A Tough Act to Follow:
Contrast Effects in Financial Markets*

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Abstract

We present evidence of contrast effects in financial markets: investors mistakenly perceive information in contrast to what preceded it, leading to significant distortions in market reactions to firm earnings announcements. Earnings news today seems more (less) impressive if yesterday's earnings surprise was bad (good). Consistent with contrast effects, we find that the stock price reaction to an earnings announcement is negatively related to the earnings surprise announced by large firms in the previous day. In addition, 1) return reactions are inversely affected by earnings surprises released yesterday, but not by earnings released further in the past or the future, 2) a similar inverse relation exists for firms that release earnings sequentially within the same day, and 3) the mispricing reverses over the long run. We present a number of tests to show that our results cannot be explained by a key alternative explanation involving information transmission from the previous earnings announcement. Further, the results cannot be explained by strategic timing, changes in risk, or trading frictions.

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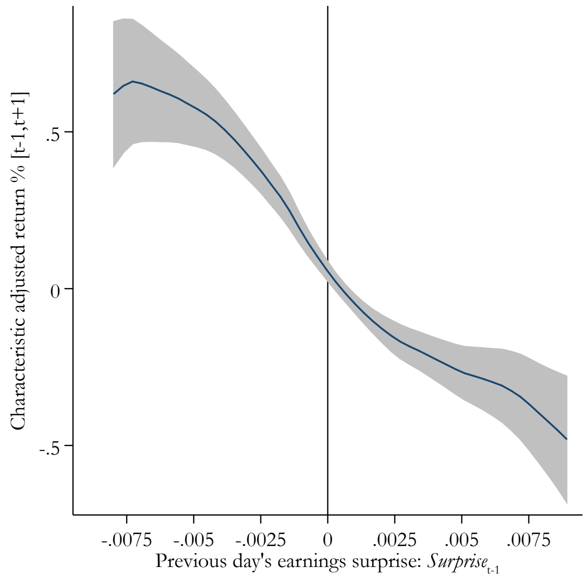
Figure 1



Return of firms that announced earnings today vs. the value-weighted average earnings surprise of large firms that announced earnings in the previous trading day (conditional on own earnings surprise).

> ***Socrates:*** *Could you tell me what the beautiful is?*
> ***Hippias:*** *For be assured Socrates, if I must speak the truth, a beautiful maiden is beautiful.*
> ***Socrates:*** *The wisest of men, if compared with a god, will appear a monkey, both in wisdom and in beauty and in everything else. Shall we agree, Hippias, that the most beautiful maiden is ugly if compared with the gods?*
>
> -Plato

People often interpret information by contrasting it with what was recently observed. For example, Pepitone and DiNubile (1976) show that subjects judge crimes to be less severe following exposure to narratives of very egregious crimes. Kenrick and Gutierres (1980) show that male students rate female students to be less attractive after viewing videos of beautiful actresses. References to such "contrast effects" are also pervasive in our popular culture. People complain about having "a tough act to follow" when they are scheduled to perform following a great performance. Writers use literary foils to exaggerate a character's traits through juxtaposition with a contrasting character. Fashion designers use shoulder pads and peplum hips to create the illusion of a comparatively smaller waist. In all of these cases, contrast effects bias our perception of information. We perceive signals as higher or lower than their true values depending on what else was recently observed.

Contrast effects have the potential to bias a wide variety of important real-world decisions. They may distort judicial perceptions of the severity of crimes, leading to unfair sentencing. At firms, comparisons with the previously reviewed candidate could lead to mistakes in hiring and promotion decisions. An unconstrained firm may make mistakes in investment choices by passing on a positive NPV project because it does not look as good as other options or investing in a negative NPV project because it looks better than even worse alternatives. Finally, at the household level, contrast effects could cloud key decisions such as mate choice and housing search.

In these examples, contrast effects potentially lead to costly mistakes, but it may be difficult for researchers to cleanly measure the bias. Measurement is complicated by the possibility that the decision-makers face unobserved quotas or resource constraints that make comparisons across multiple cases optimal. In addition, researchers often lack precise data on how decision-makers perceive information. Possibly because of these challenges, most of the existing research on contrast effects has focused on controlled laboratory experiments. Evidence from the field is more limited. Outside of the lab, Bhargava and Fisman (2014) show contrast effects in mate choice using a speed dating field experiment and Simonsohn and Loewenstein (2006) and Simonsohn (2006) show contrast effects in consumer housing and commuting choices.

Our paper tests whether contrast effects operate in another important real world setting: financial markets. The financial setting is particularly interesting because we can test whether contrast effects distort equilibrium prices and capital allocation in sophisticated markets. Full-time professionals making repeated investment decisions may be less prone to such a bias than individuals making infrequent dating or real estate decisions. Moreover, the limited field evidence examines contrast effects in household decision-making, but prices in financial markets are determined through interactions among many investors. Thus, cognitive biases among a subset of investors may not affect market prices given the disciplining presence of arbitrage. And yet, if contrast effects influence prices in financial markets, it would represent an important form of mispricing: prices react not only to the absolute content of news, but also to a bias induced by the relative content of news.

In this paper, we test whether contrast effects distort market reactions to firm earnings announcements. Quarterly earnings announcements represent the main recurring source of firm-specific news released by publicly-traded US firms. Prior to the earnings announcement, financial analysts and investors form expectations of what they believe earnings will be. Earnings surprises, i.e., the extent to which actual earnings exceed or fall short of those expectations, are associated with large stock price movements because they represent new information that shifts expectations of firm prospects.

We explore how the stock price reaction to an earnings announcement made by a firm today depends on the level of the earnings surprises announced by other large firms in the previous day. Earnings announcements are typically scheduled weeks before the announcement, so whether a given firm announces following positive or negative surprises by another firm is likely to be uncorrelated with the firm's fundamentals. The theory of contrast effects predicts a *negative* relation between the return reaction to today's earnings surprise and yesterday's surprise, holding today's earnings surprise constant. The intuition is that news today will not seem as impressive if yesterday's earnings surprises were very positive. Conversely, today's earnings surprise will seem more impressive if yesterday's earnings surprises were very disappointing.

The downward sloping pattern in Figure 1 illustrates our main finding. The figure shows a local linear plot of returns surrounding a firm's earnings announcement relative to the value-weighted average earnings surprise announced by large firms in the previous trading day. The figure demonstrates a strong negative relation: controlling for today's earnings news, the return reaction to today's earnings announcement is inversely related to yesterday's earnings surprise. The effect is sizable – a change in yesterday's earnings surprise from the worst to the best decile corresponds to a 43 basis point lower return response to today's earnings announcement.

We explore the basic relation in Figure 1 and demonstrate that it is robust. Using regression analysis, we show that the negative pattern holds regardless of whether we control for the level of today's earnings surprise or how we measure yesterday's earnings surprise: the surprise relative to various measures of analyst expectations or return-based measures. Unlike many anomalies which focus on small-cap firms, we find that contrast effects significantly distort the returns of large firms. A contrast effects trading strategy using portfolios comprised of only firms in the top quintile of size yields four factor daily alphas of 10-15 basis points on days in which the strategy can be implemented, yielding abnormal returns of 7-13% per year. We also examine contrast effects within industry. We find that the effect for large firms is strong both within and across industries, although contrast effects primarily operate through within-industry comparisons for smaller firms.

We present three additional pieces of evidence in support of the contrast effects hypothesis. First, returns for firms announcing today are negatively related to earnings surprises released by other firms on $t-1$, but are not significantly related to lagged earnings surprises on $t-2$ and $t-3$ or future earnings surprises on $t+1$ and $t+2$. This is consistent with the transitory nature of contrast effects as found elsewhere, in which individuals react primarily to the most recent observation. It also shows that our results are due to the precise ordering of earnings announcements rather than slower-moving time trends. Second, we find similar contrast effects among earnings released sequentially within the same day. Morning earnings surprises have a strong negative impact on the returns of firms that announce in the afternoon. Conversely, the returns of firms that announce in the morning are not impacted by afternoon earnings surprises. Third, the returns distortion reverses over the long run, which is consistent with contrast effects causing mispricing that is eventually corrected.

While our findings are consistent with the theory of contrast effects, one may be concerned that we are capturing information transmission from earlier earnings announcements. For concreteness, suppose that firm A announces a positive earnings surprise on day $t-1$ and firm B is scheduled to announce earnings on day t. Empirically, we find that B tends to experience low returns, conditional on its actual earnings surprise. Can information transmission explain this empirical pattern?

Most studies of information transmission focus on the case of positive correlation in news, in which good news for "bellwether" firms convey similar information for other firms (e.g., Anilowski et al., 2007 and Barth and So, 2014). We begin by showing that explanations based on positive correlation in news, where A's positive surprise is good news for B, cannot account for our results because we examine B's *cumulative return* from $t-1$ to $t+1$ (starting at market close on $t-2$ before A announces). If there is positive correlation in news, A's positive surprise should predict positive cumulative returns for firm B, not the negative pattern we find in the data. Thus, to account for the results, an information transmission explanation requires negative correlation in news where A's positive surprise is bad news for B (e.g., A competes with B for resources). In this case, B should experience negative returns on $t-1$ when A first announces. We find no support for negative information transmission in the data. Empirically, A's earnings surprise has no predictive power for B's earnings surprise after we account for slower moving time trends at the month level. Further, the market does not behave as if news relevant to firm B is released on day $t-1$, as we find no relation between A's earnings surprise and B's return on day $t-1$.

One may still be concerned that the results are due to a negative correlation in news and a *delayed* reaction to information. For example, A's $t-1$ positive surprise may contain negative news for B, but the market does not react to this information until day t, when B is featured in the media as it announces its earnings. Note that this type of delayed reaction is only a concern if A's earnings surprise contains news about B's prospects other than B's earnings. If A's announcement simply provided information for B's earnings, this predicts a zero relationship between A's earnings surprise and B's cumulative return after controlling for B's actual earnings. Delayed reaction, and information transmission more generally, are also inconsistent with two important features of the data. First, we find that return reactions are distorted by salient surprises in $t-1$, but not by slightly earlier surprises in $t-2$ or $t-3$. If earlier announcements convey information, one would expect similar effects for these earlier salient surprises. Second, any information transmission, delayed or not, should not lead to the long-run reversals observed in the data. These reversals are instead suggestive of corrections of a short-term bias.

Altogether, we show that most plausible variants of the information transmission story cannot explain our results. The remaining information transmission story that we cannot rule out is the following: A's $t-1$ announcement contains information for B, but the market does not react to this information until day t. On day t, there is a biased response to this information which reverses over time. Further, A's news is negatively correlated with B's prospects (beyond B's earnings), and such information is only released on day $t-1$ but not by firms announcing on days $t-2$ or $t-3$. While we cannot rule out such a story, we believe that the well-founded psychological motivation based on contrast effects offers the more parsimonious explanation of our findings.

Another potential concern is that firms may advance or delay their earnings announcements or manipulate the earnings announcement itself through discretionary accruals (e.g., Sloan, 1996; DellaVigna and Pollet, 2009; and So, 2015). However, such strategic manipulation will only bias our results if they alter firm earnings as a function of the earnings surprises released by other firms on day $t-1$. Firms publicly schedule when they will announce their earnings and almost always do so at least a week before they actually announce (Boulland and Dessaint, 2014). The earnings *surprises* of other firms are, by definition, difficult to predict because they measure surprises relative to expectations. Therefore, it is unlikely that firms can strategically schedule to follow other firms with more or less positive surprises. Further, manipulation of the earnings number itself takes time and is unlikely to occur within a single day as a reaction to other firms' earnings surprises. To directly test strategic timing, we separately examine earnings announcements that moved or stayed relative to the calendar date of the firm's announcement for the same quarter in the previous year. We find similar results for the restricted sample of stayers.

A final potential concern is that earnings surprises on day $t-1$ impacts the risk or trading frictions associated with the announcement on day t, so the return difference is compensation for risk or trading frictions. Fixed firm-specific loadings on risk factors are unlikely to explain our results because we use characteristic adjusted returns (raw return minus the return of a portfolio of similar firms in terms of size, book-to-market, and momentum) in our analysis. To explain our results, a more negative earnings surprise yesterday must increase day-specific trading frictions or betas on risk factors. We instead find that risk loadings, return volatility, volume, and other measures of liquidity do not vary by the earnings surprise in $t-1$.

One of the main contributions of our paper is to further the understanding of how psychological biases found in the lab manifest in real-world settings (e.g., Levitt and List, 2007b,a; Chen, Moskowitz, and Shue, 2014). Our findings suggest that contrast effects persist outside the laboratory in a market setting where prices are determined by interactions among many investors including potentially deep-pocketed arbitrageurs. Our findings also contribute to the literature on biased reactions to earnings announcements, which has shown that investors underreact to a firm's own earnings news (Ball and Brown, 1968; Bernard and Thomas, 1989,1990; and Ball and Bartov, 1996), predictable seasonal information (Chang et al., 2014), and information in the timing of announcements (DellaVigna and Pollet, 2009; So, 2015; Boulland and Dessaint, 2014). Relative to the existing research, we show how prices are affected by the announcements of *other* firms that announced recently. Further, much of the research in behavioral finance documents price distortions among small firms. We show that contrast effects affect even the largest firms.

Our evidence underscores how important decisions are often distorted by comparisons to benchmarks that should be irrelevant. Thus, our research is related to a large theory literature on context-dependent choice and reference points (e.g., Kahneman and Tversky, 1979; Koszegi and Rabin, 2006 , 2007).[1] In particular, our empirical results are broadly consistent with recent models of relative thinking by Cunningham (2013), Bordalo, Gennaioli, and Shleifer (2015), and Bushong, Rabin, and Schwartzstein (2015), although our setting lacks specific features of these models such as choice sets over goods. Investors in our financial setting also resemble FAST thinkers in Bordalo, Gennaioli, and Shleifer (2015), who have both partial recall and biased reactions to what is recalled.

Finally, our findings are related to research in behavioral finance examining investor behavior based on how positions performed since they were purchased (Shefrin and Statman, 1985; Odean, 1998), how exciting certain stocks are relative to others in the market (Barber and Odean, 2008), and how a position compares to the other holdings in an investor's portfolio (Hartzmark, 2015). Relative to this literature which focuses on the trading patterns of individual investors, we test how contrast effects in the perception of news affect equilibrium market prices for large cap stocks.

[1]While closely related to this literature, contrast effects (as typically described in the psychology literature) refer to a simple directional phenomenon in which larger values of the recently observed signal makes the next signal appear smaller in comparison, and vice versa. Most descriptions of contrast effects do not require discontinuous or kinked responses around a reference point (as in prospect theory, with recent empirical applications in, e.g., Baker, Pan, and Wurgler, 2012 and DellaVigna et al., 2014) or a choice framework to identify which reference points to use or where to allocate attention.

1 Data

1.1 Sources

We use the I/B/E/S detail history file for data on analyst estimates of what a specific firm's earnings will be upon announcement. We examine the quarterly forecasts of earnings per share and merge this to information on daily stock returns from CRSP and firm-specific information from Compustat. Data on the market excess return, risk-free rate, SMB, HML and UMD portfolios as well as size cutoffs all come from the Kenneth French Data Library.

Our analysis uses data on the date of an earnings announcement from the I/B/E/S file. Thus, when we refer to day t, we are referring to the calendar date of the announcement. Day $t-1$ refers to the most recent calendar date where the market was open prior to t. DellaVigna and Pollet (2009) highlight a potential concern regarding earnings announcement dates as reported in I/B/E/S: some recorded dates coincide with the date that each earnings announcement was first published in the Wall Street Journal, which may occur one day after the date in which the earnings was announced through other means. Our main analysis uses I/B/E/S announcement dates because we hope to capture when investors pay attention to earnings announcements. Especially early in the sample (which contains the bulk of the errors), the date of publication in the Wall Street Journal as listed in I/B/E/S may be a better measure of when each firm's earnings announcement is most salient. Regardless, the specific choice of announcement date data is empirically not important to our findings as we show in Section 7 that our results are very similar utilizing the DellaVigna and Pollet (2009) date correction. The results are also similar in the more recent sample period, which has a lower rate of date-related errors.

For most of our analysis, we examine daily returns that have been characteristic-adjusted, following the procedure in Daniel et al. (1997). Specifically, using CRSP daily returns, we sort stocks into NYSE quintiles based on size, book value of equity divided by market value of equity (calculated as in Fama and French, 1992), and momentum calculated using returns from $t-20$ to $t-252$ trading days (an analogue to a monthly momentum measure from months $m-2$ to $m-12$). We then match each stock's return to a portfolio of stocks that match each of these three quintiles. Our measure of the characteristic-adjusted return is a stock's return on day t minus the return of the characteristic-matched portfolio on day t.

1.2 Measuring earnings surprise

A key variable in our analysis is the surprise for a given earnings announcement.[2] Broadly defined, earnings surprise is the difference between the announced earnings and the expectations of investors prior to the announcement. To measure surprise, we need an estimate of the expectations of investors. We follow a commonly-used method in the accounting and finance literature and measure expectations using analyst forecasts prior to announcement. This measure is available for a long time-series and does not require us to take a stand on specific modeling assumptions (for example, assuming a random walk with drift as in Bernard, 1992). Analysts are professionals who are paid to forecast future earnings. While there is some debate about what their goal is and how unbiased they are (e.g., McNichols and O'Brien, 1997; Lin and McNichols, 1998; Hong and Kubik, 2003; Lim, 2001; and So, 2013), our tests only require that such a bias is not correlated with the surprises of other firms in the day before a firm announces earnings. Given that we only use forecasts made before the $t-1$ firm announces (forecasts from day $t-2$ or earlier), such a bias is unlikely to exist.

Similar to DellaVigna and Pollet (2009), we take each analyst's most recent forecast, thereby limiting the sample to only one forecast per analyst, and then take the median of this number within a certain time window for each firm's earnings announcement. In our base specification, we take all analyst forecasts made between two and fifteen days prior to the announcement of earnings. We choose fifteen days to avoid stale information yet still retain a large sample of firms with analyst coverage. To show that these assumptions are not driving the results, we present variations of this

[2]We follow the literature on earnings announcements in characterizing earnings news as the surprise relative to expectations. We focus on surprise rather than levels because whether a given level of earnings is good or bad news depends on firm-specific circumstances that are captured by measures of investor expectations. In addition, stock prices should reflect current information – the stock market return response to earnings announcements represents the change in valuation of the firm which should depend on the change in earnings relative to expectations. Moreover, the financial press typically reports earnings announcement news in terms of how much earnings beat or missed forecasts. Therefore, the earnings surprise is likely to be the measure of earnings news that is most salient to investors.

measure in Section 7 utilizing longer windows of 30 and 45 days prior to announcement and also using the direct return reaction to the announcement as a measure of earnings surprise.

To make the magnitude of the surprise comparable across firms, we follow DellaVigna and Pollet (2009) and scale the difference between the actual surprise and the median analyst forecast by the share price of the firm from three trading days prior to the announcement. Thus, our estimate of the earnings surprise for firm i on day t can be written as:

$$surprise_{it} = \frac{\left(actual\ earnings_{it} - median\ estimate_{i,[t-15,t-2]}\right)}{price_{i,t-3}} \tag{1}$$

To examine the impact of contrast effects, we need a measure of the surprise occurring on the previous day taking into account that multiple firms may have announced earnings. The ideal variable would focus on the earnings announcements in $t-1$ that were salient as this would be the most likely comparison group in the minds of investors when they consider and evaluate the current day's announced earnings. While we do not have an exact measure of the salient surprise in $t-1$, we utilize a number of proxies and focus most of our analysis on large firms. A firm's market capitalization is related to how much attention that firm receives. One measure we use is simply the surprise of the largest firm to announce on day $t-1$. A second measure, which we use as our baseline, is the value-weighted surprise among all large firms announcing on day $t-1$. We define large firms as those with market capitalization (measured three days before the firm's announcement) above the NYSE 90th percentile of market capitalization in each month. If multiple large firms announced earnings on the previous trading day, we take the value-weighted average of these firms' surprise measures, using each firm's market capitalization three days prior to the firm's announcement. Thus, our baseline measure of yesterday's salient surprise is:

$$surprise_{t-1} = \frac{\sum_{i=1}^{N} \left(mkt\,cap_{i,t-4} \times surprise_{i,t-1}\right)}{\sum_{i=1}^{N} mkt\,cap_{i,t-4}} \tag{2}$$

To reduce the influence of outliers, we winsorize $surprise_{it}$ at the 1st and 99th percentile and take the weighted average to create our $surprise_{t-1}$ measure. After creating $surprise_{t-1}$, we again winsorize at the 1st and 99th percentiles. In addition, in Section 7, we present alternative formulations where we value-weight all firms that announced in $t-1$ or take the equal-weighted average among all large firms.

In later regression analysis, each observation represents an earnings announcement by firm i on day t. In a slight abuse of notation, when we discuss $suprise_t$, we refer to a firm's own earnings surprise on day t, omitting the i subscript. When we discuss $surprise_{t-1}$, we refer to the salient earnings surprise released by large firms on the previous trading day.

1.3 Summary statistics

Table 1 describes the data used in our baseline specification. Our sample begins in 1984 and ends in 2013. For our main analysis, we examine how the return reaction for a firm that announces earnings on day t relates to the salient earnings surprise of other firms released on day $t-1$, controlling for the firm's own earnings surprise. Thus, to be included in the sample, a firm must have at least one analyst forecast in our dataset between days $t-2$ and $t-15$ prior to the announcement. In addition, we require a non-missing measure of $surprise_{t-1}$, which means at least one firm above the 90th percentile of market-capitalization announced their earnings on day $t-1$ and at least one analyst forecasted earnings for this firm between days $t-16$ and $t-3$. After applying these filters and requiring the firm with an announcement on day t to have non-missing characteristic adjusted returns, we are left with 76,062 unique earnings announcements.

Examining the characteristic adjusted returns row, we see that days with an earnings announcement are associated with positive characteristic adjusted returns of 16 basis points, or raw returns of 17 basis points. This is the earnings announcement premium described in Beaver (1968), Frazzini and Lamont (2007), and Barber et al. (2013). Table 1 also shows that the typical earnings surprise is approximately zero (a mean of -0.0003 and a median of 0.0002). The market cap row shows the mean market capitalization in our sample is roughly \$7 billion, while the 25th percentile of market cap is \$440 million, implying that we have many small firms in our sample. Nevertheless, our baseline analysis will focus on larger firms because we value-weight each observation. We find a similar pattern when examining analyst coverage (number of forecasts from $t-15$ to $t-2$). For many firms, we see only one analyst forecast and the median number of forecasts is two, while the mean number of forecasts is nearly four. Thus, a small number of firms are covered heavily by many analysts. The final row describes the number of firms above the 90th percentile that announced on the previous trading day that are used to construct the $surprise_{t-1}$ variable. The median of this variable is 6 with a mean of 7.5, so in general multiple firms comprise the $surprise_{t-1}$ measure.

2 Results

2.1 Baseline results

In our baseline specifications, we test how the price response to a given earnings surprise is impacted by the earnings surprise announced by large firms on the previous trading day. A major determinant of the price response to any earnings announcement will of course be the level of earnings surprise that the firm actually announces. The theory of contrast effects predicts that, conditional on the level of surprise today, the return response to a given earnings announcement will be inversely related to yesterday's salient earnings surprise. Thus, our baseline specification allows for a direct impact of earnings surprise, contrast effects, and controls for time effects as follows:

$$char.\ adj.\ return_{i,[t-1,t+1]} = \beta_0 + \beta_1 \cdot surprise_{t-1} + surprise\ bin_j + \delta_{ym} + \varepsilon_{it} \tag{3}$$

The dependent variable is firm i's three-day characteristic adjusted return from $t-1$ to $t+1$. In later sections, we discuss why including $t-1$ in our return window helps to rule out an alternative explanation involving information transmission of positively correlated news. This returns measure is regressed on controls for firm i's own earnings surprise as well as $surprise_{t-1}$. We impose as little structure as possible on the price response to the firm's own earnings surprises by creating twenty equally sized bins based on the size of the earnings surprise. Grouping the surprise level as dummy variables means we non-parametrically allow each magnitude of surprise to be associated with a different level of average return response. δ_{ym} represents year-month fixed effects. In all regressions, unless otherwise noted, we value-weight each observation using the firm's market capitalization three days prior to the firm's announcement, scaled by the average market capitalization in that year, in order to focus on the more economically meaningful firms.[3] We cluster the standard errors by date.

$Surprise_{t-1}$ is our measure of yesterday's earnings announcement surprise and the coefficient β_1 is our main measure of contrast effects. The contrast effect hypothesis predicts that, all else equal, if yesterday's salient surprise was more positive, any given surprise today will appear worse by comparison. If yesterday's salient surprise was more negative, today's surprise will appear better. Thus, contrast effects predict a negative coefficient on β_1.

Table 2 shows the estimates of β_1 and strongly supports the hypothesis that there are significant contrast effects in the return response to earnings. For our first estimate of the salient earnings surprise, we use the earnings surprise of the largest firm to announce in the previous day. To make sure this firm is salient, we include only observations where the firm is above the 90th percentile of the NYSE market capitalization cutoff. The coefficient is -0.501 and highly significant.

Examining only the largest firm is a coarse measure of the salient earnings surprise from the previous day if there were multiple large firms that announced. For example, if both Apple and Goldman Sachs announced earnings on the same day, it makes sense that both announcements would be salient events to a large number of investors and neither announcement should be wholly ignored. Column 3 of Table 2 measures $surprise_{t-1}$ using the equal-weighted mean of all firms that announced in the previous day and were above the 90th percentile of market capitalization. We estimate a significant β_1 of -0.896. Finally, Column 5 uses the value-weighted mean of the earnings surprise of all firms that announced yesterday, leading to a significant β_1 of -0.781. This value-weighted measure implicitly assume that the relative market cap of large firms that announced on $t-1$ is a good proxy for the relative salience of their announcements.

In the even-numbered columns of Table 2, we add year-month fixed effects and find that the

[3] Average market capitalization has increased over time. To avoid overweighting observations simply because they occur in more recent years, we scale market capitalization by the average in each year. In untabulated results, we find that omitting this scaling leads to materially similar results.

estimates drop slightly in magnitude, but remain highly significant, suggesting that aggregate time trends cannot explain our results. In later tables, we use the value-weighted salient surprise with year-month fixed effects in Column 6 as our baseline specification.

Using the estimated β_1 of -0.721 from Column 6, we estimate that an increase in yesterday's salient earnings surprise from the average earnings surprise in the worst decile (-0.22%) to the average in the best decile (0.37%) is associated with lower returns of 43 basis points. To get a sense of magnitudes, we can compare this result to a robust anomaly in asset pricing: the earnings announcement premium (Frazzini and Lamont, 2007; Barber et al., 2013). With no information other than the fact that earnings will be announced on a given day (typically known well in advance of the date), an equal-weighted strategy going long stocks with earnings announcements earns abnormal returns in our sample of 17 basis points from $t-1$ to $t+1$. If we value-weight, as we do for our estimates of contrast effects, the earnings announcement premium is 8 basis points from $t-1$ to $t+1$. Thus, the impact of contrast effects is of a similar magnitude to, if not greater than, other well-known return anomalies related to earnings announcements.

Table 2 shows the regression analog to the local linear plot in Figure 1, which we discussed in the Introduction. The figure shows that contrast effects induce a negative relation between the return reaction to today's earnings surprise and yesterday's salient surprise. We can alternatively visualize contrast effects as a vertical shift in the typical return response to a given level of the firm's own earnings surprise. In Figure 3 Panel A, we graph the return response on the y-axis against the earnings surprise announced on day t on the x-axis. The figure shows that, when a firm announces better news, it tends to experience higher returns.

In Panel B, we show how $surprise_{t-1}$ shifts the normal return reaction to the firm's own earnings surprise. In blue, we show the return response for firms that announce following a very positive $surprise_{t-1}$ (top decile). The red line shows the return response for firms that announce following a very negative $surprise_{t-1}$ (bottom decile). Unsurprisingly, for both groups, there is a strong positive relation between a firm's returns around announcement and the firm's own earnings surprise. More importantly, the figure shows that the blue line lies consistently below the red line, demonstrating that the return response to a firm's own earnings surprise is shifted down significantly if yesterday's surprise was in the highest decile as compared to the lowest decile. The figure also shows that the magnitude of the contrast effect is fairly uniform across the support of earnings surprises released today. In other words, very good salient surprises yesterday makes all earnings surprises today look less impressive, and the magnitude of this difference does not differ substantially based on the level of surprise released today.

Overall, we find empirical results strongly consistent with the main prediction of the contrast effects hypothesis. In the next three sections, we present additional evidence in support of contrast effects.

2.2 Lead and lag effects

Previous tests of contrast effects in laboratory or non-financial settings have shown that subjects tend to contrast the current observation with the observation that occurred directly prior rather than other earlier observations. For example, in the context of speed dating, Bhargava and Fisman (2014) finds that the appearance of the person whom you spoke with directly prior to the current person has a large impact on the current dating decision, but that this effect is limited to the prior subject only. Thus, if a similar type of contrast effect accounts for the pattern that we observe in Table 2, the effect should be strongest for salient surprises that occurred at day $t-1$, and weaker for those on days $t-2$ and $t-3$.

The first column of Table 3 Panel A examines this hypothesis by adding further lags of surprises on $t-2$ and $t-3$ to our base specification. To ensure that our return measure allows for a response to information covering the entire time period (see Section 3), we examine the characteristic adjusted return from $t-3$ to $t+1$ as the dependent variable.

We find a strong and significant negative relation between the previous day's salient surprise and the return response to firms announcing today. Meanwhile, we find very little relation between returns and earlier surprises on $t-3$ and $t-2$. Further, we can reject that the return reaction to $t-1$ surprises is equal to the reactions to $t-2$ or $t-3$ surprises with p-values below 0.1. The pronounced negative correlation with respect to $t-1$ is also inconsistent with most alternative explanations of the empirical results (explored in later sections). These other explanations do not predict that the specific short-term ordering of past earnings announcements will impact the return reaction. Thus, the results support the hypothesis that contrast effects are responsible for the strong negative coefficient found on $surprise_{t-1}$.

Next, we examine how return reactions to firms announcing today are affected by future surprises announced on days $t+1$ and $t+2$. We use characteristic adjusted returns from $t-1$ to $t+2$ as our dependent variable, to allow for the return reaction of a firm that announces on day t to respond to these future earnings announcements. While our empirical specification allows for such an effect, it may be less likely to occur because it would require that investors revise their initial perceptions of day t announcements in light of subsequent earnings announcements released in the following two days. In Column 2 of Table 3 Panel A, we find no significant relation as the coefficients on the surprises at $t+1$ and $t+2$ are small, vary in sign and are insignificant.

Almost any empirical exercise involves the worry that there is a mechanical relation due to specification choice. In addition to providing a test for the transitory nature of contrast effects, Table 3 Panel A Columns 1 and 2 offer a placebo test for this concern. If the negative coefficient on $surprise_{t-1}$ is mechanically due to our choice of specification, then the coefficients on $t-2$ or $t+1$ should be similarly biased. Given that we do not find such a relation, we feel confident that our empirical choices are not mechanically driving the result.

2.3 Same-day contrast effects

The analysis presented so far has examined contrast effects across consecutive days. We can also examine contrast effects within the same day. We present the following analysis as supplementary evidence to our baseline estimates because data on the within-day timing of earnings announcements is only available for announcements after 1995. Further, some firms do not preschedule the exact hour of announcement even though they do pre-commit to the exact date of announcement.

Nevertheless, we can explore whether the within-day data support the contrast effects hypothesis.

We use the fact that firms generally announce earnings either slightly before market open or slightly after market close. We expect the earnings surprises of large firms that announce in the morning to have a negative impact on the return response for firms that announce later in the afternoon. Earnings surprises of large firms that announce in the afternoon could also have a negative impact on the (2-day) return response for firms that announce earlier in the morning. While our empirical specification would capture such an effect, it may be less likely to occur because it would require that investors revise their initial perceptions of morning earnings announcements in light of subsequent earnings announcements released in the afternoon.

To explore same-day contrast effects, we first categorize firms as announcing before market open (prior to 9:30 am) or after market close (after 4:00pm).[4] We measure the salient earnings surprise as described previously, but with two changes. First, for each day t, we calculate two salient surprises: the surprise of large firms that announced before market open ($AM\ surprise_t$) and the surprise of large firms that announced after market closure ($PM\ surprise_t$). Second, for our return measure, we examine the return measured from the close on $t-1$ to the close on $t+1$ as this window includes both the response to the AM or PM surprises as well as the response to the firm's own announcement (as discussed in later sections, this return window helps to rule out an information transmission story involving positive correlation in same-day news).

We start by regressing the returns of firms that announce their earnings after market close on $AM\,surprise_t$, with the same controls described in Equation 3. Table 3 Column 3 shows a coefficient of -1.26 on the AM surprise variable. This same-day measure of contrast effects is slightly larger than the across-days measures estimated in earlier tables. Thus, if anything, the contrast effect is slightly larger when measured intra-day than when measured across days.

Next, we explore whether PM surprises have a negative impact on the return response for firms that announce earlier in the morning. Note, the return window (which extends to $t+1$), does not preclude such an effect as investors could revise their response to morning announcements due to new information released in the afternoon. If, on the other hand, investors only perceive information

[4] We exclude firms announcing in the interim time period (roughly 8% of the value-weighted average of firms).

relative to what was viewed previously, and do not revise their valuations, then we should find no effect of PM surprises on return reactions to morning announcements. In Column 4 of Table 3 Panel A, we find a negative but small and insignificant coefficient on the $PM\ surprise_t$. Thus, within the same day, investors exhibit behavior consistent with contrast effects, but only significantly with respect to previously observed salient surprises.

2.4 Long run reversals

If contrast effects are a psychological bias that leads to mispricing, then the negative coefficient on $surprise_{t-1}$ represents a deviation from the fundamental return response to a firm's earnings news. This mispricing should reverse over time if prices eventually converge to fundamental value. Table 3 Panel B examines the return patterns subsequent to the earnings announcement and finds evidence consistent with contrast effects causing mispricing that is reversed in the long run. All columns in the table estimate our baseline specification, using different return horizons as the dependent variable. The first column examines the characteristic adjusted return from $t-1$ to $t+1$ while Column 2 examines the return from $t+2$ to $t+25$. Over this period, we see that the large negative coefficient in Column 1 is reversed slightly. As indicated by Column 3, which examines the return from $t-1$ to $t+25$, the overall contrast effect is still apparent but no longer statistically significant. Extending the window further, Column 4 shows that from $t+2$ to $t+50$, there is a significant return reversal relative to the original change in prices from $t-1$ to $t+1$. If we include the initial announcement period as in Column 5, we find that $surprise_{t-1}$ has a close-to-zero impact on long run returns from $t-1$ to $t+50$. This suggests that contrast effects leads to mispricing that is fully reversed within the next couple of months after the earnings announcement.

3 Information transmission

While our empirical findings are consistent with the theory of contrast effects, one may be concerned that information transmission from the earlier earnings announcement might account for the empirical patterns we observe. We use a simple example to discuss the implications of various theories of information transmission. For this example, assume that firm A announces a positive earnings surprise on day $t-1$ and firm B is scheduled to announce earnings on day t. Our empirical evidence implies that following A's positive surprise, B is likely to experience low returns conditional on its actual earnings surprise. Can information transmission explain this empirical pattern?

Most studies of information transmission in firm news announcements focus on the case of positive correlation in news, in which A's positive surprise is good news for B (e.g., good news for B's earnings or future investment opportunities). For example, Anilowski, Feng, and Skinner (2007) and Barth and So (2014) study "bellwether" firms whose news convey similar information for other firms. We begin by showing that an information transmission story involving *positive* correlation in news cannot explain our results. If there is positive correlation in news, then A's positive surprise is good news for B, so B should experience positive returns on day $t-1$ when this good news is released. Then, B might experience lower returns on day t for a given level of earnings surprise (measured using analyst forecasts made prior to $t-1$) because its good news was released early, on day $t-1$. However, A's positive surprise should not negatively affect B's *cumulative return* from $t-1$ to $t+1$. Our results cannot be explained by positive correlation in news because our analysis uses B's cumulative returns (measured starting at market close in $t-2$, before A announces). Positive correlation in news implies a positive correlation between $A's$ surprise and B's cumulative returns, not the negative relation we observe in the data.

Thus, for information transmission to explain our results, there must be *negative* correlation in news, so A's positive surprise is bad news for B (e.g., A competes with B for resources). A negative correlation in news could generate a negative empirical relation between A's surprise and B's cumulative return. However, we show that negatively correlated information transmission, or information transmission of any form, is unlikely to account for our results for two reasons. First, we show that $surprise_{t-1}$ does not predict day t earnings surprises after accounting for slower moving time trends. Second, markets do not react as though negatively (or positively) correlated information is released on day $t-1$ through the salient surprises of other firms.

In Table 4 Panel A, we examine whether $surprise_{t-1}$ predicts the earnings surprises of firms scheduled to announce in the following day. Column 1 regresses the earnings surprise on day t (i.e., the surprise relative to analyst forecasts made on or before $t-2$) on the salient surprise released on day $t-1$. We find that there is a positive and significant relation. However, Column 2 indicates that this is wholly driven by slower-moving time variation. The correlation disappears after we control for year-month fixed effects. Columns 3 and 4 utilize bin measures of surprise (rather than the level measure used in the first two columns) to ensure the results in Columns 1 and 2 are not driven by outliers or the specific scaling. We again find no relation once monthly time variation has been accounted for. Patterns in surprises are related to fluctuations in slow-moving general economic conditions, not the day-to-day fluctuations in earnings surprises.

These results show that A's earnings surprise does not predict B's earnings surprise. Therefore, if A's positive surprise contains negative news about B, it must contain negative news about B's prospects other than just B's earnings.[5] If markets are efficient, then B's stock price should decline on $t-1$ when this information is first released. In Panel B of Table 4, we test whether the market responds as if the salient surprise on day $t-1$ conveys information for the firm scheduled to release earnings on day t. In Columns 1 and 2 (with and without year-month fixed effects), we find no significant relation between $suprise_{t-1}$ and the $t-1$ returns of firms that will announce the next day. Columns 3 and 4 examine open-to-open returns to make sure that we account for market reactions to earnings released after market close on $t-1$. The results are materially unchanged. There is no evidence of either positively or negatively correlated information transmission. The market does not behave as if there is information released by firm A that is relevant for firm B on day $t-1$.

In the previous table, we found insignificant and close-to-zero estimates of information transmission. However, the analysis could be aggregating a subsample in which information is transmitted with other cases where no information is transmitted, thereby adding noise to the analysis and attenuating our estimates. To check that our results are not driven by a subsample of observations

[5] A secondary reason why A's positive surprise must contain negative news about B's prospects other than just B's earnings to match our results is that we directly control for B's earnings surprise relative to previous analyst forecasts in our baseline regressions. If A's surprise only revealed information about B's earnings surprise, we should estimate a zero coefficient on yesterday's salient surprise after controlling for B's actual earnings surprise.

where the market believes information is transmitted, we look at cases for which the market reacted as if no information was transmitted in $t-1$. In this sample, we expect to find no evidence consistent with contrast effects if the results are actually driven by information transmission.

In Columns 1 and 2 of Table 5, we examine only firms that announce on day t with a characteristic adjusted return of less than 1% in absolute magnitude on day $t-1$. Within this subsample, in which close-to-zero information is transmitted on day $t-1$, we continue to find a significant negative relation between cumulative returns around announcement and the $t-1$ salient surprise. We estimate a coefficient of -0.627 for $suprise_{t-1}$, which is very close to the -0.721 we find when examining the entire sample. Column 2 repeats the analysis for firms where the return reaction on $t-1$ was even smaller, at less than 0.5% in absolute value and finds a similar pattern. Finally, in Column 3, we restrict the sample to observations for which no *negatively* correlated information was transmitted on $t-1$ (i.e., we exclude negative return reactions to positive salient surprises and positive return reactions to negative salient surprises). We focus on negatively correlated information transmission because positively correlated information predicts the opposite empirical pattern for cumulative returns to that observed in the data. We again find similar results using this limited sample. Altogether, we show that limiting the sample to observations where the market reacts as if no information, or no negatively correlated information, was released on day $t-1$ yields similar results to the rest of the sample. This suggests that we are capturing contrast effects rather than information transmission with our empirical tests.

At this point, one may still be concerned that *delayed* reaction to information transmission could explain the empirical results. A's $t-1$ positive earnings surprise may contain negative news for B, but the market does not react to this information until t. Rational investors may react with a delay if the interpretation of A's news for B's prospects depends on the level of B's earnings surprise. For example, A's good news may be bad news for B, but only if B's own earnings surprise is high. We test for such interaction effects in Table 5 Panel B by interacting $suprise_{t-1}$ with various measures of the firm's own earnings surprise: the raw level, 20 bins, and quintiles for the firm's own earnings surprise. In each of the three specifications, we find no evidence of strong interaction effects. Further, we continue to find a negative direct relation between returns and the previous day's salient surprise, even after we allow for interaction effects. These results show that yesterday's salient surprise negatively impacts the return reaction to today's earnings announcement, and the extent of this distortion does not depend significantly on the level of today's earnings surprise.

Absent the interaction effects, boundedly rational investors may still react to A's information about B with a delay because investors do not think about firm B until day t when B becomes more salient due to news coverage surrounding its earnings announcement. Note that this type of delayed reaction is only a concern if A's $t-1$ news is negatively correlated with news for B (positive correlation would predict the opposite relation to what we observe in the data). In addition, delayed information transmission is only a concern if A's news contains news about B's prospects other than B's earnings (if A's earnings news simply provided information for what B's earnings surprise will be at t, this predicts no relation between A's earnings surprise and B's cumulative return after controlling for B's actual earnings surprise).

Delayed reaction and information transmission more generally are also inconsistent with two important features of the data. First, we find that return reactions to $t-1$ surprises are significantly stronger than the close-to-zero return reactions to $t-2$ or $t-3$ surprises. If previous announcements convey information, one would expect similar effects for these earlier surprises. Second, any information transmission, delayed or not, should not lead to long-run reversals. Our finding of long run reversals is more consistent with corrections of mispricing induced by contrast effects bias.

Altogether, we show that most plausible variants of the information transmission story cannot explain our results. While it is impossible to rule out all information stories, what remains is a very specific and complex information transmission story which must contain the following elements:

1. $A's$ $t-1$ positive surprise must contain negative information for B.

2. The negative information relates to B's prospects other than just B's earnings.

3. $B's$ return reaction does not depend on the interaction between $A's$ surprise and B's surprise, so rational investors should not wait until day t to react to information released on day $t-1$.

Nevertheless, the market does not react to this information until day t.

4. When the market does react to this information on day t, it reacts in a biased manner, leading to a long run reversal.

5. The relevant information for firm B is only contained in $t-1$ salient surprises, but not in earlier salient surprises released on $t-2$ or $t-3$.

While this complex information transmission explanation is impossible to reject, we feel that our contrast effects hypothesis offers a more parsimonious explanation of the empirical results that is based on a well-known and intuitive psychological phenomenon.

4 Contrast effects without conditioning on today's surprise

So far, we have shown that the return response to a given earnings announcement is inversely related to yesterday's salient earnings surprise, *conditional* on the level of surprise today. Controlling for the firm's own earnings surprise in our baseline regression primarily serves to increase the explanatory power of the regression and reduce noise in the estimation procedure. In general, we showed in Section 3 that the earnings surprise of the firm announcing on day t is not correlated with the earnings surprises of other firms released in the previous day, after controlling for slower moving time trends. Therefore, we should continue to find a negative relation between the return response to a given earnings announcement and yesterday's salient earnings surprise, *unconditional* on the firm's own surprise today. Omitting the firm's own earnings surprise as a control variable should lead to more noise in our regression fit, but should not systematically bias the coefficient on $surprise_{t-1}$.

Table 6 Panel A presents results without controlling for the announced earnings surprise. We continue to find a robust negative coefficient on yesterday's salient surprise, although the R^2 declines as expected. Column 1 examines the impact without year-month fixed effects and finds a coefficient of -0.481 while Column 2 adds the fixed effects and finds a coefficient of -0.757. The numbers are not statistically different than the results where we controlled for the announced level of earnings surprise in Table 2 Columns 5 and 6. Figure 2 Panel B shows the graphical analogue of these tests using a local linear regression. Similar to the pattern in Panel A, we see a strong negative relation between $surprise_{t-1}$ and the return response to the earnings announced on day t.

One important implication of not conditioning on a firm's announced earnings surprise is that there is no longer a look-ahead bias when we examine the return response. We can predict day t and future returns using information available on day $t-1$. Thus, it would be possible to trade based on the magnitude of the previous day's salient earnings surprise and earn predictably higher or lower returns on firms that release earnings the next day. To accurately measure return responses without any look-ahead bias, we modify our regression specification slightly. First, we exclude year-month fixed effects because they are estimated using future days within the same month. Second, we change our return window from $[t-1, t+1]$ to $[t, t+1]$ so it does not include returns on $t-1$. Finally, we move from close-to-close returns (the conventional return measure in the finance literature) to open-to-open returns. To implement a strategy using close-to-close returns, one needs to know $surprise_{t-1}$ as of market close on day $t-1$. However, many firms announce earnings immediately after market close. To make our regression more closely resemble a trading strategy without lookahead bias, we examine returns from market open to market open (calculated as in Lou, Polk, and Skouras, 2015).

Table 6 Panel A shows that our results are similar using these adjustments. The odd-numbered columns exclude year-month fixed effects. Column 3 and 4 examine open-to-open returns from $t-1$ to $t+1$ while Columns 5 and 6 limit the return period from t to $t+1$. We estimate coefficients of -0.672 without year-month fixed effects and -0.898 with year-month fixed effects, both highly significant. If anything, the return results are larger when the returns examined are actually tradable.

This finding is also shown in graphical form in Figure 4. In Panel A, the red line represents the value-weighted average cumulative characteristic adjusted returns of a simple strategy that buys firms announcing earnings today if the salient surprise in $t-1$ was negative. The blue line represents the cumulative returns of a strategy that buys firms announcing earnings today if the salient surprise in $t-1$ was positive. We find that the red line lies above the blue, indicating that it pays to buy firms announcing today if yesterday's salient surprise was negative. Panel B examines return reactions following more extreme salient surprises released on $t-1$ (above the 75th percentile or below the 25th percentile based on the distribution of $surprise_{t-1}$ in the previous quarter). The gap between the red and blue lines increases and we find that the average return after announcement is significantly higher when $surprise_{t-1}$ was in the lowest quartile than when $surprise_{t-1}$ was in the highest quartile.

As discussed earlier, we usually observe positive returns on earnings announcement days. This is the earnings announcement anomaly, as shown in Frazzini and Lamont (2007) and Barber et al. (2013). The magnitude of the coefficients in Table 6 and the fact that the blue line in Figure 4 is not significantly positive shows that contrast effects are strong enough to counteract the impact of the earnings announcement premium.

As a final robustness check, we examine whether it is possible to construct a calendar-time trading strategy based on contrast effects that generates abnormal returns. The purpose of this analysis is not to find the maximum alpha attainable to traders, but rather to show the robustness of our results to a different specification. Calendar time asset pricing offers a different risk adjustment than the characteristic adjusted returns used elsewhere in the paper. In addition, the trading strategy uses daily diversified value-weighted portfolios that more closely resemble what investors might hold. The strategy equal-weights trading days (and value-weights multiple earnings announcements within the same day) while the baseline regressions value-weight each earnings announcement.

The trading strategy is a daily long-short strategy. On days where the salient surprise at $t-1$ was low (below a certain cutoff), we buy firms scheduled to announce on day t and short the market, holding this portfolio for days t and $t+1$. On days where the salient surprise at $t-1$ was high (above a certain cutoff), we go long the market and short firms scheduled to announce on day t. Again, we hold this portfolio on days t and $t+1$. Each daily portfolio is value-weighted based upon the market capitalization at $t-3$ of the firms announcing earnings on each day. Following the asset pricing literature which assumes that investors will only invest if they are able to diversify their holdings across several firms, we require at least five stocks to announce per day for the strategy to be active in Columns 1 and 2. We relax this restriction in Columns 3 and 4. We focus our trading strategy on large firms in the top quintile of the market that account for our findings (see Table 9). We utilize Fama-French regressions in which portfolios returns are regressed on the market, size, book to market and momentum factors.

Table 6 presents the results. First, we examine the trading strategy utilizing the cutoff of zero: if $surprise_{t-1}$ is not positive, we go long firms that announce earnings on day t and short the market. If $surprise_{t-1}$ is positive, we short announcers on day t and go long the market. We find a significant daily alpha of 11 basis points. Next, we use more extreme cutoffs in forming our portfolios and go long when $surprise_{t-1}$ is below the 25th percentile (relative to the distribution of salient surprises in the previous quarter) and short if $surprise_{t-1}$ is above the 75th percentile. With these more extreme cutoffs, we expect contrast effects to be more pronounced. Consistent with this, we see a larger daily alpha of 20 basis points with a t-statistic greater than 3. In Columns 3 and 4, we allow portfolios with fewer than five stocks per day, which increases the exposure to idiosyncratic risk, but allows an increase in the number of days in which the trading strategy can be implemented. We see a similar pattern with slightly lower alphas for both choices of cutoffs.

We can compound these daily alphas to estimate the annual alpha of a contrast effects trading strategy (shown in the bottom row of the table). If the trading strategy could be implemented every trading day, 15 basis points per day would yield an annual abnormal return of roughly 45%. However, firms tend to cluster earnings announcement around earnings seasons and not all trading days contain earnings announcements. The trading strategy can only be implemented if there exists a non-missing salient surprise in the relevant cut-off categories in the previous trading day. For example, in the first column which assumes that investors only trade when they are able to diversify across five or more stocks, we can implement the strategy an average of 64 trading days per year (roughly 25% of total trading days) which yields an abnormal annual return of 7%. The slightly lower alphas from the last two columns of Table 6 can be earned on more trading days per year, leading to higher annual abnormal returns of between 11% to 13%.

5 Strategic timing of earnings announcements

Previous research has shown that firms may advance or delay their earnings announcements relative to the schedule used in the previous year or manipulate the earnings announcement itself (e.g., through adjustment of discretionary accruals). However, these types of strategic manipulation will only bias our results *if they alter firm earnings announcements as a function of the earnings surprises released by other firms on day* $t-1$. Such short-run manipulation within a single trading day is unlikely to occur. Firms typically publicly schedule when they will announce their earnings more than a week before they actually announce (Boulland and Dessaint, 2014). The earnings *surprises* of other firms are, by definition, difficult to predict because they measure surprises relative to expectations. Therefore, it is unlikely that firms can strategically schedule to follow other firms with more or less positive surprises. Further, manipulation of the earnings number itself takes time and is unlikely to occur within a single day as a reaction to the earnings surprises made by other firms on day $t-1$.

To directly test strategic timing, we separately examine earnings announcements that moved or stayed the same relative to the calendar date of the announcement for the same quarter in the previous year. Firms typically report their earnings on roughly the same day every year, with small changes, e.g., to announce on the same day of the week (So, 2015). Thus, in order for strategic timing to explain our results, it must be the firms that deviate from their normal earnings announcement date that drive our results. We follow So (2015) and examine the calendar date a firm announces its earnings versus the firm's announcement date for the same quarter one year ago. We categorize firms as having moved their earnings date forward or backwards if it differs from their previous same-quarter date by five or more days. We find roughly 80% of firms keep the date the same, 10% move it forward by more than 5 days and 10% move it backwards.

We examine these sets of firms in Table 7 Panel A and find that strategic timing cannot account for the negative relation between return reactions and salient surprises at $t-1$. Firms that did not greatly move their announcement date have a large negative coefficient of -0.778 that is statistically significant at the 1% level. Firms that moved their announcements forward or backwards have insignificant estimates of contrast effects with large standard errors. Under the strategic timing hypothesis, we should have found that firms that shifted their earnings announcement data accounted for the negative relation, while firms that kept their normal announcement dates displayed no significant relation. Instead, we observe the opposite pattern.

6 Risk and trading frictions

Another possible concern is that firms become more exposed to systematic risk factors based on the earnings surprise announced by other firms the previous day. Because our analysis uses characteristic adjusted returns, differences in firm-specific stable loadings on standard risk factors are unlikely to explain our results. In order to account for our results, it must be that the previous day's salient earnings surprise shifts a firm's exposure to risk on its announcement day. A more negative surprise yesterday leads to higher loadings on risk factors today, and then investors demand a higher return as compensation for the increased risk.

Table 7 Panel B tests for such a channel. We modify our base specification so the characteristic adjusted return is regressed on four factors (market excess return, SMB, HML, and momentum) along with interactions of those factors with $surprise_{t-1}$. The emphasis of this test is on the interaction term. If a firm's covariation with market factors is systematically larger when there are more negative surprises on the previous day, we would expect to see large negative coefficients for these interaction terms. Examining characteristic adjusted returns in Column 1 and raw returns in Column 2, we find no support for this hypothesis. Two coefficients are significant at the 10% level, but they are positive. None of the coefficients are significantly negative. Thus, fixed or time-varying loadings on standard risk factors are unlikely to account for our results.

Another possible concern is that our findings are due to a liquidity premium. For a liquidity premium to explain our results, it must be that a more negative salient surprise yesterday predicts lower liquidity for firms announcing today, so that the the higher return is compensation for the lower liquidity. In Table 7 Panel B, we show that yesterday's salient surprise does not appear to be correlated with today's volume or bid-ask spread, two proxies for liquidity.[6]

An alternative version of a liquidity story relates to capital constraints. Suppose there is limited capital to be invested in the purchase of stocks and on day $t-1$, a firm releases especially good news. Capital may flow into this firm, so that there is less capital available to invest in other firms, leading to a lower price response when a firm announces at t. We first note that this story is unlikely to apply in our context because even a large firm announcing on $t-1$ is small relative to the substantial amount of liquid capital invested in US large cap stocks. We can also test this story directly. These capital constraints imply that there should be lower returns for all other firms, not only for firms announcing on day t. In untabulated results, we find that, if anything, there is a positive correlation between $surprise_{t-1}$ and the market return (excluding firms announcing on $t-1$ and t) which suggests that liquidity issues due to limited capital do not account for the results.

Finally, we check that our results cannot be explained by a risk premium associated with tail risk. For example, if a lower salient surprise in $t-1$ leads to greater crash risk for firms scheduled to announce on day t, rational investors will demand a premium to compensate them for this crash risk. Figure 5 shows the distribution of returns for the highest and lowest quintile of $surprise_{t-1}$. There does not appear to be a significant difference in either tail of the two distributions, suggesting that the empirical results are not be explained by a rational fear of extreme negative returns based on the previous day's salient surprise.

7 Robustness and heterogeneity

7.1 Alternative measures

This section examines whether our results are robust to alternative choices in the construction of the variables used in the baseline analysis. One concern is that analyst forecasts may not represent

[6] In addition to our standard set of control variables, we also include firm fixed effects to account for the substantial heterogeneity in liquidity across different firms. The firm fixed effects mean that we are identifying changes in within-firm announcement day liquidity as a function of variation in the salient earnings surprise released by other firms in the previous day.

market expectations (because they are stale or because analysts are biased or uninformed). If so, our measure of $surprise_{t-1}$ may not capture true market surprise. Therefore, we utilize an alternative measure, the value-weighted $[t-2, t]$ characteristic adjusted return for large firms that announced on day $t-1$. Our returns-based measure of the salient surprise on $t-1$ is:

$$return\ surprise_{t-1} = \frac{\sum_{i=1}^{N}\Big(mkt\,cap_{i,t-4} \times char.\ adj.\ return_{i,[t-2,t]}\Big)}{\sum_{i=1}^{N} mkt\,cap_{i,t-4}} \tag{4}$$

Table 8 Panel A Column 1 uses this measure and finds a similar result as in our baseline. We find a significant coefficient of -0.051 on the new $return\ surprise_{t-1}$ measure. The average return response in the lowest and highest deciles of salient return surprise is -3.9% and 4.3%, respectively. Thus, an increase from the lowest to the highest decile for $return\ surprise_{t-1}$ is on average associated with a decrease in returns of 42 basis points.

In Table 2, firms above the 90th percentile of market capitalization were used to calculate $surprise_{t-1}$. To examine the robustness of the results to the choice of the size cutoff, Columns 2 and 3 of Table 8 Panel A measure yesterday's value-weighted average surprise using all firm's above the 85th and 95th percentiles of market capitalization, respectively. Both measures yield similar values to the measure using the 90th percentile cutoff. The next column value-weights all firms that announced earnings on $t-1$ in the calculation of the salient surprise, regardless of market capitalization. This causes the coefficient on salient surprise to decrease in absolute magnitude, although it remains significant. The reduced magnitude is consistent with the earnings announcements of small firms yesterday receiving less attention and being noticed by fewer people. Including smaller firms in the measure of salient surprise may add noise to the estimate of what investors were actually paying attention to yesterday.

As discussed earlier in Section 1.1, our main analysis uses I/B/E/S dates which, in the early years of our sample, sometimes records the date when the earnings announcement was first published in the Wall Street Journal rather than when the information was released through other means (usually one day earlier). In Column 5 of Table 8 Panel A, we show that our results are very similar utilizing the alternative DellaVigna and Pollet (2009) date correction, which compares the announcement date listed in I/B/E/S with that in Compustat.[7]

Until this point, all analyst-based measures of earnings surprise have been constructed with forecasts from $t-15$ to $t-2$. The first two columns of Table 8 Panel B measure earnings surprise using analyst forecasts from $t-30$ to $t-2$ and from $t-45$ to $t-2$. Including more stale forecasts causes the coefficient on salient surprise to decline in absolute magnitude to -0.534 and -0.348, respectively. These results are consistent with more stale forecasts being worse measures of the actual earnings surprise, although the results also reflect the inclusion of a number of small firms with one forecast occurring more than 15 days before their announcement.

In Column 3, we scale $surprise_{t-1}$ by the sum of the squared size weights of each firm comprising the weighted-mean calculation. This accounts for the fact that the weighted average over a greater number of firms has a smaller standard deviation. We find materially similar results. Finally, in Column 4, we equal-weight each observation. In all previous results, we value-weighted regressions using the $t-3$ market cap of the firm announcing earnings today. Using equal-weights, we find a negative but insignificant coefficient on $surprise_{t-1}$. This is consistent with later results in Sections 7.2 and 7.3, in which we show that our measure of contrast effects is driven by investors comparing the earnings surprises of large firms to those of other large firms. Contrast effects also affect the return response for smaller firms, but the comparisons primarily occur within an industry.

7.2 Size and analyst coverage

In our baseline analysis, we focus on large firms both in terms of the measure of yesterday's surprise and in terms of weighting observations for firms announcing earnings today (all regressions are

[7] For the DellaVigna and Pollet (2009) date correction, we only include announcements contained in both datasets where the date is the same or is different by no more than one trading day. We then use the following rules: 1) If I/B/E/S has a time stamp for the time of the announcement within the day, we use the I/B/E/S date. 2) If the announcement dates in Compustat and I/B/E/S agree, we use this date if it is on or after January 1, 1990 and the previous trading date if it occurred prior to January 1, 1990. 3) If the Compustat date is the trading day before the I/B/E/S date, we use the Compustat date. 4) If the I/B/E/S date is the trading day before the Compustat date, we use the I/B/E/S date.

value-weighted unless otherwise noted). We focus on earnings surprises released by large firms in $t-1$ because their earnings surprises are likely to be more salient to investors. In Table 9, we explore how the magnitude of the contrast effect varies with the size of the firm releasing earnings today. The first column breaks the coefficients down by size quintile of the firm releasing earnings on day t. We find that the smaller quintiles have the expected negative coefficients, but these coefficients are smaller in magnitude and insignificant, while the largest (fifth) quintile is driving the results. Our findings are not driven only by small firms as is the case with many other asset pricing anomalies.

However, it is important to note that these results do not prove that contrast effects are weak for small firms. Rather, we could measure strong contrast effects for large firms announcing today because investors tend to contrast large firms releasing earnings today with other large firms that released earnings yesterday. Investors of smaller firms may tend to contrast the earnings of small firms with that of other similar firms that released earnings yesterday. However, because multiple firms release earnings on $t-1$, it is difficult for us, as econometricians, to identify which firms are salient to investors for each small firm announcing earnings today. This is a point that we explore in detail in Section 7.3, where we show that contrast effects are sizable and significant for smaller firms once we look within industries.

The second column explores heterogeneity in the number of analysts covering firms that release earnings today. In general, the more interest the market has in a given firm, the more analysts will cover that firm's earnings announcement. We examine contrast effects separately for firms covered by one analyst, two analysts, and three or more analysts. We find a monotonic increase in contrast effects of 0.004 for firms with one analyst, -0.661 for two analysts, and -0.825 for three or more analysts. The only statistically significant estimate is that for firms with three or more analysts. These results again show that our findings are not driven by small firms with little analyst coverage. However, we again caution that these results do not imply that investors in firms with little analyst coverage do not suffer from contrast effects. Rather, these investors may contrast these smaller, niche firms with a specific set of other similar small firms that we have difficulty identifying.[8]

[8] We face the additional measurement challenge that the earnings surprises of small firms are measured with greater error because our measure of market expectations is likely to be noisier due to reduced analyst coverage. This

Finally, we explore how our results vary over time. We examine the effect separately decade by decade and find that our results have not declined in recent years. The effect grows monotonically from -0.526 in the 1980s, -0.586 in the 1990s, -0.725 in the 2000s, and -0.906 after 2010. The estimates for each time period are not significantly different from one-another. However, the monotonic increase in the magnitude of the effect over time is consistent with (1) reduced attenuation bias over time due to more precise estimates of $surprise_{t-1}$, and (2) contrast effects increasing with the salience of $surprise_{t-1}$, which may have received more attention over time due to increased financial news coverage. These results also show that our findings are not driven only by the early period of our sample and have, if anything, grown stronger over time. In addition, the large estimate of contrast effects in the 2000s and after shows that our results are unlikely to be driven by date recording errors in the early period in I/B/E/S.

7.3 Industry contrast effects

As discussed in the previous section, while we find stronger evidence of contrast effects among larger firms, it remains possible that contrast effects also strongly affect the returns of smaller firms. Investors may compare smaller firms to a subset of similar firms that announced in the previous day. If so, our baseline empirical specification will underestimate the true magnitude of contrast effects for small firms announcing on day t because we measure the salient surprise in $t-1$ as the value-weighted average of earnings surprises among large firms that announced in $t-1$.

It is difficult to know what the right comparison group is for any firm, but one reasonable possibility is other firms in the same industry. In this section, we explore how contrast effects depend on whether the firms announcing today and yesterday belong to the same industry. We find that contrast effects for large firms are strong both within and across industries, while contrast effects primarily operate through within-industry comparisons for smaller firms.

In Table 10, we modify our baseline specification to include two measures of $suprise_{t-1}$: one based on other firms announcing in the same industry as the firm announcing on day t and one based

implies that we may control for the actual earnings surprises of small firms with more error.

on other firms in different industries. To form these two salient surprise measures, we continue to use the value-weighted average surprises of firms above the 90th percentile of market capitalization, under the assumption that, even within industry, larger firms are more likely to be more salient.[9] We present results using the very broad Fama French 5 industry classification as well as the slightly narrower Fama French 12 industry classification.[10] We also caution that companies may be related in a variety of ways that matter to investors, and these relations will be imperfectly captured by any industry classification system. Thus, the results are based on a noisy proxy of what we think investors are paying attention to.

A limited number of large firms (median of 6) announce earnings on $t-1$ and there are usually fewer firms in the same industry as the firm announcing on day t than firms in different industries. This implies that the standard deviation of the different-industry salient surprise will be relatively smaller, as the average of a larger sample has a smaller standard deviation. To make the magnitudes of the coefficients on the $t-1$ salient surprises in the same- and different-industry samples comparable, we scale each salient surprise by the sum of the squared size weights of each firm comprising the weighted-mean calculation. While this scaling makes the coefficients for the same and different industry salient surprises comparable to one another, the magnitude of these coefficients should not be compared to those in other tables. In addition, if no firm announced within the same (different) industry on $t-1$, we set the relevant $surprise_{t-1}$ variable to zero and include a dummy variable equal to one when the same (different) industry $surprise_{t-1}$ is missing for that observation.

Table 10 Columns 1 and 2 modifies our baseline specification to use the two separate measures of salient surprise on day $t-1$. Column 1 is value-weighted by the market capitalization of the firm announcing earnings today while Column 2 is equal-weighted. Thus, Column 1 overweights larger firms relative to Column 2. We find that, when large firms are overweighted, the magnitude of the contrast effect is similar within and across industries. When smaller firms are weighted more

[9]In untabulated results, we find a similar pattern if we expand the definition of salient surprise to allow for the inclusion of smaller firms that announced on $t-1$.

[10]We do not use more narrowly-defined industry classification systems because a limited set of firms announce earnings on $t-1$. If we use very narrowly-defined industries, we often lack another firm announcing within the same industry.

heavily as in Column 2, the contrast effect is large and significant only within the same industry and there is a small and insignificant contrast effect for firms in different industries. In Column 3, we allow for different effects for large firms (above median market capitalization) and small firms (below the median) announcing on day t. We find that small firms exhibit a large contrast effect when compared to other firms in the same industry, but not to firms in different industries. The contrast effect for large firms is approximately equal within and across industries. We find a similar pattern in Columns 3 through 6, when we move from the Fama French 5 to the Fama French 12 industry classification system. However, the differences by firm size are not statistically significant, as indicated by the p-values at the bottom of the table. One possible explanation is that industry classification is a coarse proxy for the comparison groups actually used by investors.

Overall, these results are consistent with a world in which investors in smaller firms pay more attention to previous announcements by other firms in the same industry. Meanwhile, investors in larger firms pay attention to the recent earnings announcements of other large firms, regardless of industry similarity.

8 Conclusion

We present evidence of contrast effects in sophisticated financial markets: investors mistakenly perceive information in contrast to what preceded it. We examine stock price reactions to earnings announcements of publicly-traded US firms. The scheduling of when earnings are to be announced is usually set several weeks before the announcement, so whether a given firm announces following positive or negative surprises by other firms is likely to be uncorrelated with the firm's fundamentals. We find that the reaction to an earnings announcement is inversely related to the level of earnings surprise announced by large firms in the previous day. This implies that market prices react to the relative content of news instead of only reacting to the absolute content of news.

The existing empirical literature on contrast effects mainly comes from laboratory settings and the limited field evidence focuses on households making infrequent dating or real estate decisions.

Our results show that contrast effects affect equilibrium prices and capital allocation in sophisticated markets. In this setting, professionals make repeated investment decisions based on earnings announcements and market prices are determined through the interactions among many investors.

Our results suggest that contrast effects have the potential to bias a wide variety of important real-world decisions, including judicial sentencing, hiring and promotion decisions, firm project choice, and household purchase decisions. In addition to causing decision errors, contrast effects may also provide a psychological basis for preferences, such as internal habit formation, that are assumed in many influential models in macroeconomics and finance. Under internal habit formation, individuals value gains in consumption relative to previous experience rather than only its absolute level. These preferences could arise because past high levels of consumption lead individuals to perceive any amount of current consumption as lesser in comparison.

To attain a clean measure of contrast effects, we chose a financial setting in which firms cannot strategically use contrast effects as they publicly commit to the date of an earnings news announcement several weeks ahead of time. However, our results imply that, in other settings, agents with discretion over the timing of information disclosure may schedule the release of news in order to take advantage of contrast effects bias. For example, a firm with very bad news to release may try to release that news after another firm releases even worse news, so that its own news does not appear as negative in comparison. Such strategic manipulation of market biases may be a promising direction for future research.

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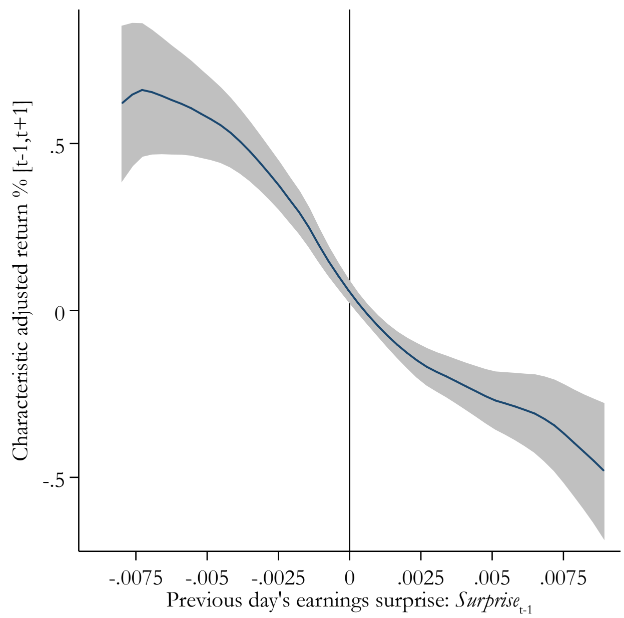
Figure 2
Return Reaction to Earnings $\boldsymbol{Surprise_{t-1}}$

This graph shows the relation between the characteristic adjusted returns from $[t-1, t+1]$ of firms that announced earnings on day t and the salient surprise ($surprise_{t-1}$) announced by other firms on day $t-1$ (calculated as the value-weighted earnings surprises of large firms that announced earnings on day $t-1$), estimated using a value-weighted local linear regression with the optimal bandwidth. We define a "large" firm as a firm with market capitalization at $t-4$ exceeding the 90th percentile cutoff of the NYSE index in that month. Gray areas indicate 90 percent confidence intervals. Panel A reports return residuals after controlling for 20 bins in terms of the firm's own earnings surprise. Panel B reports unconditional returns without controlling for the firm's own earnings surprise, demeaned by the value-weighted average return in the sample.

Panel A: Conditional on Own Earnings Surprise



Panel B: Unconditional

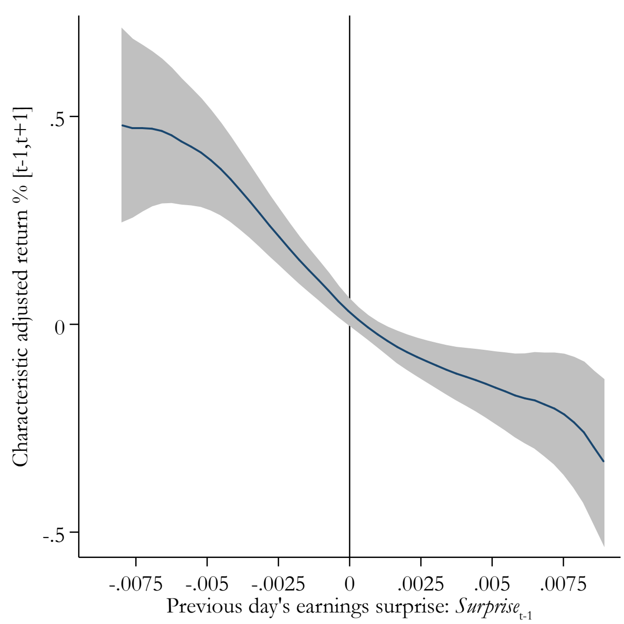
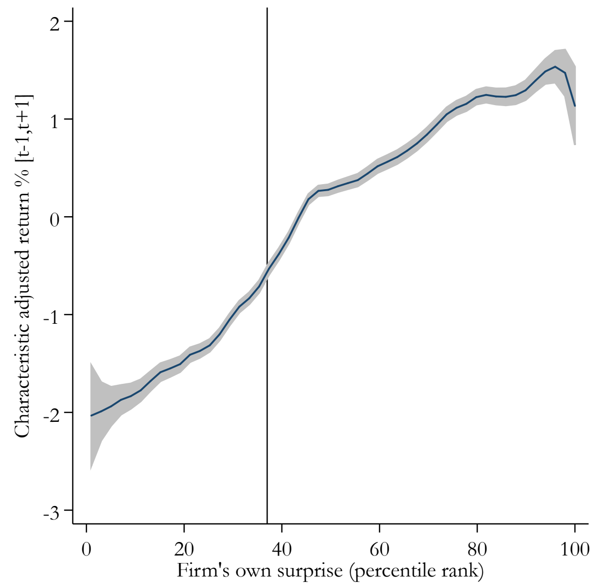


Figure 3
Return Reaction to Own Earnings Surprise

This graph shows the return reaction to a firm's own earnings surprise, and how that varies with $surprise_{t-1}$. Each line plots the value-weighted characteristic adjusted return $[t-1, t+1]$ of firms that announced earnings on day t against the percentile ranks of the the firm's own earnings surprise, estimated using a value-weighted local linear regression with the optimal bandwidth. Panel A examines the entire sample, unconditional on $surprise_{t-1}$. Panel B shows two subsamples: return reactions following $surprise_{t-1}$ in either the lowest or highest deciles. Gray areas indicate 90 percent confidence intervals.

Panel A: Unconditional on $Surprise_{t-1}$



Panel B: Top and Bottom Decile of $Surprise_{t-1}$

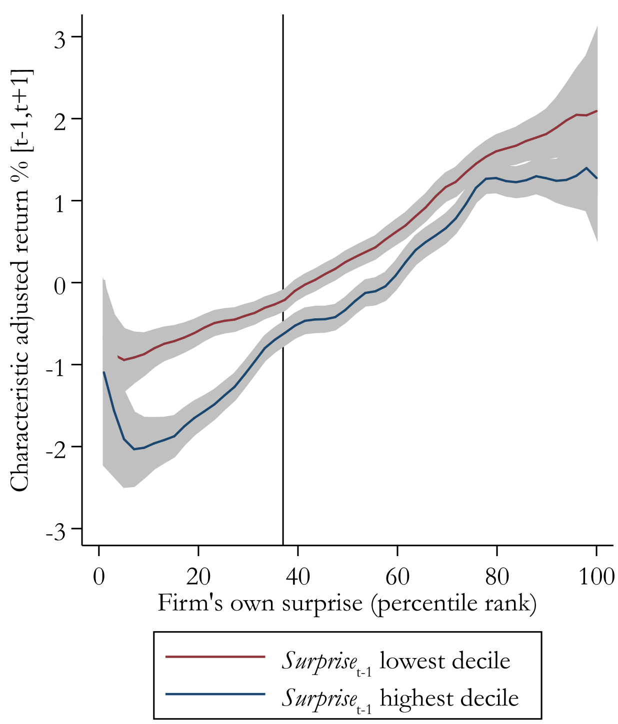
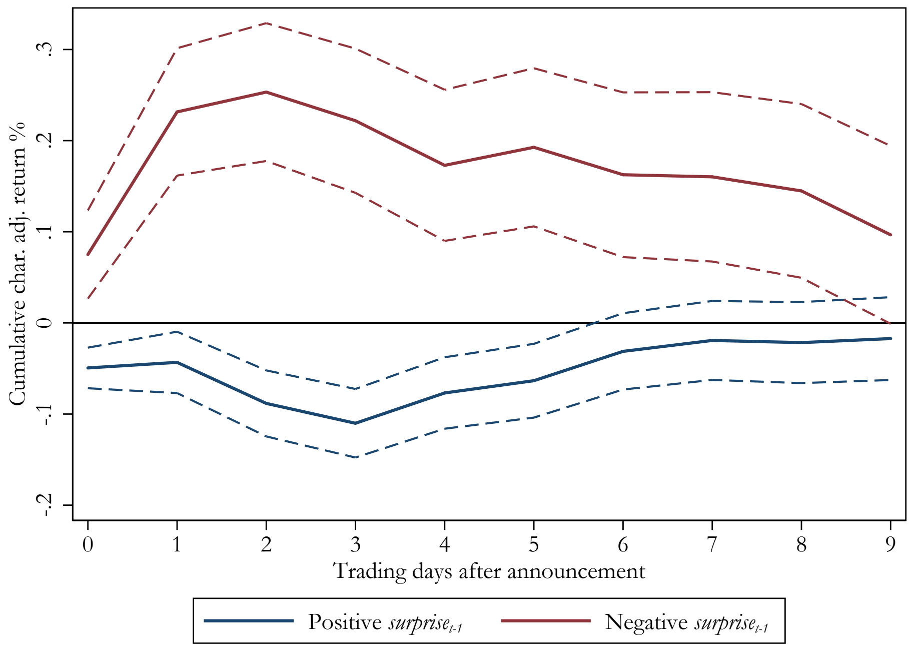


Figure 4
Cumulative Characteristic Adjusted Returns

This graph plots the cumulative value-weighted characteristic adjusted returns starting at market open on day t of firms that announce on day t, conditional on $surprise_{t-1}$. In Panel A, we examine subsamples where $surprise_{t-1}$ was negative or positive. In Panel B, we examine subsamples whether $surprise_{t-1}$ was below the 25th percentile or above the 75th percentile relative to its distribution over the previous quarter. The dotted lines indicate 90 percent confidence intervals.

Panel A: Positive vs. Negative $Surprise_{t-1}$



Panel B: Above 75th Percentile vs. Below 25th Percentile $Surprise_{t-1}$

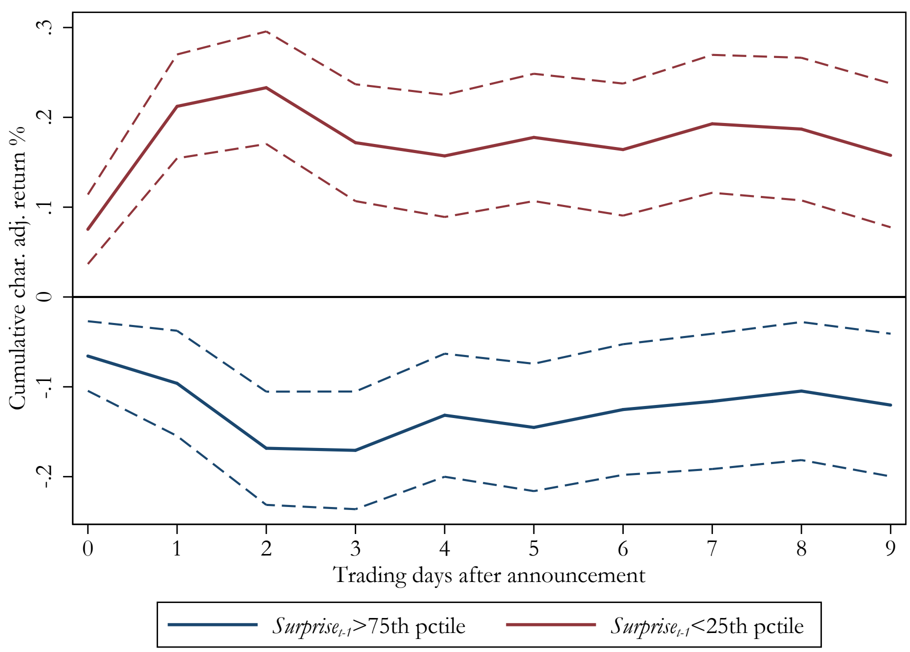


Figure 5
Distribution of Returns by $Surprise_{t-1}$

This graph shows the distribution of characteristic adjusted returns $[t-1, t+1]$ of firms that announced earnings on day t split into two samples based on $surprise_{t-1}$. The red line contains firms that announced the day after a $surprise_{t-1}$ in the highest quintile while the blue lines contains firms that announced after a $surprise_{t-1}$ in the lowest quintile. Distributions are estimated using a kernel density estimator.

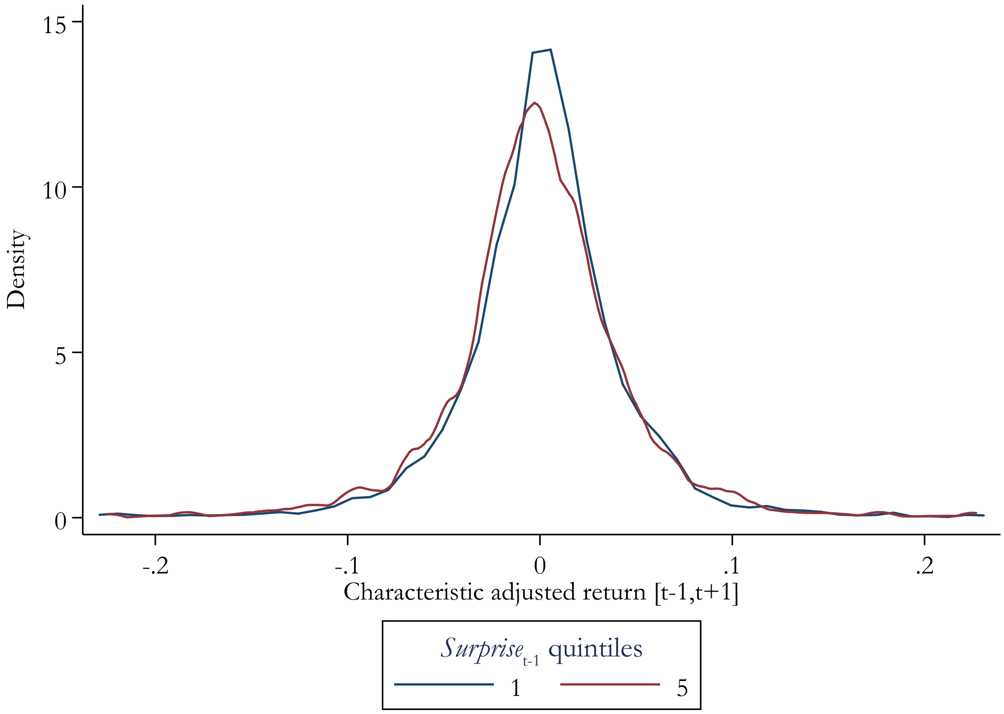


Table 1
Summary Statistics

This table presents summary statistics for the main variables used in our analysis using data from 1984 to 2013. The earnings surprise is measured as $(actual - forecast)/price_{t-3}$ where $forecast$ is the median of each analyst's most recent forecast that is released within 15 days of the announcement, excluding t and $t-1$. Characteristic adjusted returns are the return of a firm minus the return of a portfolio matched on quintiles of market capitalization, book-to-market ratio, and momentum. $Surprise_{t-1}$ is our baseline measure of the salient surprise released by other firms in the previous trading day. It is calculated as the value-weighted earnings surprise of all large firms that announced in the previous trading day. We define a "large" firm as a firm with market capitalization three days before its earnings is announced that exceeds the 90th percentile cutoff of the NYSE index in that month.

	N	Mean	SD	P25	P50	p75
Surprise (t)	76062	-0.0003	0.0138	-0.0003	0.0002	0.0015
Characteristic adjusted return [t-1, t+1]	76062	0.0016	0.0671	-0.0297	0.0007	0.0330
Return [t-1, t+1]	76062	0.0017	0.0503	-0.0181	0.0000	0.0211
Market cap (t-3), ($M)	76062	7679	24100	441	1491	5069
Number of analysts	76062	3.727	3.674	1	2	5
Surprise (t-1), value weighted	76062	0.0005	0.0017	0.0000	0.0004	0.0010
Number of surprises (t-1), large firms	76062	7.546	5.782	3	6	12

Table 2
Baseline Results

This table explores the relation between return reactions for firms that announce earnings today and the earnings surprises of other firms that announced in the previous trading day. The characteristic adjusted return from $[t-1, t+1]$ for announcing firms is regressed on various measures of the salient earnings surprise from $t-1$ and additional controls. Characteristic adjusted returns are the return of a firm minus the return of a portfolio matched on quintiles of market capitalization, book-to-market ratio, and momentum. Surprises for the firms announcing today and in the previous trading day are measured as $(actual - forecast)/price_{t-3}$ where $forecast$ is the median of each analyst's most recent forecast that is released within 15 days of the announcement, excluding t and $t-1$. We define a "large" firm as a firm with market capitalization three days before its earnings is announced that exceeds the 90th percentile cutoff of the NYSE index in that month. Columns 1 and 2 measure $surprise_{t-1}$ as the earnings surprise of the largest firm (conditional on it being a large firm) announced in the previous trading day. Columns 3 and 4 measure $surprise_{t-1}$ using the equal-weighted earnings surprise of all large firms that announced in the previous trading day. Columns 5 and 6 measure $surprise_{t-1}$ as the value-weighted earnings surprise of all large firms that announced in the previous trading day. All regressions include controls for 20 equally sized bins in terms of the earnings surprise of the firm that announced today. Even-numbered columns also include controls for year-month fixed effects. We refer to Column 6 as our baseline specification in later tables. Observations are value-weighted by the $t-3$ scaled market capitalization of the firm announcing earnings today. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Characteristic adjusted return $[t-1, t+1]$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Surprise_{t-1}$ of largest firm	-0.501***	-0.338**				
	(0.141)	(0.153)				
$Surprise_{t-1}$ large firms, EW mean			-0.896***	-0.779***		
			(0.211)	(0.225)		
$Surprise_{t-1}$ large firms, VW mean					-0.781***	-0.721***
					(0.184)	(0.197)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes	No	Yes
R^2	0.0530	0.0742	0.0535	0.0747	0.0534	0.0747
Observations	76062	76062	76062	76062	76062	76062

Table 3

Additional Support for Contrast Effects

This table provides further evidence of contrast effects. Panel A Columns 1 and 2 examine the impact of $t-3$, $t-2$, $t-1$, $t+1$, and $t+2$ salient surprises. The dependent variable in Columns 1 and 2 is the characteristic adjusted return over the windows $[t-3,\, t+1]$ and $[t-1,\, t+2]$, respectively. Dummy variables are included for instances where there is a missing salient surprise of the indicated day. p-values are from the test of whether the $t-1$ coefficient is equal to the indicated coefficient. Panel A Columns 3 and 4 explore contrast effects within the same day. We classify an earnings announcement as "AM" or "PM" based on whether it was released before market open or after market close. Column 3 regresses the $[t,\, t+1]$ characteristic adjusted returns of firms that released PM announcements on the value-weighted surprises of large firms that released AM announcements. Column 4 regresses the $[t,\, t+1]$ characteristic adjusted returns of firms that released AM announcements on the value-weighted surprises of large firms that released PM announcements. Panel B shows the relation between $surprise_{t-1}$ and long run return reactions. Return windows are as labeled in column headers. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Lags and Leads and Same-Day Contrast Effects

	Longer lags and leads		Own PM announcement	Own AM announcement
	(1)	(2)	(3)	(4)
$Surprise_{t-3}$	-0.288			
	(0.184)			
$Surprise_{t-2}$	0.244			
	(0.224)			
$Surprise_{t-1}$	-0.725***	-0.723***		
	(0.216)	(0.242)		
$Surprise_{t+1}$		0.0117		
		(0.291)		
$Surprise_{t+2}$		-0.194		
		(0.327)		
AM surprise of others			-1.256**	
			(0.566)	
PM surprise of others				-0.404
				(0.285)
p-value: (t-3) = (t-1)	0.0819			
p-value: (t-2) = (t-1)	0.000795			
p-value: (t+1) = (t-1)		0.0467		
p-value: (t+2) = (t-1)		0.185		
Own $surprise_t$ controls	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
R^2	0.0739	0.0656	0.146	0.0988
Observations	76042	76052	19364	17901

Panel B: Long Run Return Windows

	$[t-1, t+1]$	$[t+2, t+25]$	$[t-1, t+25]$	$[t+2, t+50]$	$[t-1, t+50]$
	(1)	(2)	(3)	(4)	(5)
$Surprise_{t-1}$	-0.721***	0.156	-0.580	1.097**	0.389
	(0.197)	(0.362)	(0.375)	(0.544)	(0.549)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.0747	0.0202	0.0388	0.0254	0.0338
Observations	76062	75886	75886	74795	74795

Table 4
Information Transmission

This table explores whether $surprise_{t-1}$ conveys information about firms that will announce earnings today. Panel A examines whether $surprise_{t-1}$ predicts the earnings surprise that will be announced on day t. The dependent variable in Columns 1 and 2 is the earnings surprise of the firm that announces on day t. The dependent variable in Columns 3 and 4 is the bin (1 through 20, equally sized) for the earnings surprise of the firm that announces on day t. Panel B explores the day $t-1$ return reaction of the firm scheduled to announce on day t to $surprise_{t-1}$. The dependent variable is the $t-1$ characteristic adjusted return for the firm scheduled to announce on day t, measured as close-to-close returns in Columns 1 and 2 and open-to-open returns in Columns 3 and 4. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Surprise Predictability

	$Surprise_t$		20 bins in $surprise_t$	
	(1)	(2)	(3)	(4)
$Surprise_{t-1}$	134.2***	-26.45	0.165***	0.0117
	(32.63)	(27.17)	(0.0605)	(0.0601)
Own $surprise_t$ controls	No	No	No	No
Year-month FE	No	Yes	No	Yes
R^2	0.00290	0.0653	0.00218	0.0320
Observations	76062	76062	76062	76062

Panel B: Return Response to Potential Information Release

	Close-to-close char adj ret $[t-1]$		Open-to-open char adj ret $[t-1]$	
	(1)	(2)	(3)	(4)
$Surprise_{t-1}$	0.0295	-0.0758	0.106	0.0529
	(0.105)	(0.102)	(0.123)	(0.118)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes
R^2	0.00000998	0.0221	0.000133	0.0216
Observations	76062	76062	61867	61867

Table 5

Further Tests of Information Transmission

Panel A explores contrast effects within the subsample of observations for which information transmission from $surprise_{t-1}$ to firms announcing on day t is unlikely to have occurred. In Column 1, the sample is restricted to observations for which the $t-1$ characteristic adjusted returns of the firm announcing earnings today moved by less than 1% in either direction and Column 2 restricts the sample to cases where the return moved by less than 0.5%. Column 3 examines the sample with no negatively correlated information transmission, i.e., we exclude negative (positive) return reactions to positive (negative) $surprise_{t-1}$. Panel B examines whether contrast effects are related to an interaction between $surprise_{t-1}$ and the announced surprise on day t. Column 1 measures the surprise today using the level, Column 2 measures it using 20 equally sized bins, and Column 3 uses quintiles. For brevity, we report only the interaction effects, but all direct effects are included in the regressions. The dependent variable in Panel A is the open-to-open $[t, t+1]$ characteristic adjusted return of the firm announcing earnings on day t. The dependent variable in Panel B is the same as in our baseline specification–the close-to-close $[t-1, t+1]$ characteristic adjusted return of the firm announcing earnings on day t. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sample with No Evidence of Information Transmission

	$\lvert Ret_{t-1}\rvert < 0.01$	$\lvert Ret_{t-1}\rvert < 0.005$	No neg corr info transmission $[t-1]$
	(1)	(2)	(3)
$Surprise_{t-1}$	-0.627***	-0.614*	-1.289***
	(0.242)	(0.340)	(0.275)
Return type	Open-open	Open-open	Open-open
Own $surprise_t$ controls	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
R^2	0.101	0.133	0.0870
Observations	27451	15082	31212

Panel B: Interaction Effects

	Characteristic adjusted return $[t-1, t+1]$		
	(1)	(2)	(3)
$Surprise_{t-1}$	-0.765***	-1.095***	-0.888*
	(0.204)	(0.423)	(0.526)
$Surprise_{t-1}$ x own surprise	19.36		
	(26.62)		
$Surprise_{t-1}$ x own surprise (20 bins)		0.0417	
		(0.0375)	
$Surprise_{t-1}$ x own surprise quintile 2			-0.181
			(0.702)
$Surprise_{t-1}$ x own surprise quintile 3			0.247
			(0.702)
$Surprise_{t-1}$ x own surprise quintile 4			0.554
			(0.684)
$Surprise_{t-1}$ x own surprise quintile 5			0.249
			(0.737)
Year-month FE	Yes	Yes	Yes
R^2	0.0304	0.0717	0.0715
Observations	76062	76062	76062

Table 6
Unconditional Relation (Not Controlling for Own Surprise)

Panel A presents regressions similar to those in Table 2, except that they exclude the firm's own surprise as control variables. Odd-numbered columns also exclude year-month fixed effects. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. Panel B presents the abnormal returns to portfolios formed based upon $surprise_{t-1}$. On days where $surprise_{t-1}$ is below a cutoff, we long stocks with an earnings announcement on day t and short the market and do the opposite when $surprise_{t-1}$ is above a cutoff. The position is held for days t to $t+1$. We include only stocks with a market capitalization above the 80th percentile of the NYSE. Columns 1 and 2 include only portfolios where there are at least 5 stocks with earnings announcements on each day while Columns 3 and 4 include any day with at least one stock announcing earnings. Columns 1 and 3 utilize a cutoff of 0 for $surprise_{t-1}$, while Columns 2 and 4 utilize a cutoff of being below the 25th or above the 75th percentile of $surprise_{t-1}$, respectively. We compute abnormal returns from a four factor model by regressing portfolio returns on the market, SMB, HML and UMD risk factors. Each portfolio is value-weighted by the stocks announcing earnings on day t. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Unconditional Results

	Close-to-close $[t-1,t+1]$		Open-to-open $[t-1,t+1]$		Open-to-open $[t,t+1]$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Surprise_{t-1}$	-0.481***	-0.757***	-0.537***	-0.820***	-0.672***	-0.898***
	(0.177)	(0.203)	(0.202)	(0.226)	(0.191)	(0.223)
Own $surprise_t$ controls	No	No	No	No	No	No
Year-month FE	No	Yes	No	Yes	No	Yes
R^2	0.000393	0.0225	0.000467	0.0207	0.000805	0.0215
Observations	76062	76062	61840	61840	61840	61840

Panel B: Abnormal Returns to Trading Strategy

	5 or more stocks		Any number of stocks	
	(1)	(2)	(3)	(4)
Alpha %	0.109**	0.199***	0.101**	0.153***
	(0.0448)	(0.0540)	(0.0492)	(0.0560)
MktRf	-0.0113	-0.00318	-0.0836**	-0.0339
	(0.0364)	(0.0409)	(0.0416)	(0.0465)
SMB	0.0711	-0.0981	0.0855	0.0368
	(0.0717)	(0.0823)	(0.0831)	(0.0927)
HML	0.103	0.136	0.123	0.222**
	(0.0775)	(0.0867)	(0.0845)	(0.0928)
UMD	0.0584	0.0283	-0.0139	0.00316
	(0.0505)	(0.0578)	(0.0568)	(0.0624)
Long cutoff: $Surprise_{t-1}$	< 0	$< 25^{th}$ pctile	< 0	$< 25^{th}$ pctile
Short cutoff: $Surprise_{t-1}$	> 0	$> 75^{th}$ pctile	> 0	$> 75^{th}$ pctile
Observations	1300	846	2183	1554
Annual return %	7.36	8.78	11.61	12.65

Table 7

Strategic Timing of Earnings Announcements, Changes in Risk and Trading Frictions

This table tests whether the negative relation between return reactions and $surprise_{t-1}$ is driven by changes in the scheduling of announcements or changes in risk or trading frictions. In Panel A, $\Delta date$ is the difference between the day of the current earnings announcement and the previous year's same-quarter earnings announcement (e.g., for a firm announcing on March 15, 2004 that previously announced on March 12, 2003, $\Delta date = 3$). Panel B Columns 1 and 2 test whether the negative relation is driven by changes in risk, as measured by the betas of the market, SMB, HML, and UMD risk factors. We regress the characteristic adjusted return (Column 1) or the raw return (Column 2) on the four factors, year-month fixed effects, $surprise_{t-1}$, and the interaction between $surprise_{t-1}$ and the four factors. Panel B Columns 3 and 4 test whether the negative relation is driven by changes in liquidity, measured as the log of daily dollar volume in Column 3 and the log of the bid-ask spread in Column 4. Measures of liquidity vary greatly across firms so Columns 3 and 4 include firm fixed effects. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Strategic Timing of Earnings Announcements

	Characteristic adjusted return $[t-1, t+1]$	
	(1)	(2)
$Surprise_{t-1}$ x abs(Δ date)$<=$5	-0.778***	
	(0.222)	
$Surprise_{t-1}$ x abs(Δ date)$>$5	-0.346	
	(0.497)	
$Surprise_{t-1}$ x Δ date$<$-5		0.900
		(0.713)
$Surprise_{t-1}$ x abs(Δ date)$<=$5		-0.784***
		(0.222)
$Surprise_{t-1}$ x Δ date$>$5		-0.791
		(0.659)
Own $surprise_t$ controls	Yes	Yes
Year-month FE	Yes	Yes
R^2	0.0755	0.0758
Observations	70272	70272

Panel B: Changes in Risk and Trading Frictions

	Char adj ret $[t-1, t+1]$	Raw ret $[t-1, t+1]$	Log(volume)	Log(bid-ask)
	(1)	(2)	(3)	(4)
$Surprise_{t-1}$	-0.778***	-1.061***	3.087	1.411
	(0.200)	(0.250)	(4.825)	(5.532)
Mkt-rf x $surprise_{t-1}$	0.120	-1.508		
	(7.424)	(9.274)		
SMB x $surprise_{t-1}$	-22.99	-18.79		
	(16.61)	(23.35)		
HML x $surprise_{t-1}$	11.10	42.40		
	(23.99)	(29.35)		
UMD x $surprise_{t-1}$	23.80*	51.61***		
	(13.66)	(16.25)		
Own $surprise_t$ controls	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
R^2	0.0758	0.216	0.891	0.754
Observations	76062	76062	75910	68909

Table 8
Alternative Measures of Surprise

This table shows that our baseline results are robust to alternative measures and sample restrictions. All variables and weights are as defined in Table 2, except for the following changes. Panel A Column 1 measures the salient surprise in $t-1$ as the value-weighted average of the return response to the $t-1$ earnings announcements of other firms above the 90th percentile of market capitalization. In Columns 2 and 3, $surprise_{t-1}$ is calculated using firms that announced in $t-1$ that exceeded the 85th and 95th percentile size cutoffs of the NYSE index in that month, respectively. In Column 4, $surprise_{t-1}$ is calculated using the value-weighted surprise of all firms that announced in the previous trading day, regardless of size. Column 5 uses announcement dates based on the filters from DellaVigna and Pollet (2009). Panel B Columns 1 and 2 calculate own surprise and $surprise_{t-1}$ using the median of each analyst's most recent forecast released with the past 30 or 45 days, respectively, excluding days t and $t-1$. Column 3 scales $surprise_{t-1}$ by the sum of the squared size weights of each firm comprising the weighted-mean calculation of $surprise_{t-1}$. Column 4 re-estimates the baseline regression, but equal-weights each observation instead of of value-weighting. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Different Value-Weighted Measures

	Characteristic adjusted return $[t-1, t+1]$				
	(1)	(2)	(3)	(4)	(5)
Return surprise$_{t-1}$, VW mean	-0.0510**				
	(0.0218)				
$Surprise_{t-1}, > 85^{th}$ pctile		-0.782***			
		(0.182)			
$Surprise_{t-1}, > 95^{th}$ pctile			-0.715***		
			(0.212)		
$Surprise_{t-1}$, all firms				-0.473***	
				(0.137)	
$Surprise_{t-1}$, adjusted dates					-0.652***
					(0.206)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.0742	0.0749	0.0715	0.0541	0.0782
Observations	75044	79875	66609	76062	62438

Panel B: Different Forecast Windows, Scaling, and Weighting

	Characteristic adjusted return $[t-1, t+1]$			
	(1)	(2)	(3)	(4)
$Surprise_{t-1}$, forecasts[t-30,t-2]	-0.534***			
	(0.176)			
$Surprise_{t-1}$, forecasts[t-45,t-2]		-0.348**		
		(0.161)		
$Surprise_{t-1}$, scaled SD			-0.355***	
			(0.100)	
$Surprise_{t-1}$, EW regression				-0.213
				(0.159)
Own $surprise_t$ controls	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
R^2	0.0664	0.0664	0.0746	0.0737
Observations	121617	150232	76062	76062

Table 9
Heterogeneity

This table shows how contrast effects vary by size and analyst coverage of the firm announcing today. In Column 1, $surprise_{t-1}$ is interacted with indicators for five quintiles for the size (as measured in $t-3$, using quintile cutoffs of the NYSE index in that month). In Column 2, $surprise_{t-1}$ is interacted with indicators for the number of analysts covering the firm announcing earnings today (the number of distinct analysts that released forecasts in the past 15 days excluding day t and $t-1$). In Column 3, we estimate separate effects for each decade in the sample. All direct effects of size quintiles or number of analysts are included in the regression. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Characteristic adjusted return $[t-1, t+1]$		
	(1)	(2)	(3)
$Surprise_{t-1}$ x size quintile 1	-0.369		
	(0.474)		
$Surprise_{t-1}$ x size quintile 2	-0.361		
	(0.450)		
$Surprise_{t-1}$ x size quintile 3	-0.284		
	(0.399)		
$Surprise_{t-1}$ x size quintile 4	0.203		
	(0.293)		
$Surprise_{t-1}$ x size quintile 5	-0.813***		
	(0.214)		
$Surprise_{t-1}$ x (num analysts = 1)		0.00369	
		(0.514)	
$Surprise_{t-1}$ x (num analysts = 2)		-0.661	
		(0.420)	
$Surprise_{t-1}$ x (num analysts >= 3)		-0.825***	
		(0.220)	
$Surprise_{t-1}$ x 1980s			-0.526
			(0.348)
$Surprise_{t-1}$ x 1990s			-0.586
			(0.615)
$Surprise_{t-1}$ x 2000s			-0.725**
			(0.282)
$Surprise_{t-1}$ x 2010s			-0.906**
			(0.368)
Own $surprise_t$ controls	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
R^2	0.0750	0.0750	0.0747
Observations	76062	76062	76062

Table 10
Industry Match

This table explores how contrast effects vary with industry match between the firm announcing earnings today and the firm announcing in the previous trading day. $Surprise_{t-1}\,same\,industry$ is the salient earnings surprise in $t-1$, calculated using only firms in the same industry as the firm announcing today. $Surprise_{t-1}\,dif\,industry$ is the salient earnings surprise in $t-1$, calculated using only firms in a different industry as the firm announcing today. To make the magnitudes of the coefficients on the $t-1$ salient surprises comparable, we scale each salient surprise by the sum of the squared size weights of each firm comprising the weighted-mean calculation. Small (large) firm is a dummy variable equal to one if the $t-3$ size of the firm announcing earnings today is below (above) the median NYSE market capitalization in that month. p-values are for the test of whether a given same-industry coefficient is equal to its different-industry analogue. All other variables and weights are as defined in Table 2. Standard errors are clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Fama French 5 Industries			Fama French 12 Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
$Surprise_{t-1}$ same industry	-0.340***	-0.308***		-0.268*	-0.331**	
	(0.128)	(0.114)		(0.155)	(0.139)	
$Surprise_{t-1}$ dif industry	-0.339**	-0.0246		-0.326**	-0.0472	
	(0.144)	(0.112)		(0.133)	(0.0985)	
$Surprise_{t-1}$ same industry x small firm			-0.457**			-0.566**
			(0.224)			(0.275)
$Surprise_{t-1}$ dif industry x small firm			-0.199			-0.244
			(0.208)			(0.195)
$Surprise_{t-1}$ same industry x large firm			-0.336**			-0.258
			(0.131)			(0.159)
$Surprise_{t-1}$ dif industry x large firm			-0.343**			-0.328**
			(0.147)			(0.135)
Regression weights	Value	Equal	Value	Value	Equal	Value
p-value: same=dif	0.995	0.109		0.788	0.106	
p-value: same=dif, small firms			0.431			0.369
p-value: same=dif, large firms			0.974			0.755
Own $surprise_t$ controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0748	0.0739	0.0749	0.0745	0.0738	0.0745
Observations	76062	76062	76062	76062	76062	76062