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Abstract

How do market prices adjust towards their equilibrium values? Donald Trump's election, an aggregate surprise that shook up the prices of all stocks, provides an ideal setting to investigate this question. Indeed, the ratio of price spreads among stock returns relative to aggregate market volatility on the first post-election day was one of the greatest seen in this century. Markets assessed the correct direction of relative price moves by individual stocks impressively quickly. The vast majority of stocks moved in the appropriate direction on the first day. However, given the extreme shock, iterations were required to get relative prices to converge to the right levels. To illustrate, return continuation from day 1 to day 2 was extreme by historical standards. Momentum persisted for three days and was followed by a brief reversal before prices settled. Since little new information was released after the election – a fact that we confirm by analyzing both transition team announcements and news flows – these return patterns represented movement toward a new equilibrium, and not a moving equilibrium. Stock return predictability was primarily driven by the part of first-day returns explained by firm characteristics, such as corporate taxes and foreign revenues, not by residual returns. The returns associated with a range of firm characteristics persisted for several days. Our results support prominent theories of slow but predictable diffusion of information into stock prices.

JEL Classification: G12, G14, H25, O24

Keywords: Stock returns, Momentum, reversal, election surprise, Market Efficiency, predictability, price contribution analysis, corporate taxes, trade policy, event study

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Paths to Convergence:
Stock Price Behavior After Donald Trump's Election*

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Abstract

How do market prices adjust towards their equilibrium values? Donald Trump's election, an aggregate surprise that shook up the prices of all stocks, provides an ideal setting to investigate this question. Indeed, the ratio of price spreads among stock returns relative to aggregate market volatility on the first post-election day was one of the greatest seen in this century. Markets assessed the correct direction of relative price moves by individual stocks impressively quickly. The vast majority of stocks moved in the appropriate direction on the first day. However, given the extreme shock, iterations were required to get relative prices to converge to the right levels. To illustrate, return continuation from day 1 to day 2 was extreme by historical standards. Momentum persisted for three days and was followed by a brief reversal before prices settled. Since little new information was released after the election – a fact that we confirm by analyzing both transition team announcements and news flows – these return patterns represented movement toward a new equilibrium, and not a moving equilibrium. Stock return predictability was primarily driven by the part of first-day returns explained by firm characteristics, such as corporate taxes and foreign revenues, not by residual returns. The returns associated with a range of firm characteristics persisted for several days. Our results support prominent theories of slow but predictable diffusion of information into stock prices.

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1 Introduction

This paper studies the price-adjustment process for individual stocks after a news shock that differentially affected their future performance. Understanding this process is of fundamental importance, but opportunities to analyze it cleanly are rare. Although markets reprice all assets each day, everyday price moves reflect both contemporaneous changes in assets' fundamental values (or "equilibrium prices") and corrections of potential under- or overreaction to changes in equilibrium prices on previous days (delayed adjustment).

By contrast with typical days, the days immediately following the 2016 US Presidential election – when stock prices were shocked significantly – offers an excellent opportunity to glean insights into this process for three reasons. First, the Election's outcome was a significant surprise (on the morning of Election Day, Trump's chances were 17% on Betfair and 28% on FiveThirtyEight). Second, the two candidates' proposed policies differed markedly along multiple dimensions, so that the outcome should have been expected to have very different impacts on virtually all firms, depending on factors such as their tax situation or foreign exposure. Third, there were no prominent announcements by the new administration on policies or priorities during this period; no senior appointments were made. Thus, the most important additional news that became available to market participants consisted of post-election analyses and political analysts' discussions of the incoming administration's likely priorities. Such news is unlikely to have had meaningful impact on assets' fundamental values relative to news imparted by Trump's victory.

This third fact – the paucity of follow-on news – distinguishes the 2016 Election from most large aggregate shocks. After such shocks, such as the 2007/2008 financial crisis, the news flow that impacts fundamental values of comparable magnitude lasts several days, and sometimes weeks. Furthermore, relative to some other surprise events of aggregate importance, such as the attack on Pearl Harbor in December 1941, the terrorist attacks of September 11, 2001, or the downgrade of US sovereign debt in August 2011, the aggregate stock market move after the 2016 election was significant but hardly monumental.[1] This makes it easier to gauge how the

[1] Following the Pearl Harbor attack, the S&P composite index fell by 4.37% on December 8, 1941, with another fall of 3.23% on December 9 as the US declared war against Japan (see Cutler, Poterba, and Summers (1989)). Markets remained closed for four days after the September 2001 terrorist attacks, but the S&P 500 index dropped by 4.92% as they reopened on September 17. After the US downgrade, the S&P 500 index fell by 6.66% on August 8, 2011 but bounced back by 4.74% on the following day. As for the 2016 election, while stock index futures fell sharply on

price adjustment process plays out in the cross-section of stocks. Specifically, the findings are more robust to the particular way that abnormal returns are computed than in settings where individual stocks' returns are mostly driven by their exposure to market-wide moves.

How well did the market meet the considerable challenge of quantifying the consequences of the election for the value of thousands of individual firms? Focusing on the first ten days after the election, we find that, strikingly, investors updated their relative pricing of US stocks in the appropriate *direction* already on the first day. However, the market took 5 to 6 days to settle on the appropriate *magnitude* for the price adjustment following the initial aggregate surprise.

We employ a four-step analysis to develop these results. We first document that following the aggregate surprise, market-wide price spreads (the cross-sectional variation in US single stock returns as proxied by the interquartile range of daily stock returns, that is, the spread between the 75th and the 25th percentiles of returns) rose sharply on the day after the election. Since the beginning of this century, larger price spreads have gone hand in hand with higher overall market uncertainty (as proxied by the VIX index). This was the case, for example, on some days during the financial crisis. The 2016 post-election days were distinctive in that the large cross-sectional price spreads occurred in a period of relatively low aggregate market volatility. Our specific indicator is the *Spread-ratio*, the interquartile range of stock prices normalized (divided) by the VIX index. For example, on November 9, 2016 (the day after the election) this *Spread-ratio* was 0.31, the fourth-highest level since 2000 (with the three highest values occurring as the dotcom bubble began to deflate), and the ratio still stood above the 99th percentile of all observed values on both November 10 and 11. The Spread-ratio returned to its average level only five trading days after the election.

Overall, the first step of our analysis shows that intense repricing took place. But it does not tell us whether the direction of the repricing was correct. The second step of our investigation,

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election night as the outcome of the election became known, the S&P 500 finished up 1.11% on the day following the election, rose a further 0.63% through day 6 and 1.19% through day 10, after which movements were modest. These movements occurred even though the negative forecasts for the aggregate stock market had a strong empirical foundation. Notably, in a study of asset price moves in conjunction with salient events in advance of the election, Wolfers and Zitzewitz (2018) find a strong positive relation between prediction market odds of Clinton winning and the returns on all major US equity index futures. While the divergence in the stock market's ex ante and ex post view regarding this particular election outcome is an interesting puzzle outside the scope of this paper, a positive short-term aggregate market reaction to a surprise Republican Presidency is in line with historical experience (Snowberg, Wolfers, and Zitzewitz, 2007). Over the full term of administrations, large excess returns are realized under Democrat Presidents (Santa-Clara and Valkanov, 2003), which is another puzzle outside the scope of this paper.

therefore, traces how stocks zeroed in on the new equilibrium. We ask three questions: To which extent do price spreads increase or reverse, that is, is there momentum or reversal? How fast does price discovery take place? And how informative are first-day returns?

The market's process of zeroing in on the new equilibrium produced a highly unusual cross-sectional return predictability for several days after the election. Relative stock prices moved in the appropriate direction on the first day, but much too little. Figure 1 strikingly illustrates the extent of the delayed price-level adjustment during the post-election period. It shows the performance of a long-short portfolio of stocks – buying the top decile and selling the bottom decile – constructed at the close of the first day after the election (November 9, 2016) based on realized returns on that day. That portfolio earns a cumulative return of almost 8% over the following three days (days 2 - 4), but then gives back about 2% on days 5 and 6. To put things in perspective, for the 87-year period from January 1927 through March 2013, Daniel and Moskowitz (2016) report annualized returns on long-short momentum portfolios of 17.9%, as compared here to nearly 6% in 6 days and nearly 7% in 10 days after the election.

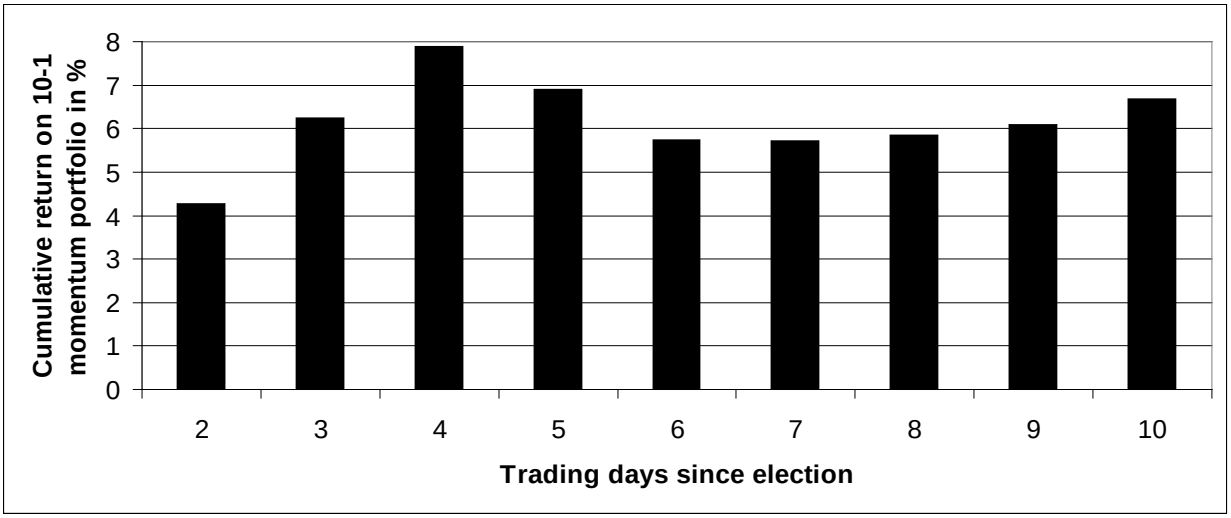


Figure 1: Cumulative returns on a long-short momentum portfolio after the election. This figure shows the cumulative returns on a long-short momentum portfolio (top decile minus bottom decile) formed on the basis of stock returns on the first day after the election (November 9, 2016) and held until the tenth day (November 22, 2016). The sample consists of sufficiently liquid US stocks based on trading volume on November 8, 2016 (see Section 2 for details of the sample construction).

The strength of return continuation from day 1 to day 2 after the election produced a rank order correlation of 0.45, an extreme by historical standards. Return continuation persisted for

two more days, with single stock returns on days 3 and 4 also exhibiting strongly positive correlations with cumulative abnormal returns up to those days. These days of initial continuation were followed by reversals, which we interpret as part of a zeroing in process. Returns on day 5 and more modestly on day 6 correlated negatively with the cumulative abnormal returns up to those days. Overall, this pattern suggests initial underreaction, followed by mild overreaction (consistent with models such as Barberis, Shleifer and Vishny (1998) and Hong and Stein (1999)), rather than general overreaction to news (De Bondt and Thaler, 1985).

The strong predictability of daily returns from post-election cumulative returns reflects the fact that some information had yet to be impounded into prices. It lasted for five days. Progressively, however, the predictability of returns with past post-election cumulative returns diminished in absolute value, and the relationship essentially ended after day 6. Reflecting this pattern of continuation and then moderate reversal, the cross-sectional variance of stocks' cumulative returns rose substantially faster than the cumulative variance of daily returns through day 4. The difference between these two quantities then declined moderately on days 5 and 6 and from then on varied little.

How swift was price discovery? Unbiasedness regressions reveal that the first day had particularly large information content, and that, due to the continuation and reversal taking place over days 3 through 6, prices already at the end of day 2 or 3 (depending on whether raw or abnormal returns are used) offered an unbiased estimate of their day-10 values. Still, refinement on relative prices persisted through the sixth day.

Strikingly, for a full two thirds of firms, abnormal continuation returns from day 2 through day 10 had the same sign as the first-day abnormal return. What is more, the information content of first-day returns was so large that they were nearly as informative predicting the Nth day's returns as cumulative returns over the first $N - 1$ post-election days.

We interpret the persistence of price movements as reflecting a slow information diffusion process. It took the market a number of days to accurately quantify the impact of the election. An alternative possibility, which we evaluate in the third step of our analysis, is that considerable new information flowed into the market in the days after the election, and that that information pointed in the same direction, say to lower future tax rates, or that policies were announced that would reverse benefits for specific firms, thus leading to reversal.

To investigate this possibility we first directly analyze announcements by Trump and his transition team as well as the news flow in the media. We find few policy-relevant announcements and, consistently, a decreasing number of articles on all key topics of the campaign – taxes, trade, health care, and immigration – in the 10 days following the election. Second, we document that it is relatively unusual, historically speaking, for individual stock returns to exhibit reversals (as observed on days 5 and 6) when the aggregate market moves in the same direction, suggesting that no market-wide news shook up stock prices on these days. Third, we investigate whether the return patterns differ across categories of stocks formed on characteristics that are unlikely to be correlated with news releases. If continuation were driven by additional news coming out, we would not expect differences in return continuation across these stocks.

We find, however, that such differences are present in the data. Specifically, momentum is more pronounced among firms with low dispersion of analyst forecasts (a proxy for the certainty of information before the election, suggesting that investors are underweighting the new information due to the election), and in stocks with low analyst coverage. These results support two leading explanations of momentum, namely, Barberis, Shleifer, and Vishny's (1998) conservatism bias theory and Hong and Stein's (1999) slow information diffusion theory. Moreover, we show that the extreme long-short portfolio (long the top decile of first-day performers, short the bottom decile) reached its equilibrium level substantially faster than the middle long-short portfolio (long the sixth decile, short the fifth decile). It thus appears that market participants focused on the stocks most strongly affected by the aggregate surprise. Such a focus is understandable given the larger potential payoff from a swift appropriate pricing for those stocks. These patterns by themselves do not reject the additional news hypothesis, but a far-from-parsimonious version of that hypothesis would be required to explain them. Overall, the weight of the evidence tilts in favor of the delayed adjustment hypothesis.

The fourth and final step of our analysis investigates the sources of the observed momentum. To understand whether the return continuation documented in Figure 1 merely reflects investors' "following the winners" or their processing the consequences of the election's outcome for stock prices, we decompose the explanatory power of first-day returns into two components. The first relates to the firm characteristics that explain which firms won or lost on the first day. For example, prior work shows that investors (a) responded very strongly to the expected corporate

tax cut, bidding up the prices of high-tax firms and bidding down those of low-tax firms, and (b) recognized that domestically-focused companies would fare better, for various reasons (Wagner, Zeckhauser, and Ziegler, 2017). From these characteristics – and standard variables such as firm size, revenue growth, and industry fixed effects – we compute the predicted first-day return. The second component is the unexplained part of the first-day return, the residual. Our analysis reveals that the part of first-day returns explained by the above firm characteristics predicts continuation returns much more powerfully than does the residual. An investor who, at the end of the first day, formed a long-short (LS) portfolio (top decile minus bottom decile) based on predicted stock returns (model-LS) earned cumulative returns of 8% from day 2 through day 10, whereas a long-short portfolio based on residual stock returns (resid-LS) earned less than 3%. Overall, these results suggest that delayed information processing, rather than pure feedback trading, explains momentum in this event.

Having established that firm characteristics drive the observed momentum, we then investigate which of the factors that explain returns were most quickly absorbed into prices. For this, we use the method developed in Wagner, Zeckhauser, and Ziegler (2017) (henceforth WZZ). The method follows the spirit of the price contribution methodology commonly used in the market microstructure literature. It estimates daily cross-sectional regressions using cumulative returns from the election through each of the first ten days. The resulting coefficients quantify the cumulative price impact of the different variables through a particular day, allowing assessing the speed at which they were impounded into prices. WZZ discuss the relative speed of tax rates and other tax-related factors. When including additional cross-sectional drivers of returns, a striking pattern emerges: all factors persist in influence, and none has a first-day impact that is close to its ten-day impact. More specifically, the cash effective tax rate (ETR) and revenue growth were the factors affecting prices most swiftly, while foreign revenue was the slowest. A likely explanation for the fast convergence of the cash ETR is the importance that taxes played in Trump's expected policies and the relative ease of assessing their impact by contrast with firms' foreign exposure.

Overall, the results show that markets met the challenge of assessing the correct *direction* of relative price moves of individual stocks impressively quickly, but they required more time to get the *levels* right. Different drivers of ultimate price levels were impounded into prices at

varying speeds. These findings support models of slow but predictable diffusion of information into stock prices

The analysis proceeds as follows. Section 2 presents the data. Section 3 investigates price spreads following the 2016 election. Section 4 traces the process by which the market honed in on the right relative price levels of individual stocks. Section 5 analyzes whether this process reflects slow digestion of information already available on November 9 or the emergence of additional news in the 10-day window that we analyze. Section 6 investigates the sources of return momentum after the election. Section 7 concludes.

2 Data and abnormal return computations

We obtain daily data on all US common stocks (with the exception of closed-end funds) traded on NYSE, Amex and Nasdaq from CRSP. Our sample period ranges from January 2, 1999 through December 31, 2016. (Our actual analyses begin in January 2000, but we download an extra year of data to estimate betas for our abnormal return computations, which are detailed below.) As is common in the literature, we exclude stocks with prices below $5 from our analysis. Furthermore, to avoid letting illiquid stocks affect our results, we drop the bottom decile of stocks based on dollar trading volume from our sample. We refer to the remaining stocks as sufficiently liquid US stocks in the rest of the paper.

To avoid introducing biases in our results, we apply these sample selection criteria on the trading day immediately preceding the beginning of the period over which the respective analyses are conducted. We keep these stocks in the sample even if they no longer meet the criteria on later days (unless a stock is delisted, in which case we take the delisting return from CRSP into account). For instance, for our main analysis, which considers daily (close-to-close) returns over the ten trading days following the election (from Wednesday November 9, 2016 through Tuesday November 22, 2016), we select the stocks included in the sample based on the data on November 8, 2016, and use the same stocks for the entire November 9 – 22 period. For historical analyses spanning longer periods, we apply the above criteria on a rolling basis. For example, whenever we conduct a historical analysis of the properties of one-day returns, we select the stocks considered each day using data from the prior trading day. Similarly, whenever the underlying analysis spans, say, ten trading days, we select stocks on the trading day

preceding the first day of each ten-day period considered and then hold that set of stocks fixed for the entire ten-day period.

We conduct all our analyses with three sets of returns: raw returns, abnormal returns calculated with respect to the CAPM, and abnormal returns calculated with respect to the Fama-French three-factor model. All abnormal returns are computed *before* applying the above selection criteria, as a stock's status may change during the sample period. To compute these abnormal returns, we obtain daily data for the market excess return, the size and value factor returns (Fama and French, 1993), and the return on the riskless asset from Ken French's website. Betas are estimated using one year of daily data, and are then used to compute the abnormal returns for the following quarter.[2] For instance, abnormal returns for the first quarter of the year 2000 are based on betas estimated using data for 1999, while abnormal returns for the third quarter of 2016 (the quarter of the election) are based on betas estimated from daily returns from October 1, 2015 through September 30, 2016. To obtain CAPM-adjusted returns, we first estimate each stock's market beta from an OLS regression of daily stock returns in excess of the riskless asset return on the market excess returns. We then compute abnormal returns for all days in the following quarter as the daily excess return on the stock minus beta times the market excess return. We compute Fama-French-adjusted returns in a similar fashion. Throughout the paper, all returns are reported in percentage points. The analysis in Sections 5 and 6 also use company-specific data.

3 Price spreads following the 2016 election

This section examines the cross-sectional variation in single stock returns, both during the months around the election and from a historical perspective. The main result that emerges is that the repricing that took place in the few days after the election was extraordinary in magnitude.

Figure 2 shows the interquartile range of single stock returns for the period from October through December 2016; it reveals a clear message. The dispersion of stock returns, which indicates intensive repricing in the cross-section, spiked right after the election and remained at an elevated level for several days. While the interquartile range of returns was 1.6 percentage

[2] Data are available for the entire estimation window for most firms. When this is not the case, betas are estimated using returns from the date the firm was first traded through the end of the estimation window, provided that at least 126 daily return observations are available for that firm. If fewer than 126 observations are available, no abnormal returns are computed for that firm to avoid having our results affected by imprecise beta estimates.

points on November 8, it shot up to 4.5 percentage points on November 9. By the sixth day after the election, it had returned to 2 percentage points, a level corresponding to its long-run median, and just below its long-run mean of 2.3 percentage points.

Price spread activity then settled down. The daily interquartile range remained below two percentage points until November 30, 2016. The modest level of 1.6 percentage points on the day before the election is almost as low as the levels typical of holiday periods, such as Black Friday or the December 26-31 period, where traders are in vacation mode. This suggests that on the day before the election, November 8, investors were not taking new big bets.

While the stock-return dispersion immediately after the election was very large, such dispersion might simply indicate large aggregate uncertainty. Therefore, we next normalize the interquartile range by the VIX index to obtain a measure that we call the *Spread-ratio*.

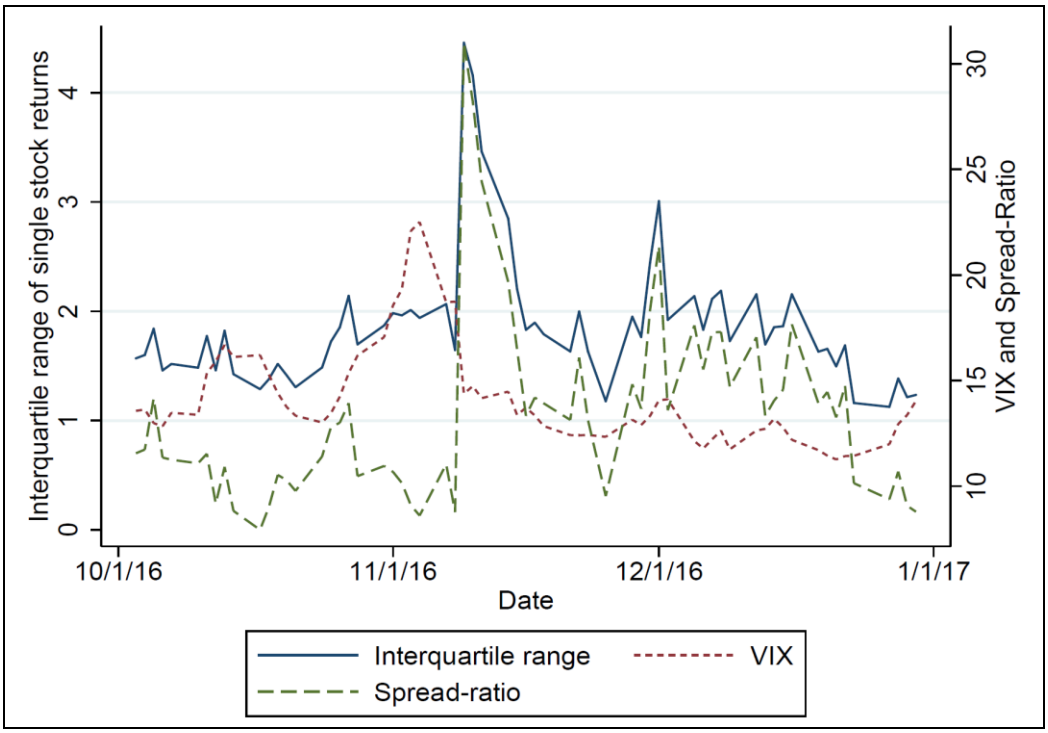


Figure 2: Repricing around the election.
This figure shows the interquartile range of daily single stock returns (left axis), market-wide volatility as proxied by the VIX index (right axis), and the interquartile range to VIX ratio (Spread-ratio, expressed in percentage points, right axis). It covers the period from October 1, 2016 through December 31, 2016. The sample consists of all sufficiently liquid US stocks.

Figure 2 shows that the VIX increased ahead of the election (following the revelation, by then-FBI director Comey, that the investigation into Secretary Clinton's email server had been

reopened due to the discovery of additional emails). It then started falling before the election as the investigation was closed without new findings a couple of days later. After a brief overnight spike on election night, the VIX fell further as the result became known. The Spread-ratio, meanwhile, which stood at only 0.09 in the evening of November 8, soared to 0.31 on November 9, and remained extremely high at 0.28 and 0.24 on November 10 and 11, respectively.

Using the Spread-ratio to measure the intensity of repricing in the cross-section is intuitive. The numerator measures the cross-sectional dispersion of returns in a manner robust to outliers, while the denominator measures the standard deviation of market returns.[3] Figure 3 shows that the two quantities are strongly positively associated. In the period 2000-2016, their correlation is 0.69.[4] This finding is not immediately obvious. One might have expected that because VIX indicates bad times and asset prices correlate more strongly in bad times, the spread of returns might be smaller when VIX is high. This is not the case for two reasons. First, since betas differ across stocks, larger market moves imply more cross-sectional dispersion in stock returns. Second, empirically, when market volatility increases, idiosyncratic return volatility tends to rise as well (though less strongly). Technically, the increased correlation of returns in turbulent periods arises not due to falling idiosyncratic volatility, but to the fact that assets' total volatilities rise less strongly than their systematic volatilities. Given that systematic and idiosyncratic returns are orthogonal, this still leaves room for idiosyncratic return volatility to rise as well.

As Figure 3 also shows, an intriguing finding about the post-election period is not so much the large magnitude of the interquartile range of single stock returns per se, but the extreme combination of relatively low market volatility and a relatively high interquartile range during

[3] Recent work has demonstrated that beyond its intuitive appeal, economic policy uncertainty (EPU) is associated with both stock price volatility and negative movements in investment and employment in policy-sensitive sectors (Baker, Bloom, and Davis, 2016). We chose to normalize by the VIX index rather than EPU because VIX is a direct measure of that volatility, and it correlates much more strongly with the interquartile range (0.69 versus 0.22).

[4] Performing the analysis using logs of the VIX and the interquartile range yields a similar picture (their correlation is marginally higher at 0.71), and leads to the same conclusions. Ideally, we would divide the measure of the dispersion of single stock returns by a measure of realized market volatility. However, estimates of this volatility based on a single day of data are quite noisy. Therefore, we use the VIX index, which is computed from the prices of S&P 500 index options and reflects (risk-neutral) expectations of market volatility. We use the VIX rather than the CBOE Russell 2000 volatility index (RVX) because the latter captures the volatility of smaller stocks rather than that of the overall market, and Russell 2000 options are much less liquid than S&P 500 options. We also investigated the relationship between the interquartile range and estimates of volatility computed using the absolute value of daily market returns and the Garman-Klass estimator, which uses open, high, low and close prices for the day. Both of these alternative measures are strongly correlated with the interquartile range, but their correlations are somewhat lower, with values of 0.63 and 0.68, respectively.

the three days following the election (highlighted in the figure). That extreme combination makes the period ideal to study repricing in the cross-section of stocks.

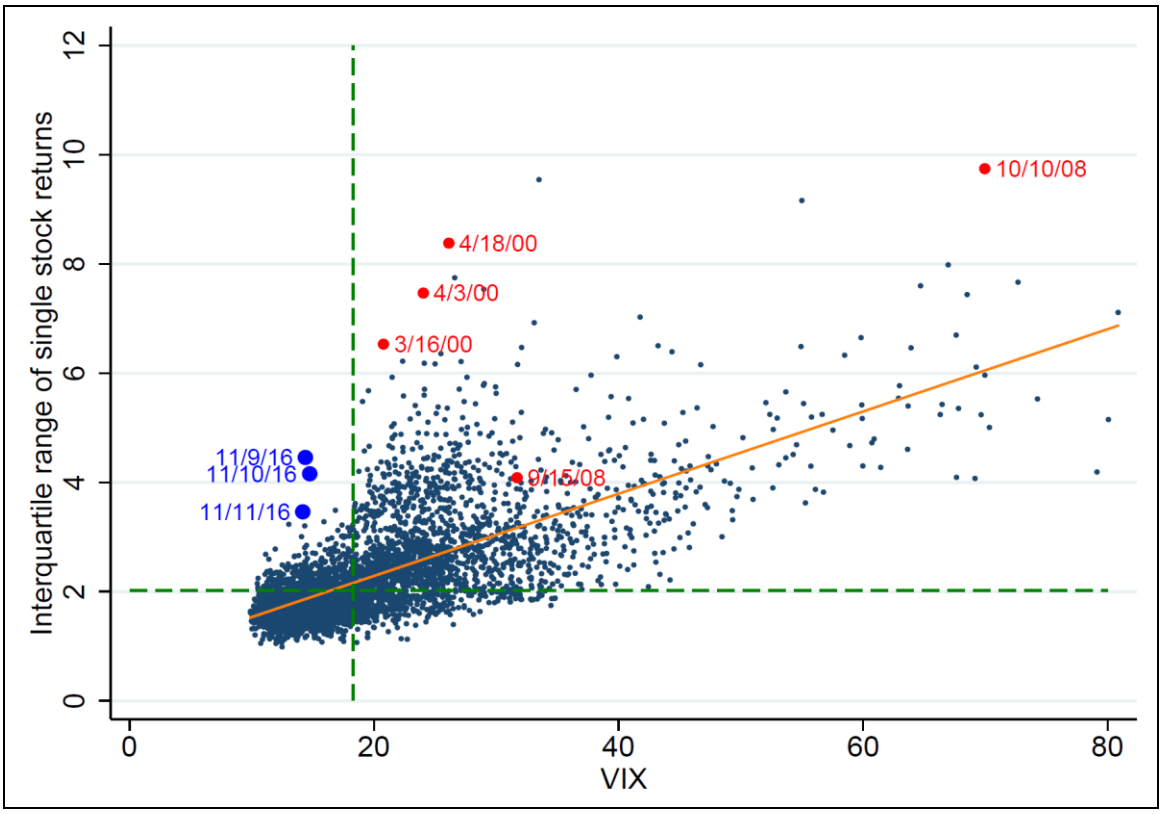


Figure 3: Market volatility (VIX) and interquartile range of single stock returns. This figure shows a scatter plot of the VIX market volatility index and the interquartile range of single stock returns during the period from January 1, 2000 through December 31, 2016. The dashed lines depict the medians of the two variables, and the solid line the OLS regression estimate of their relationship. The sample consists of all sufficiently liquid US stocks.

To put this finding into perspective, a few other points highlighted in Figure 3 should be considered. As expected, the raw interquartile range reached very high levels during the financial crisis; the maximum value in the sample was 9.7 percentage points on October 10, 2008. However, those were days of significant overall market stress and uncertainty – although the S&P 500 fell by only about 1.2% on that same day on a closing basis, it experienced an intraday swing of over 10%. The VIX stood at 69.95, so that the Spread-ratio was only 0.14. Similarly, on the day of the Lehman bankruptcy (September 15, 2008), the Spread-ratio stood at only 0.13. It turns out that the value of the Spread-ratio on November 9, 2016 was, at 0.31, the fourth-highest value in our sample of 4,276 trading days, and the November 10 value of 0.28 was the 9th highest

in the sample. Even the November 11 value, 0.24, was the 18th highest in the sample and well above the 99th percentile of 0.21. Thus, after the 2016 Presidential election, the Spread-ratio remained above the 99th percentile for three successive days. Intense repricing was taking place over these days. The three highest values ever reached were 0.32 on April 18, 2000, and slightly above 0.31 on both March 16 and April 3, 2000. On all three days, substantial market moves (up and down) in technology stocks took place as the dot-com-bubble was deflating. Figure 4 shows the histogram of the values of the ratio from 2000 to 2016.

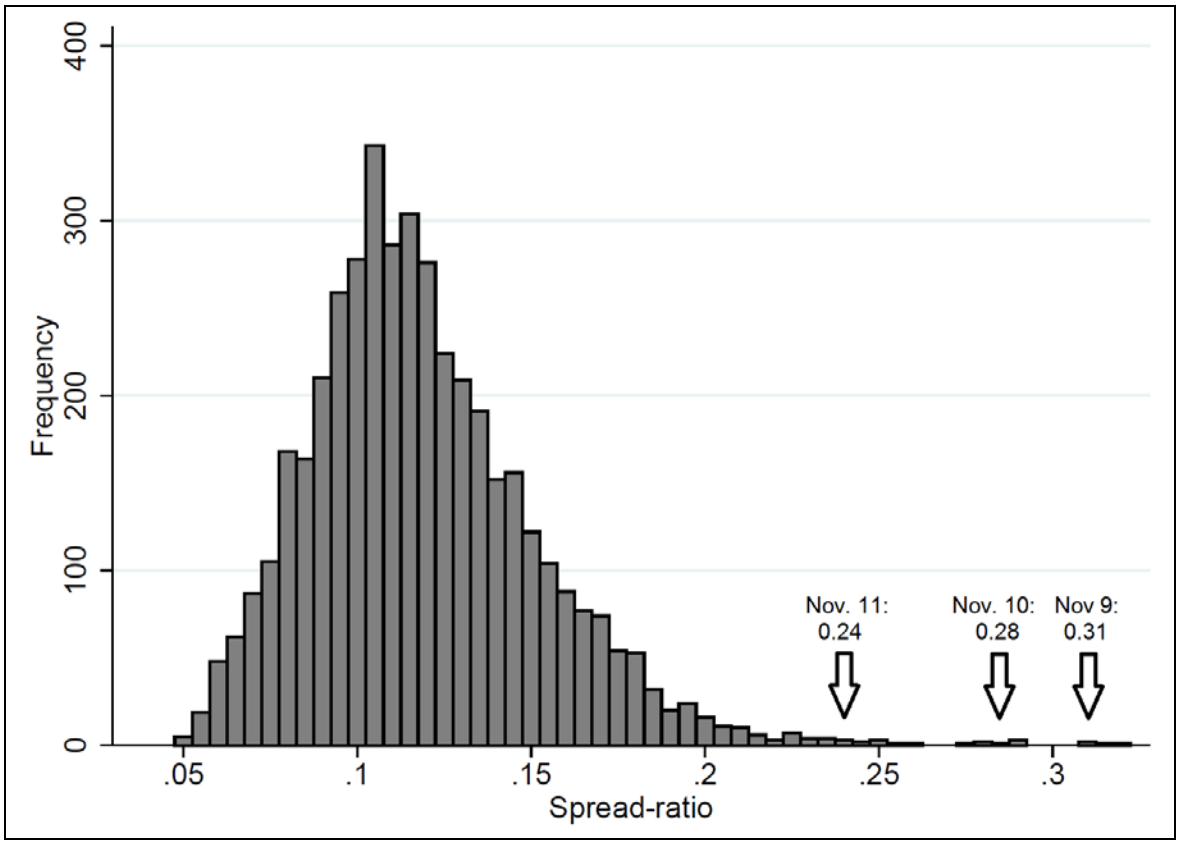


Figure 4: Histogram of Spread-ratios from January 1, 2000 through December 31, 2016. This figure shows the distribution of Spread-ratios (ratio of interquartile range of daily stock returns to VIX) during the identified period. The sample consists of all sufficiently liquid US stocks.

4 Continuation, reversals and convergence in single-stock returns after the election

Section 3 established that significant repricing of stocks began right after the election, but lasted for several days. Given the sheer amount of information it had to process, how effective was the market in getting the direction right at the outset? And how long did investors need to zero in on the appropriate magnitude of individual stock price moves following the aggregate surprise? To answer these questions, we now turn to the process and speed of price adjustment for individual stocks in the first 10 days after the election.[5]

The analysis proceeds as follows. Section 4.1 studies return continuations and reversals after the election. If by the end of the first day all information were already impounded in prices, first-day returns should not predict second-day returns. If, by contrast, the repricing challenges facing markets were so large that first-day price moves were excessive or, worse, went in the wrong direction, we would see a reversal. The third possibility, return continuation, would be consistent with right-direction movements, coupled with underreaction. Then, we examine days beyond day 2 and determine how long it took until past returns lost predictive power, thus indicating that the market had iterated to its new equilibrium. Finally, we investigate the cumulative impact of return continuations and reversals during the first 10 days after the election by comparing the cross-sectional variances of one-day returns with the variances of cumulative returns.

Section 4.2 then considers the pace of price discovery. Unbiasedness regressions, which regress the overall returns on the 10 days on the cumulative returns through day $t < 10$, reveal the speed at which the market zeroed in on the new equilibrium.

Finally, Section 4.3 examines the specific information content of first-day returns.

Before embarking on this analysis, it is useful to reflect on the relative advantages of using raw returns, CAPM-adjusted returns, or Fama-French-adjusted returns in our setting. That is, how much should one control for when trying to understand the cross-sectional adjustment process following the aggregate surprise? Small stocks dramatically outperformed large stocks and value stocks outperformed growth stocks during the time period under study. It is possible

[5] Of course, ten trading days is a somewhat arbitrary period. The settling-down of the Spread-ratio in Figure 2 implies that some information was processed during the first weekend, maybe because the weekend gave investors time to reflect on the implications of the election. Adding another week seems sensible. We thus round up to 10 days. As shown in Section 5.1, no material new information about upcoming policies became known in this time period.

that this outperformance could itself be driven by the new administration's expected policies.[6] To the extent that the market, size, and value factor returns reflect investors' assessing the consequences of the election surprise for asset prices, taking out these components risks controlling too much, thus blurring the picture. We will, consequently, present most of our results for each of raw, CAPM-adjusted, and Fama-French-adjusted returns. Most results differ little across the three types of returns, and we discuss the reasons for any notable differences.

4.1 Momentum and reversal after the election

4.1.1 Return continuation from day 1 to day 2 after the election

The Spearman rank correlation between returns on November 9 and returns on November 10 was 0.45, and an OLS regression of the latter on the former yields a slope of 0.24, both highly statistically significant. A scatter plot of raw single stock returns during the first two days after the election, shown in Figure 5, shows the strength of the one-day continuation.

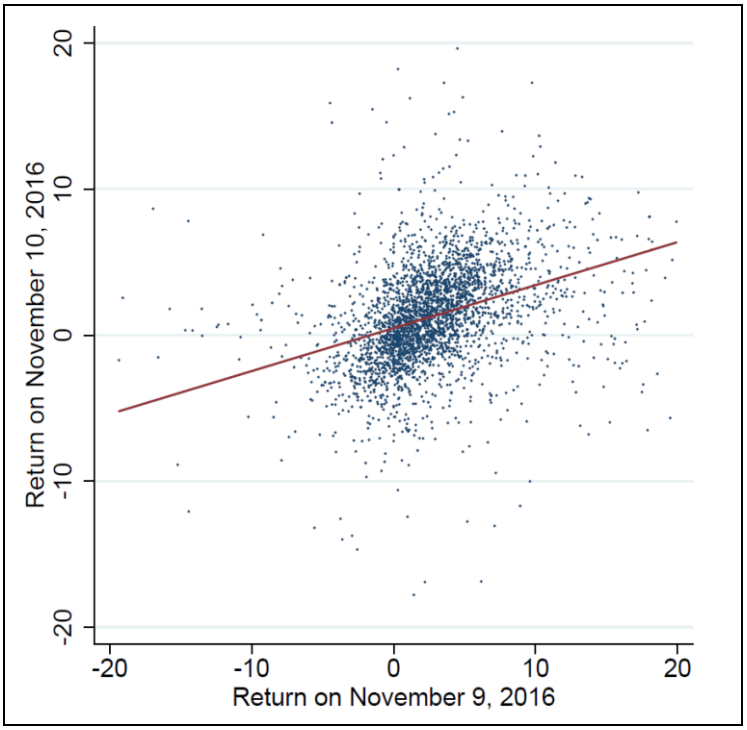


Figure 5: Returns on individual stocks on November 10 against returns on November 9. The sample consists of all sufficiently liquid US stocks based on trading volume on November 8.

[6] Wagner, Zeckhauser, and Ziegler (2017) argue that in this particular time period, the superior performance of the size and value factors was in part related to expected changes in tax policy. They show that firms with high loadings on the size and value factors have higher effective tax rates on average.

To understand how impressive is this 0.45 rank order correlation (ROC), we compare it to historical experience. Figure 6 shows the histogram of the ROCs between returns on two consecutive trading days during the period from January 1, 2000 through December 31, 2016. The mean and median values of ROC are negative, consistent with the short-term reversal tendency documented in the literature.[7] It turns out that out of the 4,276 trading day pairs since the beginning of 2000, the ROC between November 9 and November 10 returns is the second highest. When using CAPM-adjusted or Fama-French-adjusted returns, the ROC between November 9 and November 10 is respectively the highest and second highest in the period.[8]

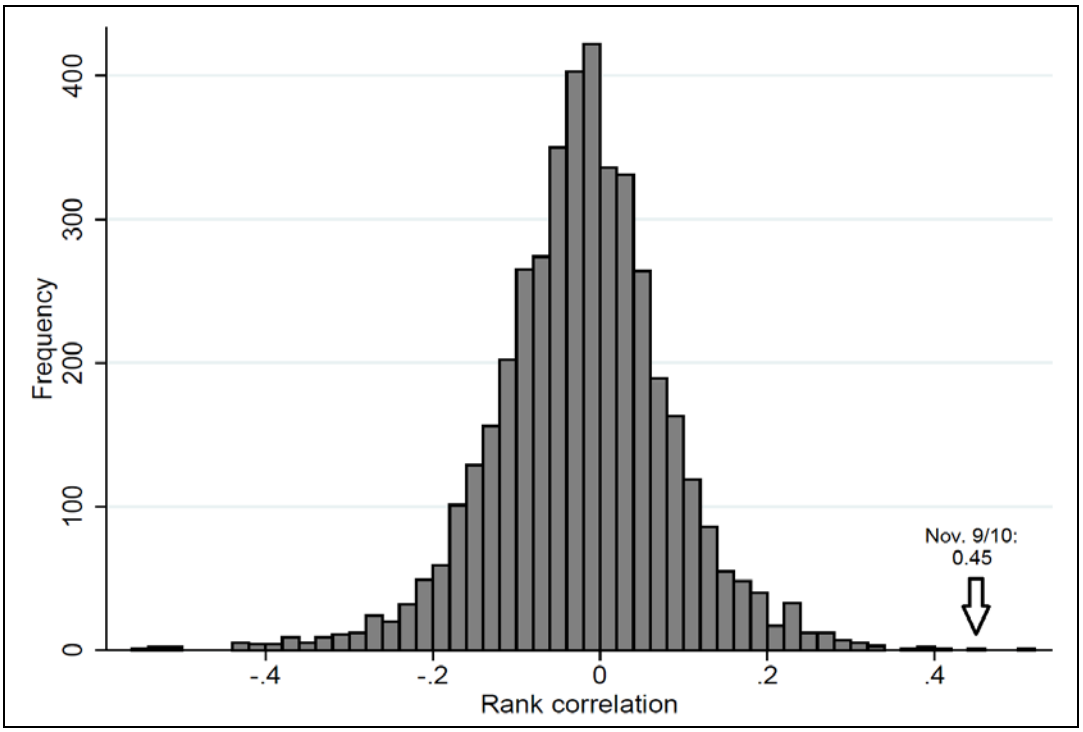


Figure 6: Histogram of rank correlations of raw returns between one day and the next. This figure shows the histogram of the Spearman rank correlations between returns on two consecutive trading days during the period from January 1, 2000 through December 31, 2016. The underlying sample used each day consists of all sufficiently liquid US stocks.

[7] See Jegadeesh (1990) and Lehmann (1990). Jegadeesh and Titman (1995) show that the empirical patterns are consistent with inventory-based microstructure models.

[8] For raw returns, the highest ROC in the sample is that between Friday, June 24, 2016 (the day after the Brexit vote) and Monday, June 27, 2016. That value, however, was driven to a large extent by the size of the market moves at that time. When using CAPM-adjusted returns, the ROC on that pair of days drops far below the value for the November 9/10 pair. For Fama-French adjusted returns, the highest ROC in the sample is that between July 16 and July 17, 2008 (for which no particular events can be identified, though the financial crisis was unfolding on these days).

4.1.2 The zeroing-in process

This subsection investigates how long predictability lasted after the election. Thus, it considers whether returns on day *t* are related to cumulative returns through day *t* – 1. Table 1 shows that cumulative returns significantly predicted next-day returns through day 6. Through day 4, there was continuation (positive correlation). For returns on day 5 and, more modestly, on day 6, by contrast, brief return reversals took place, before the correlation again turned positive on day 7 (but insignificant for raw and CAPM-adjusted returns).

Table 1: Return predictability.

The table shows the relation between returns on days 2 – 10 after the election (November 10 through 22) and cumulative returns from the election through the previous day, using Spearman rank correlations and regression coefficients. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Trading days since election	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A: Raw returns									
Spearman rank correlation	0.450***	0.276***	0.191***	-0.255***	-0.155***	0.033*	0.032*	-0.074***	0.077***
	(0.017)	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Regression slope	0.244***	0.110***	0.046***	-0.052***	-0.032***	0.001	-0.006	-0.007	0.002
	(0.021)	(0.012)	(0.008)	(0.008)	(0.007)	(0.011)	(0.006)	(0.006)	(0.006)
Panel B: CAPM-adjusted returns									
Spearman rank correlation	0.436***	0.272***	0.175***	-0.320***	-0.134***	-0.003	0.051***	-0.157***	0.098***
	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)	(0.020)	(0.019)	(0.019)	(0.020)
Regression slope	0.230***	0.107***	0.041***	-0.071***	-0.027***	-0.010	-0.001	-0.018**	0.003
	(0.022)	(0.013)	(0.008)	(0.008)	(0.008)	(0.012)	(0.007)	(0.007)	(0.007)
Panel C: Fama-French-adjusted returns									
Spearman rank correlation	0.441***	0.224***	0.254***	-0.334***	-0.165***	0.082***	0.078***	-0.210***	0.182***
	(0.018)	(0.020)	(0.019)	(0.018)	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)
Regression slope	0.299***	0.128***	0.090***	-0.085***	-0.036***	0.014	0.012*	-0.039***	0.032***
	(0.027)	(0.016)	(0.010)	(0.008)	(0.007)	(0.009)	(0.006)	(0.006)	(0.007)

Figure 7 illustrates these results graphically using binned scatter plots of the returns on days 2 through 10 against the cumulative returns through the prior day. The relation, which is very steep on the second day, progressively flattens on days 3 and 4 and then reverses on day 5. The magnitude of the reversal is similar to that of the return continuation on day 4, and smaller than the continuations observed on days 2 and 3. The relation between returns on day 6 and prior cumulative returns is also negative, but substantially smaller in magnitude. The association becomes negligible on days 7 through 10. In terms of regression coefficients, the progressive flattening phenomenon also holds when using CAPM-adjusted or Fama-French-adjusted returns, as seen in Figure 8. However, the ROCs increase in absolute value during the last two days. We

do not have a compelling explanation for this last finding. The regression coefficients also become statistically significant in the case of Fama-French-adjusted returns at the end of the 10-day period; however, they are very small in magnitude.

In sum, through a process of strong continuation followed by a moderate reversal (after a possible overshoot), the market essentially took 5 or 6 days to accurately assess appropriate relative prices for individual stocks following the aggregate surprise.

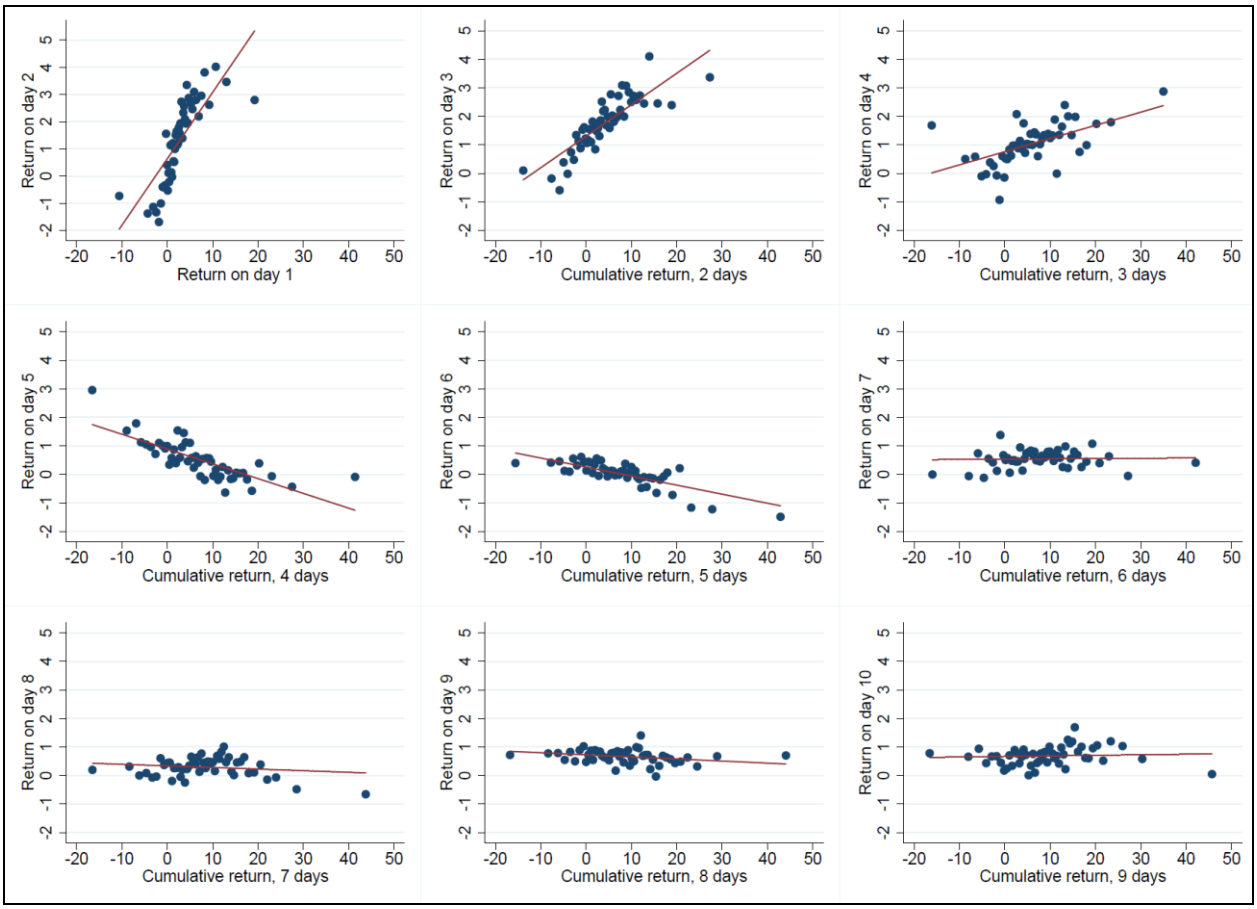


Figure 7: Return predictability.

Binned scatter plots of daily returns on days 2 – 10 after the election (November 10 through 22) against cumulative returns from the election through the previous day.

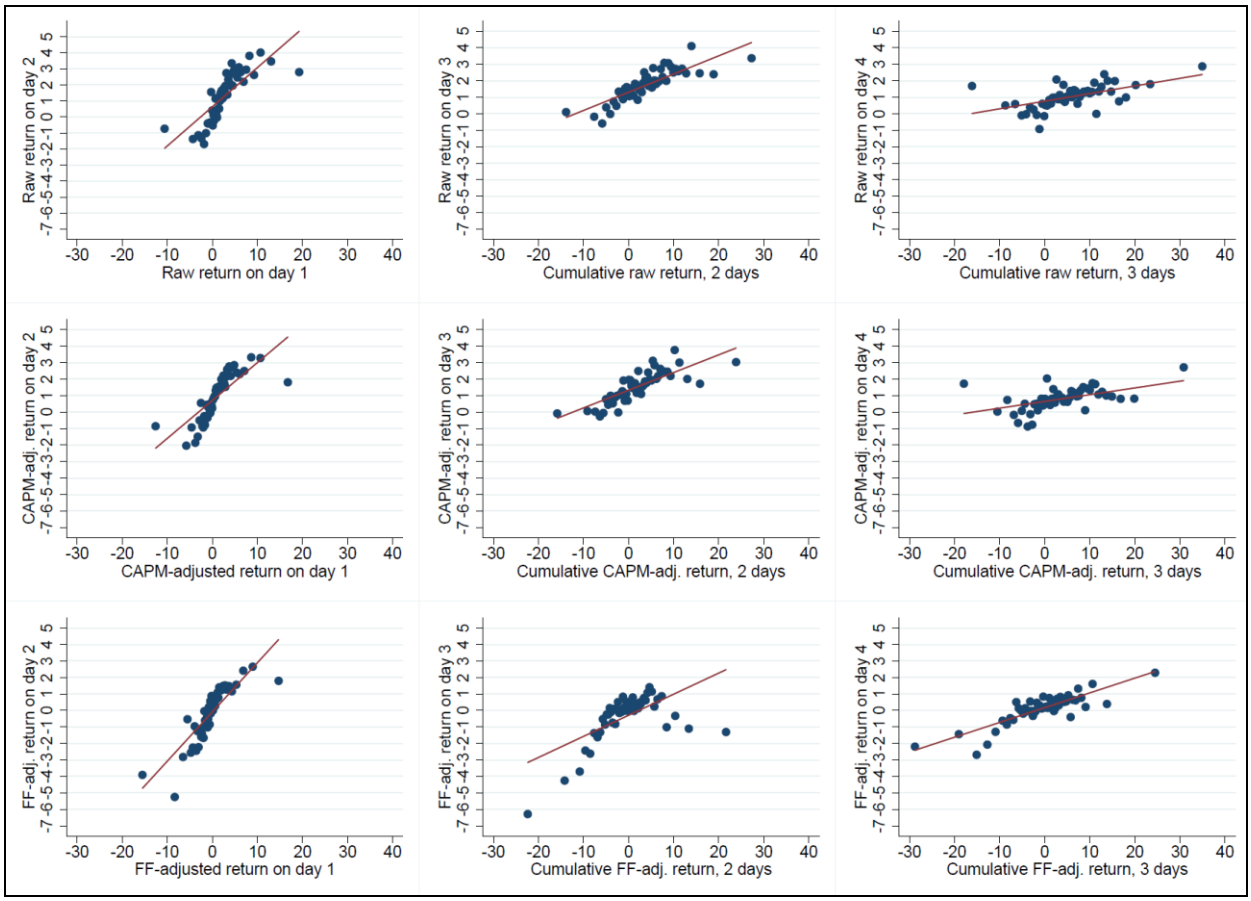


Figure 8: Return predictability with different adjustments of returns.

This figure shows binned scatter plots of returns on days 2 – 4 after the election (November 10 through 12) against cumulative returns from the election through the previous day for different sets of returns. The top panels consider raw returns, the middle panels CAPM-adjusted returns, and the bottom panels Fama-French-adjusted returns.

4.1.3 Variance differences

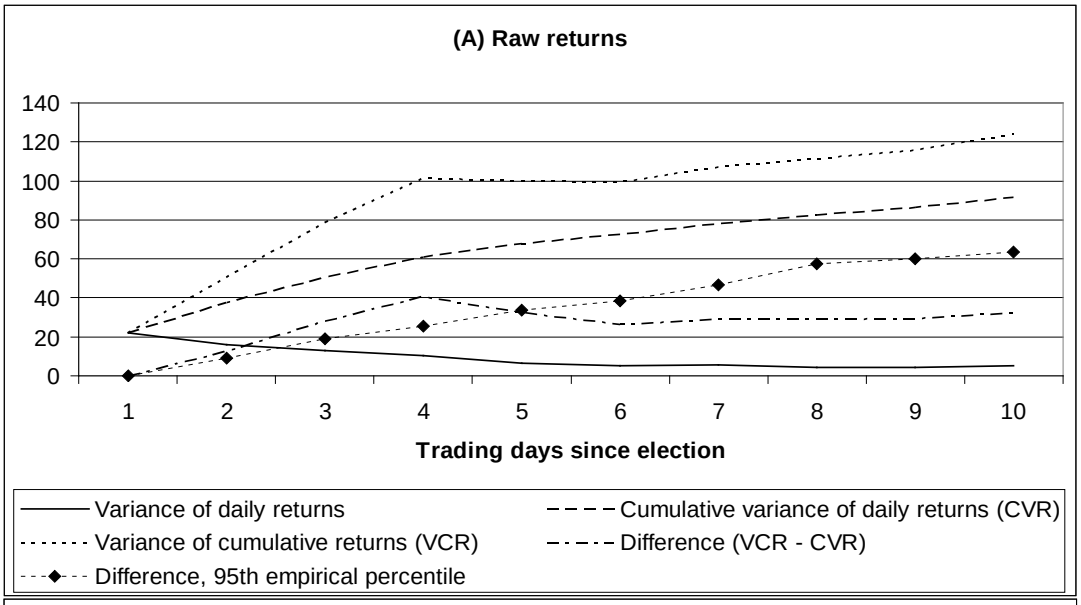
This section investigates the cumulative impact of return continuations and reversals during the first 10 days after the election. It does so by comparing the cross-sectional variances of one-day returns with those of cumulative returns. The underlying idea is similar to that of the variance ratio tests in Campbell and Mankiw (1987), Cochrane (1988), Lo and MacKinlay (1988), and Poterba and Summers (1988). These studies rely on the fact that if returns are serially uncorrelated, for a sufficiently long sample, the variances of *k*-period returns will be proportional to *k*, where the constant of proportionality is the variance of one-day returns. This method is not directly applicable in our case for two reasons. First, we only have a single event and, accordingly, a short sample period. Second, return variability exhibits considerable variation after the election, spiking on the first day and progressively declining thereafter (recall Figure 2).

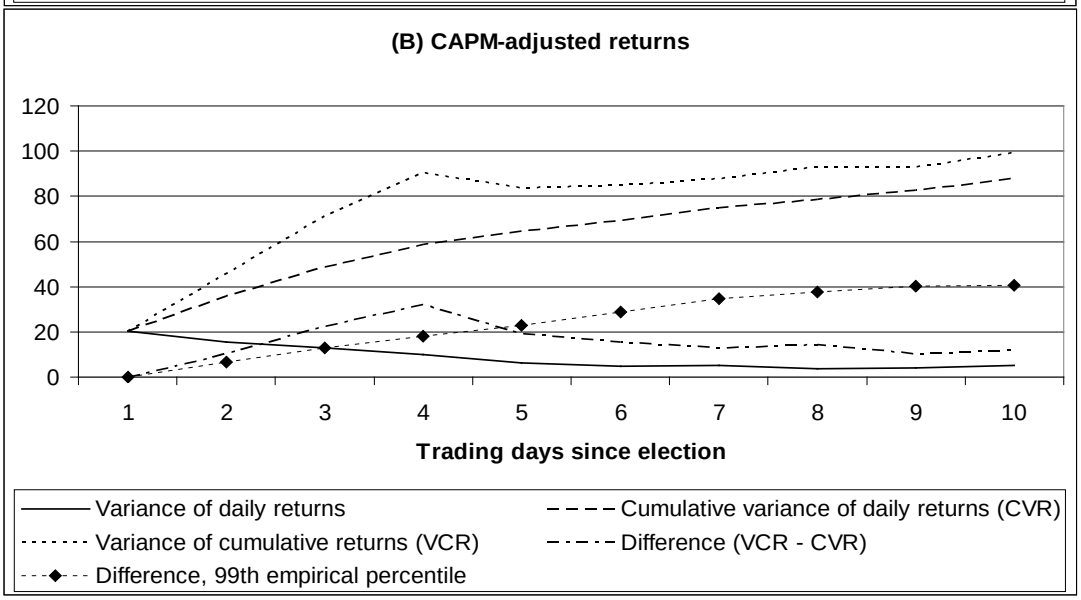
Given these facts, we adapt the variance ratio methodology to our setting in two ways. First, we compute variances using the cross-section of assets. Second, in order to prevent changes in daily variances from mechanically affecting the results, we gauge the impact of return continuation and reversals using differences in variances rather than variance ratios. Specifically, on each day after the election, we compute the cross-sectional variance of returns (raw, CAPM-adjusted, and Fama-French-adjusted) on that day and of the cumulative returns through that day. If returns were uncorrelated, the variance of cumulative returns would equal the sum of the daily variances through that day. Thus if the variance of the cumulative returns on a particular day greatly exceeds the sum of the daily variances, that would indicate considerable (positive) covariance in returns through that day. Moreover, the difference between the two variance measures on a given day reflects the cumulative impact of return continuation and reversals through that day.

Figure 9 shows the results of this analysis. The patterns differ little across the three types of returns reported in the different panels. The variance of daily returns, shown by the solid line, declines as prices settle; consequently, the cumulative variance of daily returns (CVR), shown by the dashed line, exhibits a concave pattern. However, the variance of cumulative returns (VCR), shown by the dotted line, rises by significantly more than warranted by the one-day variances assuming independence through the fourth day after the election. Thus, this finding indicates that the cumulative impact of the momentum documented in Section 4.1.1 on returns is rather strong. Indeed, the difference VCR minus CVR, shown by the dashed-dotted line, increases sharply during the first four days. It then decreases noticeably on days 5 and 6, reflecting the impact of the return reversals taking place on those days. Thereafter, the variance difference hovers around the level reached on the sixth day, reflecting the declining magnitudes of continuations and/or reversals in the last days of the sample. To put these results in perspective, Figure 9 also reports the 99th percentile of the empirical distribution of the variance difference over the 2000-2016 period. Clearly, the rise in the variance difference arising during the four days after the 2016 election is extremely unusual.

Note that although the variance differences in the three panels exhibit very similar patterns, they are larger for raw returns than for CAPM-adjusted and Fama-French-adjusted returns. This should be expected. It reflects the fact that the continuation in market, size, and value factor returns after the election mechanically leads to a larger difference between the two variance

measures through the factor exposures when using raw returns. Conversely, the results in Panels B and C also imply that returns experience strong continuations even after these factors are taken into account.





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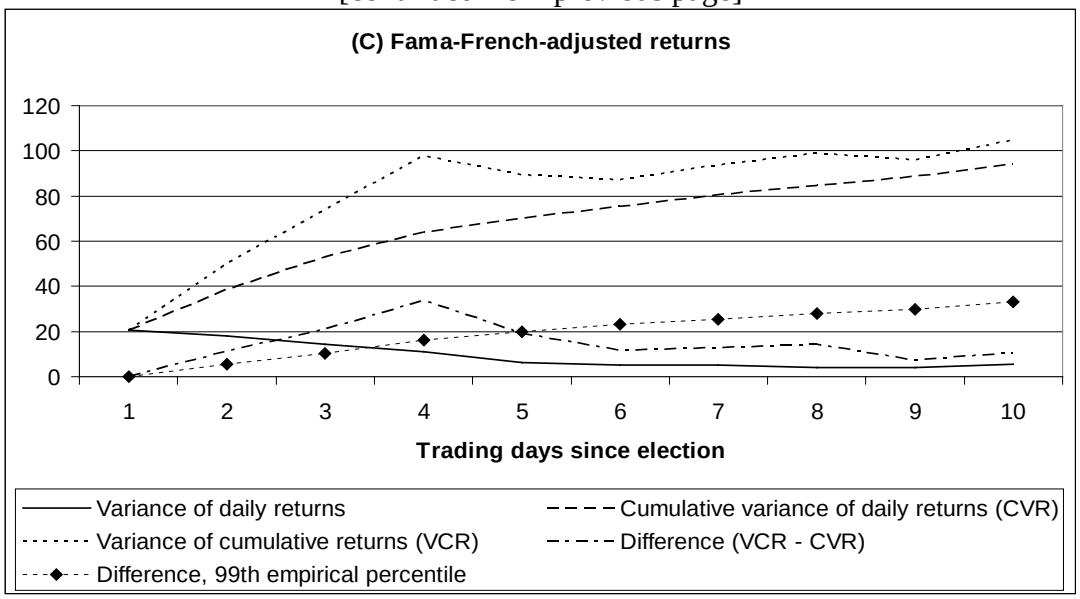


Figure 9: Variance differences.

This figure compares the cumulative variance of one-day returns and the variances of cumulative returns after the election. Panel A uses raw returns, Panel B CAPM-adjusted returns, and Panel C Fama-French-adjusted returns. The sample consists of sufficiently liquid US stocks based on trading volume on November 8, 2016. The 99th percentile of the empirical distribution is based on data for all sufficiently liquid US stocks from January 1, 2000 through December 31, 2016.

4.2 How fast did price discovery take place?

This section asks: How rapidly did prices move towards their 10th-day value? To provide an answer, we borrow from the price discovery literature (Biais, Hillion, and Spatt, 1999; Barclay and Hendershott, 2003), employing so-called unbiasedness regressions. In the above analysis we predict returns one day ahead by regressing returns on day t on the cumulative returns through day $t - 1$. In unbiasedness regressions, we instead regress cumulative returns over 10 days on cumulative returns through day $t < 10$ for different values of t. These regressions reveal two things: First, the slope coefficient measures the unbiasedness of pricing. A regression coefficient above (below) one means that there is return continuation (reversal) from day $t + 1$ through day 10. A coefficient indistinguishable from one means that prices on day t have – on average – reached the level they will attain on day 10 (though there may be continuation offset by reversal in the remaining days). Second, the R^2 value shows what fraction of the overall price discovery has taken place by a given day.

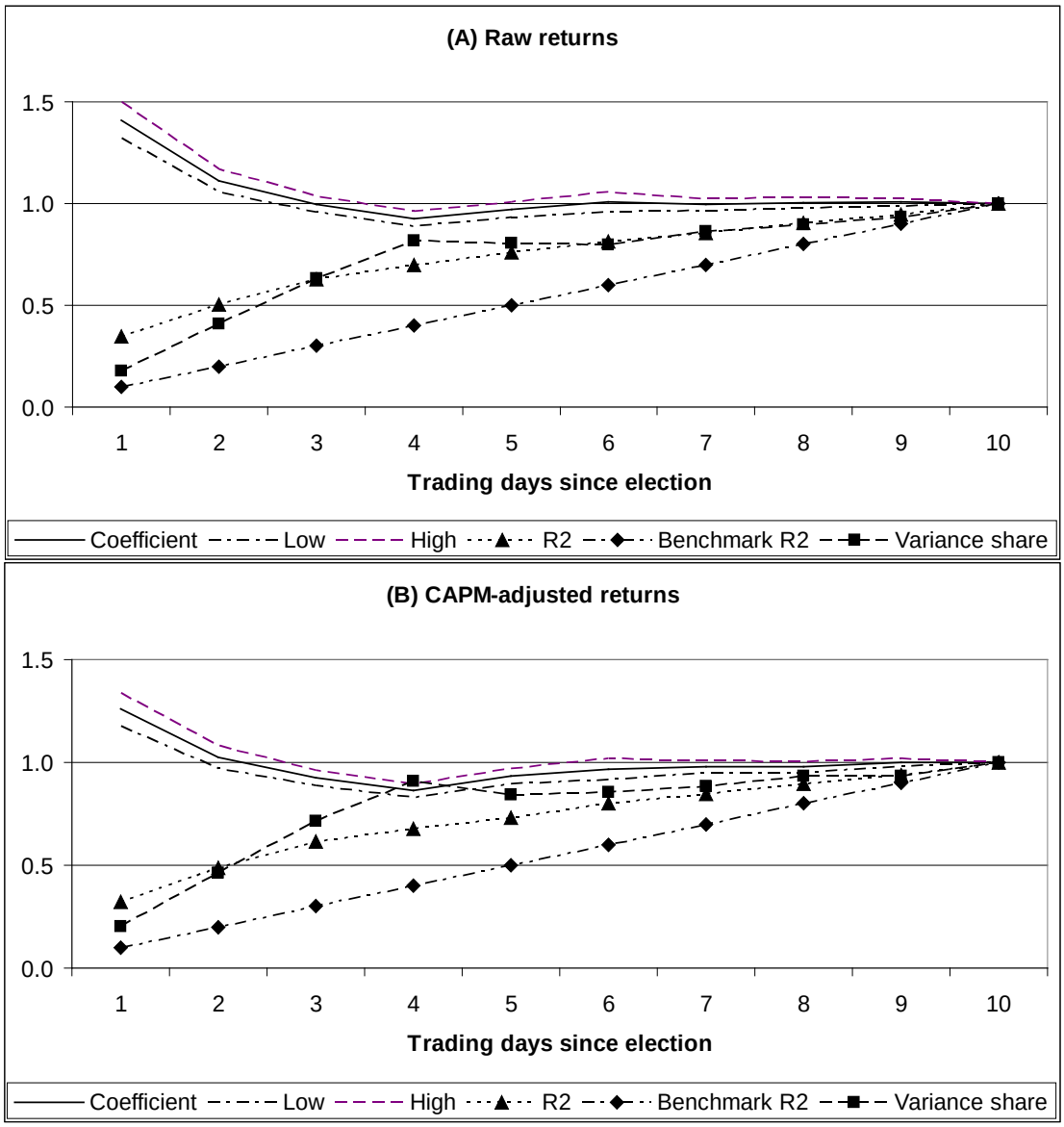
Figure 10 reports the coefficient estimates (with 95% confidence bounds) and R^2 from these regressions. As can be seen by comparing the different panels, the patterns again differ little across the three types of returns.

The coefficients become statistically indistinguishable from one already on the second or third day, depending on the returns considered. We had seen in Section 4.1.2 that there was some continuation on days 3 and 4, followed by reversal on days 5 and 6. These opposite movements essentially balanced out, implying that prices at the end of the second or third day already offered an unbiased estimate of their day-10 values.

If the amount of price discovery were constant across days, R^2 would lie on a straight line starting at zero on Election Day, going to 10% at the end of day 1, and reaching one on the 10th day. Price discovery is stronger (weaker) than average whenever R^2 is steeper (flatter) than that benchmark straight line. As can be seen, R^2 jumps to over 30% on the first day, more than three times as large as could be expected if price discovery occurred at a constant rate. From then on, however, it proceeds roughly linearly to reach its final value of one. This suggests that first-day returns had far greater information content, something we explore in more detail in Section 4.3.

Since our analysis seeks to understand the process of price adjustment after a major shock, benchmarking the regression R^2 values against a straight line – equal price discovery over time – may not be the most informative test. In fact, we would expect price discovery to be stronger right after the major news – the election's outcome – became known. A better approach is to benchmark the regression R^2 against the share of the cross-sectional variance of cumulative returns that has accrued through day t, $\text{var}(r_t)/\text{var}(r_T)$, where r_t denotes cumulative returns from the election through day t and T = 10 the end of our window of analysis. That benchmark is reported as "Variance share" in Figure 10. Comparing R^2 to the variance share indicates whether the share of accrued price discovery taking place through day t is higher or lower than could be expected based on the corresponding share of accrued return variability. Whenever R^2 lies above the variance share benchmark, price discovery from the election through day t exceeds price variability, indicating that price discovery up to that time is relatively efficient. Conversely, an R^2 below the benchmark indicates less price discovery than price variability, implying inefficient price discovery. If price discovery were equally efficient over time, R^2 would lie on the benchmark line.

The results in Figure 10 reveal that price discovery is very efficient on the first day, and to a lesser extent on the second day. On days 3 and 4, R^2 rises much less than the share of accrued price variability, presaging the price reversals on days 5 and 6. From the close of days 6 or 7 onwards, the amount of price discovery is broadly in line with what one would expect based on return variability.



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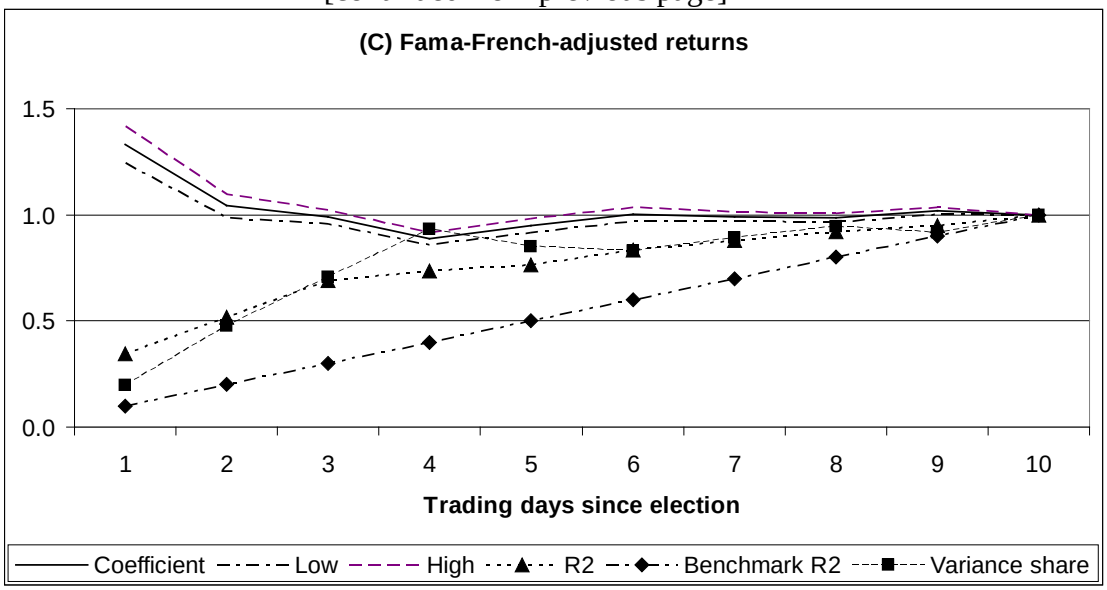


Figure 10: Unbiasedness regressions.

This figure reports the coefficients, confidence intervals, and R^2 values from unbiasedness regressions of cumulative returns until the tenth day after the election on cumulative returns through a given day, as well as Benchmark R^2 values (a straight line positing equal price discovery on each day) and the share of return variability of cumulative returns that accrues through day *t*. Panel A uses raw returns, Panel B CAPM-adjusted returns, and Panel C Fama-French-adjusted returns. The sample consists of sufficiently liquid US stocks based on trading volume on November 8, 2016.

4.3 Information content of first-day returns

To reiterate, Section 4.1 showed that there was extreme return continuation from November 9 to 10. Given that there were no salient political or policy news stories on these two days beyond assessments of the election itself, this continuation pattern provides convincing evidence of delayed information processing, a theme of this paper.

In this section, we take a closer look at the information contained in first-day returns. The substantial information content of first-day returns is strikingly illustrated by the following observation: For 66% of stocks, the abnormal continuation return from day 2 through day 10 has the same sign as the first-day abnormal return.

Table 2 assesses the information content of first-day returns more formally. It reports the relation between the returns on November 9 (the day after the election) and the daily returns on each of the next 9 trading days, November 10 through November 22. Interestingly, the correlations found in Table 2 are very similar to those in Table 1. This implies that the

information content of first-day returns was so large that they were nearly as informative predicting the *N*th day's returns as were cumulative returns over the first $N - 1$ post-election days.

Section 4 reveals substantial persistence of price movements. Was this due to slow digestion of information already available on November 9, or did significant new, albeit consistent information emerge in the days that followed? Section 5 evaluates the new information explanation.

Table 2: The information content of first-day returns.

The table shows the relation between returns on days 2 – 10 after the election (November 10 through November 22) and first-day (November 9) returns, using Spearman rank correlations and regression coefficients. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Trading days since election	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A: Raw returns									
Spearman rank correlation	0.450***	0.234***	0.198***	-0.163***	-0.171***	0.006	0.027	0.002	0.030*
	(0.017)	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Regression slope	0.244***	0.121***	0.088***	-0.054***	-0.078***	-0.012	-0.001	0.007	-0.001
	(0.021)	(0.015)	(0.019)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.013)
Panel B: CAPM-adjusted returns									
Spearman rank correlation	0.436***	0.231***	0.170***	-0.232***	-0.148***	-0.032*	0.041**	-0.067***	0.037**
	(0.018)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
Regression slope	0.230***	0.113***	0.074***	-0.088***	-0.067***	-0.029***	0.008	-0.012	0.000
	(0.022)	(0.016)	(0.020)	(0.011)	(0.013)	(0.012)	(0.010)	(0.011)	(0.013)
Panel C: Fama-French-adjusted returns									
Spearman rank correlation	0.441***	0.190***	0.204***	-0.247***	-0.156***	0.030	0.040**	-0.101***	0.091***
	(0.018)	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)
Regression slope	0.299***	0.132***	0.133***	-0.108***	-0.081***	-0.004	0.018*	-0.035***	0.040***
	(0.027)	(0.020)	(0.022)	(0.013)	(0.015)	(0.012)	(0.011)	(0.012)	(0.013)

5 Information processing or new information?

Section 4 argued that the return patterns on the days after the election appeared to reflect honing-in to a new equilibrium. The logical alternative is that additional news in the days after the election caused shifts in fundamental values that had the same or opposite cross-sectional patterns as the November 9 news. Under this interpretation, the return patterns documented above would not reflect gradual price adjustment to a stable equilibrium, but immediate adjustment to a shifting equilibrium. In this section, we seek to disentangle these two views. We do this in three ways. First, we directly analyze the intensity and content of the post-election news flow. Second, we contrast the reversals in individual stock returns on days 5 and 6 with the

aggregate market moves on those days. Third, we provide evidence that the strength of the return patterns differs across stocks categorized by plausible proxies for the expected adjustment speed, but arguably unrelated to the news flow. Such a pattern would not emerge if markets were, each day, immediately incorporating news coming out on that day.

5.1 News flow after the election

News is released every day, and the post-election period is no exception. Could the news flow after the election have been sufficient to cause the patterns documented in Section 4? Note that additional news as such would not produce such patterns. Rather, for additional news to explain the observed momentum and reversal, it would also need to (at least approximately) confirm or reverse the specific cross-sectional return patterns observed on November 9. Types of news that would qualify would be, for example, if the party controlling the House or the Senate had only become known after November 9, if the President-Elect had made unexpected policy announcements that went further than or backtracked on his campaign pledges, or if he had made cabinet appointments that caused investors to revise their expectations about the strength with which announced policies would be pursued.

Although a huge number of news stories were published in the days following the election shock, their content on these counts was modest, and seems insufficient to have caused the patterns that we document. First, it was known by the end of election night that the Republicans would keep control of both chambers of Congress.[9] Second, while selections for a number of White House staff positions were announced during the ten days, no cabinet appointments that revealed something about upcoming policies were made, and no senior economic officials were named.[10] More generally, President-Elect Trump made few substantive announcements in the time period we are considering, and none altered what was known about his policies. The words “tax”, “trade”, “health care”, and “immigration” – four key topics of the campaign – did not

[9] There was little doubt before the election that the Republicans would keep control of the House. As for the Senate, at 2.55 a.m. ET on November 9, CBS announced "Sen. Pat Toomey wins Pennsylvania Senate race, CBS News projects. The GOP will keep control of the Senate."

[10] On November 13, President-elect Trump announced selections for Chief Strategist and Senior Counselor to the President as well as Chief of Staff (in that order). On November 18, he announced selections for Attorney General, National Security Advisor, and CIA Director. On November 20, he tweeted “General James "Mad Dog" Mattis, who is being considered for Secretary of Defense, was very impressive yesterday. A true General's General!” General Mattis was announced as Secretary of Defense on December 1.

appear in any of Trump's tweets between November 9 and 22.[11] The American Presidency Project documents 23 releases of news by the Transition Team, most of which concern summaries of congratulatory phone calls from foreign governments. The only ones that contain policy news were about the above-mentioned White House staff appointments.[12]

As a further check on whether news about upcoming policies became known in the days following the election, we investigate media coverage of key policy areas during that period. If a major announcement on such policies had happened during that period, we would expect to see a spike in media coverage of that topic. To assess whether this was the case, we collect data on the number of media articles containing certain keywords from Bloomberg.[13] We search for news in the above-mentioned key policy areas (the corresponding keywords are shown in parentheses): Taxes ("Tax cut", "Tax reform", "Tax rate", "Corporate tax"), trade ("Tariff", "Tariffs", "Protectionism", "Trade war", "NAFTA", "Renegotiate", "Foreign firms"), health care ("Healthcare reform", "Obamacare repeal"), and immigration ("Border wall", "Trump wall", "Immigration"). We aggregate the number of articles on each topic by day and standardize the resulting total to be 100 on November 9. Figure 11 shows a steeply decreasing number of articles on each of the four topics following November 9.[14] The number of articles that did appear undoubtedly reflects some echo effect, with newly published articles regurgitating the content of articles from previous days. Thus, we would not expect news coverage of the topics to vanish immediately. However, if major news on these topics had hit the wire, we would see an increase in the number of articles. This would be particularly true of news suggesting that Trump would soft pedal his campaign pledges on taxes and/or trade, which is the type of news that would be required to account for the price reversals on days 5 and 6. No such spikes in news coverage are observed during the sample period, confirming the findings from our detailed study of the

[11] Most of the tweets were of a relatively personal nature. The perhaps most policy-relevant ones were as follows: On November 16, President-Elect Trump tweeted "Very organized process taking place as I decide on Cabinet and many other positions. I am the only one who knows who the finalists are!" On November 18, he announced: "Just got a call from my friend Bill Ford, Chairman of Ford, who advised me that he will be keeping the Lincoln plant in Kentucky - no Mexico". The full list of tweets can be found at https://factba.se/.

[12] See http://www.presidency.ucsb.edu/transition2017.php.

[13] We use the Bloomberg News Trend (NT) function, which reports the number of times that a certain word or word combination has appeared in news stories on a given day. The news counts are derived from over one hundred authoritative global sources. The data are available historically but are missing for November 11, 2016.

[14] It is a coincidence that the total number of articles on the four tax topics is the same on November 9 and November 10.

announcements by the Transition Team that little additional information hit markets after November 9.

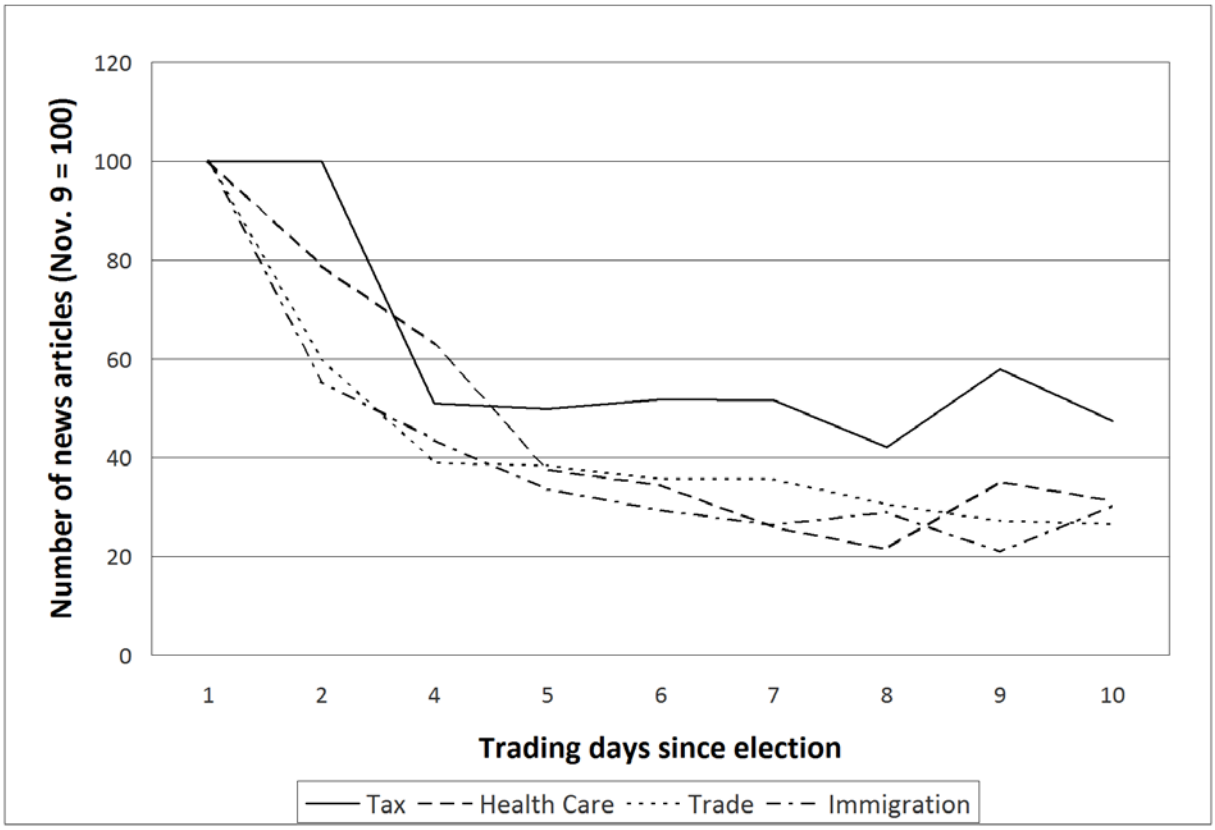


Figure 11: News flow after the election.

The figure plots news coverage on four key topics after the election. From Bloomberg, we collect data on the number of media articles containing certain key words on the key topics of taxes, health care, trade, and immigration (see the text for details of the search terms used). In each category, we normalize the sum of articles to be 100 on November 9. Data for November 11 are missing on Bloomberg.

A review of the leading news stories reveals that some industries received substantial coverage.[15] For example, a Bloomberg News story published on November 10 was titled "Trump Team Says President-Elect Will Dismantle Dodd-Frank Act," presumably to the benefit of financial stocks. In a Wall Street Journal interview on November 11 (released at around 6 p.m. online), the President-Elect suggested that he might take a more flexible view of what to do with

[15] In contrast to industries, the media rarely discussed individual companies. Indeed, a LexisNexis search of the Wall Street Journal and the New York Times reveals that in over 1'000 articles (in various versions, print and online, of the two outlets) containing the word "Trump", specific companies were mentioned rarely, with the top three companies being Facebook (17 mentions), Twitter (7 mentions), and JP Morgan Chase (6 mentions).

the Affordable Care Act, consequential legislation for the healthcare industry. He mentioned the key topics of his agenda in a November 13 interview with CBS, but provided no specifics. A Bloomberg News story on November 14 led with "Trump Win Doesn't Get Pharma Off the Hook on High Drug Prices". It is conceivable that such news stories provided additional impetus or pushback for individual industries, obscuring our view on the adjustment of prices to the election result. However, Table A-1 in the Supplementary Appendix shows that Section 4's results hold after controlling for industry fixed effects, or when excluding financial services, healthcare, and pharmaceutical companies.

Overall, little news flow occurred after the election, and none occurred that clearly would indicate further shifts in the equilibrium values of stock prices sufficient to explain the effects reported in Section 4.

5.2 Rank order correlations and aggregate price moves

A key feature of the honing-in process discussed in Section 4 is the reversal that took place on days 5 and 6 – that is, stocks that did relatively best on days 1 through 4 did relatively worst on days 5 and 6, and vice versa. To the extent that this reversal was driven by the release of additional news, we would expect the move in the overall market to have reversed as well. This was, however, not the case. The market had been notably up on each of days 1 through 4, with a cumulative increase of 2.19% through day 4.[16] The market was up 0.80% on day 5, the first reversal day, and experienced a mere 0.12% dip on day 6.

Large negative cross-sectional rank-order correlations are rare and, as we would expect, are usually associated with a contemporaneous reversal in the overall market. This would happen if the news that drove the initial spreads and the overall market itself reversed. In our 17-year sample with 4,276 trading days, for raw returns, there are 100 instances where the rank-order correlation of daily returns with cumulative returns during the previous four days fell below the value of -0.25 reported in Table 1, but all but seven of them are associated with a contemporaneous reversal in the overall market. For CAPM-adjusted returns, there are only 18 days with a reversal stronger than the value of -0.32 from Table 1, and all but four are associated with a reversal in the aggregate market. For Fama-French-adjusted returns, there are only 15 days with a reversal stronger than the value of -0.33 in Table 1, and only two of them are not

[16] Market excess returns and riskless rate downloaded from Ken French's website.

associated with a market reversal. Thus, cross-sectional reversals as strong as the one on day 5 are quite unusual; those that are not accompanied by a contemporaneous reversal in the overall market are rare beasts indeed. This suggests that on day 5 investors felt that the price spreads from the initial event, the election surprise, had gone somewhat too far, rather than some new news had reversed the initial news.

5.3 Differences among stocks

Our final investigation of the additional news explanation analyzes whether the strength of the return patterns differs across categories of stocks. We form categories based on characteristics that are unlikely to be correlated with the news flow, but are likely to be correlated with the speed of incorporation of news into prices. In the extreme, if markets were, on each day, immediately incorporating news coming out that day, we would not expect differences in return continuation across these groups of stocks. As this section illustrates, however, such differences are present in the data. Moreover, they are in line with what theories of delayed adjustment and costly information processing predict.

5.3.1 Behavioral theories of momentum

Prominent behavioral theories of momentum predict cross-sectional differences in return continuation. To the extent that this is the case in the post-election period, this would support the notion that such patterns reflect the digestion of the election outcome by the market rather than a response to additional news. We focus on the theories due to Hong and Stein (1999) and to Barberis, Shleifer, and Vishny (1998).

Hong and Stein (1999) show that momentum arises if private information diffuses gradually across the investing public and investors cannot extract information from prices as is commonly done in rational expectations models. Their model predicts that momentum will be stronger in firms with less analyst coverage, a prediction for which Hong, Lim and Stein (2000) find empirical support. Although the Hong and Stein (1999) model considers a setting with heterogeneous investors who observe different pieces of private information, it has implications for our setting. The election outcome as such was public information, but individual investors are likely to have had pieces of private information that led to different expectations about a Trump Administration's policies and their impact on firm values.

The top panel of Table 3 reports the strength of return continuation between November 9 and November 10 for different groups of stocks built based on residual analyst coverage (the residual of a regression of the log of 1 plus the number of analysts covering a stock on the log market value of equity) on September 30, 2016.[17] The results for both raw and CAPM-adjusted returns accord with the predictions of the Hong and Stein (1999) model. Momentum between November 9 and November 10 is almost three times larger for firms in the bottom quartile of residual analyst coverage than for firms in the top quartile, and about twice as large for firms below the median than for firms above it. For Fama-French-adjusted returns and for the following days (not reported to conserve space), the difference is not pronounced.

Barberis, Shleifer and Vishny (1998) develop an alternate, also prominent, theory of momentum. They show that momentum will derive from investors' conservatism. Their theory draws on a phenomenon well documented by psychologists: individuals are too slow to change their beliefs in the face of new evidence. In experiments, Edwards (1968) finds that individuals update their posteriors in the right direction, but by too little in magnitude relative to the rational Bayesian benchmark. This result bears strong parallels with our finding that after the election, prices overwhelmingly moved in the right direction, but not enough. As Barberis, Shleifer and Vishny (1998) note, conservatism implies that investors facing a public announcement – election results being a salient case – will underweight its information content relative to the less useful evidence used to form their priors.

What does conservatism imply for the strength of post-election momentum in different categories of stocks? Trump's victory shook up firms' future profitability, but investors' pre-election priors obviously did not take the realized election outcome into account. Hence, if investors tend to give too much weight to their priors relative to the new information, this will cause momentum to be greater among stocks where their prior uncertainty was low. Great uncertainty by analysts and presumably investors will be reflected in the substantial dispersion of analysts' earnings forecasts. Thus, following Barberis, Shleifer and Vishny (1998) , conservatism predicts that momentum should be more pronounced in firms with low dispersion in analysts' forecasts. The results in the bottom panel of Table 3 show that this is indeed the case for raw and CAPM-adjusted returns; for Fama-French-adjusted returns, no difference is discernible in the data.

[17] The results when using residual coverage on the day before the election are very similar.

In sum, these results support the predictions of Hong and Stein (1999) and Barberis, Shleifer and Vishny (1998), and they suggest that post-election return patterns reflect investors' processing the implications of the election outcome rather than the effect of additional news. To account for the observed phenomena, the additional news explanation would require the news that came out after November 9 to have had a stronger impact on the fundamental value of firms with low analyst coverage and forecast dispersion. While one cannot definitely rule out the possibility that the news had that property, it seems highly unlikely.

Table 3: Return continuation – differences among stocks.

The table shows coefficients of a regression of November 10 returns on returns on November 9. The three rows in each panel use raw, CAPM-adjusted, and Fama-French-(FF-)adjusted returns, respectively. Column (1) presents results for the full sample. Columns (2) to (5) present results for quartiles 1 to 4 of the split variable indicated in the panel heading: Residual analyst coverage in the top panel and analyst dispersion in the bottom panel. Residual analyst coverage is the residual of a regression of the log of 1 plus the number of analysts covering a stock on the log market value of equity. Analyst coverage and analyst dispersion are obtained from IBES as of September 30. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Return on Nov 10 (Raw, CAPM-adjusted, FF-adjusted -- matching the explanatory variable)						
Split variable:	**Residual Analyst Coverage**						
Sample:	All	Q1	Q2	Q3	Q4	Bottom half	Top half
Raw return on Nov 9	0.243***	0.367***	0.315***	0.199***	0.134***	0.344***	0.169***
	(0.022)	(0.040)	(0.048)	(0.038)	(0.040)	(0.032)	(0.028)
CAPM-adjusted return on Nov 9	0.229***	0.363***	0.297***	0.192***	0.122***	0.332***	0.159***
	(0.023)	(0.042)	(0.050)	(0.039)	(0.042)	(0.034)	(0.029)
FF-adjusted return on Nov 9	0.291***	0.345***	0.298***	0.244***	0.281***	0.323***	0.270***
	(0.027)	(0.051)	(0.051)	(0.044)	(0.057)	(0.037)	(0.037)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Return on Nov 10 (Raw, CAPM-adjusted, FF-adjusted -- matching the explanatory variable)						
Split variable:	**Analyst dispersion**						
Sample:	All	Q1	Q2	Q3	Q4	Bottom half	Top half
Raw return on Nov 9	0.252***	0.434***	0.371***	0.259***	0.144***	0.403***	0.183***
	(0.022)	(0.056)	(0.052)	(0.039)	(0.036)	(0.038)	(0.027)
CAPM-adjusted return on Nov 9	0.239***	0.420***	0.352***	0.252***	0.131***	0.384***	0.171***
	(0.023)	(0.062)	(0.052)	(0.040)	(0.037)	(0.040)	(0.028)
FF-adjusted return on Nov 9	0.301***	0.311***	0.291***	0.300***	0.300***	0.299***	0.301***
	(0.028)	(0.063)	(0.052)	(0.044)	(0.047)	(0.040)	(0.035)

5.3.2 The speed of repricing in the middle and in the extremes

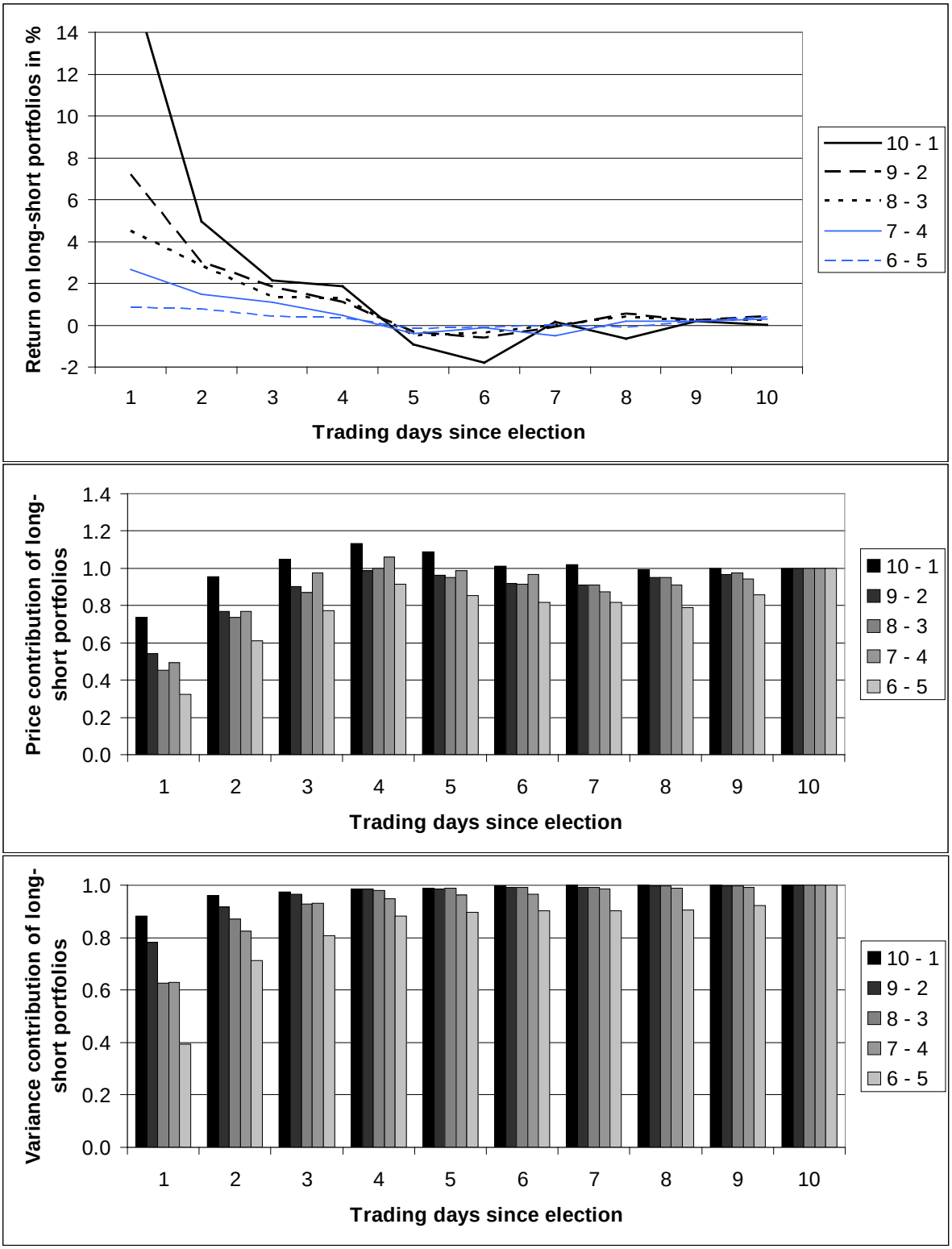
Besides the behavioral aspects discussed in the prior section, simple cost-benefit considerations also predict differences in the speed of price adjustment across stocks under the delayed-adjustment story, but not under the additional-news hypothesis. Specifically, in the former case, investors should reprice those stocks for which the stakes are higher faster, while under the additional-news hypothesis, all stocks should be repriced at approximately the same speed. To assess what actually happened after the election, this section investigates whether the share of repricing that took place early on is larger for stocks that reacted particularly strongly on the first day than for weak initial responders.

Figure 12 compares the returns on five long-short portfolios. Portfolio 10-1 uses the extreme deciles of first-day returns, 6-5 the middle ones, etc. Panel A considers raw returns, Panel B CAPM-adjusted returns, and Panel C Fama-French-adjusted returns. Focusing first on raw returns, the top panel shows the daily returns on the long-short portfolio. (The first-day return could not be achieved in practice, but those on subsequent days can.) That panel shows that all portfolios converge: by close of day 7, the daily returns for all five portfolios are essentially zero. The reversals on days 5 and 6 discussed in Section 4.2 are clearly visible. The figure reveals that the extreme portfolio drives the reversal on day 6.

The middle and bottom panels contrast the speed of price convergence across the different portfolios. Specifically, the middle panel reports the portfolios' cumulative price contribution over time, computed as the share of the ten-day cumulative return of each portfolio that has accrued through each of days 1 through 10. The bottom panel shows the portfolios' variance contribution, i.e., the share of the ten-day cumulative variance of the portfolio's returns that has accrued through each of days 1 through 10. Both price contribution and variance contribution are higher for the extreme (10-1) portfolio than for the middle (6-5) portfolio, indicating faster convergence for the former.

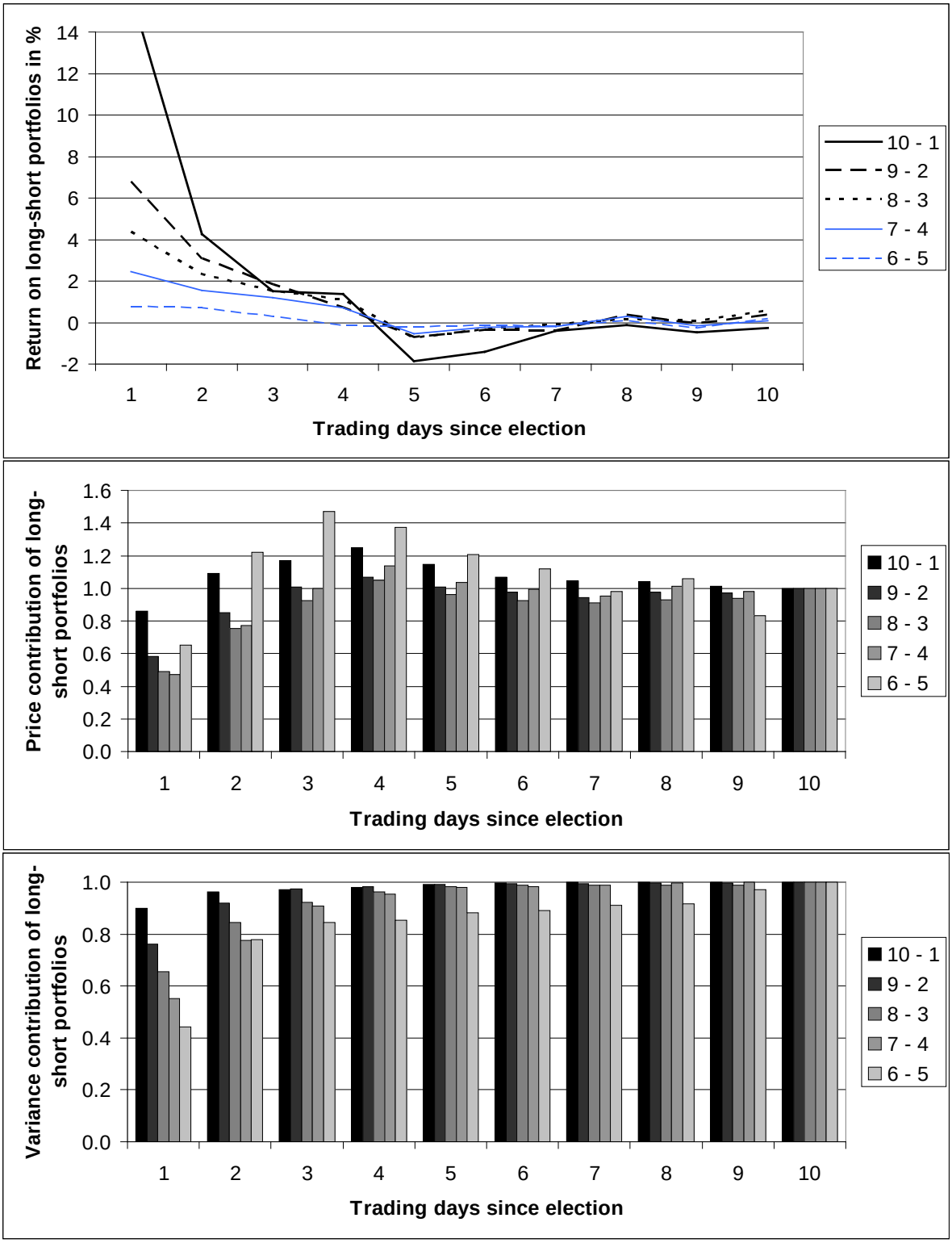
Panels B and C show similar results for CAPM-adjusted and Fama-French-adjusted returns, respectively. A slight difference is that as can be seen in the price contribution charts, the 6-5 portfolio overshoots on days 2 and 3. However, this portfolio earns essentially zero returns overall, implying that the daily contribution is noisy. The variance contribution chart shows this as well.

(A) Raw returns



[Figure continued on the next page]

(B) CAPM-adjusted returns



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(C) Fama-French-adjusted returns

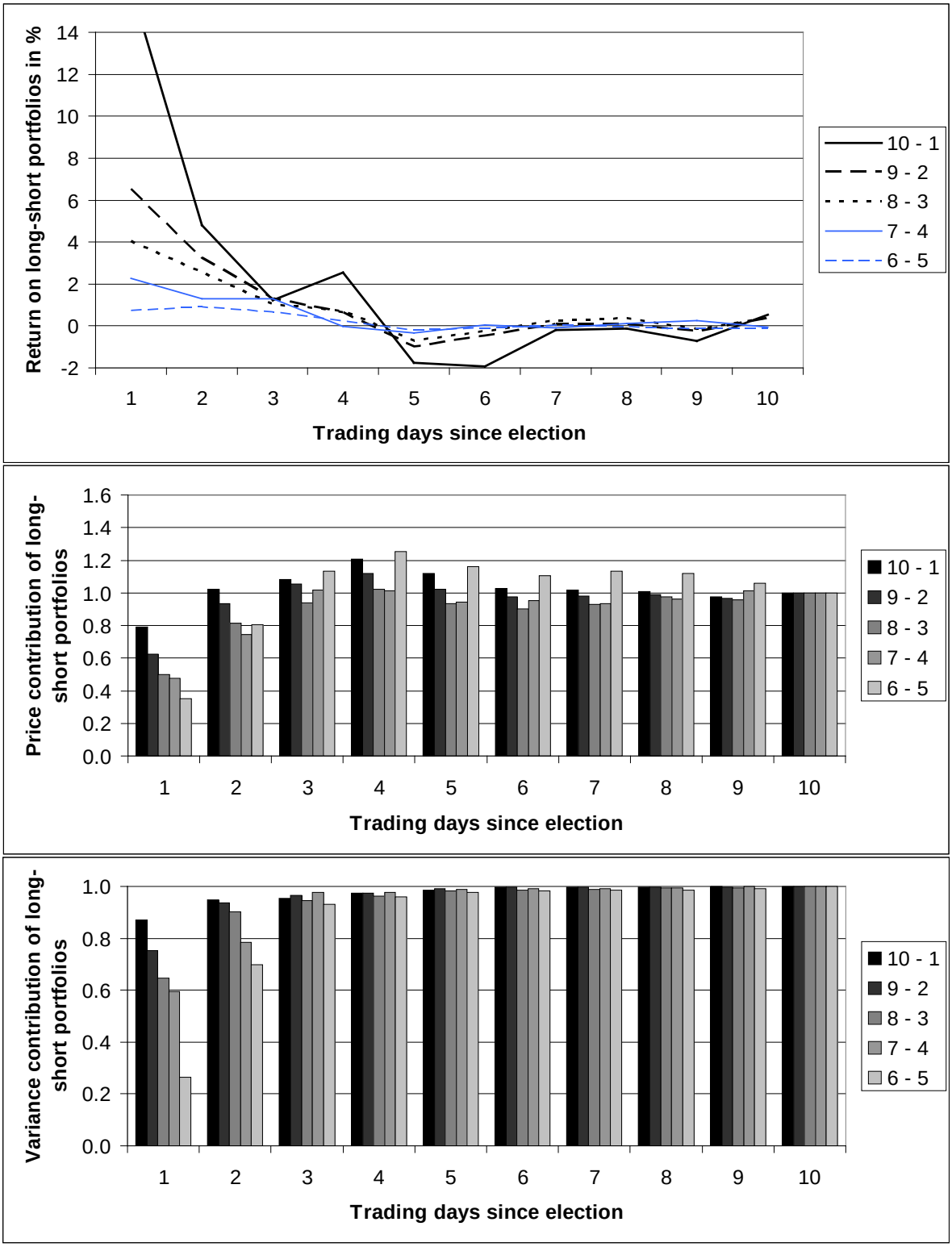


Figure 12: The speed of repricing in the middle and in the extremes.
[detailed caption on next page]

This figure shows the daily returns of different long/short portfolios formed based on first-day returns, and their price and variance contributions. The *cumulative price contribution* measures the share of the ten-day cumulative return of each portfolio that has accrued through day *t*. The *cumulative variance contribution* measures the share of the ten-day cumulative variance of the portfolios' returns that has accrued through day *t*. Panel A considers raw returns, Panel B CAPM-adjusted returns, and Panel C Fama-French-adjusted returns. The sample consists of sufficiently liquid US stocks based on trading volume on November 8, 2016.

These results are consistent with market participants prioritizing the analysis of stocks that offer the largest potential payoff from getting the pricing right. These are the stocks most strongly affected by the aggregate surprise, namely the 10-1 portfolio. These results provide further evidence that limited information processing lies behind the momentum observed when looking at all stocks. This positive relation between profit potential and adjustment speed hints that accelerating information processing may be expensive.

6 The sources of return continuation

This section analyzes the factors underlying the observed convergence patterns. Section 6.1 decomposes the explanatory power of first-day returns to identify the underlying drivers of the observed momentum. Section 6.2 conducts a price contribution analysis that identifies the speed at which firms' fundamental characteristics were incorporated into prices.

6.1 A decomposition analysis

The findings above provide strong evidence that the post-election days produced extraordinary return continuation. This section decomposes the explanatory power of first-day returns in order to identify the underlying drivers of the observed momentum, i.e., whether the return continuation merely reflects investors' "following the winners" as opposed to their processing the consequences of the election's outcome for stock prices. Intuitively, the observed momentum can have two sources. One potential source would be firm characteristics that explain which firms won or lost on the first day. The second potential source would be the unexplained part of the first-day return, namely the residual.

To make matters concrete, consider an investor who has observed the first-day returns. In addition to just following the winners (as defined by the observed returns), this investor might opt for two more sophisticated choices. S/he can bet that the fundamental factors that could be

assessed to have driven part of the stock price reaction on the first day were correct in direction, but have not been priced in completely in terms of magnitude. This investor would, then, invest in a portfolio made up of companies that are predicted to do well based on a model of how fundamental characteristics determine stock returns. Alternatively, the investor might bet that the fact that a stock has done better or worse than expected based on the empirical model for first-day returns, as indicated by its residual, will effectively predict subsequent returns. In order to assess whether momentum is driven by investors' "following the winners" or their processing the consequences of the election's outcome for stocks' fundamental values, we investigate which of these three strategies – "following the winners", using fundamental factors, or using residual returns – earns the highest subsequent returns.

Specifically, at the end of the first day, we build long-short (top decile minus bottom decile) portfolios based on stock returns at the end of the first day. Three alternative stock returns are used to sort firms into deciles: raw returns, CAPM-adjusted returns, and Fama-French-adjusted returns. In turn, for each of these three sets of returns, the sort is based on three different quantities: (a) observed stock returns, (b) stock returns predicted by a cross-sectional model, (c) the residuals (that is, (a) minus (b)). (Note that, in the case of CAPM-adjusted and Fama-French-adjusted returns, the observed stock returns are themselves residuals since they are obtained as raw returns minus the returns predicted from the common factors multiplied with each firm's loadings on these factors. We shall nevertheless refer to them as observed returns.)

Predicted first-day returns are computed using the empirical model reported in Table A-3 in the Appendix.[18] This analysis builds on WZZ, though it employs a somewhat larger sample. The results show that already on day 1 investors (i) responded very strongly to the expected corporate tax cut, bidding up the prices of high-tax firms relative to low-tax firms, and (ii) assessed that domestically-focused companies would do better in the new era, for various reasons. The firms'

[18] We obtain explanatory variables from Bloomberg and Compustat Capital IQ, and use the most current accounting data for all companies. For most companies, this means the December 31, 2015 data. However, several companies have fiscal years that end in other months. Thus, we have several companies for which calendar year 2016 data are included. Where Compustat data are missing for the most recent year, they are replaced with prior-year data. The market value of equity is PRRC_F*CSHO, percent revenue growth is 100*(SALE-SALEt-1)/SALEt-1, profitability is 100*pretax income / assets = 100*(PI/AT), and the cash effective tax rate (cash ETR) is the percent cash taxes paid relative to current year pretax income (adjusted for special items), that is, 100*(TXPD/(PI-SPI)). As in Dyreng, Hanlon, Maydew, and Thornock (2017), in the cross-sectional regressions we restrict the sample to those firms with positive pre-tax income as well as a tax rate below 100%. Percent revenue from foreign sources is from Bloomberg, supplemented by data computed from Compustat segment data. Descriptive statistics are in Table A-2 in the Appendix.

cash effective tax rate (ETR) and percentage of revenue from foreign sources are the prime independent variables employed to capture these two effects. In addition, the model includes standard variables and industry fixed effects. Larger firms and, perhaps surprisingly, firms with high revenue growth performed worse after the election, whereas profitability had no robust impact on returns.

Then, we track the cumulative raw returns on the three long-short portfolios formed on observed, predicted, and residual first-day returns from day 2 through day 10.

Figure 13 presents the results. Consider Panel A. The "observed" columns replicate Figure 1 in the Introduction, showing the returns of investors who merely "followed the winners." Here, our interest is in the "model" and "residual" columns. Strikingly, the portfolio formed on the part of returns that is predicted by the above firm characteristics earns the greatest continuation returns. An investor who formed a long-short portfolio (top decile minus bottom decile, LS, with stocks in both legs being equally weighted) based on predicted stock returns (model-LS) earned cumulative returns of 8% from day 2 through day 10, whereas a long-short portfolio based on residual stock returns (resid-LS) earned about 3%. From day 2 through day 4, the model-LS portfolio performed strongly and then saw only a minor reversal on days 5 and 6. By contrast, while the resid-LS portfolio also made gains on days 2 through 4, it gave up part of these gains in the subsequent two days.[19]

A similar picture emerges when forming the LS portfolios based on CAPM-adjusted returns of the first day. Here, Panel B shows that the model-LS portfolio earned 7% and the resid-LS portfolio barely 2%.

Finally, Panel C presents the results when the LS portfolios are formed based on Fama-French-adjusted returns of the first day. The absolute returns of portfolios built from observed, model, and residual returns are much lower than those in the other two panels. This reduction in performance is intuitive. By forming the LS portfolio on Fama-French-adjusted returns, the investor selects stocks adjusting for (and thus setting aside) the fact that the market and in particular size and value factors reaped positive returns on the first day; thus a portfolio less exposed to these three factors is formed. Since the three factors' positive performance continued for a few days, the resulting portfolio's performance is reduced. Another way to interpret these

[19] Note that the returns on portfolios formed based on model and residual returns do not need to add up to the returns on portfolios formed based on observed returns. A stock can be in both the model-LS and the resid-LS portfolios, or could even be held long in one and short in the other.

results, as compared to those in Panels A and B, is that the underlying empirical model partially picks up the first-day move in the Fama-French factors and uses it to profit.[20] However interpreted, the results in Panel C exhibit the same striking difference in performance between the model-LS and resid-LS portfolios as Panels A and B. This confirms that return continuation came primarily from the part of returns explained by firm characteristics rather than from residuals.

In sum, these results suggest that pure feedback trading (following the winners) cannot be the primary explanation of momentum after this event. If it were, we would not expect most of the continuation returns to be associated with the firm characteristics. Rather, the results point towards momentum being driven by delayed processing of information about the level of fundamentals and/or their relevance for firm value.

[20] As mentioned in Section 4, loadings on size and value are positively correlated with tax rates. However, loadings on size and value are also positively correlated with foreign revenue. Since cash ETR and foreign revenue explain returns with opposite signs (cash ETR entering positively, and foreign revenue entering negatively), it was a priori not obvious how the Fama-French adjustment would affect this analysis.

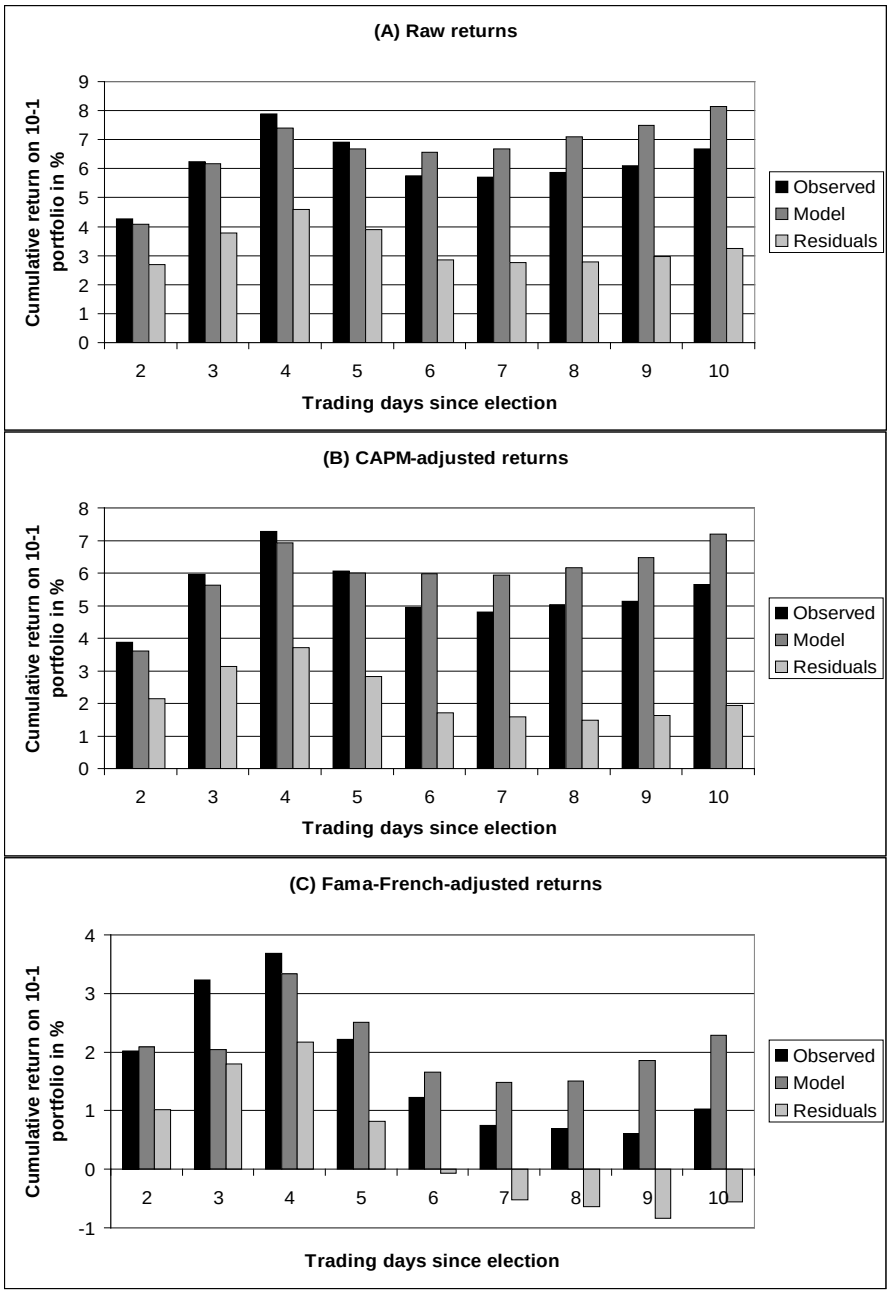


Figure 13: Cumulative returns on long-short portfolios (top decile minus bottom decile) formed on observed, model-predicted, and residual first-day returns.

Predictions come from a cross-sectional regression of first-day returns on firm characteristics (size, revenue growth, profitability, cash ETR, and foreign revenue, as well as industry fixed effects following Wagner, Zeckhauser, and Ziegler (2017), reported in Table A-2). Panel A estimates the model and forms the initial portfolios using raw returns, while Panels B and C respectively employ CAPM-adjusted and Fama-French-adjusted returns. The sample consists of sufficiently liquid US stocks based on trading volume on November 8, 2016.

6.2 Which factors moved first?

The previous section shows that model-predicted first-day returns strongly predicted return continuations from the second through the tenth day. This indicates that there was an insufficient response to the factors that produced day 1's returns. Hence, those factors also predicted for subsequent days. Presumably, however, different factors were priced in at different speeds. To determine which factors drove returns most swiftly, we use the method that WZZ developed building on the price contribution methodology commonly used in the market microstructure literature. We estimate daily cross-sectional regressions using cumulative returns for each of the first T = 10 days. We then track the evolution of the betas of the different factors over time. Letting $\beta^i_{0,t}$ denote the regression coefficients corresponding to each cross-sectional factor i estimated using cumulative stock returns from the election through day $t \leq 10$, the *cumulative price contribution* measure for each variable i, $PC^i_{t,T}$, is computed as

$$PC^i_{t,T} = \frac{\beta^i_{0,t}}{\beta^i_{0,T}}, \tag{1}$$

where we use the convention that $\beta^i_{0,0} = 0$. By construction, $PC^i_{0,T} = 0$ and $PC^i_{T,T} = 1$ for all i. Thus, $PC^i_{t,T}$ provides a measure over time of the share of the overall price move in the cross-section of stock returns associated with factor i that has taken place by day t.

This price contribution analysis reveals how rapidly prices traveled toward their ten-day level, but it does not measure the pace of decline in price uncertainty. To assess that speed, we conduct an additional analysis for variances rather than for returns. Formally, the *cumulative variance contribution* for variable i on day t, $VC^i_{t,T}$, is given by

$$VC^i_{t,T} = \frac{\sum_{s=1}^{t} (\beta^i_{0,s} - \beta^i_{0,s-1})^2}{\sum_{s=1}^{T} (\beta^i_{0,s} - \beta^i_{0,s-1})^2}. \tag{2}$$

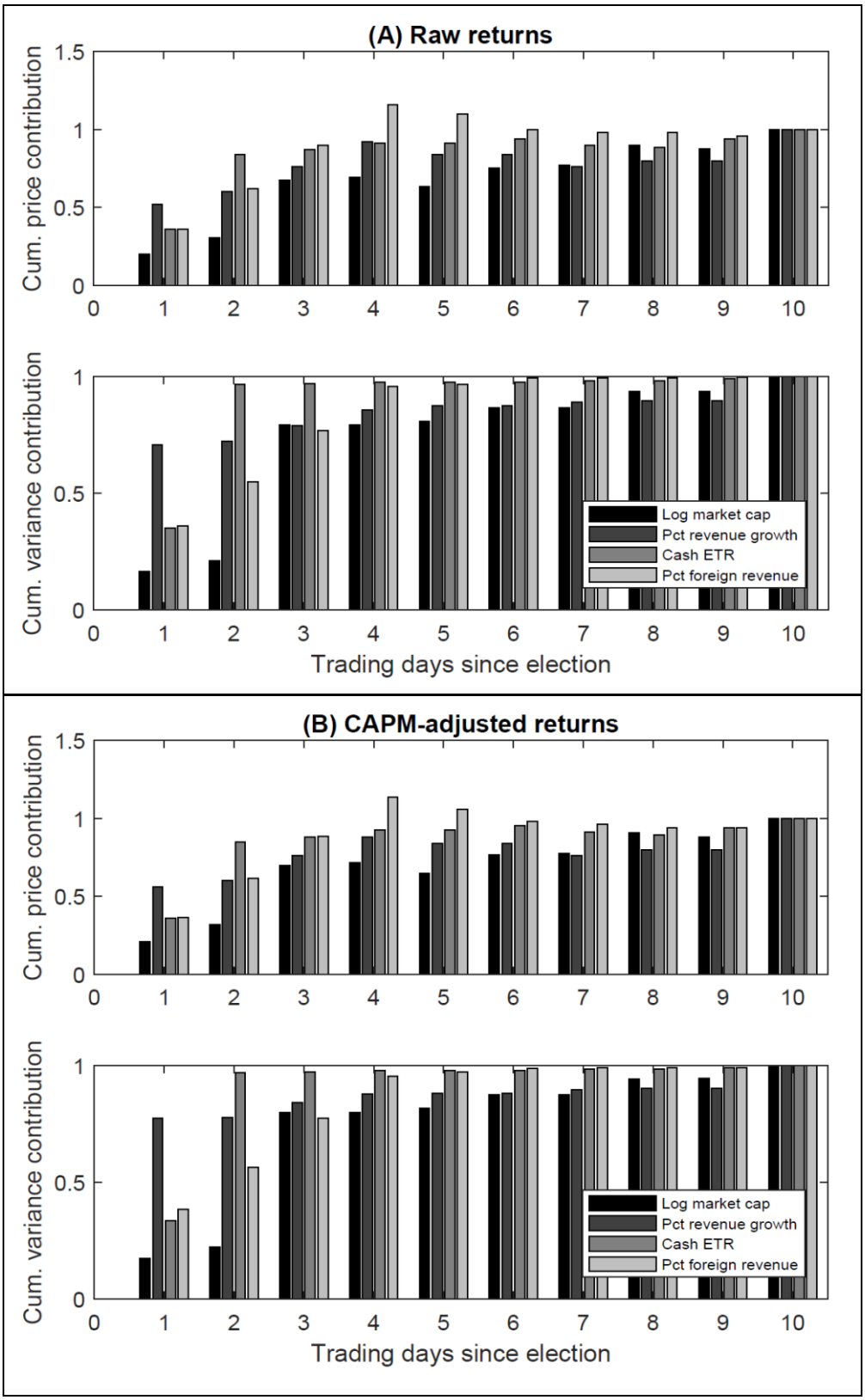
Here, too, by construction, $VC^i_{0,T} = 0$ and $VC^i_{T,T} = 1$ for all i, and $VC^i_{t,T}$ measures the share of the price uncertainty associated with factor i that has been resolved by day t.

Before presenting results, let us first illustrate the difference between the two measures. If the one-day response of two variables equals their T-day response but the first settles after the first day and the second keeps moving around for several days, the price contribution on the first

day will be one for both variables, but variance contribution for the first variable will exceed that for the second.

WZZ discuss the relative speeds at which tax rates and other tax-related factors (NOL carryforwards, interest payments, deferred tax liabilities) were priced in. We apply that method more broadly here so as to incorporate additional firm characteristics, thus treating corporate tax rates, though important, as only one of several relevant factors.

The results for raw, CAPM-adjusted, and Fama-French-adjusted returns are reported in Figure 14 (we omit profitability since, as discussed in Section 6.1, its impact on returns is insignificant). The most striking finding is that all cross-sectional drivers exhibit continuation. Indeed, for none of the factors does the first-day impact come close to its ten-day impact. While revenue growth is priced in at around 50% on the first day, the other factors get incorporated at closer to 30%. Second, as the variance contribution results in the lower panels show, the price impact of the cash ETR and revenue growth converged the fastest. While revenue growth moved faster initially, the cash ETR essentially settled at its ten-day value by the second day, with its variance contribution reaching 95%. WZZ argue that quantifying the consequences of the election for firms with significant foreign exposures is particularly complex. Indeed, the results show that the impact of foreign revenue converged slowly. Its price contribution overshot on days 4 and 5, and its variance contribution needed four trading days to cross the 90% mark. A likely explanation for the rapid convergence of the cash ETR is the widely recognized importance given to taxes in Trump's expected policies.



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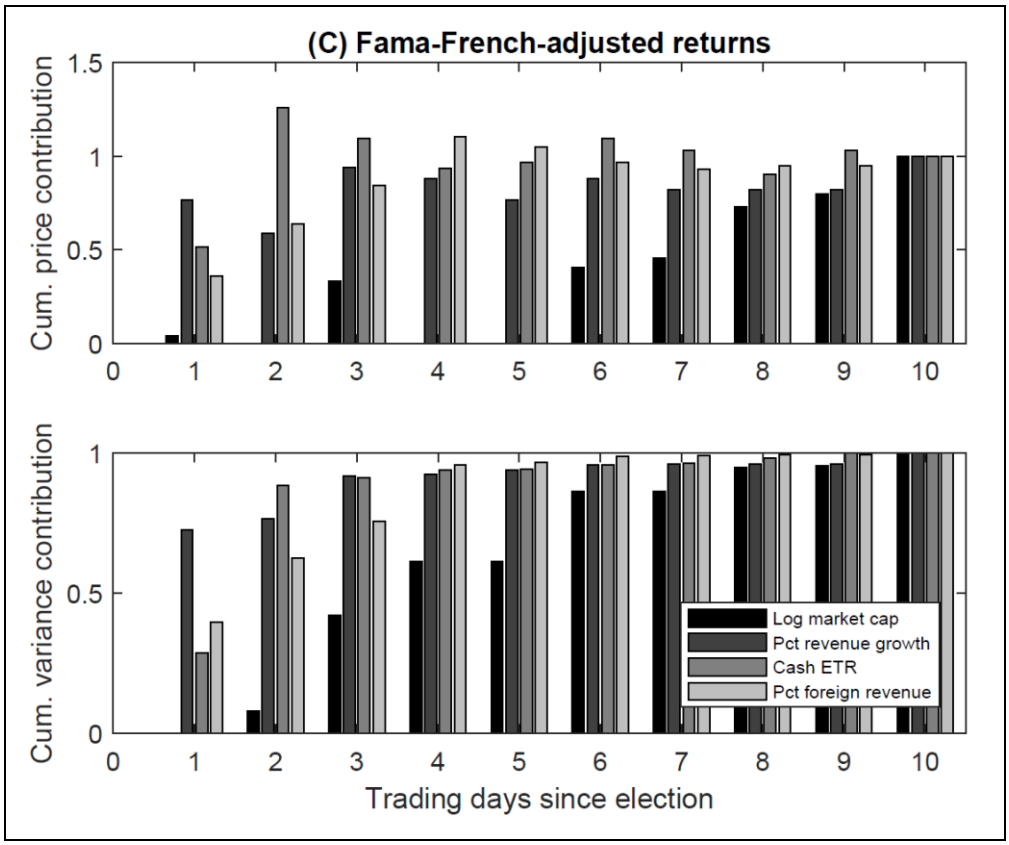

Figure 14: Price and variance contribution.

This figure shows the cumulative price (upper panels) and variance (lower panels) contributions of the different return drivers during each of the ten trading days following the election. The *cumulative price contributions* for the different cross-sectional explanatory variables (market cap, revenue growth, etc.) measure the share of the overall price move in the cross-section of stock returns associated with that variable that has taken place by day *t*. The *cumulative variance contributions* measure the share of the price uncertainty related to each of the variables that is resolved by day *t*. Panel A considers raw returns, Panel B CAPM-adjusted returns, and Panel C Fama-French-adjusted returns. The sample consists of sufficiently liquid US stocks based on trading volume on November 8, 2016.

7 Conclusion

Donald Trump's surprising victory in the 2016 US Presidential election provides an excellent opportunity to study the price adjustment process in stock markets. This aggregate surprise produced a massive price spread as investors speculated on the policies that the Trump Administration would introduce. Investors updated their relative pricing of stocks substantially, and in the appropriate direction on the first day after the election. However, the market essentially took 5 to 6 days to settle on the appropriate magnitude of the relative price adjustment following the aggregate surprise. Specifically, return continuation from day 1 to day 2 was extreme by historical standards, and post-election cumulative returns were strongly correlated with subsequent daily returns for five days. Momentum persisted for three days. A brief reversal followed, and then prices settled. Stock return predictability was primarily driven by the part of day 1 returns predicted by firm characteristics, such as corporate taxes and foreign revenues, as opposed to residual returns on day 1. These results suggest that lack of information processing, rather than pure feedback trading (following the winners), explains momentum in this event.

A large literature studies momentum and associated phenomena, such as the post-earnings announcement drift. The leading explanations offered are conservatism and representativeness bias (Barberis, Shleifer, and Vishny, 1998), overconfidence about private information and biased self-attribution (Daniel, Hirshleifer, and Subrahmanyam, 1998), positive feedback trading resulting from extrapolative expectations, stop-loss orders, margin calls, or portfolio insurance strategies (De Long, Shleifer, Summers, and Waldmann, 1990), and endogenous positive feedback trading due to the gradual diffusion of private information (Hong and Stein, 1999). Our results tend to support models that imply initial underreaction due to the slow incorporation of information, followed by a modest correction due to slight overshooting. Models of initial overreaction, followed by even greater overreaction, fail to explain the data.

Aggregate surprises come frequently to the stock market. Those that shake stocks in differing directions, thus producing significant price spreads, are less common. Ones as extreme as the Trump election are quite rare. The market did a good but highly incomplete job of pricing stocks the day after Trump's victory. Momentum pushed stocks in the following days, with different identifiable factors affecting prices at different rates. This event was a salient case study that supports the theory of slow but predictable diffusion of information into stock prices.

References

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Quarterly Journal of Economics 131, 1593-1636.

Barberis, N., Shleifer, A., Vishny, R.W., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307-343.

Barclay, M.J., Hendershott, T., 2003. Price discovery and trading after hours. Review of Financial Studies 16, 1041-1073.

Biais, B., Hillion, P., Spatt, C., 1999. Price Discovery and Learning during the Preopening Period in the Paris Bourse. Journal of Political Economy 107, 1218-1248.

Campbell, J.Y., Mankiw, N.G., 1987. Are output fluctuations temporary? Quarterly Journal of Economics 102, 857-880.

Cochrane, J., 1988. How big is the random walk in GNP? Journal of Political Economy 96, 893-920.

Cutler, D., Poterba, J., Summers, L.H., 1989. What Moves Stock Prices? Journal of Portfolio Management 15, 4-12.

Daniel, K.D., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. The Journal of Finance 53, 1839-1885.

Daniel, K.D., Moskowitz, T.J., 2016. Momentum Crashes. Journal of Financial Economics 122, 221-247.

De Bondt, W.F.M., Thaler, R.H., 1985. Does the Stock Market Overreact? The Journal of Finance 40, 793-805.

De Long, J.B., Shleifer, A., Summers, L., Waldmann, R.J., 1990. Positive Feedback Investment Strategies and Destabilizing Rational Speculation. The Journal of Finance 45, 379-395.

Edwards, W., 1968. Conservatism in Human Information Processing. In: Kleinmuntz, B. (Ed.) Formal Representation of Human Judgment. John Wiley and Sons, New York, NY, pp. 17-52.

Fama, E., French, K., 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33, 3-56.

Hong, H.G., Lim, T., Stein, J., 2000. Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. The Journal of Finance 55, 265-295.

Hong, H.G., Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance 54, 2143-2184.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. The Journal of Finance 45, 881-889.

Jegadeesh, N., Titman, S., 1995. Short-horizon return reversals and the bid-ask spread. Journal of Financial Intermediation 4, 116-132.

Lehmann, B.N., 1990. Fads, Martingales, and Market Efficiency. Quarterly Journal of Economics 105, 1-28.

Lo, A., MacKinlay, A.C., 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. Review of Financial Studies 1, 41-66.

Poterba, J., Summers, L.H., 1988. Mean reversion in stock returns: Evidence and implications. Journal of Financial Economics 22, 27-60.

Santa-Clara, P., Valkanov, R., 2003. The Presidential puzzle: political cycles and the stock market. The Journal of Finance 58, 1841-1872.

Snowberg, E., Wolfers, J., Zitzewitz, E., 2007. Partisan impacts on the economy: Evidence from prediction markets and close elections. Quarterly Journal of Economics 122, 807-829.

Wagner, A.F., Zeckhauser, R.J., Ziegler, A., 2017. Company stock price reactions to the 2016 election shock: Trump, taxes and trade. Journal of Financial Economics Forthcoming

Wolfers, J., Zitzewitz, E., 2018. What did financial markets think of the 2016 election? American Economic Association Papers and Proceedings Forthcoming

Appendix

Table A-1: Return predictability.

The table shows a variation of Table 1. It presents the relation between returns on days 2 – 10 after the election (November 10 through 22) and cumulative returns from the election through the previous day, using regression coefficients, and either controlling for Fama-French 30 industry fixed effects, or leaving out firms from the financial, health care, and pharmaceutical industries. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Trading days since election	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A: Raw returns									
Controlling for industry fixed effects									
Regression slope	0.213***	0.107***	0.042***	-0.042***	-0.026***	-0.004	-0.005	-0.007	0.010*
	(0.022)	(0.013)	(0.009)	(0.009)	(0.007)	(0.012)	(0.006)	(0.005)	(0.005)
Leaving out financials, health care, pharma									
Regression slope	0.287***	0.103***	0.043***	-0.056***	-0.018*	-0.020	-0.000	0.004	0.026***
	(0.027)	(0.015)	(0.011)	(0.013)	(0.009)	(0.018)	(0.007)	(0.008)	(0.009)
Panel B: CAPM-adjusted returns									
Controlling for industry fixed effects									
Regression slope	0.199***	0.103***	0.036***	-0.059***	-0.020**	-0.014	0.000	-0.015**	0.011*
	(0.023)	(0.013)	(0.009)	(0.009)	(0.008)	(0.012)	(0.007)	(0.006)	(0.006)
Leaving out financials, health care, pharma									
Regression slope	0.270***	0.099***	0.034***	-0.077***	-0.012	-0.035*	0.003	-0.011	0.025**
	(0.029)	(0.015)	(0.011)	(0.013)	(0.011)	(0.018)	(0.008)	(0.011)	(0.011)
Panel C: Fama-French-adjusted returns									
Controlling for industry fixed effects									
Regression slope	0.237***	0.116***	0.066***	-0.070***	-0.026***	0.001	0.011*	-0.024***	0.032***
	(0.025)	(0.015)	(0.010)	(0.009)	(0.007)	(0.010)	(0.006)	(0.006)	(0.007)
Leaving out financials, health care, pharma									
Regression slope	0.348***	0.190***	0.093***	-0.104***	-0.009	0.012	0.021***	-0.044***	0.064***
	(0.036)	(0.023)	(0.011)	(0.010)	(0.008)	(0.014)	(0.008)	(0.009)	(0.010)

Table A-2: Descriptive statistics.

This table presents descriptive statistics for the cross-sectional regressions underlying the results in Section 6.1. The sample consists of sufficiently liquid US stocks based on trading volume on November 8, 2016 (see Section 2 for details). All returns are reported in percentage points. AR indicates abnormal return, and CAR indicates cumulative abnormal return. CAPM-adjusted returns are computed as the daily excess return on the stock minus beta times the market excess return from Ken French's website, where beta is estimated on daily excess returns from October 1, 2015 through September 30, 2016. Fama-French-(FF-)adjusted returns are computed as the excess return on the stock minus the sum of its factor exposures times the factor returns, where the factor exposures are computed on daily market excess return, size, and value factor returns (obtained from Ken French's website) from September 30, 2015 to September 30, 2016. Market value of equity is from Bloomberg. The following variables are taken from Compustat or are computed based on Compustat data (Compustat mnemonics in capitals in parentheses): Percent revenue growth ($100*(SALE-SALE_{t-1})/SALE_{t-1}$), Profitability (100*pretax income / assets = 100*(PI/AT)), and cash taxes paid in percent of current year pretax income, adjusted for special items (Cash ETR = 100*(TXPD/(PI-SPI))). Percent revenue from foreign sources is from Bloomberg, supplemented by data computed from Compustat segment data.

	Obs	Min	P25	Mean	Median	P75	Max	Std. Dev.
Raw return on Nov 9	3009	-31.26	0.27	2.75	2.30	4.72	43.13	4.68
CAPM-adjusted AR on Nov 9	2911	-33.99	-1.26	1.07	0.66	3.06	42.01	4.50
Fama-French-adjusted AR on Nov 9	2911	-37.25	-2.48	-0.40	-0.53	1.52	42.09	4.54
10-days cumulative return from Nov 9 to Nov 22	3002	-50.00	3.20	10.04	9.33	16.31	124.28	11.14
10-days CAR (CAPM-adjusted) from Nov 9 to Nov 22	2904	-52.78	-1.55	4.58	4.03	10.26	101.68	9.97
10-days CAR (FF-adjusted) from Nov 9 to Nov 22	2904	-68.99	-5.90	-1.08	-0.59	4.59	89.94	10.24
Ln Market value of equity (US$ millions)	2919	-0.11	6.31	7.48	7.36	8.52	13.31	1.67
Percent revenue growth	2878	-100.00	-3.95	17.49	4.44	16.19	3380.13	135.04
Profitability	2955	-266.04	-0.22	1.48	3.19	8.68	1520.75	34.03
Cash effective tax rate (ETR) in percent	2034	0.00	9.00	21.37	21.67	31.47	70.79	14.39
Percent revenue from foreign sources	2149	0.00	0.00	28.75	20.00	48.38	100.00	30.58

Table A-3: Determinants of the stock price reaction to the election.

This table presents OLS regressions of individual stock returns on the cash ETR, foreign revenue, firm characteristics, and Fama-French 30 industry fixed effects. The time periods covered are November 9, 2016 (columns 1-3) and the 10-day cumulative returns from November 9, 2016 through November 22, 2016 (column 4-6). Columns 1 and 4 use raw returns, columns 2 and 5 use CAPM-adjusted returns, and columns 3 and 6 use Fama-French-adjusted returns. The sample consists of US stocks that are sufficiently liquid based on trading volume on November 8, 2016. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Days:		Nov 9		10-days cumulative Nov 9 - Nov 22		
Returns:	Raw	CAPM-adjusted	FF-adjusted	Raw	CAPM-adjusted	FF-adjusted
Cash effective tax rate (ETR) in percent	0.025***	0.024***	0.016*	0.069***	0.067***	0.031*
	(0.009)	(0.009)	(0.009)	(0.020)	(0.018)	(0.017)
Percent revenue from foreign sources	-0.018***	-0.019***	-0.021***	-0.050***	-0.052***	-0.058***
	(0.003)	(0.003)	(0.003)	(0.008)	(0.007)	(0.008)
Ln(Market value of equity)	-0.395***	-0.398***	-0.016	-1.978***	-1.894***	-0.387***
	(0.054)	(0.053)	(0.053)	(0.133)	(0.121)	(0.127)
Percent revenue growth	-0.013***	-0.014***	-0.013***	-0.025***	-0.025***	-0.017**
	(0.004)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Profitability	0.004	0.008	0.025**	-0.017	-0.006	0.070**
	(0.010)	(0.009)	(0.011)	(0.022)	(0.022)	(0.033)
Constant	5.452***	4.054***	-0.019	22.465***	17.321***	1.406
	(0.731)	(0.719)	(0.730)	(1.905)	(1.791)	(1.933)
Observations	1,554	1,544	1,544	1,554	1,544	1,544
R-squared	0.178	0.173	0.121	0.305	0.306	0.141
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes