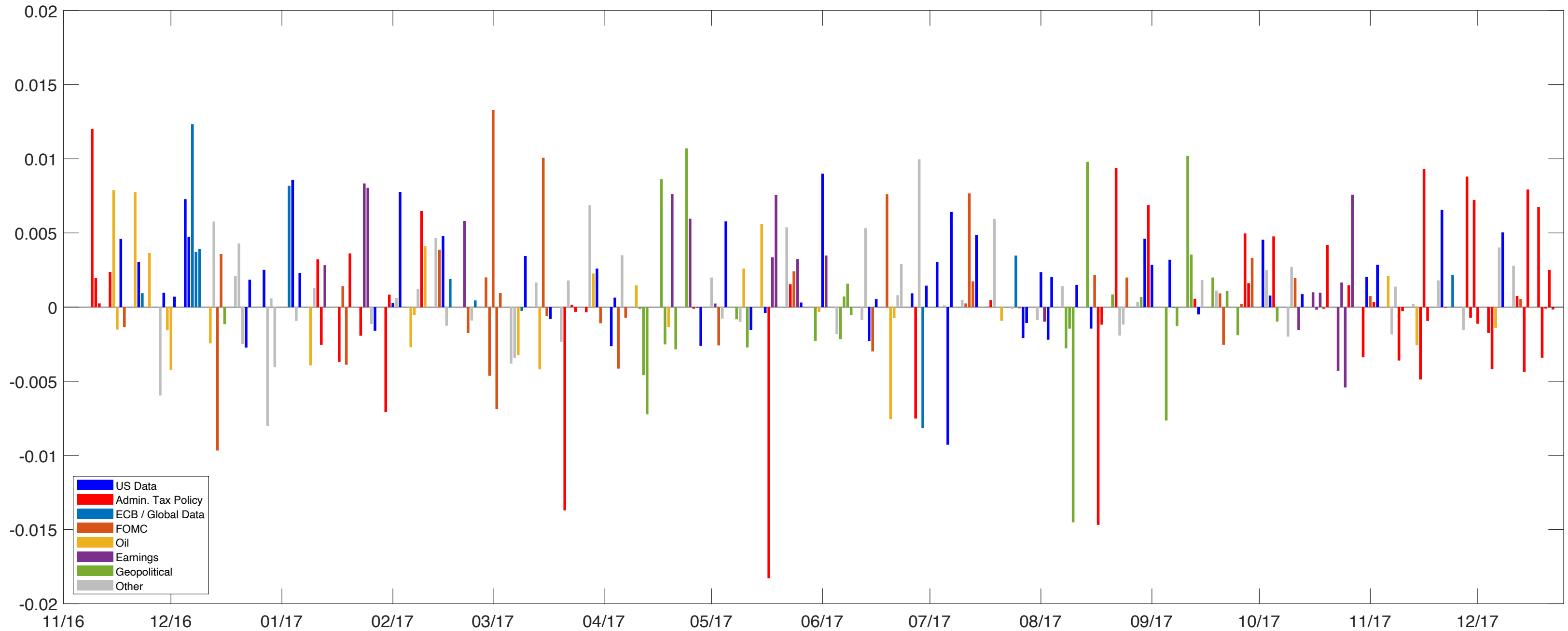


Figure 6: **Human Daily Attribution: Full Sample**

This figure shows the category for which each day's return is attributed based on the human-audited news approach. The height of each bar shows the daily CRSP value-weighted index returns from November 9, 2016 to December 22, 2017.

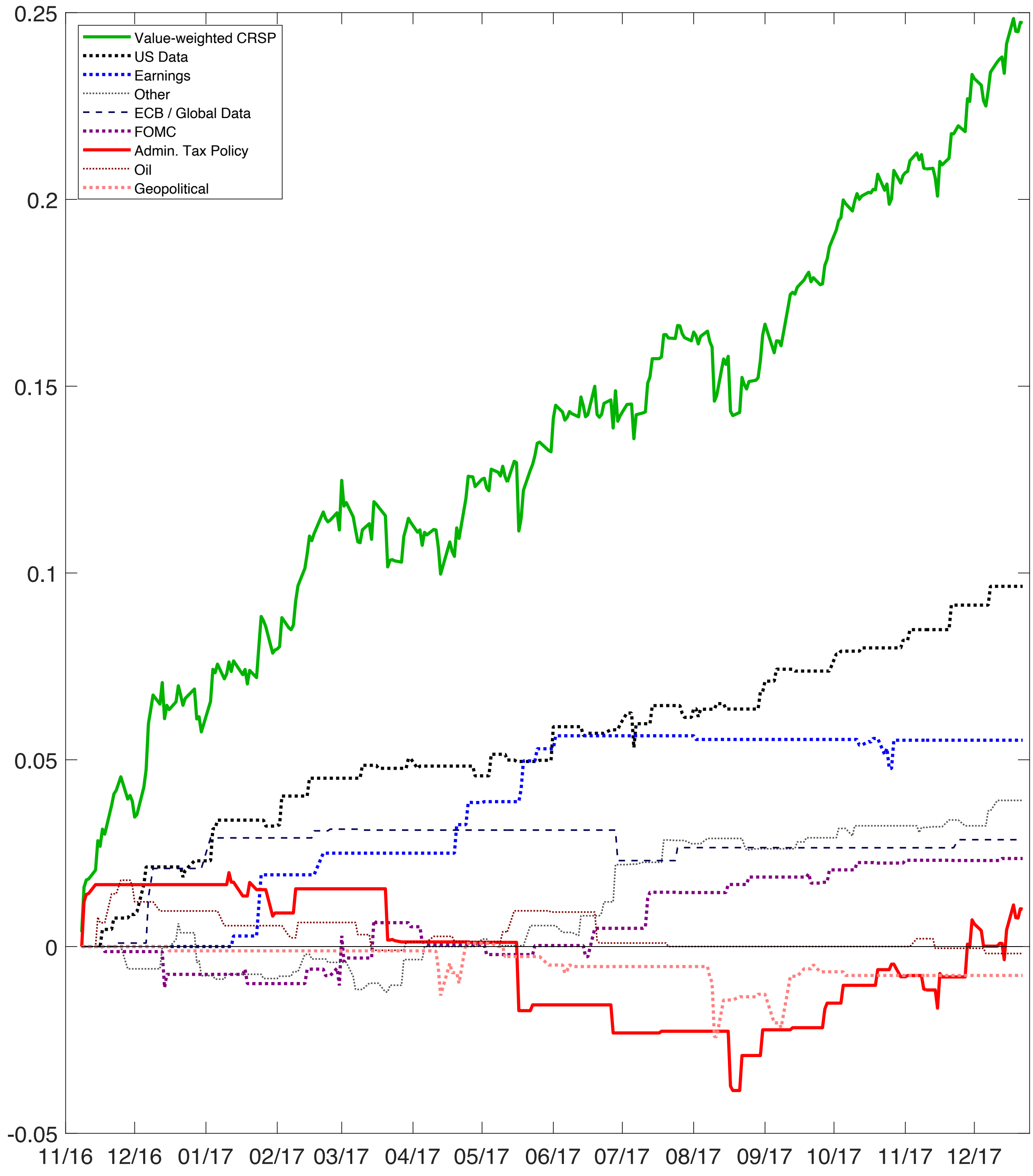


Figure 7: **Cumulative Returns Based On Human Daily Attribution**

This figure shows the cumulative CRSP value-weighted index return for the full sample (November 9, 2016 to December 22, 2017) as well as the cumulative returns for each category based on the human-audited daily attribution.

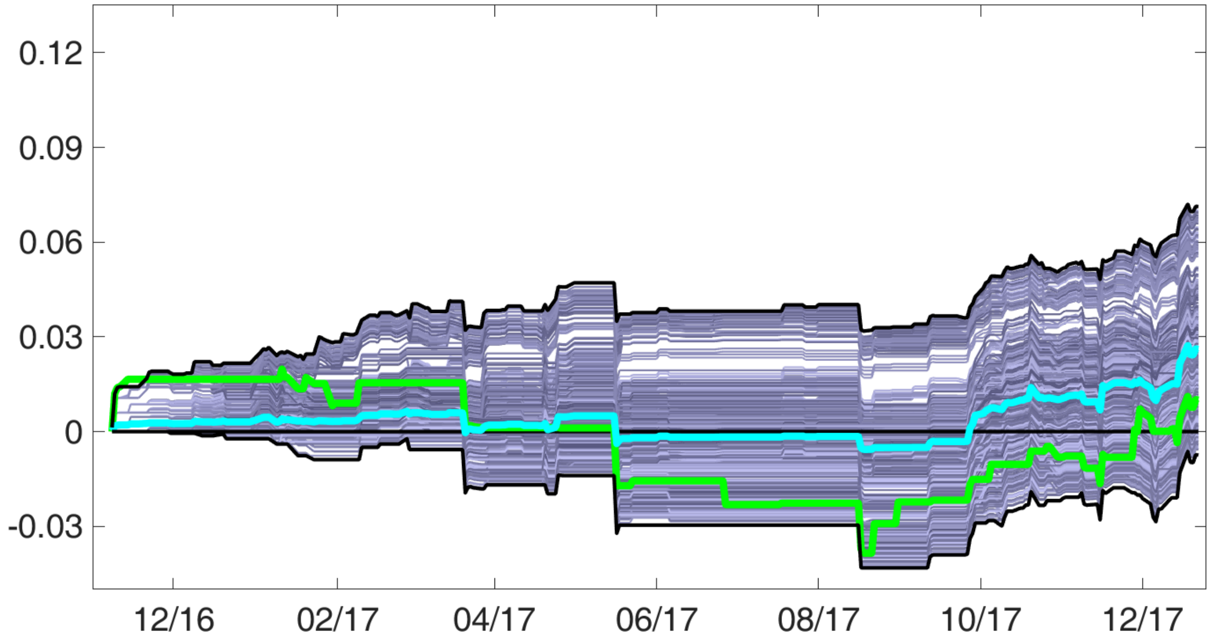


Figure 8: **Taxes: Cumulative Return Based on Various Machine-Based Attributions**

This figure shows the cumulative return for the Tax category based on 1,536 different possible machine-based daily attribution specifications. The returns are based on the daily CRSP value-weighted index and are associated each day with a category based on the highest normalized value from each respective machine-based attribution. The gray lines show the various machine specifications, the blue line shows the average of these specifications on each day, and the black lines show the maximum and minimum. The human-audited daily attribution is shown in green for comparison.

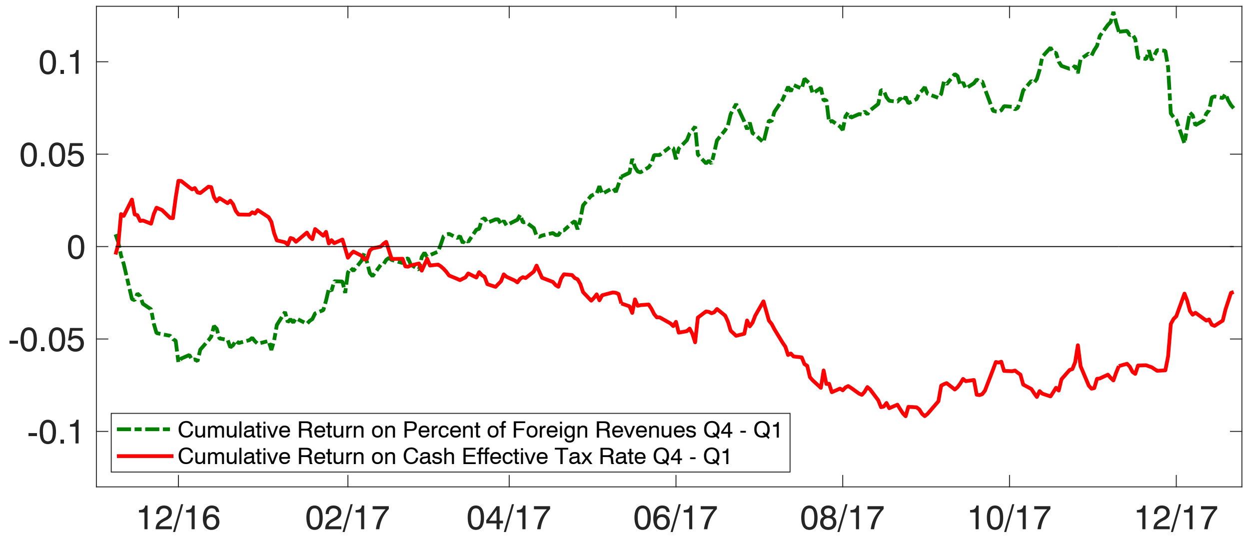


Figure 9: **Performance Comparison of Firms on Foreign Sector and Tax Exposure**

The green dotted line shows the difference in cumulative returns between portfolios of the highest and lowest quartiles of firms by percent of revenues from foreign sources. The portfolios are value-weighted and quartiles are formed based on the percentage of foreign revenues for each firm in fiscal year 2015. The red line shows the difference in cumulative returns between portfolios of the highest and lowest quartiles of firms by cash effective tax rate. The portfolios are value-weighted and quartiles are formed based on firm's 5-year cash effective tax rate. The sample goes from November 9, 2016 to December 22, 2017.

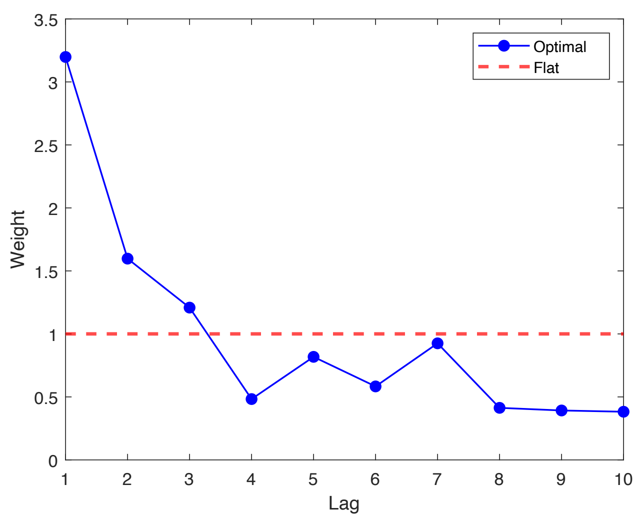
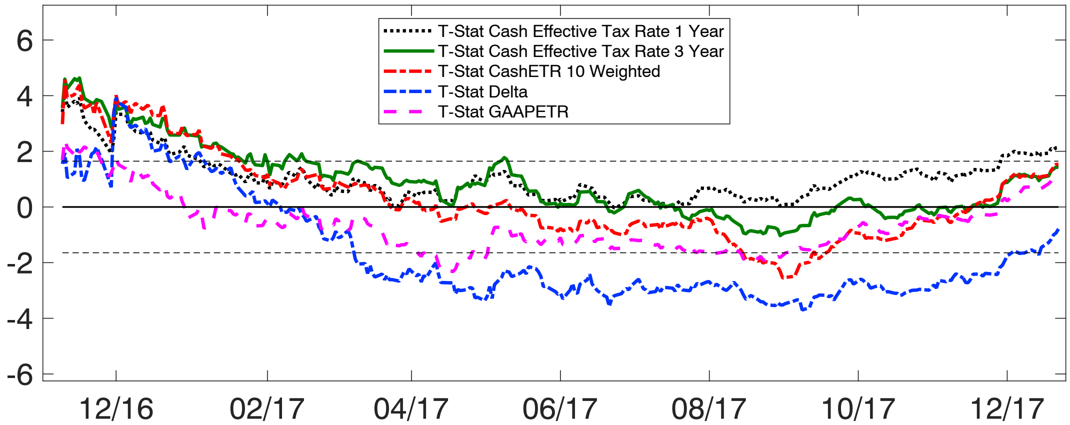
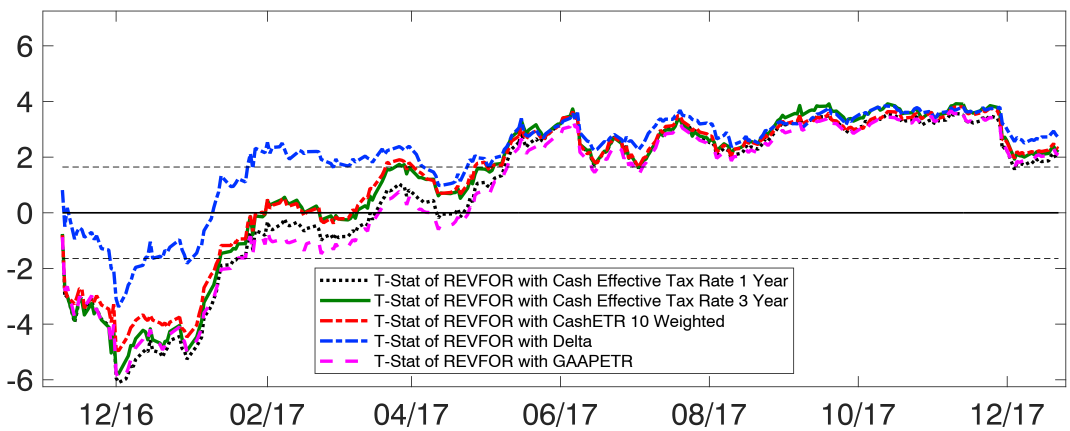


Figure 10: **Optimal Weights For CashETR Prediction**

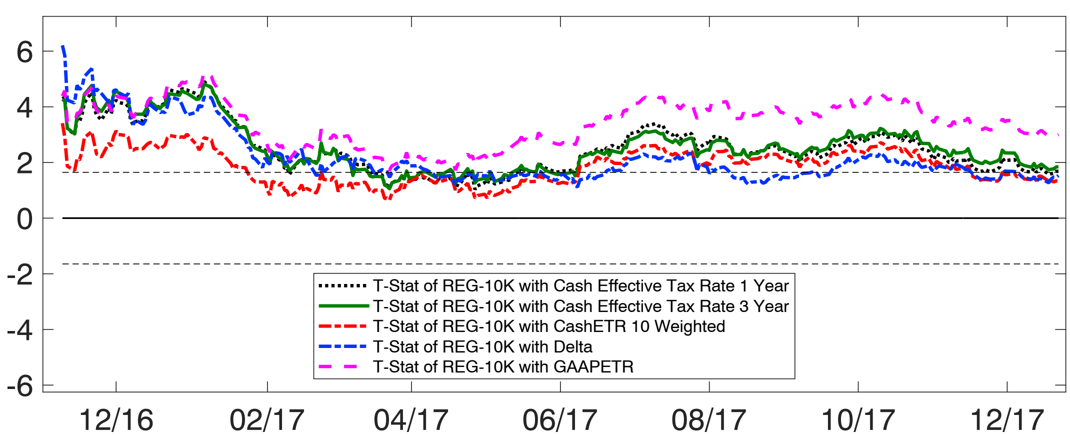
This figure compares the optimal weights (solid line) on lags of TXPD and PI in predicting current CashETR to the standard, flat weights (dashed line) used by Dyreng, Hanlon, and Maydew (2008) to construct CashETR10. The optimal weights solve equation (1) and construct the optimal predictor, CashETR10^w.



(a) Tax Measures



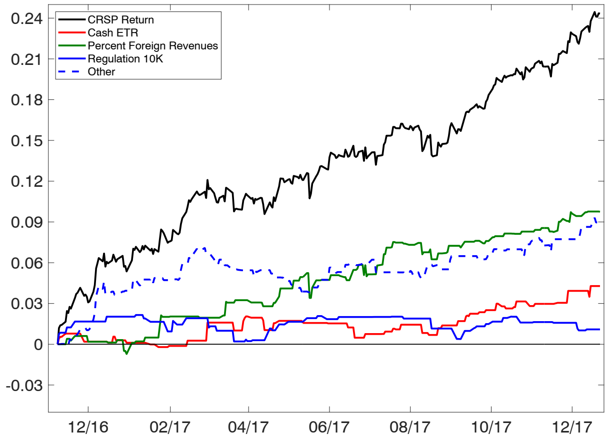
(b) Percent Foreign Revenues



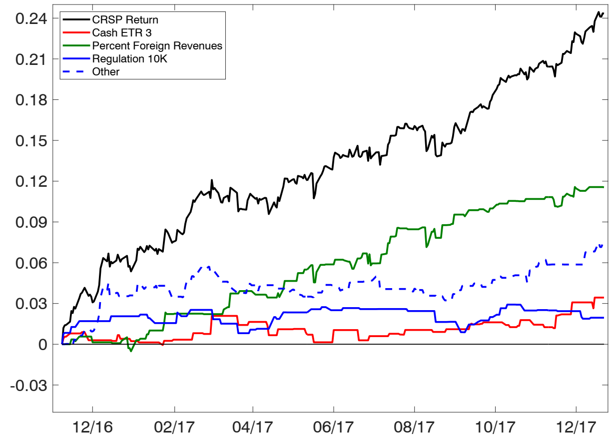
(c) Regulation 10-K Measures

Figure 11: **Recursive *t*-Stats for Tax Measures, % Foreign Revs. and Reg. 10-K**

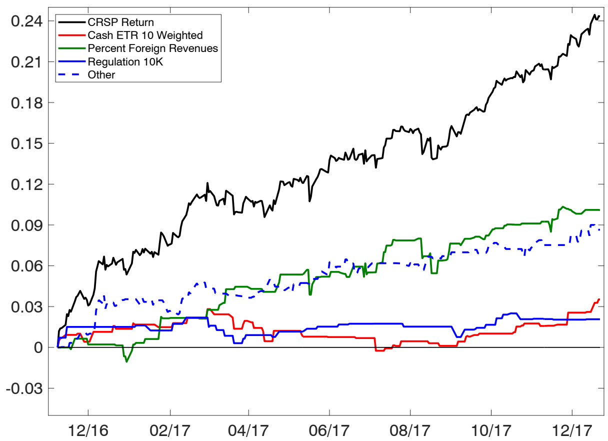
This figure shows the *t*-stats for the different tax measures in conjunction with the foreign revenues and regulation 10-k measure in regressions of cumulative returns across recursive horizons from November 9, 2016 to time t. The regressions cover the sample cross-section of firms as outlined in Table 9 and include the same control variables. The top panel displays the results for the five specifications for each tax measure, the middle panel displays the REVFOR *t*-Stats across each of the tax specifications, and the bottom panel displays the *t*-Stats for the regulations measure across the tax specifications.



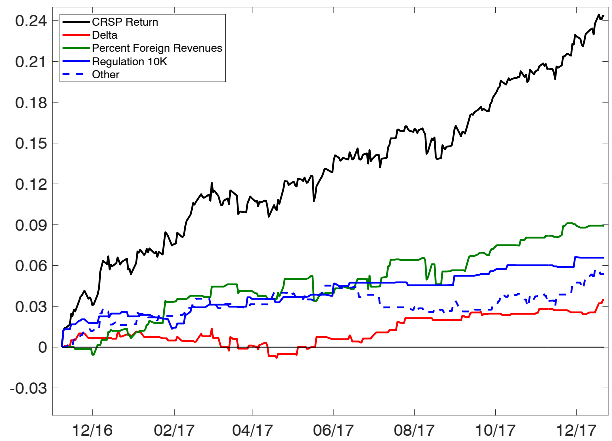
(a) CashETR



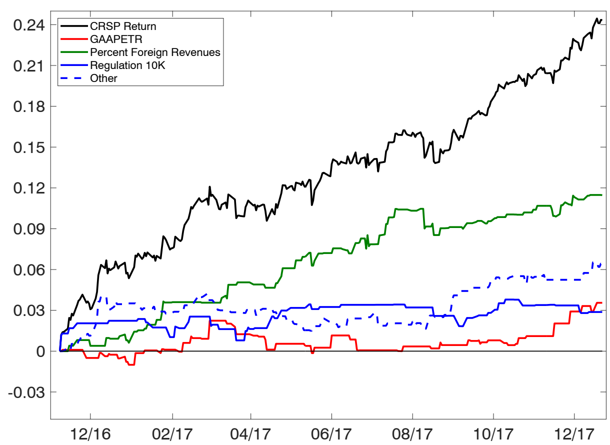
(b) CashETR3



(c) CashETR10^{w}



(d) Delta



(e) GAAPETR

Figure 12: **Cumulative Returns Based on Cross-Sectional Regression Attribution**

This figure shows the cumulative CRSP value-weighted index return for the full sample (November 9, 2016 to December 22, 2017) as well as the cumulative returns for each category – Tax Measure, Percent Foreign Revenues, Regulation-10K, and Other – based on the cross-sectional regression attribution. Market returns for a given day are attributed to one of the four categories based on the t-stats from cross-sectional regressions of daily firm-level returns on the explanatory variables outlined in Table 9. The regressions cover the sample cross-section of firms as outlined in Table 9.

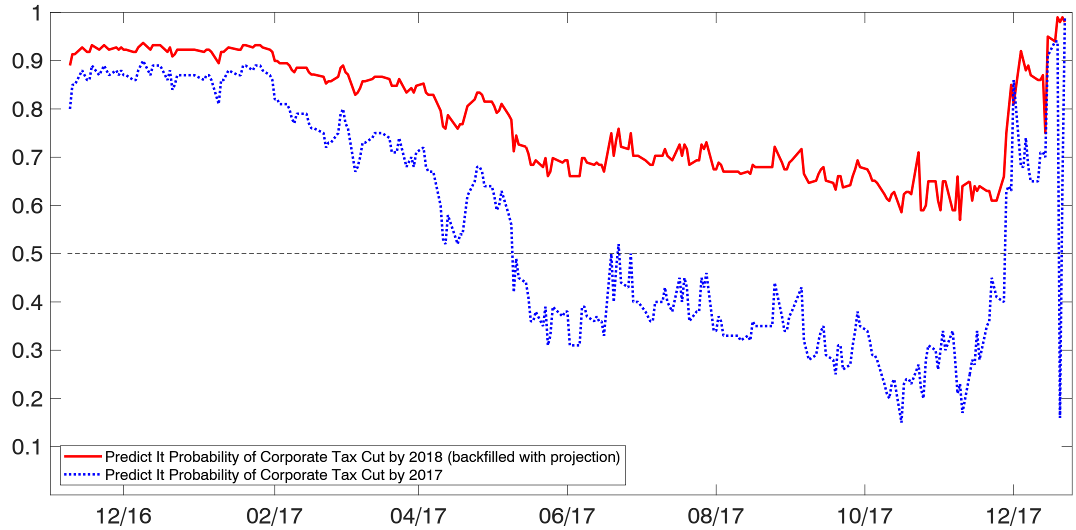
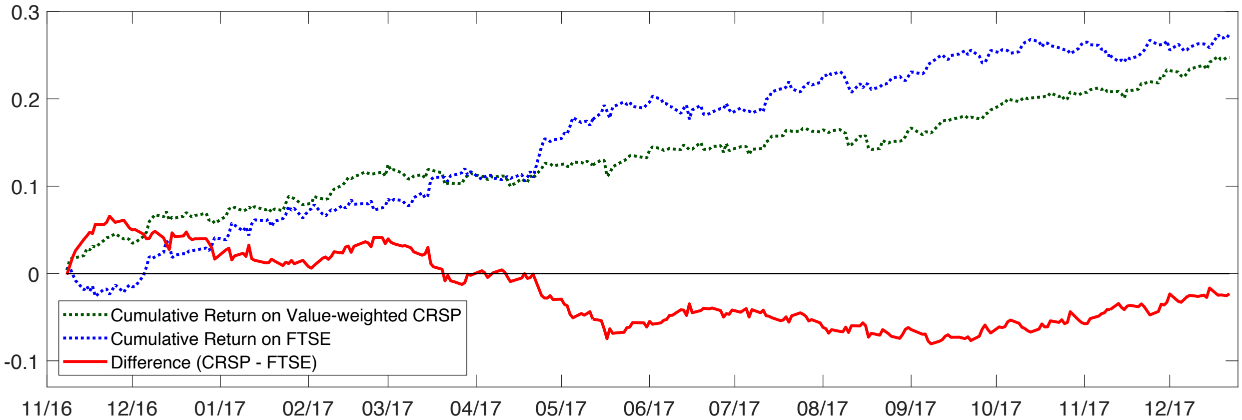


Figure 13: **PredictIt Probabilities of Passage of Corporate Tax Legislation**

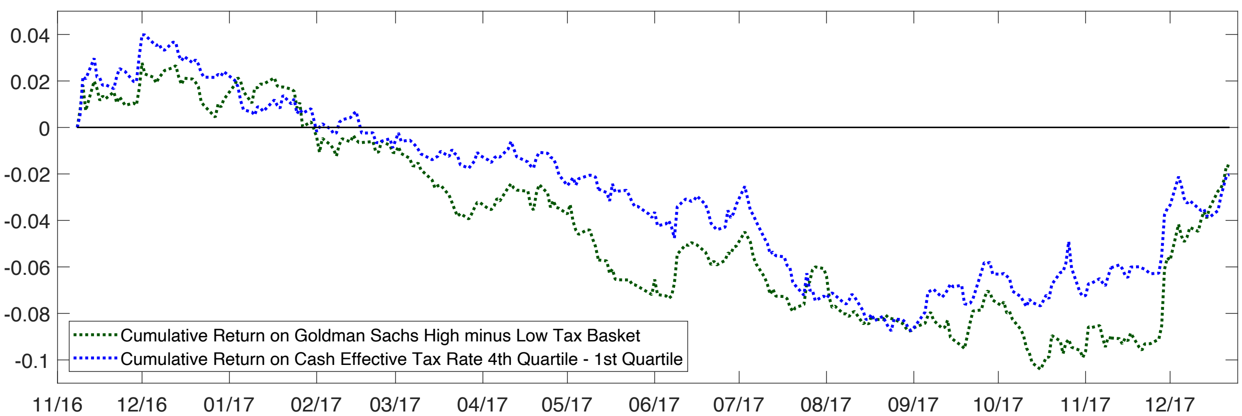
This figure shows the probability of tax legislation based on the PredictIt market. The blue lines shows the raw probability of a corporate tax legislation by the end of 2017. The red line shows the probability of corporate tax legislation by the end of 2018. Since the contract was not offered until October 24, 2017, we construct the 2018 probability prior to this date by regressing the 2018 probability measure onto the 2017 measure when both metrics were available, then using the estimated coefficients to backfill the 2018 measure using the observed 2017 measure.

Figure 14: **The Prospect of Tax Legislation – Full Sample, Part 1 of 2**

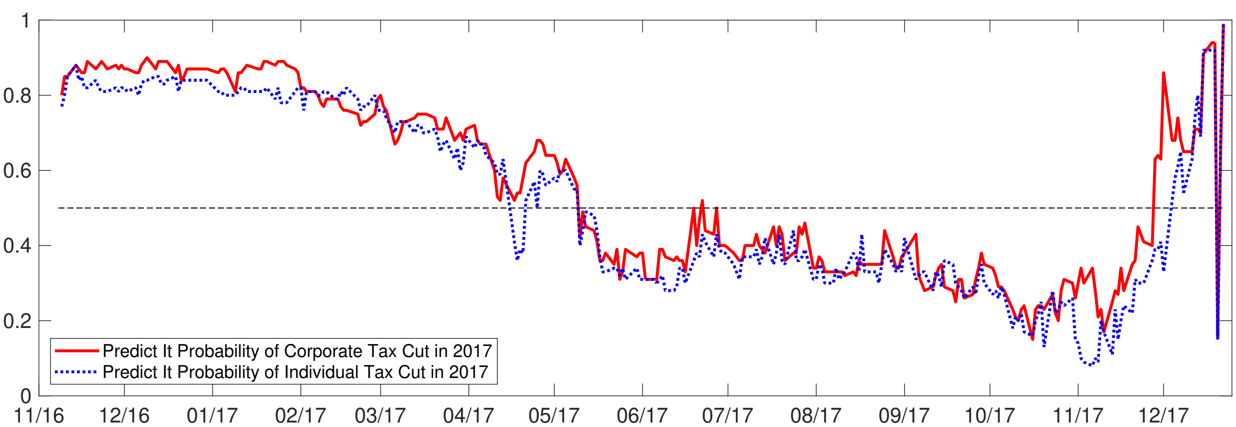
This figure shows the different measures (besides the human-audited attribution) of the prospect of tax legislation outlined in Section 6 over the period November 9, 2016 to December 22, 2017.



(a) CRSP vs FTSE



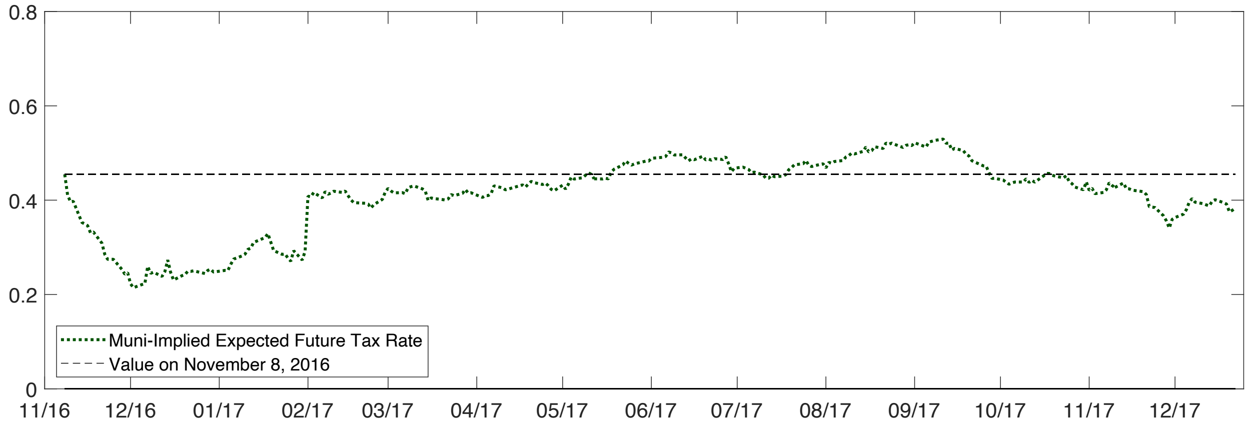
(b) Cross Section



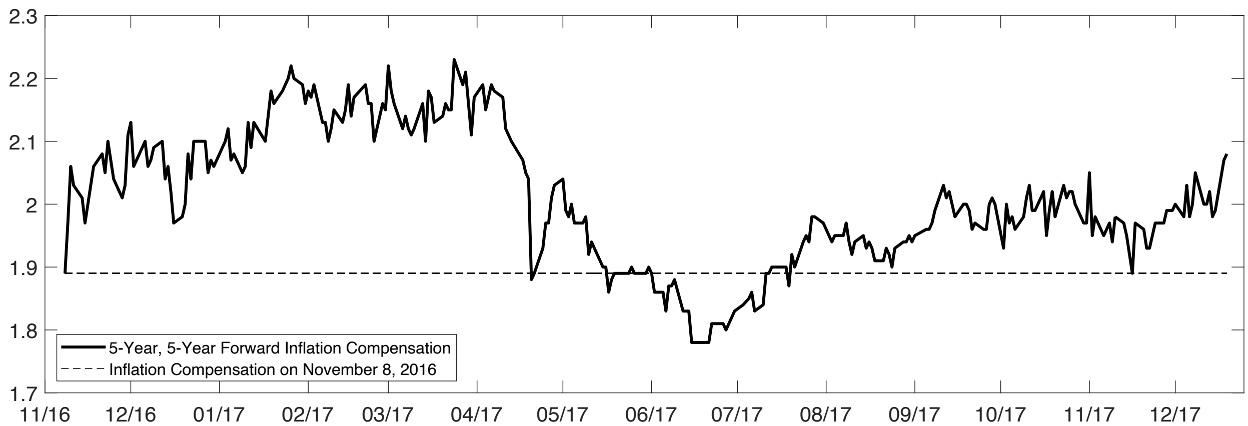
(c) PredictIt

Figure 14: **The Prospect of Tax Legislation – Full Sample, Part 2 of 2**

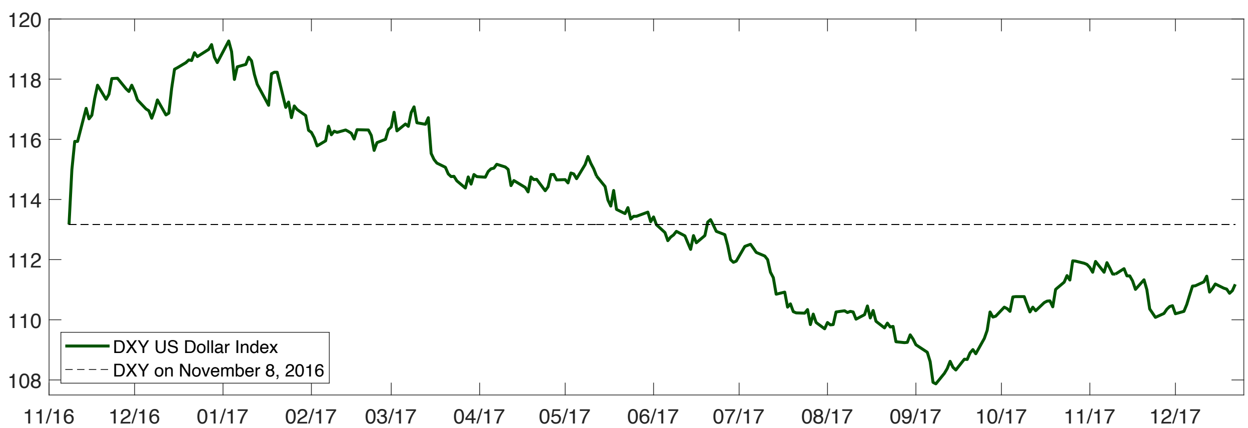
This figure shows the different measures (besides the human-audited attribution) of the prospect of tax legislation outlined in Section 6 over the period November 9, 2016 to December 22, 2017.



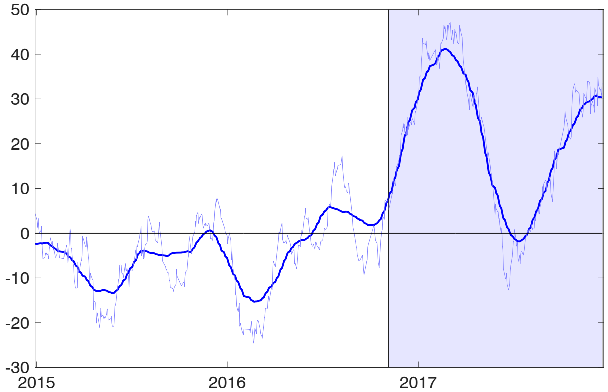
(d) Muni-Implied



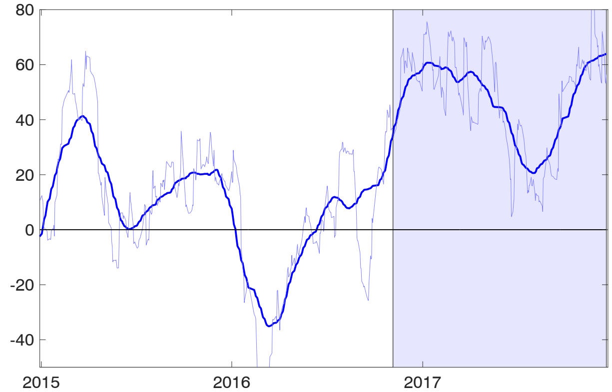
(e) Inflation Comp.



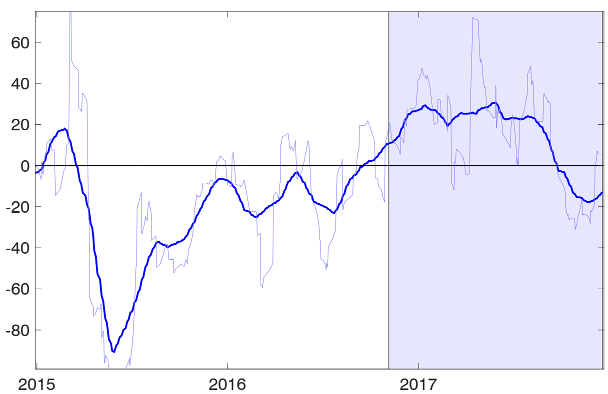
(f) Dollar Index



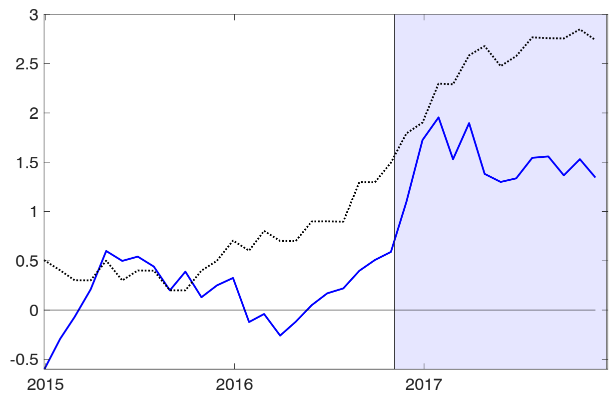
(a) Global CESI



(b) Eurozone CESI



(c) China CESI



(d) Eurozone and UK Inflation

Figure 15: **Citigroup Economic Surprise Indices and Foreign Inflation**

This figure shows the Citigroup Economic Surprise Indices for the Global Economy, Eurozone, and China from 2015 to 2017. The black vertical lines indicate November 8, 2016 and the blue shaded regions represents the 283 days after the election. The thin blue line plots the raw index while the dark blue line represents the 50-day moving average. A positive surprise index indicates aggregate news releases are above expectations for a given day, while a negative index reflects news that is below-expectations. We obtained the Economic Surprise Indices from Bloomberg. The figure also shows the inflation for the Eurozone (solid blue line) and the United Kingdom (dashed black line) from the January 2015 to December 2017. Inflation is measured as the 12-month percentage growth in the Consumer Price Index for the respective region or country from the OECD's Main Economic Indicators.

Internet Appendix for 283 Days

A Machine Daily Attribution

In this section, we consider an alternative daily attribution that some may consider relatively more objective. Although we tried to be as careful as possible when reading the news and determining the primary driver on each of the 283 days, it is possible that biases and inconsistencies could arise that may affect the results. To address this concern, we apply a machine technique that employs the Bloomberg News Trend Function. The Bloomberg News Trend Function allows for us to count the number of times a specific word or phrase has been used in various major news outlets on any given day.

Similar to the human-audited news attribution, we track news on several key topics: (1) Tax Policy, (2) US Data, (3) Earnings, (4) FOMC, (5) Geopolitical, (6) Global / ECB, (7) Oil, and (8) Other. The terms that we search for tax policy include, "tax cut", "tax reform", "tax rate", "corporate tax", "tax cuts", "tax bill", "Cohn", and "endanger tax cut." For US Data, we track "CPI", "retail sales", "nonfarm", "ISM", "GDP." For Earnings, we track "earnings" and "record earnings." For the category FOMC, we search "FOMC", "Yellen", "Dudley", and "Federal Reserve." For the Geopolitical category, we track "North Korea" and "Syria." For the Global Data / ECB category, we track "ECB" and "global data." For the Oil category, we search "OPEC", "oil minister", and "production cut." Lastly, for the Other cateogry, we track "deregulation" and "stress test."

It's crucial to note that although the machine approach is relatively more objective, it still requires a vast number of choices and assumptions. For instance, in terms of normalizing the search terms above, should one do so over the 283 days or over a longer window? If the window is longer and begins before this time period, should the window also be recursive or static? For example, the term "tax cuts" may have been used relatively infrequently up until the day of the election, when it saw a large increase in results based on our search. But a full sample normalization over the following 283 days would characterize the mentions on the day of the election to be minimal relative to the days in November and December of 2017 when the law was actually passed. This can be seen more clearly in Figure A.1, which shows that how you normalize can make a big difference in terms of which days are considered most important. Under one approach (longer recursive window up through time t, blue line), the attribution would pick up the day of the election as an important day for the Tax Policy category term because the words had rarely been mentioned up to that point, whereas the other approach (full sample of 283 days, orange line) would judge it to be relatively unimportant compared to what happened 250 days later. In Figure A.1, the human audited daily attribution is included as well and roughly lines up with the majority of days in which normalized values spiked.

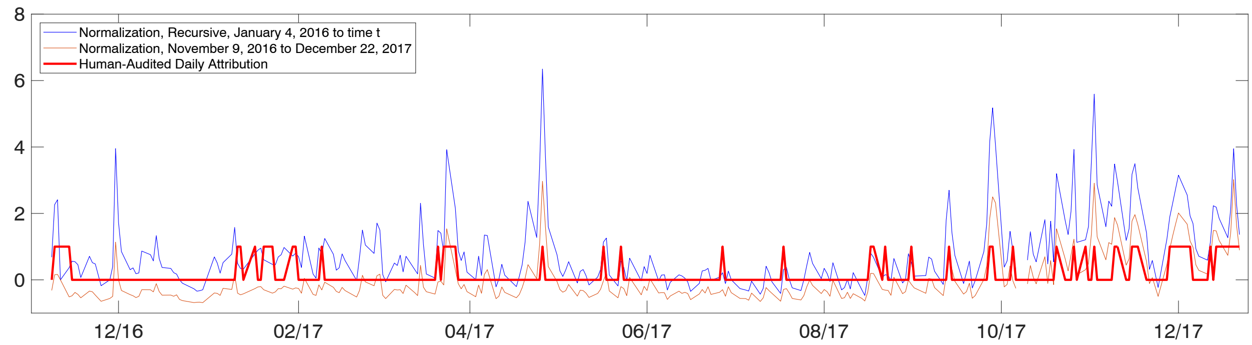


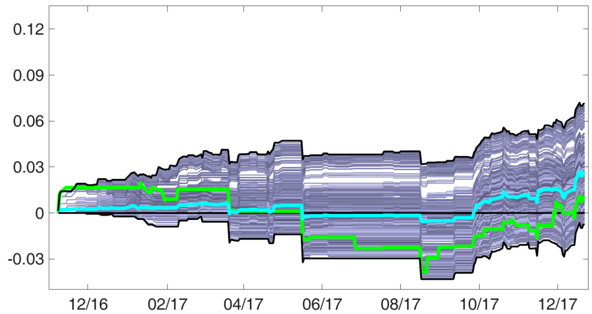
Figure A.1: **Normalization Comparisons for Machine Approach to Tax Policy Days**

This figure compares the human-audited attribution (thick red line) of tax policy days to two alternative normalizations for the machine-based daily attribution for the full sample from November 9, 2016 to December 22, 2017. The thin blue line shows the machine-based value for tax policy news when a recursive normalization is used, whereas the thin orange line shows the machine-based value for tax policy news when normalization is done based on the full 283 day sample from November 9, 2016 to December 22, 2017.

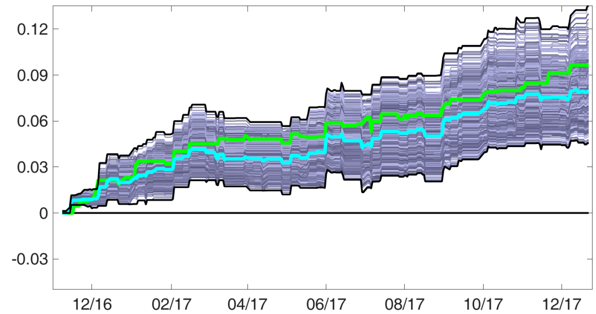
This issue, along with many others, calls for relying on not just one specification but instead taking into account the numerous possibilities. Accordingly, we evaluate over 1,500 specifications based on different assumptions and modeling choices. Specifically, we run the exercises across eight dimensions: (1) four approaches for normalizing the keywords, (2) three approaches for creating thresholds to assign days to the Other category, (3) two ways to place weight on the highest and second-highest normalized value for a given day, (4) two ways to construct the US data category, (5) four ways to define the Other category to also incorporate trade and immigration, (6) inclusion of "OPEC" in the Oil category, (7) whether or not to include "global data" in the ECB / Global category, and (8) excluding "stress test" from the Other category. The full details and description of these choices are presented in Section A.1 and the end result is 1,536 possible specifications.

We assign primary drivers to each of the 283 days based on the category with the highest normalized value. Figure A.2 show the cumulative return over the 283 days assigned to each category based on this process. The blue line represents the average of these cumulative returns across the 1,536 specifications and the green line represents the cumulative return based on the human-audited daily attribution for comparison. The rest of the specifications are in gray with the maximum and minimum values at each point in time highlighted in black.

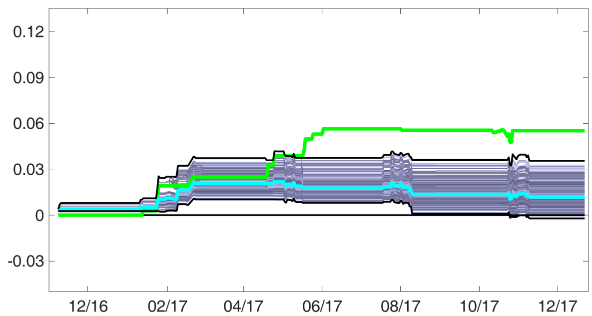
Tax Policy. In terms of the Tax Policy as shown in the upper left panel of Figure A.2, there are several takeaways. First, in the initial months after the election, most of the specifications do not attribute much to days in which Tax Policy was the most cited topic. This is because, relatively speaking, deregulation scored higher marks on the normalization routine during this time period. One possible explanation for this is that regulatory changes were able to be enacted much sooner with most coming from the executive branch or through executive order. This can be seen in the lower right panel for the Other category, where the average (blue line) does jump up in the initial months. Second, the major declines in this category can be seen on March 21, May 17, and August



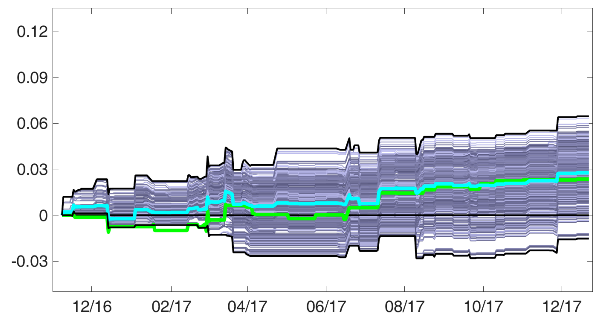
(a) Tax



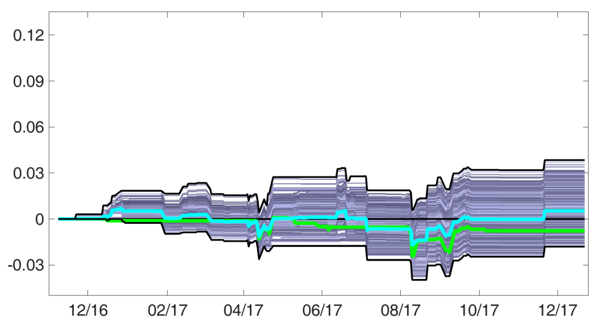
(b) US Data



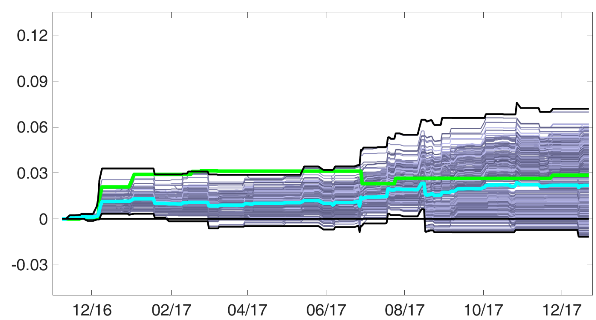
(c) Earnings



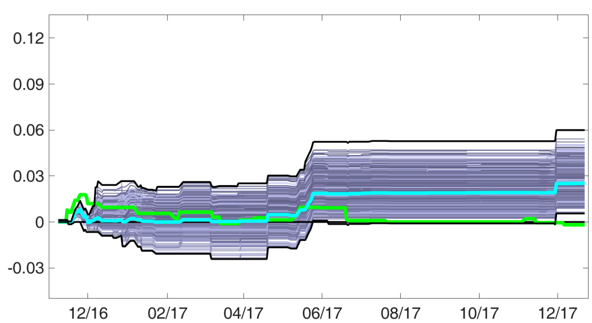
(d) FOMC



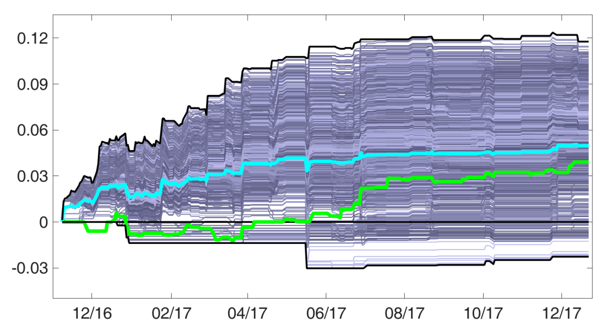
(e) Geopolitical



(f) Global



(g) Oil



(h) Other

Figure A.2: **Cumulative Returns Based On Various Machine-Based Attributions**

This figure shows the cumulative return for each category based on 1,536 different possible machine-based daily attribution specifications. The returns are based on the daily CRSP value-weighted index and are associated each day with a category based on the highest normalized value from each respective machine-based attribution. The gray lines show the various machine specifications, the blue line shows the average of these specifications on each day, and the black lines show the maximum and minimum. The human-audited daily attribution is shown in green for comparison.

17, 2017. These days were associated with failure to pass healthcare legislation, the announcement of Robert Mueller as special counsel, and news of the potential resignation of Gary Cohn. Note that both the human-audited attribution and many of the the machine-based specifications picked up these days as having important tax policy implications, despite the fact that they may seem unrelated to tax policy. That's because investors reportedly viewed these events as endangering the prospect of future tax legislation, for obvious reasons.

Beyond August, both the average and the human-audited attribution rise largely in tandem with the numerous days in which progress was made on the way to passing the Tax Cuts and Jobs Act. We find that the average net aggregate market return after adding up all the Tax Policy days was 2.61%, which is slightly higher than the human attribution of 0.99%. Interestingly, the most optimistic specification yields a 7.12% return, while the most pessimistic is -0.75%. In other words, the most optimistic specification implies less than a third of the 25% return can be attributed to tax policy, which is remarkable.

US Data. Out of all the categories, US Data provides the clearest positive impact across the 1,536 specifications [Figure A.2, Panel (b)]. Upon adding all the days in which US Data was judged to be most important, the net market return is 7.93%, which is not far off from the human attribution's 9.64%. As shown in an earlier section, the US Data was generally positive for most of the time period and was the largest contributor to the overall 25% return.

FOMC. The FOMC category, shown in Figure A.2 Panel (d), lines up fairly closely to the human attribution, with the net return associated with FOMC days being 2.36% for the human attribution and 2.77% for the machine. The several consecutive lower-than-expected CPI prints over this time period likely led to multiple days associated with more accommodative than expected communications coming from the Federal Reserve.

Geopolitical, Earnings, Global, and Oil. The net impact of the Geopolitical category [Panel (e)] was the smallest of the eight categories. Conflicts with North Korea and Syria seemed to be the main drivers over this time period, with the human attribution computing a -0.77% impact while the machine-driven technique yielding a 0.53%.

Earnings [Panel (c)] seemed to have the biggest difference between the machine technique and the human attribution. We attributed positive days to earnings such as May 19 when there was strong reports by industrials such as Deere & Company and Autodesk, but the machine thought this day had below average discussion in the news about earnings. The Global category [Panel (f)] captures many of the ECB announcements that happened early in the sample, and also seemed to find more days near the end of the sample that were driven by global data. The human attribution only captured 12 days for this category with a net return of 2.86%, while the machine attributed 26 days to this category with a net return of 2.19%.

With respect to the Oil category [Panel (g)], the human attribution and the machine both capture the days in which OPEC headlines were seen as good news for the oil sector, but the human attribution ends up capturing more days that contributed negatively to the market following reports surrounding supply gluts and cooperation failures. For example, the machine attributed positive days like November 30, 2017 to Oil, a day in which OPEC decided to extend production cuts until the end of the next year, whereas the human attribution gave this day to Tax Policy as Senator McCain announced his support for the Senate Tax Bill. This helps explain some of the gap between the two approaches, in which the machine suggests a net positive return of 2.52% with 19.19 days and the human attribution is -0.19% with 25 days.

Other. The net impact of the Other category is one of the largest of the eight categories, as seen in Figure A.2, Panel (h). As further outlined in Internet Appendix A.1, the Other category takes on several formulations across the 1,536 specifications. Specifically, we allow it to be assigned days when the maximum normalized value across the different categories does not meet a given threshold. For example, some of the approaches assign a day to the Other category if none of the other categories have a normalized value above 0 or 0.5. This is meant to capture scenarios where there doesn't seem to be a primary driver, which can often happen. Alternatively, we also allow immigration and trade keywords (further outlined in Internet Appendix A.1) to be a part of the Other category. With this context, it becomes clear why the Other category has the widest range of cumulative returns across the 1,536 specifications. The average across the machine specifications is 4.98% with 44.41 days, and the human attribution yields 55 days and a net return of 3.91%. As previously mentioned, most of the gains in this category came in the early months, when it may have been easier to enact regulatory changes through the executive branch (relative to the tax policy changes which required action from Congress). With "deregulation" being one of the main keywords in this category, our analysis leaves open the possibility that this aspect of policy may have had a relatively more important role than tax policy in the overall 25% market return.

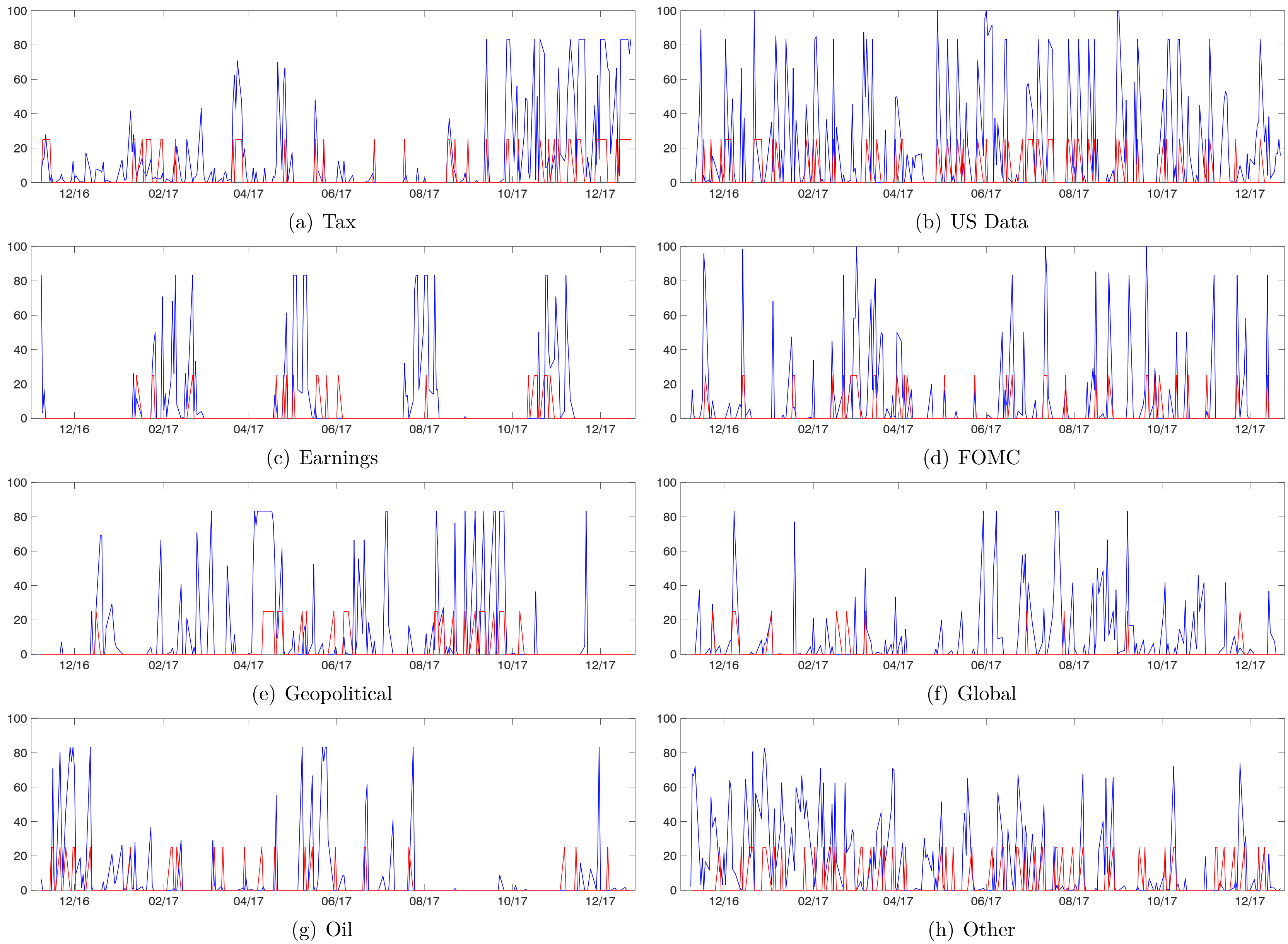
To provide some additional perspective, we also plot the percent of specifications that have the maximum normalized value (i.e., attribution) for a given category on each of the 283 days in Figure A.3 against the human attribution (red line). Overall, we view this robustness exercise as a valuable check on our more subjective human attribution. The machine attribution roughly confirms our previous findings that US Data was a key driver of the market returns and that Tax Policy days were important and positive, on net, but also relatively small. Table A.1 provides further details on the average number of days and net return on those days compared to the human attribution.

				Number of Days				
Category	Taxes	US Data	Earnings	FOMC	Geopol.	Global	Oil	Other
Human Attrib.	52	53	21	36	29	12	25	55
Machine Avg.	42.6	58.6	28.4	31.2	33.5	26.1	19.2	44.4
25th-75th %	[26 57]	[51 66]	[25 32]	[25 37]	[28 39]	[20 33]	[15 23]	[33 62]
Min - Max	[18 80]	[41 85]	[18 44]	[16 54]	[19 52]	[12 45]	[10 36]	[0 91]

				Returns				
Category	Taxes	US Data	Earnings	FOMC	Geopol.	Global	Oil	Other
Human Attrib.	0.99	9.64	5.52	2.36	-0.77	2.86	-0.19	3.91
Machine Avg.	2.61	7.93	1.19	2.77	0.53	2.19	2.52	4.98
25th-75th %	[1.9 3.2]	[6.8 8.8]	[0.6 1.6]	[1.7 3.7]	[-0.2 1.2]	[0.5 3.8]	[1.8 3.0]	[1.8 7.7]
Min - Max	[-0.8 7.1]	[4.5 13.4]	[-0.2 3.5]	[-1.5 6.4]	[-1.8 3.8]	[-1.1 7.1]	[0.5 6.0]	[-2.2 11.7]

Table A.1: **Comparison of Machine-Attribution Specifications to Human Attribution**

This table compares the daily attribution of the machine-based method to the human-audited daily attribution. The top panel compares the number of days across the entire sample (November 9, 2016 to December 22, 2017) associated with each category based on the human attribution to the average number of days associated with the machine-based specifications. The top panel also shows the interquartile range and full range for the number of days across the specifications. The bottom panel compares the cumulative CRSP value-weighted returns associated with each category based on the human attribution to the distribution of cumulative returns using the machine-based attribution method.



(a) Tax (b) US Data

(c) Earnings (d) FOMC

(e) Geopolitical (f) Global

(g) Oil (h) Other

Figure A.3: **Comparison of Machine-Attribution Specifications to Human Attribution**

This figure compares the daily attribution of the machine-based method to the human-audited daily attribution. The blue line shows the percentage of the 1,536 machine-based specifications that attribute each day to a given category. The red line shows the human-audited daily attribution for comparison.

A.1 Machine Specifications

In this section, we provide further details that correspond to the over 1,500 specifications that we use for the machine-based textual analysis. As previously stated, we apply a machine technique that employs the Bloomberg News Trend Function. The Bloomberg News Trend Function allows for us to count the number of times a specific word or phrase has been used in various major news outlets on any given day.

We recognize the numerous choices and assumptions that go into this process, and for that reason rely on a host of specifications for this analysis rather than a single one. Specifically, we run the exercises across eight dimensions: (1) four approaches for normalizing the keywords, (2) three approaches for creating thresholds to assign days to the Other category, (3) two ways to place weight on the highest and second-highest normalized value for a given day, (4) two ways to construct the US data category, (5) four ways to define the Other category to also incorporate trade and immigration, (6) inclusion of "OPEC" in the Oil category, (7) whether or not to include "global data" in the ECB / Global category, and (8) excluding "stress test" from the Other category. The rest of this section provides more details on each of these dimensions.

Normalizations As mentioned in the main text, the choice of normalization can make a meaningful difference. Normalizing in this context involves subtracting the mean and dividing by the standard deviation for each keyword. Normalizing over a static window of the full 283 days may understate the use of keywords in the initial months of the sample. For instance, the taxes keywords were heavily used near the end of the sample in comparison to the beginning of the sample. Normalizing in this way would tend to put virtually no weight on taxes at the beginning of the sample (this can be seen by Figure A.1). An alternative approach would be to use an expanding recursive window that begins before the election. By looking over a longer sample and avoiding the look-ahead bias present with the other method, it may better capture the real-time evaluation of news that investors must react to in the real-world (i.e., investors can only evaluate news based on information up to time t).

				Number of Days				
Category	Other (1)	Other (2)	Other (3)	Other (4)	Tax (1)	Tax (2)	Tax (3)	Tax (4)
Human Attrib.	55	–	–	–	52	–	–	–
Machine Avg.	43.5	50.9	44.6	38.6	21.2	32.5	61.9	54.6
Min - Max	[0 81]	[0 90]	[0 84.3]	[0 75]	[18 26]	[26 43]	[47 80]	[44 68]

				Returns				
Category	Other (1)	Other (2)	Other (3)	Other (4)	Tax (1)	Tax (2)	Tax (3)	Tax (4)
Human Attrib.	3.91	–	–	–	0.99	–	–	–
Machine Avg.	4.04	5.12	5.72	5.03	2.49	2.66	2.39	2.88
Min - Max	[-2.3 10.2]	[-1.0 11.0]	[-0.8 11.7]	[-1.1 11.1]	[1.3 3.9]	[1.4 4.0]	[-0.7 6.9]	[0.2 7.1]

Table A.2: **Impact of Different Normalizations**

For these reasons, we construct specifications for this dimension in four ways: (1) Static window November 9, 2016 to December 22, 2017, (2) Static window January 4, 2016 to December 22, 2017, (3) Recursive expanding window starting on January 4, 2016 to time t (initial end date being November 9, 2016), and (4) Recursive expanding window starting on June 3, 2016 to time t (initial end date being November 9, 2016). We find that the differences between the static windows is very small, while the differences between the dynamic windows is also small. However, the difference between the static and dynamic windows does seem to be important (as shown in Figure A.1). Interestingly, we find that without the dynamic windows, the machine attribution attributes hardly any days in the initial part of the 283 day sample to taxes. This is inconsistent with our human attribution, in which we judged the days after the election to be important Tax Policy days.

Thresholds for Assigning Days to the "Other" Category For the human attribution, there were many days in which there was no obvious driver for the market's moves. These days often had extremely low volatility and the market return was very small (this can be seen in Figure 6 in the main text). To capture this possibility and to avoid over-attributing days to certain categories even when the news for that day was below average, we also evaluate specifications in which the maximum normalized value across categories needs to be above a certain threshold.

This leads us to considering three ways of constructing specifications along this dimension: (1) No threshold, (2) if the category with the highest normalized value is less than 0, assign the day to Other instead and (3) assign the day to "Other" if the maximum normalized value is less than 0.5. The latter two categories increase the number of days, as seen in Table A.3

Number of Days						
Category	Other (1)	Other (2)	Other (3)	Tax (1)	Tax (2)	Tax (3)
Human Attrib.	55	–	–	52	–	–
Machine Avg.	32.6	38.6	61.9	45.2	43.1	39.5
Min - Max	[0 70]	[4 73]	[28 90]	[21 80]	[18 77]	[18 70]

Returns						
Category	Other (1)	Other (2)	Other (3)	Tax (1)	Tax (2)	Tax (3)
Human Attrib.	3.91	–	–	0.99	–	–
Machine Avg.	4.82	4.26	5.85	2.63	2.73	2.45
Min - Max	[-0.01 11.5]	[-2.2 11.1]	[-0.2 11.8]	[-0.8 7.0]	[-0.6 7.1]	[-0.5 6.7]

Table A.3: **Impact of Different Thresholds for Assigning to "Other" Category**

Different weighting for highest and second-highest normalized values Assigning all the weight to a single category likely overstates the importance of any one category. We look further into how much this matters for our analysis by assigning a weight of 2/3 to the category with the highest normalized value and 1/3 to the category with second-highest normalized value. Table A.4 shows that in terms of the days assigned to each category, not much changes. In terms of returns, both the "Other" category and the "US Data" lose ground while the "Tax Policy" category gains ground. This might be because the tax policy may not have been the most important on various days but was still heavily reported on. With that said, the return attributed to tax days is still just 3.00% on average for this specification.

			Number of Days			
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)
Human Attrib.	55	–	52	–	52	–
Machine Avg.	44.3	44.5	42.9	42.3	57.1	60.1
Min - Max	[0 89]	[0.6 90.6]	[18 80]	[18 79.6]	[41 85]	[44 83]

			Returns			
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)
Human Attrib.	3.91	–	0.99	–	9.64	–
Machine Avg.	5.22	4.74	2.21	3.00	8.59	7.28
Min - Max	[-2.2 11.7]	[-2.2 11.1]	[-0.7 5.1]	[1.2 7.1]	[5.9 13.5]	[4.5 10.7]

Table A.4: **Different Weighting for Second-Highest Normalized Value**

Different ways to construct the US data category The US Data is formulated under two approaches. The first approach, creates three subcategories and the keywords are averaged within each subcategory: (1) "CPI" and "Retail Sales", (2) "Nonfarm", and (3) "ISM" and "GDP". The US Data category needs to be split into three subcategories because if we were to average across all of the words at the same time, the majority of the US Data keywords would be very low on any given day (because there would be no news to report for most of these variables), which would bring down the normalized value for the entire category. By splitting the subcategories in this way, it ensures that US Data days are not systematically underweighted. The second approach is similar to the first approach but excludes "ISM" from the third subcategory. Table A.5 shows there is very little difference for the "Other" category and "Tax" category, while the US Data captures a few more days with just "GDP" in the third subcategory. It could be that the "GDP" term may be more general, which allows it to pick up more days as a standalone keyword. None of the other categories besides US Data have more than a 1 day difference across the two specifications.

	Number of Days					
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)
Human Attrib.	55	–	52	–	52	–
Machine Avg.	44.9	44.0	42.7	42.4	56.1	61.1
Min - Max	[0 91]	[0 89]	[18 80]	[18 78.6]	[41 78]	[45 85]

	Returns					
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)
Human Attrib.	3.91	–	0.99	–	9.64	–
Machine Avg.	5.11	4.84	2.55	2.67	7.57	8.29
Min - Max	[-2.2 11.4]	[-2.2 11.7]	[-0.7 6.8]	[-0.3 7.1]	[4.5 11.5]	[5.3 13.5]

Table A.5: **Different ways of constructing US Data Category**

Incorporating trade and immigration In this section, we explore four additional ways of constructing the "Other" category. The first approach involves a single subcategory with the keywords "deregulation" and "stress test." The second approach assumes no keywords for the "Other" category, but allows days to be added to the category based on the thresholds described earlier. The third approach adds another subcategory to the first approach based on keywords associated with "trade", specifically "tariff", "tariffs", "protectionism", "tradewar", "NAFTA", "renegotiate", and "foreign firms." The fourth approach replaces the "trade" subcategory with a category related to "immigration," with the keywords "border wall", "Trump wall", "immigration", and "caravan." Again, subcategories are used because they represent sufficiently different keywords and combining them and averaging would likely understate their impact.

				Number of Days				
Category	Other (1)	Other (2)	Other (3)	Other (4)	Tax (1)	Tax (2)	Tax (3)	Tax (4)
Human Attrib.	55	–	–	–	52	–	–	–
Machine Avg.	46.7	16.8	59.1	55.0	41.9	48.2	39.9	40.3
Min - Max	[19 80]	[0 52]	[31 90.6]	[26 88]	[18 70]	[19 80]	[18 66]	[18 66]

				Returns				
Category	Other (1)	Other (2)	Other (3)	Other (4)	Tax (1)	Tax (2)	Tax (3)	Tax (4)
Human Attrib.	3.91	–	–	–	0.99	–	–	–
Machine Avg.	5.89	-0.01	7.42	6.64	2.42	3.60	2.14	2.26
Min - Max	[0.1 11.5]	[-2.2 2.5]	[2.4 11.7]	[2.8 10.9]	[-0.7 4.7]	[1.3 7.1]	[-0.5 3.9]	[-0.7 4.3]

Table A.6: **Impact of Incorporating Trade and Immigration**

Table A.6 shows the implications of the different approaches and there are several takeaways. First, formulations (3) and (4) which include trade and immigration, respectively, lead to a greater number of days attributed to the "Other" category and slightly fewer days devoted to the "Tax" category. We also then see larger returns attributed to the "Other" category and lower returns associated with "taxes." This suggests that incorporating trade and immigration keywords weighs on the return associated with Tax days. Second, excluding "Other" keywords as in the second approach leads to a higher number of days attributable to tax policy along with a higher return. This seems intuitive, as there may be overlap on news days associated with the various terms. However, the return is still only 3.60% on average under this formulation for the tax policy. Third, trade seems to have a relatively bigger impact according to our exercise relative to immigration. Yet the difference when including these terms only moves the average for the "Other" category up by about 1.5%, indicating that trade was not perhaps as important in 2017 as it was in the years that followed.

				Number of Days				
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)	ECB (1)	ECB (2)
Human Attrib.	55	–	52	–	53	–	12	–
Machine Avg.	43.5	45.3	41.6	43.5	57.6	59.5	31.0	21.1
Min - Max	[0 89]	[0 90.6]	[18.6 76]	[18 80]	[41 85]	[43 82.6]	[15 44.5]	[12.3 33]

				Returns				
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)	ECB (1)	ECB (2)
Human Attrib.	3.91	–	0.99	–	9.64	–	2.86	–
Machine Avg.	5.01	4.94	2.36	2.85	7.28	8.58	3.91	0.47
Min - Max	[-2.2 11.5]	[-2.2 11.7]	[-0.7 6.6]	[-0.5 7.1]	[4.5 12.0]	[5.7 13.5]	[1.9 7.2]	[-1.1 3.1]

Table A.7: **Including and Excluding "global data" from ECB / Global category**

Including and Excluding "global data" from ECB / Global category Table A.7 shows what happens if we exclude "global data" in formulation (2). Specifically, the far right column shows the attribution when the ECB category excludes "global data." Intuitively, the number of days that are assigned to this category fall quite a bit, leaving it closer to the human-audited attribution. Likewise, the return associated with this category also falls to 0.47%. The days that were previously characterized as "global data" have broadly shifted to the other categories. Similarly, the return on these days shift towards the Tax and US Data category, with both higher by 0.5% and 1.3%, respectively.

	Number of Days							
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)	FOMC (1)	FOMC (2)
Human Attrib.	55	–	52	–	53	–	36	–
Machine Avg.	39.2	49.5	43.7	41.5	59.7	57.4	34.2	32.9
Min - Max	[0 81.3]	[0 90.6]	[18 80]	[18 80]	[41 85]	[41 85]	[20 52]	[18.6 52]

	Returns							
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)	FOMC (1)	FOMC (2)
Human Attrib.	3.91	–	0.99	–	9.64	–	2.36	–
Machine Avg.	3.76	6.19	2.61	2.60	8.34	7.52	3.24	2.31
Min - Max	[-2.2 9.3]	[-2.2 11.7]	[-0.7 7.1]	[-0.3 7.1]	[5.9 13.5]	[4.5 12.4]	[-0.4 6.4]	[-1.5 6.5]

Table A.8: **Including and Excluding "stress test" from Other category**

Including and Excluding "stress test" from Other category Table A.8 shows in formulation (1) what happens if the term "stress test" is included along with the term "deregulation" in the "Other" category. Formulation (2) excludes "stress test." One can see that including the term lowers the number of days attributed to the "Other" category. With fewer days, the average return assigned to the "Other" category falls by 2.43%. This decline in the return is offset by increases in US Data and FOMC days, with close to 1% point increases. It appears that by including the term "stress test", it effectively downweights the "deregulation" term because they are averaged together within the "Other" category. However, more importantly, this choice doesn't seem to affect the average return associated with the "Tax" category, as the difference in return between the two formulations is just 1 basis point.

				Number of Days				
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)	FOMC (1)	FOMC (2)
Human Attrib.	55	–	52	–	53	–	36	–
Machine Avg.	44.4	39.4	42.6	42.6	58.6	57.9	31.2	32.3

				Returns				
Category	Other (1)	Other (2)	Tax (1)	Tax (2)	US Data (1)	US Data (2)	FOMC (1)	FOMC (2)
Human Attrib.	3.91	–	0.99	–	9.64	–	2.36	–
Machine Avg.	4.98	6.00	2.61	2.03	7.93	7.00	2.77	3.08

Table A.9: **Isolating “deregulation” in Other category**

Isolating “deregulation” within Other category Table A.9 shows in formulation (2) what happens if we isolate the term “deregulation” while also removing any of the other thresholds for attributing to the Other category, leaving us with 64 specifications. Formulation (1) is the default configuration as shown in the main text. One can see that isolating the “deregulation” term does lead to a higher return associated with the Other category, at around 6.00%. It also leads to fewer days, as the attribution is no longer attributing days to the Other category when the normalized values across all the categories are relatively low. The isolation of “deregulation” seems to take some of the days that were attributed to taxes, as the return associated with the tax category declines to 2.03%. Under this interpretation, 8.03% of the close to 25% return could be attributed to days in which administration policies were deemed most important.

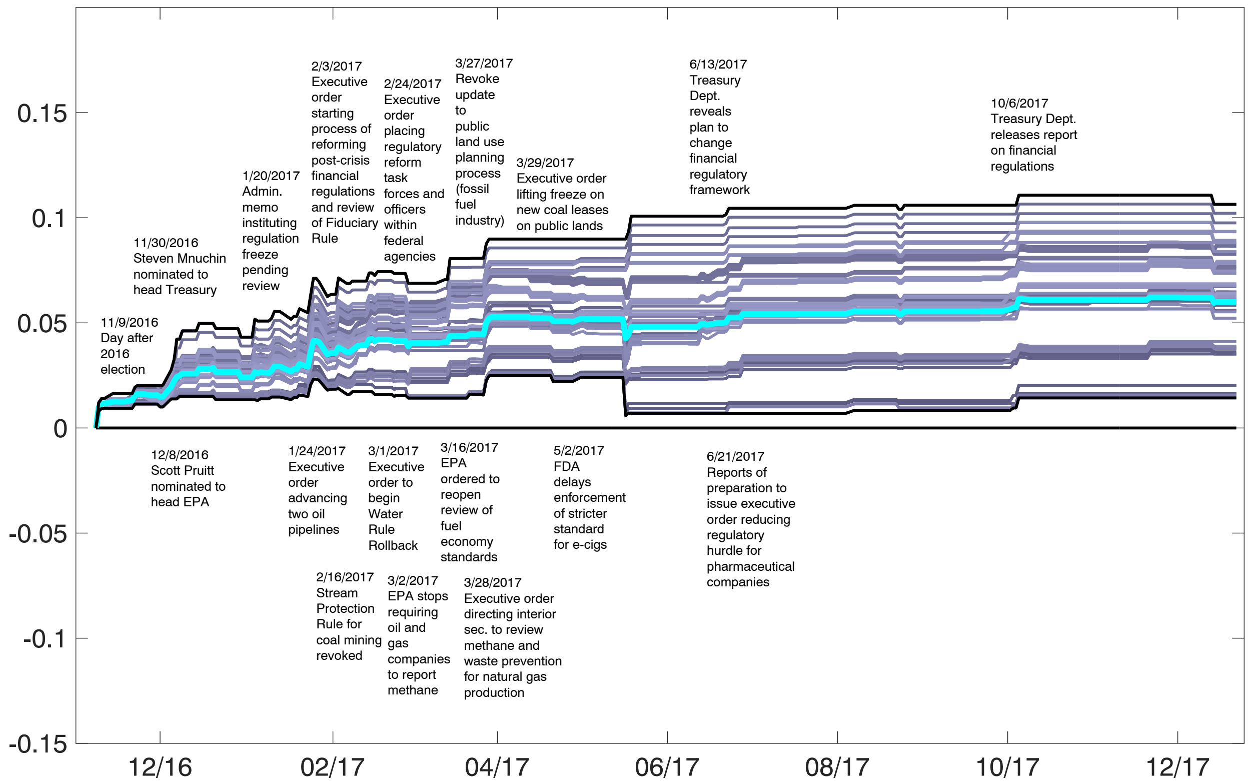


Figure A.4: **Machine Attribution: Keyword "Deregulation" Nov. 2016 to Dec. 2017**

Figure A.4 shows that most of the gains attributed to the keyword for "deregulation" came in the first several months. This is consistent with the notion that these items had less difficulty being implemented either via executive order or through the legislature with the Congressional Review Authority.

B Cross-Sectional Regression Data

This section outlines the data used for the firm-level regressions in Section 4. Our data covers the firms in the Russell 3000 as of November 8, 2016. Daily stock return data was pulled from CRSP and were adjusted for splits and dividends. Returns were winsorized at the 1st and 99th percentile. Firm-level financial data was provided by Compustat for fiscal year 2015, with the exception of the percentage of revenues from foreign sources which comes from Bloomberg. We supplemented this data with Compustat Segment data if a firm was missing the percent of foreign revenues from Bloomberg. We dropped firms that had a percent of foreign revenues less than 0 or greater than 100. The cash effective tax rate (CashETR) is calculated as cash taxes paid ($TXPD$) divided by pretax income adjusted for special items ($PI - SPI$) and multiplied by 100. GAAP ETR equals a firms' total income taxes based on the Generally Accepted Accounting Principles (TXT) divided by pretax income (PI) multiplied by 100. Following the previous literature, we trim the CashETR and GAAP ETR measures at 0% and 100%. Firms with negative pretax income were dropped in regression specifications which use CashETR or GAAP ETR. The Δ tax measure equals cash taxes ($TXPD$) adjusted for the change in income tax refund ($TXR_t - TXR_{t-1}$) minus the prevailing statutory tax rate, then divided by the market value of assets which is equal to total assets (AT) plus the market value of equity ($PRCC * SHO$) minus shareholders' equity (SEQ). Following Henry and Sansing (2018), we winsorized the Δ measure at the 1st and 99th percentile. The regulation exposure measure comes from each firm's 2015 Form 10-K Item 1A. In all regressions, we use the log of the market value of equity. Revenue growth is calculated as the percentage growth of total net sales from 2014 to 2015. Profitability is pretax income divided by total assets multiplied by 100. Each of the control variables is winsorized at the 1st and 99th percentiles.

C Municipal-Implied Tax Rates

Denote the future expected tax rate at time t as

$$\tau_t = 1 - \frac{Y_{m,t}}{Y_{c,t}} \tag{A.1}$$

where $Y_{m,t}$ is the yield at time t on a municipal bond, $Y_{c,t}$ is the yield at time t on a taxable bond with similar maturity and risk. We can estimate the average expected future tax rate, τ with the following equation

$$Y_{m,t} = (1 - \tau) * Y_{c,t} + \varepsilon_t. \tag{A.2}$$

Generalizing to a case where $Y_{c,t}$ does not have the same exposure to risk as $Y_{m,t}$, we have

$$Y_{m,t} = (1 - \tau) * Y_{c,t} + \lambda F_t + \varepsilon_t. \tag{A.3}$$

where F_t is a vector of relevant risk factors at time t and λ is the average exposure of municipal bond yields to those risks. We follow Wu and Yoo (2017) and estimate the following Kalman filter

$$Y_{m,t} = R_t \beta_t + \varepsilon_t \tag{A.4}$$

$$\beta_t = \beta_{t-1} + v_t \tag{A.5}$$

where $\beta_t = [(1 - \tau_t), \lambda_t]'$, $F_t = [Y_{c,t}, F_t']$, $\varepsilon_t \sim N(0, \sigma^2)$, and $v_t \sim N(0, Q)$. This provides us with a time series of τ_t adjusted for differing exposure to risk between $Y_{m,t}$ and $Y_{c,t}$.

In our implementation, we estimate a daily series of muni-implied expected future tax rates using Bloomberg BVAL Muni Benchmarks for yields on municipal bonds, $Y_{m,t}$. This yield curve is constructed with yields from high quality US municipal bonds with an average rating of Aaa from Moody's and S&P and is available daily from 2009Q1 to 2018Q4. We use the seasoned Aaa yield from FRED corrected for the difference in maturity. Specifically, these bonds have a maturity greater than 20 years. Due to the liquidity concerns with the 20-year treasury, we use the Aaa corporate yield minus the 30-year treasury plus the appropriate maturity treasury yield as the taxable bond yield, $Y_{c,t}$. For our vector of risk factors, we use proxies for both credit and liquidity risk in bond markets in general and municipal bond markets specifically. Due to data availability across the yield curve for some of these measures, we focus on a maturity of five years for our analysis.

Our credit risk measures are the Baa-Aaa credit spread and the average implied probability of default for municipal bond insurers from CDS spreads. This probability of default measure, PD_t is calculated from 5-year CDS spreads and recovery rates from Markit and is equal to

$$PD_t = \frac{1}{n}\sum_{i=1}^{n} PD_{i,t} \tag{A.6}$$

$$PD_{i,t} = 1 - exp(-\lambda_{i,t}) \tag{A.7}$$

$$\lambda_{i,t} = \frac{CDS_{i,t}}{1 - Recovery_{i,t}} \tag{A.8}$$

$PD_{i,t}$ is the implied probability of default and $\lambda_{i,t}$ is the default intensity for municipal bond insurer i at time t. Our sample of eight municipal bond insurers is taken from Chung et al. (2015).[1] Our liquidity risk measures are the on-/off-the-run treasury spread, the Pástor and Stambaugh (2003) measure, and the Amihud (2002) measure.

We construct the Pástor and Stambaugh (2003) measure of liquidity by first estimating the following regression for each municipal bond i in day t

$$r^e_{idt} = \rho_0 + \rho_1 r_{idt} + \pi_{it} sign(r^e_{idt}) Vol_{idt} + u_{idt} \tag{A.9}$$

where r_{idt} is the five-minute return of bond i on day t over the time period d, r^e_{idt} is the return in excess of the bond market return, $sign(r^e_{idt})$ is the signed indicator which equals 1 if r^e_{idt} is positive and -1 if r^e_{idt} is negative, and Vol_{idt} is the par volume of bond i traded over the time period d. We calculate the bond market returns over five-minute intervals by calculating the value-weighted return in the corporate bond markets.[2] Five-minute municipal bond returns are from MSRB and five-minute corporate bond returns are from TRACE. We use bonds with at least 10 five-minute return observations in a given day t for the estimation. We define a market-wide aggregate π_t as the equal-weighted average of π_{it}. We then obtain innovations by estimating the following equation

$$\Delta\pi_t = \alpha_0 + \alpha_1 \Delta\pi_{t-1} + \alpha_2 (\frac{M_{t-1}}{M_1}) \pi_{t-1} + e_t \tag{A.10}$$

[1] Specifically, we consider Assured Guaranty Ltd., Ambac Financial Group, Inc., Berkshire Hathaway Assurance Corp., CIFG Assurance North America Inc., Financial Guaranty Insurance Company, Municipal Bond Insurance Association, Radian Group Incorporated and XL Capital Assurance.

[2] Mergent FISD lacks data on municipal bond amounts outstanding.

where $\Delta\pi_t = (\frac{M_t}{M_1})(\pi_t - \pi_{t-1})$ and M_t is the total dollar value of all bonds at the end of day $t-1$ of all bonds traded in the corporate bond market on day t.[3]

The Amihud (2002) measure utilizes the same five-minute return data. For a municipal bond i on day t, we define

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|r_{idt}|}{Vol_{idt}} \tag{A.11}$$

We define a market-wide aggregate $ILLIQ_t$ as the equal-weighted average of $ILLIQ_{it}$. We then obtain innovations by estimating the following equation

$$\Delta ILLIQ_t = \phi_0 + \phi_1 \Delta ILLIQ_{t-1} + \phi_2 (\frac{M_{t-1}}{M_1}) ILLIQ_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} \tag{A.12}$$

where $\Delta ILLIQ_t = (\frac{M_t}{M_1})(ILLIQ_t - ILLIQ_{t-1})$.

D Global growth narrative

Throughout this study, we have appealed to the notion that global growth may have been a fairly important factor in the rise in the stock market over the 283 days in our sample. In this section, we provide some further evidence that is consistent with this narrative.

D.1 Foreign Inflation Measures

Inflation readings in the Eurozone and the United Kingdom reached multi-year highs in the year 2017. Figure A.5 shows that these increases began before the election in November. Remarkably, for the first time in over a half-decade, none of the Eurozone's 19 members had deflation in 2017. While it is certainly possible that the outcome of the U.S election may have influenced these foreign inflation prints, it is not clear what economic mechanism would be driving this phenomenon. It seems more likely that these elevated inflation prints are a function of the strong domestic performance within the respective countries.

[3] We assume that scaled volume, $\frac{M_t}{M_1}$, is similar between the corporate bond market and the municipal bond market since Mergent FISD lacks data on municipal bond amounts outstanding.

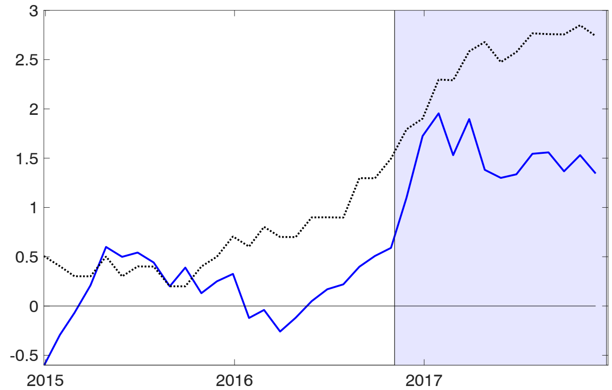


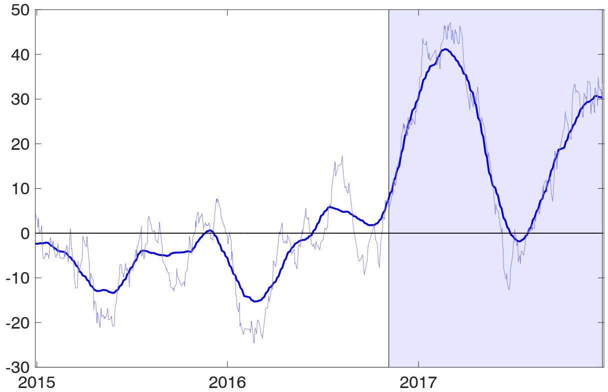
Figure A.5: **Foreign Inflation**

This figure shows inflation for the Eurozone (solid blue line) and the United Kingdom (dashed black line) from the January 2015 to December 2017. Inflation is measured as the 12-month percentage growth in the Consumer Price Index for the respective region or country from the OECD's Main Economic Indicators.

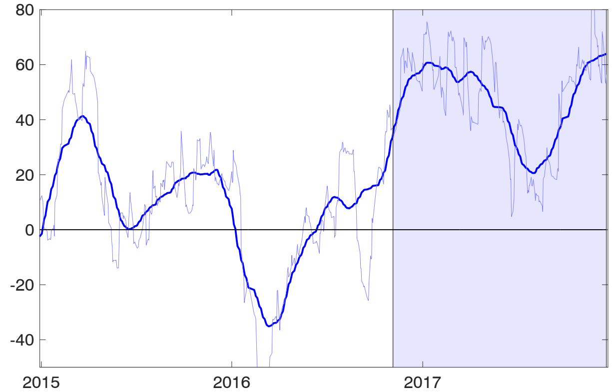
D.2 Citigroup Economic Surprise Indices

With each country having its own set of economic data releases, it can be difficult to provide a clear exposition across the many dimensions that are of interest for the various countries. For this reason, we primarily focus on the Citigroup Economics Surprise Indices (CESI), which provide quantitative measures of economic news. More formally, the CESIs are constructed daily using data surprises (i.e. actual releases versus the Bloomberg median survey across 32 economic indicators) in rolling windows of the past 3-months with some time-decay to replicate the limited memory of markets. The weights on each economic release are determined by their high-frequency historical estimated impact on FX markets, as the CESIs were originally constructed for use by FX traders. While these measures are typically mean-reverting (due to the built-in time-decay and the ebb and flow of investor expectations), they can still provide valuable insights into whether data releases in aggregate are coming in above or below expectations.

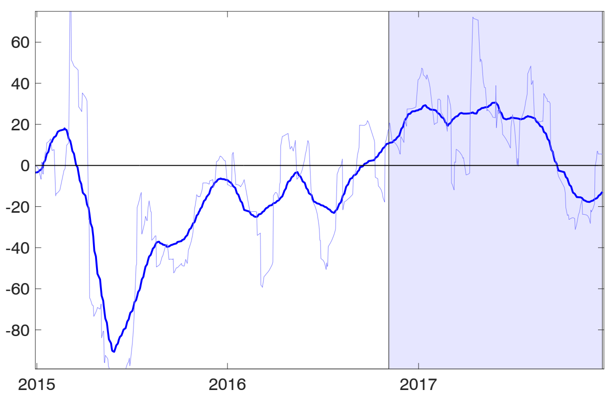
There are several takeaways from Figure A.6, which shows the raw and 50-day moving average CESIs for the Global Economy, the Eurozone, China, and the United States. First, the Global Citigroup Economic Surprise Index [Panel (a)] was almost exclusively below zero for the entirety of 2015 and into the first half of 2016. This is likely driven by the relative underperformance of China and the United States over this time period. Interestingly, the Global index bottoms out in early 2016 and then begins to rise and become positive around June 2016, five months before the election in November.



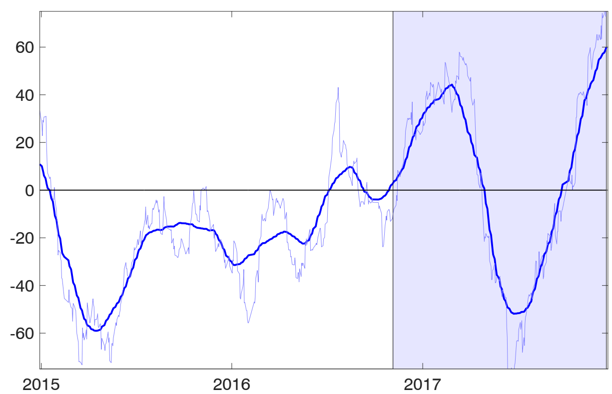
(a) Global



(b) Eurozone



(c) China



(d) United States

Figure A.6: **Citigroup Economic Surprise Indices**

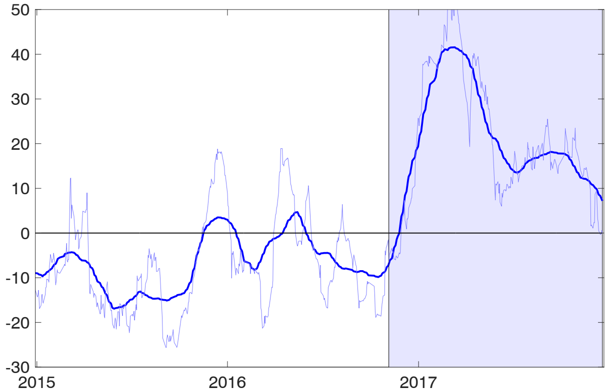
This figure shows the Citigroup Economic Surprise Indices for the Global Economy, the Eurozone, China, and the United States from 2015 to 2017. The black vertical lines indicate November 8, 2016 and the blue shaded regions represents the 283 days after the election. The thin blue line plots the raw index while the dark blue line represents the 50-day moving average. A positive surprise index indicates aggregate news releases are above expectations for a given day, while a negative index reflects news that is below-expectations. We obtained the Economic Surprise Indices from Bloomberg.

Second, the dramatic rise that begins in early 2016 and extends through the end of 2017 also occurs in the Eurozone as shown in the Panel (b) of Figure A.6. The Eurozone index stays relatively elevated for the full 283 days sample, with the figure showing its increase beginning well before the election. A number of data points can be pointed to in explaining these high readings: (1) Eurozone growth hit a 10-year high in 2017, surpassing US growth over this time period; (2) for the first time in over a half-decade, none of the Eurozone's 19 members had deflation and Eurozone CPI was above 1.5%; and (3) 2017 was the first year since the crisis that no major economy was in contraction mode. The relative outperformance of the Eurozone during this time is also consistent with the FTSE's outperformance of the CRSP-value weighted market return.

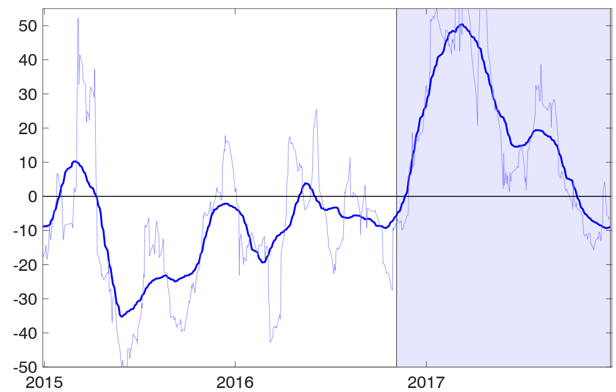
Third, we see that China [Panel (c)] seemed to reach bottom in mid-2015 and begins to steadily rise thereafter, with its 50-day moving average reaching positive territory again before the election in November. Then, for most of 2017, the moving average of the index remained at its highest level since 2012.

Fourth, the United States [Panel (d)] also seems to reach bottom in early 2015 before rising and reaching positive territory in mid-2016. We then see a relatively large increase in the final months of 2016 after the election. As has been previously discussed in the text, it is important to remember that data releases are backward looking and are reported with a lag. As such, positive data releases in November and December typically reflected data that was from the period before the election. In other words, it's likely the data releases right around the election had nothing to do with the outcome of the election. More interestingly, we see that the US Data seemed to be coming in below expectations in the middle of 2017 before rising again at the end of the sample. This is very likely due to the five consecutive below expectations CPI prints that occurred over this time period. Given that this index weights economic data releases based on their impact on FX markets, it seems plausible that data releases pertaining to inflation receive a relatively larger weight in the composition of the index. It's possible that markets over this time period instead focused on the relatively good news coming out of China and the Eurozone and the potentially more accommodative response from monetary policy given these inflation misses.

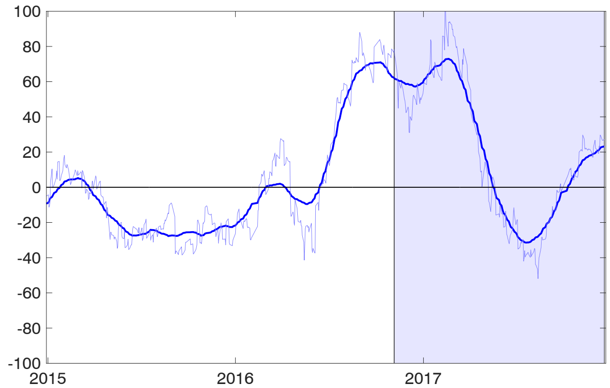
Lastly, Figure A.7 shows that the UK, Emerging Market Economies, and the BRIC countries also performed relatively well over the 283 days in our sample. In addition, the global performance over this time period was fairly elevated relative to the past 5 years. Each of these facts seems to contribute to the notion that global growth was very important over this time period. With 40% of revenues for S&P 500 firms coming from overseas, combined with the robust statistical significance of the corresponding firm characteristic in our regressions, the evidence overwhelmingly suggests that synchronized global growth played an outsized role in the 25% increase in the stock market. For historical comparison purposes, Figure A.8 shows a longer sample for the CESIs dating back to 2012.



(a) Emerging Markets

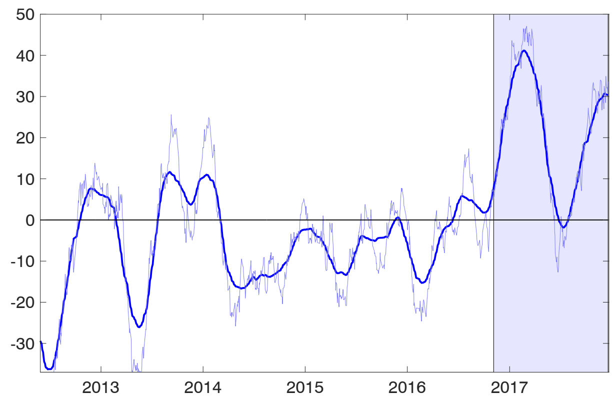


(b) BRIC (Brazil, Russia, India, China)

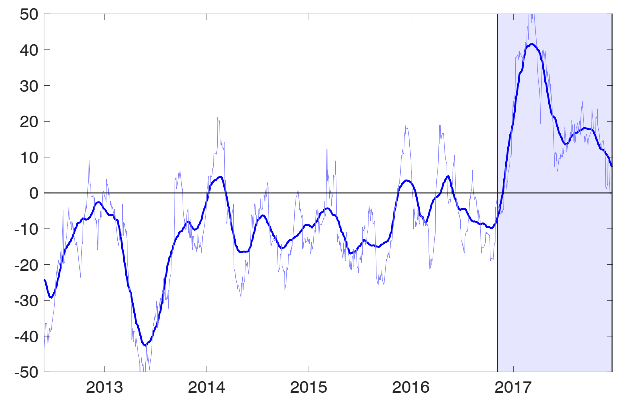


(c) United Kingdom

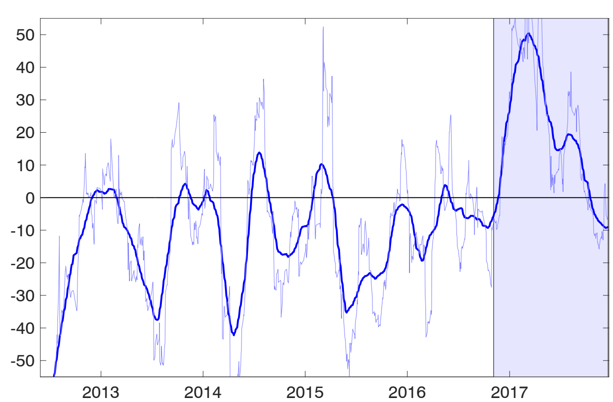
Figure A.7: **Citigroup Economic Surpise Indices, 2015-2017**



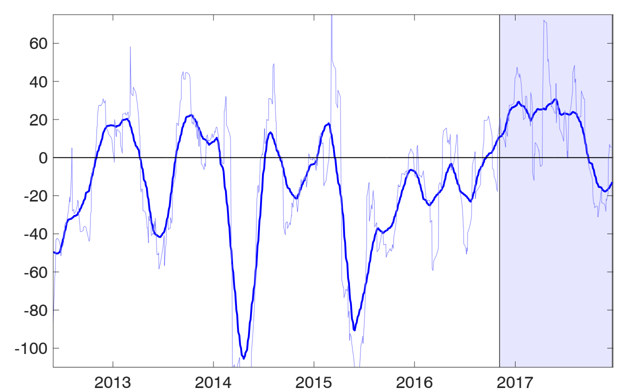
(a) Global



(b) Emerging Markets



(c) BRIC



(d) China

Figure A.8: **Citigroup Economic Surpise Indices, 2012-2017**

E Construction of Tax Baskets

E.1 Goldman Sachs

Goldman Sachs constructs a portfolio that goes long in 50 of the highest-taxed S&P 500 firms and short in 50 of the lowest-taxed firms. The idea is that firms with higher effective tax rates will outperform firms with lower effective tax rates as the prospect for tax legislation increases. The portfolio has been cited heavily in the media and was used extensively in Goldman Sachs research pieces.

The High Tax basket has a 10-year median effective tax rate of 38% while the median tax rate for the S&P500 is 28%. With regards to the firms that make up the basket, 10 of the firms are from Information Technology (e.g Visa, Intuit), 8 firms are Health Care (e.g. CVS), 7 firms are Financials (e.g. T Rowe Price, Schwab), 5 firms from Consumer Discretionary (e.g. Nordstrom, ...), 5 from Communication Services (e.g. Comcast) , and the rest are from Industrials, Energy, Consumer Staples, Materials and Utilities.

The Low Tax Basket has a 10-year median effective tax rate of around 11% and consists of 10 firms from Information Technology (e.g. Nvidia), 8 firms from Health Care (e.g. Amgen), 7 firms from Financials (e.g. Suntrust Banks), 6 from Communication Services (e.g. Walt Disney), 5 from Consumer Discretionary (e.g. Carnival), and the rest are from Industrials, Energy, Consumer Staples, Materials and Utilities.

E.2 Credit Suisse

The Credit Suisse High minus Low Tax Basket is constructed by the authors using constituents listed in a Credit Suisse US Equity Strategy piece "Stocks Ignoring Trump on Taxes," dated October 12, 2017. The index is a price-weighted daily rebalanced portfolio of the 30 firms with the highest tax rate and 30 firms with the lowest tax rate. The tax rates are based on a trailing three-year calculation.

E.3 Morgan Stanley

The Morgan Stanley High minus Low Tax Basket is obtained from Bloomberg under the identifiers MSXXHTAX and MSXXLTAX. The exact details for the construction of these series were not available.

E.4 Cash Effective Tax Rate 4th Quartile - 1st Quartile

The portfolio is value-weighted and constructed based on a firm's 5-year cash effective tax rate. The cash effective tax rate (CashETR) is calculated from Compustat as cash taxes paid ($TXPD$) divided by pretax income adjusted for special items ($PI - SPI$) and multiplied by 100. There are roughly 663 firms in each quartile. The mean tax rate in the high tax quartile is 41.5% while the mean tax rate in the bottom quartile is 0.9%. We use the 5-year horizon for expositional purposes because it represents a middle ground in terms of the various horizons that have been advocated for in the literature. For instance, Wagner, Zeckhauser, and Ziegler (2018a) suggests using 1-year horizons, while other studies such as Dyreng, Hanlon, and Maydew (2008) suggest using horizons up to 10 years.