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Weather Induced Employment Growth Surprises and the Cross-Section of Local Stock Returns

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Abstract

We find that the weather induced local employment growth surprises are positively related to the cross section of future local stock returns for up to three months without subsequent reversals. In comparison, neither weather nor reported employment growth can predict future returns. This return predictability is stronger in more weather sensitive industries, when we use weather station data closer to the county center, and for firms with lower financial reporting transparency. The employment growth surprises are also positively related to future earnings surprises. Our results are consistent with the investor underreaction explanation.

Keywords: weather, employment growth surprises, stock returns
JEL: G14, E32, O3, O4, L1, L2

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1 Introduction

Economists show that climate changes as manifested by global warming and high temperature at annual or longer horizons reduces the contemporaneous value of a variety of fundamental economic outcomes. These outcomes include productivity and economic growth (e.g., Dell, Jones, and Olken, 2012; Zivin and Neidell, 2014; Burke, Hsiang, and Miguel, 2015; Colacito, Hoffmann, and Phan, 2019; Somanathan, Somanathan, Sudarshan, and Tewari, 2021) and agriculture (e.g., Mendelsohn, Dinar, and Sanghi, 2001; Schlenker and Roberts, 2006; Lobell, Schlenker, and Costa-Roberts, 2011; Burke and Emerick, 2016).

In finance, researchers hypothesize that cloudy weather negatively affects investor mood and thus the sign of the same day stock returns. They find that stock indexes in the U.S. and internationally have a more positive daily return if the weather in the cities of the main stock exchanges is sunnier on the same day (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003). However, the evidence is mixed for individual stocks; cloudy weather near firms' headquarters is unrelated to the same day stock returns (e.g., Loughran and Schultz, 2004). Goetzmann, Kim, Kumar, and Wang (2015) study the relation between the weighted sky cloud cover across the regions of institutional investors holding a stock and the sign of the same day returns for the stock. Although they find no relation for the universe of the stocks, they show a negative relation for the stocks with the highest 20% of arbitrage costs.

Is there any other way that weather may affect stock prices? Can weather affect stock prices beyond the same day? News media, financial analysts, and policy makers often mention real time weather as a driving force for short term fluctuations in macroeconomic variables, as well as local economic activities and local company performance.[1] A natural path is to study whether real time weather can predict short term economic variables and then use the economic surprises to predict asset prices.

Wilson (2019) takes the first step to fill this void. Different from both the economics literature using weather as a fundamental explanation for contemporaneous long term

[1] A recent example is the U.S. nationwide freeze in February 2021 that affected a range of economic variables and local economic activities, especially in Texas where there are widespread power and water outages. Another example is the severe drought and heat wave in the recent years whose impact includes depleting water resources for a wide portion of the U.S.

economic outcomes and the finance literature using weather as a mood explanation for the same day stock returns, he does not directly use weather itself as the predictive variable for asset returns. Instead, he focuses on the national level weather induced employment growth surprises by first estimating the county level difference between the predicted nowcast employment growth rates given the actual and historical average weather, respectively, based on recursive out-of-sample regressions. Aggregating these county level nowcast differences of employment growth due to weather surprises to the national level, he finds that the national level nowcast difference can predict the returns of U.S. T-bonds on the employment report release day and generate statistically and economically significant abnormal returns. He also provides evidence that this aggregated weather induced employment growth surprise can weakly predict the returns of stock indexes on the employment report release day.

Complementing Wilson (2019), our paper study the cross-sectional implications of the county level weather induced employment growth surprises. Specifically, we match his county level nowcast differences of employment growth due to weather surprises, which we will refer to as the nowcast differences hereinafter, with the headquarter counties of listed firms and study whether the nowcast differences can predict the future stock returns for these firms. Although weather is likely to have only an idiosyncratic transitory impact on employment growth, fully reacting to its impact is a complex task and may require real time local weather data and a rich understanding of the local effects of weather (Wilson, 2019). He suggests that processing the weather and employment data and extracting the relevant information correctly are not a trivial task. As a result, we hypothesize that investors may not fully appreciate the weather induced local employment growth surprises in real time and hence underreact to its impact on local stock prices. If the nowcast difference is higher in a county for a given month, we expect that the stock returns for the firms headquartered in the county would be higher for some subsequent months. If the nowcast difference is lower in the county, we expect the stock returns for these firms to be lower in the subsequent months.

We are the first to test the hypothesis of whether the nowcast differences can predict future stock returns at the monthly horizon. This is a much longer horizon than, and a break from, the same day horizon in all the prior weather related asset pricing literature including Wilson (2019). At the same time, given the transitory impact of weather on employment growth, we expect the nowcast differences cannot predict long term future stock returns.

We find that the county level nowcast differences are positively and significantly related to up to three month ahead returns of local firms, consistent with our expectations. Portfolio sorting tests further show that the return spreads based on the nowcast differences generate significant abnormal returns. In comparison, neither the reported employment growth nor raw weather variables can predict future stock returns. The insignificance of all the ingredients for calculating the nowcast differences indicates that the return predictive power of the nowcast differences comes from the process to extract the return relevant information from the impact of local weather on local employment growth correctly. The insignificance of all the raw weather variables to predict future returns also suggests that the return predictability of the nowcast differences is unlikely due to investor mood.

We use two additional tests to further ascertain that the return predictive power of the nowcast differences is due to the impact of local weather on local employment growth. First, we find weaker results when we use weather station data within larger radiuses than the radius of 50 miles from a county center originally used in Wilson (2019). Second, we compare the return predictive power of the nowcast differences separately in the high and low weather sensitivity industries classified according to Wilson (2017). We find that the return predictive power is concentrated in the high weather sensitivity industries. These results suggest that the return predictive power of the nowcast differences is local and weather related.

Further, we conduct three additional tests to show that our results are consistent with the underreaction explanation. First, we examine beyond the one-month-ahead horizon, which also helps us verify whether our results are due to the overreaction explanation implicit in the mood related literature. The mood explanation would imply that the more positive nowcast differences, i.e., the more positive weather induced local employment growth surprises, should lead to more positive mood and thus greater initial overreactions in stock returns. As the overreaction reverses itself gradually, we should expect a negative relation between future stock returns and the nowcast differences as we move beyond the short term return windows. In contrast, investor underreaction would not predict any return reversal related to the nowcast differences, which is what we find. Second, if investors underreact to the future return relevant information in the nowcast differences, we would expect that investors are positively surprised when actual earnings are announced in the future months. We use sell side analyst earnings forecasts to proxy for investor earnings expectation and the standardized unexpected earnings (SUE) to measure earnings surprises. We find that the nowcast differences are positively related to future earnings surprises. Third, we also find that investors underreact more among firms with lower financial reporting quality whose financial performance are more difficult for investors to understand. Overall, our results from these three tests are consistent with the investor underreaction story that investors are not fully reacting to the weather induced employment growth surprises in real time.

Our results hold at both the individual stock level and the county level where we aggregate stocks into county portfolios according to the location of their headquarters. Our results are also robust to a variety of common control variables. In fact, the nowcast differences have an extremely low correlation with most common variables shown to predict future stock returns, suggesting that it contains additional information about future stock returns that are not contained in these variables. This may not be so surprising as the existing anomalies are mostly based on company specific information.

Note that to avoid data snooping bias, we intentionally follow Wilson (2019) closely to measure the nowcast differences for employment growth throughout the paper to establish the fact that the weather induced economic surprises of employment growth can affect local stock returns. It is possible that different specifications for employment growth or using weather to predict macroeconomic variables other than employment growth and generate the corresponding surprises could produce even greater significance, which we leave to future research.

In addition to the above mentioned economics literature using weather or climate changes to explain fundamental economic outcomes in the contemporaneous periods, our paper is also related to other economics papers using weather or climate changes to explain mortality (e.g., Deschenes and Moretti, 2009; Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2016), crime and social unrest (e.g., Field, 1992; Miguel, Satyanath, and Sergenti, 2004; Jacob, Lefgren, and Moretti, 2007; Hsiang, Burke, and Miguel, 2013), and politic changes (e.g., Brückner and Ciccone, 2011). An emerging literature shows that climate changes affect asset prices. For example, climate change risks reduce housing prices (e.g., Baldauf, Garlappi, and Yannelis, 2020; Bernstein, Gustafson, and Lewis, 2019; Murfin and Spiegel, 2020), increase muni-bond yields (e.g., Painter, 2020), affect long run discount rates (e.g., Giglio, Maggiori, Rao, Stroebel, and Weber, 2021), institutional investor attention (e.g., Krueger, Sautner, and Starks, 2020; Alok, Kumar, and Wermers, 2020), and corporate sales and cash flows (e.g., Addoum, Ng, and Ortiz-Bobea, 2020; Brown, Gustafson, and Ivanov, 2021). Complementing this literature, we study how the weather induced employment growth surprises affect future returns of local stocks. Although our focus is short term weather rather than long term climate change, there is abundant evidence that climate change increases the variability of weather and the number and severity of weather related events (e.g., Assessment, 2018). To the extent that climate changes affect weather and consequently the variations in the weather induced employment growth surprises, the impact of weather on future stock returns that we observe may become stronger in the future.[2] Further, our finding that the employment growth surprises that affect local stock returns are mostly due to high temperature is in a similar spirit to the prior findings of high temperature driving climate change effects on fundamental outcomes such as economic productivity and growth. Finally, we focus on weather and exclude natural disasters often used in the prior literature to measure climate risks from our sample. According to Wilson (2017), disasters and weather have a low correlation.

In addition to the above mentioned finance literature using cloudy weather to explain the stock returns on the same day, our paper is related to the extensive finance literature on the relation between weather and trading in individual stocks. Although evidence is mixed that cloudy weather in the headquarter regions affects individual stock trading volume on the same day (e.g., Loughran and Schultz, 2004; Goetzmann and Zhu, 2005), the weighted sky cloud cover across the regions of institutional investors in a stock can explain the perceived overpricing and trading in the stock (Goetzmann et al., 2015). Cloudy weather also delays market reactions to earnings announcements (Dehaan, Madsen, and Piotroski, 2017) and the hiring and investment decisions of firms (Chhaochharia, Kim, Korniotis, and Kumar, 2019).

[2] A formal analysis of this hypothesis in our paper is impeded though by our relatively short sample period and the fact that Wilson (2019) models the weather impact on employment growth as decade specific.

Instead of studying the direct impact of weather on stock returns, we complement this literature by studying the impact of the weather induced employment growth surprises on local stock returns. Instead of the mood perspective, we study from the perspective of task complexity to extract return relevant information from weather and employment growth correctly in real time. We also focus on whether the weather induced employment growth surprises can predict future stock returns in the months ahead instead of the relation between weather itself and stock returns on the same day. We examine all the major weather variables including temperature, precipitation, and snowfalls instead of focusing on the extent of cloudiness. We find that the county level weather induced employment growth surprises can predict future returns for the universe of stocks even though the results are stronger for local weather in closer distance and for the subsample of stocks with high weather sensitivity. In comparison, none of the weather variables can predict future monthly stock returns.

Further, consistent with the task complexity related underreaction explanation but not the mood related overreaction explanation, we do not observe any return reversal related to the nowcast differences. We also find that the nowcast differences are positively related to future earnings surprises and that the return predictive power of the nowcast differences is stronger among firms with lower financial reporting quality. Thus, complementing the investor mood channel for weather to affect stock returns, we provide evidence for the new task complexity channel through which local weather could affect local stock returns.

Since weather and its impact on local employment growth represent exogenous idiosyncratic risks to corporations, our paper is also related to the literature on idiosyncratic risks and the literature on the relation between future cash flows and stock returns. For example, the literature generally measures idiosyncratic risks with idiosyncratic volatility and shows that it has a negative relation with short term future stock returns with large reversals (e.g., Ang, Hodrick, Xing, and Zhang, 2009). Stock returns and idiosyncratic volatility could affect each other. In comparison, we find that the exogenous idiosyncratic risk of the weather induced employment growth surprises has a positive relation with short term future stock returns without reversals.

The rest of the paper is organized as follows. In Section 2, we describe the data used in the paper and explain the construction of the county-level nowcast differences following Wilson (2019). Section 3 presents evidence on how the county level employment growth surprises due to local weather can predict local stock returns. Section 4 investigates potential economic channels. Section 5 concludes.

2 Data and the county level nowcast differences

The weather data by county and month are from Global Historical Climatology Network Daily (GHCN-Daily) dataset. Employment data from the Quarterly Census of Employment and Wages (QCEW) provides non-seasonally adjusted private nonfarm employment at the county level and the monthly frequency. We start with a sample of all the firms listed on the New York Stock Exchange (NYSE), the American Stock Exchange (Amex) and Nasdaq. Stock returns and market related data are from the Center for Research in Security Prices (CRSP). Accounting data are from COMPUSTAT. The following subsections explain our data selection procedure and how we construct the nowcast differences and the county stock portfolios. It also reports summary statistics.

2.1 County level nowcast differences

To avoid data snooping bias, we closely follow the methodology in Wilson (2019) to construct the county level nowcast differences of employment growth due to weather surprises. In this subsection, we outline the key steps in the construction of the nowcast differences, which are essentially the steps described in his paper.

2.1.1 Panel data model for the county level nowcast of employment growth

We start by constructing the daily county level weather variables using weather station level data from the GHCN-Daily dataset. We obtain five daily weather station level weather variables: the daily maximum temperature, an extreme hot day indicator that equals one if the maximum temperature on that day was above 90 (32.2°C), an extreme cold day indicator that equals one if the minimum temperature was below 30°F (-1.1°C), precipitation, and snowfalls. We measure daily values of each weather variable at the county level with the inverse distance weighted averages of individual weather variables in the stations located within a radius of 50 miles from the country center. The distance is the one between a weather station and the county center. The geographic coordinates of weather stations are from the GHCN-Daily dataset and those of county centers are from the U.S. Census.[3]

We then construct five monthly county level weather variables using these daily county level weather variables: average daily maximum temperature, fraction of days in the month in which the maximum temperature was above 90°F, fraction of days in the month in which the minimum temperature was below 30°F, average daily precipitation, and average daily snowfall.

To estimate the county level nowcast of employment growth, we use the following county level panel data model.

$$\Delta_{c,t} = \gamma_t + \alpha_{c,m(t),d(t)} + \sum_{i=1}^{4}\sum_{\tau=0}^{3} \beta_{i,\tau}^{maxtemp} \cdot 1[t \in S_i] \cdot w_{c,t-\tau}^{maxtemp} + \sum_{i=1}^{4}\sum_{\tau=0}^{3} \beta_{\tau}^{k} \cdot w_{c,t-\tau}^{k} + \epsilon_{c,t} \quad (1)$$

where $\Delta_{c,t}$ is the change in log non-seasonally adjusted private nonfarm employment in county c and month t. The variables γ_t are monthly fixed effects to absorb all national common shocks. Given that QCEW data are not available on the seasonally adjusted basis at the county level, $\alpha_{c,m(t),d(t)}$, is a county-specific calendar-month $\times$ decade fixed effect, which allows the seasonal adjustment of employment growth by county and decade. The variable $w_{c,t-\tau}^{maxtemp}$ is the average daily maximum temperature measure for county c in month $t-\tau$. We interact it with a season indicator variable $1[t \in S_i]$, which is equal to 1 if month t is in Season S_i, to allow the effects of maximum temperature on employment growth to differ by season. We define the following four seasons: Winter (December-February), Spring (March-May), Summer (June-August), and Fall (September-November). The variable $w_{c,t-\tau}^{k}$ is one of the other four weather variables for county c in month $t-\tau$, and we constrain them to have the same effects on employment growth across seasons. The coefficients $\beta_{i,\tau}^{maxtemp}$ and

[3] https://www.census.gov/geographies/reference-files/time-series/geo/centers-population.html

β_τ^k are the key parameters to be estimated using data from the estimation window. They capture the effect of each of the five weather variables (k), also by season (i) for maximum temperature, on the employment growth τ months ahead.

τ takes value from zero to three to allow weather to have not only a contemporaneous effect on the current month's employment growth but also on future employment growth up to three months ahead. Wilson (2019) reports that lags beyond three months do not have any effect as shown by a Wald test that compares the three lag model to models with longer lags. These lags allow for both persistent and transitory (mean-reverting) weather effects.

In addition to the model described above, Wilson (2019) also considers a more flexible version of the model which further allows the effects of weather on employment growth to vary across the nine Census Bureau regions.[4] He finds that allowing for regional heterogeneity in the above county level panel data model does not significantly improve the explanatory power of weather for employment growth or bond returns. The improvement is tiny especially considering that allowing for regional heterogeneity adds a magnitude more explanatory variables to the model. Allowing for regional heterogeneity would not only come at the cost of drastically increasing the number of coefficients to be estimated by almost 9 times but also potentially leads to overfitting and measurement errors. As a result, we do not assume regional heterogeneity in the panel data model.

2.1.2 Model estimation and the nowcast differences

We estimate the county level panel data model using weighted least squares where the weights are log county employment in order to mitigate the influence of sparsely populated counties. These counties usually have fewer nearby weather stations, likely resulting in greater measurement error in their weather data. In addition, we winsorize employment growth at the first and 99th percentiles to mitigate the influence of measurement error and outliers in the dependent variable of this model.

[4]Wilson (2017), which focuses exclusively on predicting employment growth instead of stock and bond returns, also experiments with models that allow every coefficient estimates in equation 1 to vary by nine Census Bureau regions and ten industries. In his model to create the county level nowcast differences to predict returns, Wilson (2019) prioritizes parsimony and focuses on models with limited heterogeneity and thus many fewer coefficients to be estimated. Greater heterogeneity is not necessarily always better and could lead to overfitting and measurement error.

To produce the nowcasts, we estimate the coefficients in the county level panel data model using recursive-window samples. Specifically, we estimate the county level panel data model iteratively over the sample periods. The first month of these sample periods is always January 1980 and the end month is iterated from May 2003 to December 2018. We then match the estimated coefficients with the values of weather variables (actual weather or historical average weather) eight months ahead because the county level QCEW data releases have a lag of six to eight months.[5] Thus, the nowcast of county c's local employment growth in month t is the fitted value of the county level panel data model. To obtain the fitted value, we combine the actual or historical average values of county c's weather variables in month t and the coefficients estimated from the model over a sample period that begins from January 1980 and ends eight-month prior to month t.

To ensure a sufficient number of observations in the time-series, nowcasts are formed starting from January 2004. Hence the nowcast of local employment growth in January 2004 is computed using actual or historical average weather variables in that month and the coefficients estimated over a sample from January 1980 to May 2003. The last nowcast in our sample in December 2018 is computed using the weather variables in that month and the coefficients estimated over the January 1980 to April 2018 sample period.

We obtain two sets of nowcasts of the model. The first set is based on actual weather in the current and past three months. The second set is based on the historical average weather for that county, the related calendar months, and that decade. Note that both sets of fitted values also incorporate the impact of national factors (captured by the monthly fixed effects) and seasonal factors (captured by the county $\times$ calendar month $\times$ decade fixed effects). The nowcast differences of local employment growth in a month are the difference between the predicted employment growth based on a county's actual weather in the month and the predicted employment growth given its historical average weather over

[5]Wilson (2019) points out a caveat of the QCEW data. The QCEW data are subject to revision and real time data are unavailable. The time from the initial release (six to eight months after the reference month) to final version varies from one to four quarters. The revisions are usually tiny, less than one-twentieth of 1 percent. He also finds that even conservatively using the model estimates based on the recursive sample ending 20 months before the reference month does not make any difference in his employment growth or return estimations. This robustness is likely due to the high stability of the county level panel data model coefficient estimates as the ending month of the sample moves forward.

the calendar-month-decade. Overall, we have a panel of nowcast differences at the county level from January 2004 to December 2018 covering 3106 counties.

As an illustration of the estimation, we report in Table I the coefficient estimates and standard errors from estimating the county level panel data model over the full sample period from January 1980 to April 2018. The first through fourth columns show the estimated coefficients and their t-statistics on the contemporaneous values and the one-, two-, and three-month lagged values of the weather variables, respectively. We standardize all weather related regressors by their full-sample standard deviation so that each coefficient represents the effect on local employment growth of a one standard deviation change in each weather variable.

We find similar patterns of weather effects as in Wilson (2019) using the 1980-2015 sample. Specifically, higher temperatures have a positive and statistically significant contemporaneous effect on employment growth in all four seasons but the effect is weaker in magnitude in the falls. Precipitation and snowfalls have negative and significant contemporaneous effects on employment growth. The higher the fraction of days in a month with extreme temperature, both hot and cold, the lower the employment growth. The lagged effects of weather generally are of opposite signs to the contemporaneous effect and their statistical significance tends to vanish after two lags. Further, the weather related variables play a crucial role in explaining local employment growth. In untabulated results, excluding these variables in the estimation would reduce the adjusted R-squared from 0.548 to 0.180.

2.2 Stocks, regional portfolios and their characteristics

Our starting sample of stocks includes all the individual firms listed on the New York Stock Exchange (NYSE), the American Stock Exchange (Amex), and Nasdaq from CRSP. We hypothsize that the short term stock returns of a firm will be affected by the weather induced employment growth surprises of the county in which the firm has its corporate headquarter. Our analysis follows the prior literature that examines how the weather in a firm's headquarter region affects the firm's stock returns and trading (e.g., Loughran and Schultz, 2004; Goetzmann and Zhu, 2005) and the broad literature that studies the impact of headquarters on stock returns in general (e.g., Coval and Moskowitz, 1999, 2001; Pirinsky and Wang, 2006).

We obtain a firm's historical headquarter county using the Compustat Snapshot database and webcrawling the firm's 10-Ks filed with the SEC through EDGAR. We require stocks to have an identifiable headquarter county. We exclude penny stocks by requiring a minimum stock price of 5 dollars to be included in the sample. Upon matching stock returns to the county level nowcast differences, we obtain a sample of 7,065 unique firms located in 790 unique counties.

We also form county portfolios. We compute county portfolio returns by taking the market capitalization weighted average over returns of the firms with corporate headquarters located in the same county. To minimize potential measurement errors, we require each county portfolio to have a minimum of 5 stocks. This process yields a sample of 124 county portfolios in an average month.[6]

We use several common stock characteristics that could predict future stock returns according to the prior literature as the control variables in the empirical analyses to predict future returns. These include log of market capitalization from the previous month, book-to-market ratio (book equity/market equity), market beta, asset growth over the prior year, return on assets in the prior year, short term return reversal (past one-month return), one year return momentum (cumulative return on the stock from $t-12$ to $t-2$), and long term return reversal (cumulative return on the stock from $t-36$ to $t-13$).

For the county portfolios, we compute the corresponding characteristics as the market capitalization weighted average of characteristics across firms with corporate headquarters located in the same county.

[6] We use some alternative values for the minimum number of stocks (1 to 10) required in construction the county portfolios. Unsurprisingly, the average number of portfolios decreases as the minimum requirement increases. For example, the average number of county portfolios with a valid nowcast difference in a given month drops from 566 to 89 when the minimum stock number requirement increases from 1 to 10. Nevertheless, different minimum requirements yield qualitatively similar results for stock return predictability.

2.3 Descriptive statistics

Table II presents summary statistics. Panel A presents the mean, standard deviation and autocorrelation for the monthly county level employment growth nowcasts based on the actual and historical average weather, the nowcast differences, and the reported employment growth.[7] Panel A shows that the average nowcast difference is close to zero and is not correlated in time series. In comparison, the nowcasts based on either actual weather or historical average weather have means relatively close to that of reported employment growth. These two nowcasts are less volatile and are more correlated over time than the reported employment growth.

Panel B reports the correlations of the nowcast differences with the reported employment growth, the five weather variables, and the common stock characteristics that could predict future stock returns according to the prior literature. We find that the nowcast differences have low correlation with both the five weather variables and the reported employment growth. More importantly, the nowcast differences have almost no correlation with any common stock characteristic included as control variables. The close to zero correlations may not be surprising as the nowcast differences likely capture the impact of local weather on local payroll employment growth rather than stock specific information. The low correlations suggest that if the nowcast differences can predict future stock returns, it likely contains information about local employment growth that is relevant to the returns of local stocks beyond what common stock characteristics capture. The low correlations also suggest that any return predictability of the nowcast differences, if it exists, is probably unaffected by controlling for these stock characteristics.

[7] Although we would like to include the summary statistics for the survey based employment growth surprise, no such data exists at the county level.

3 Return predictability of the nowcast differences

3.1 Baseline predictability regression

In this section, we examine the relation between the nowcast differences and the future returns of local stocks. Using Fama and MacBeth (1973) regressions, we investigate whether the nowcast differences are related to the cross-sectional variations in the returns of individual stocks and county portfolios while controlling for common stock characteristics that may predict stock returns.

We consider two sets of test assets in our analyses: individual stocks and the county portfolios. We match the county level nowcast differences with one month ahead returns of individual local stocks and county portfolios.

For the Fama-MacBeth regressions, each month we estimate a cross-sectional regression of a test asset's one-month-ahead return on the corresponding nowcast differences. We also control for stock characteristics that are known to predict stock returns. We report the time-series average of coefficient estimates from the cross-sectional regressions along with their time-series t-statistics computed using Newey-West standard errors.

We present the results in Table III. Column 1 shows that the returns of a local stock in the next month are positively related to the nowcast difference in the county of the firm's corporate headquarters at the 1% significance level. The results indicate that the nowcast differences can predict the one month ahead returns of local stocks.

We also find evidence of the ability of the nowcast differences to predict the one month ahead returns of the county portfolios. Column 4 of Table III presents results using the county stock portfolios. The Fama-MacBeth regression coefficient estimates on the nowcast differences are also positive and statistically significant at the 1% level, similar to that for the individual stock level analysis.

In columns 2-3 of Table III, we examine for the individual stock level analysis whether the return predictive power of the nowcast differences is robust to the inclusion of other control variables that the literature has shown return predictive power. In columns 5-6, we do the same for the county portfolio level analysis. In both cases, the return predictive power of the nowcast differences is not affected by these additional control variables. With so many additional variables added, the nowcast differences are still at least significant at the 5% level. In fact, for our sample stock, only the nowcast differences are consistently significant in all the regressions, and the additional control variables may have added noise instead of information. These results are consistent with the low correlation between the nowcast differences and these control variables that we observe in Table II.

Taken together, the results presented in Table III provide supporting evidence that the county level weather induced local employment growth surprises can predict one month ahead stock returns of local firms, both at the individual stocks level and at the county portfolio level. The effect is robust to controlling for common stock characteristics that could predict future stock returns according to the prior literature.

Note that the nowcast differences are the differences between the nowcasts of local employment growth based on the actual and historical average weather. Thus, the source of its return predictability is likely the influence of local weather conditions on local employment conditions, which in turn have a significant impact on the performance of local business. Investors do not seem to fully understand local weather's impact on local employment growth in a timely fashion as the information is not fully absorbed in the stock prices in a timely fashion.

3.2 Horizon of return predictability

In this section, we further investigate whether the nowcast differences have a short or long term impact on local stock returns. Specifically, we examine whether the nowcast differences can predict the stock returns of local firms beyond the one month ahead horizon. Since weather mostly has an important short term impact on local economic activities, we don't expect that the nowcast differences have a long term impact on local stock returns.

This analysis also allows us to investigate whether there is any reversal in the return predictive power of the nowcast differences, which should help differentiate whether the return predictability of the nowcast differences is due to investor underreaction or overreaction. For example, if the return predictive power is due to investor mood, the more positive nowcast differences, i.e., the weather induced local employment growth surprises, should lead to more positive mood and thus greater initial overreactions in stock returns. As the initial overreaction reverses itself gradually, we should expect a negative relation between future stock returns and the nowcast differences as we move beyond the short term return windows. However, if our results for short term return windows are due to investor underreaction, we should not observe any return reversal related to the nowcast differences.

For brevity, for the rest of the paper, we only report the Fama and MacBeth (1973) regression results for which we use log of market capitalization, book-to-market, and market beta as control variables. Controlling for the other variables yields very similar results that are available upon request.

We repeat the analysis in the previous subsection but replace the dependent variable of one month ahead returns by the stock returns of local firms in the next six months, respectively. We find that the return predictive power of the nowcast differences is not long lasting. Table IV shows that the nowcast differences can positively predict up to three month ahead returns of individual local stocks significantly. It can only predict one month ahead returns of county portfolios significantly, probably due to the dramatically smaller sample of county portfolios. Even in this case, the t-statistic for the two month ahead returns of county portfolios is marginally insignificant. Further, none of the t-statistic is significant beyond the first two or three months, and there is no sign of a significant reversal of the initially positive relation.

Overall, we find that the local stock return predictability of the county level weather induced employment growth surprises is not long lasting. The results are consistent with the short term nature of local weather's impact on local employment growth. Further, there do not seem to be a reversal in the return predictive power of the nowcast differences, which suggests that the return predictive power is likely due to the underreaction instead of overreaction of investors.

3.3 Source of the return predictability

In this section, we investigate the source of the return predictive power of the nowcast differences. This investigation helps ensure that the return predictability is indeed local. This investigation also helps establish that the return predictive power is weather related. This investigation further helps ascertain that the return predictive power is due to the process to construct the nowcast differences instead of the model inputs of the process. This section also tries to examine whether some weather variables may have a stronger influence on the future stock returns through their impact on the employment growth surprises.

3.3.1 Source of the return predictability: Geographic distance

In our paper, we measure the nowcast differences according to the actual and historical average weather using the weather station level data from stations located within a 50 mile radius from the county center. The choice of this radius follows strictly Wilson (2019) as in all our other steps to construct the nowcast differences. The strict adhesion to the procedure of Wilson (2019) helps avoid data snooping bias.

In this section, we investigate whether the return predictive power of the nowcast differences varies with the geographic distances that we use to include weather station data. This investigation helps determine whether this is the optimal radius to predict future stock returns, as well as whether the return predictive power of nowcast differences is indeed local.

The choice of the optimal radius faces a tradeoff. A too small radius could potentially lead to an insufficient representation of local weather. Some counties may not have a nearby weather station or a sufficient number of weather stations within the chosen radius. However, a too large radius could lead to inclusion weather data from geographically distant weather stations whose weather data are less relevant to local employment growth of the focal county.

Further, if the return predictive power of the nowcast differences becomes weaker when we include the weather station data further away from the county center, the evidence would further support our hypothesis that its return predictive power is due to the investor underreaction to the impact of local weather surprises on local employment growth.

Table V displays the Fama-MacBeth regressions results when we construct the nowcast differences according to actual and historical average weather using the weather station level data within a 20, 50, 70, or 100 miles radius from the county center. Although we try to mitigate the effect of distance selection by using an inverse distance weighted procedure when we aggregate the weather station level data to the county level, the results in Table V indicate the choice of distance still matters.

In terms of the magnitude of the coefficient estimates for the nowcast differences, it decreases monotonically with the length of the radius from the county center. However, in terms of statistical significance, the nowcast differences have the greatest t-statistics when the radius from the county center is 50 miles.

Our findings support the choice of a radius of 50 miles from the county center in the construction of the county level nowcast difference. Our findings also demonstrate that the effects of local weather on local employment growth are local - weather affects future performance of local firms via the employment channel in a localized manner.

3.3.2 Source of the return predictability: Weather sensitivity

We further investigate whether the return predictive power of the nowcast differences is weather related. Specifically, we examine whether its return predictive power is stronger in industries whose output is more sensitive to weather. Confirming evidence would suggest that its return predictive power is weather related and would provide further support to our hypothesis that its return predictability is due to the investor underreaction to the county level weather induced local employment growth surprises.

Following Wilson (2017), we classify construction, mining and logging, leisure and hospitality, retail trade, and manufacturing as high weather sensitivity industries and the rest of the industries as low weather sensitivity industries. Table VI reports the results. We find that the nowcast differences are positively related to future stock returns significantly for the firms in the high weather sensitivity sample but is not significantly related to future stock returns for the firms in the low weather sensitivity sample. These results suggest that the return predictive power of the nowcast differences is weather related.[8]

3.3.3 Model vs. inputs

Next, we investigate how crucial the process to construct the nowcast differences is for its return predictive power in this section. Specifically, we examine the return predictability of the variables used to construct the nowcast differences, i.e., the five county level weather variables in the panel data regression of equation 1 and the county level reported employment growth. If these variables do not have return predictive power, the information extracted through the construction of the nowcast differences is the likely source of the return predict power of the nowcast differences.

Table VII presents the results. We find that the reported local employment growth or any of the five weather variables has no predictive power for the one month ahead returns of either individual local stocks or county portfolios. In fact, none of their coefficient estimates is statistically significant. In untabulated results, we also find that the predicted employment growth based on actual and average weather, the two variables that we use to obtain the nowcast differences, cannot predict one month ahead returns either.

Overall, our results suggest that the process that Wilson (2019) uses to obtain the nowcast differences extracts local stock return relevant information about the effect of local weather on local labor markets. Further, the source of the return predictability of the nowcast differences is unlikely due to investor mood as the weather variables themselves cannot predict stock returns.

3.4 Relative importance of each weather variable

Although each of the five sets of weather variables that we use to obtain the nowcast differences cannot predict future stock returns, they may exert different influences on the return predictability of the nowcast differences through the process that we create the nowcast differences.

[8]Note that we can only conduct this analysis at the individual stock level, not the county portfolio level, because weather sensitivity is based on industries, not geography.

In this section, we investigate this question. Specifically, we drop one set of weather variables each time in equation 1 and re-estimate equation 1 to generate a new set of nowcast differences. We then examine the return predictive power of the new set of nowcast differences. Table VIII presents the results of Fama-MacBeth regressions. Panels A and B show the results for the individual stock level and the county portfolio level, respectively.

The first row of Table VIII replicates our baseline results in Table III without any exclusion in the estimation of equation 1. The second row of Table VIII presents the results when we exclude the four average daily high temperature variables for the four seasons from the estimation of equation 1. It shows that the nowcast differences become statistically insignificant for both individual stocks and county portfolios. So the average daily high temperature is important to the return predictive power of the nowcast differences.

For the next four rows, we exclude the other four weather variables, respectively, from the estimation of equation 1. Even though the coefficient estimates of the nowcast differences are somewhat smaller in these cases, precipitation, snowfall, and % days high temperature exceeding 90°F do not seem to be very important. The nowcast differences are still significant at the 5% level when we exclude these three variables one by one from the estimation of equation 1, respectively. Excluding % days low temperature below 30F does chip away the significance of the nowcast differences somewhat more, but the nowcast differences are marginal significant statistically for individual stocks and significant at the 10% level for county portfolios in this case.

Thus, while not definitive, the overall results of this analysis suggest that average daily high temperature is the most important weather variable that contributes to the return predictability of the process of creating the nowcast differences. Our results are consistent with the economics literature showing that high temperature has a negative impact on economic growth and agricultural productivity.

Overall, the investigation about the source of the return predictive power of the nowcast differences shows that the return predictive power is due to the process to construct the nowcast differences instead of the model inputs of the process. The investigation also demonstrates that the return predictive power is indeed local related and weather related.

The investigation provides further support to our hypothesis that the return predictive power is due to the investor underreaction to the impact of local weather surprises on local employment growth.

3.5 Performance of the trading strategies based on the nowcast differences

Given the return predictability of the county level weather induced employment growth surprises, we assess the economic significance and potential trading profits of this predictability in this section. It would provide a test of the market efficiency as well.

We adopt the portfolio sorting approach commonly used in the literature. Specifically, we assign the stock universe in our sample in equal numbers into quintile portfolios according to the nowcast differences measured in month t-1. We form portfolios using the stock returns in month t. A firm would be in the lowest quintile portfolio if its nowcast difference in month t-1 is below the 20th percentile. Correspondingly, a firm would be in the highest quintile portfolio if its nowcast difference in month t-1 exceeds the 80th percentile. The other three portfolios use the 40th and 60th percentiles as the breakpoints. We also form a zero investment portfolio that invests in the highest quintile portfolio and sells short the low weather effect portfolio and focus on its returns to measure the potential profits of the trading strategies based on the nowcast differences. The sample period starts in February 2004 and ends in January 2019.

Panel A of Table IX shows the time-series averages of the average monthly returns on the quintile portfolios and the zero investment portfolio. Firms in the bottom quintile portfolio experienced an average return of 0.61% per month during the sample period, whereas firms in the top quintile earn an average monthly return of 0.83%. The 22 basis point difference in average monthly returns on the zero investment portfolio is statistically significant at 5% level.

In addition to the inferences based on the monthly returns on the zero investment portfolio, we also measure its abnormal returns relative to leading factor models including the Fama-French three-factor model (Fama and French, 1993), the Fama-French five-factor model (Fama and French, 2015), and an extended Fama-French five-factor model with the momentum factor (Carhart, 1997). Panel A shows that the alphas are 22, 24, and 24 basis points for these three factor models, respectively. All three alphas are significant at the 5% level.

We also perform portfolio sorting analysis for the county portfolios and report the results in Panels B of Table IX. Note that the number of county portfolios that can be used for portfolio sorting is many fewer compared to that of individual stocks. As a result, we sort the county portfolios into tercile portfolios to ensure a sufficient number of assets within each sorted portfolio.

Panel B of Table IX shows that the average return of the county portfolios in the highest tercile portfolio is 23 basis points per month higher than the average return of the county portfolios in the lowest tercile portfolio. The return difference is significant at the 5% level. The alphas are 27, 28, and 28 basis points for the three factor models, respectively. All three alphas are significant at the 5% level.

In Panels A and B of Table IX, the average returns increase monotonically with the ranks of the sorted portfolios. The magnitude of the potential trading profits on the zero investment portfolio is similar across different factor models and across the two panels.

Overall, the results in this section suggest that the return difference between the firms in the counties with high and low nowcast differences is statistically significant. The results are robust at both the individual stock level and the county portfolio level and for different measures of abnormal returns.

4 Underreaction: Further analysis

In this section, we investigate further whether the return predictability of the nowcast differences is due to investor underreaction. Since less financial transparency may delay the reaction of investors, we examine whether the return predictability of the nowcast differences is stronger among firms with less financial transparency measured as financial reporting quality. We also use analyst earnings forecasts for investor earnings expectation and see if the future earnings surprises are positively correlated with the nowcast differences.

4.1 Financial reporting quality

If investors underreact to the information about future stock returns contained in the nowcast differences, we expect that the underreaction of investors and consequently the relation between the nowcast differences and future stock returns are stronger among firms that have lower financial reporting quality. Firms with lower financial reporting quality are less financially transparent to investors and make the underreaction more severe. To test this prediction, we examine the relation between the nowcast differences and future stock returns in subsamples of stocks with different financial reporting quality.

The literature has often used the earnings reporting quality measure of Leuz, Nanda, and Wysocki (2003) to proxy for financial reporting quality. Following the literature, we assume that firms engaging in more earnings management have lower financial reporting quality, given that these firms exercise more discretion in reporting their earnings to investors. Specifically, we measure the financial reporting quality by the absolute value of a firm's accruals scaled by the absolute value of cash flow from operations in a fiscal year. The lower financial reporting quality makes it harder for investors to timely and fully understand and react to the earnings relevant information.

Table X reports the results for the quintile portfolio analysis when we split our sample into the high, medium, and low levels of financial reporting quality. Similar to Table IX, it reports the returns for the quintile portfolios and the long/short quintile portfolio spreads, as well as the alphas spreads for the different factor models. Results show that for the low financial reporting quality firms, the quintile portfolio spreads and the alphas of different factor models are about 40 basis point per month, with a statistical significance of at least the 5% level. In comparison, those for the medium and high financial reporting quality firms are not statistically significant. The difference between the quintile portfolio spreads and the alphas of different factor models, respectively, between the high and low financial reporting quality firms are also statistically significantly at the 5% level.

These results show that the positive relation between the nowcast differences and future stock returns are particularly strong among firms with lower financial reporting quality. They provide further support that the positive relation between the nowcast differences and future stock returns is due to investor underreaction to the information contained in the nowcast differences about future stock returns.

4.2 Earnings expectations

Our hypothesis implicitly assumes that the return predictability of the nowcast differences comes from the investors' inability to fully incorporate information in the nowcast differences into corporate earnings expectation. Thus, our hypothesis implies that the nowcast differences should be able to predict investor earnings forecast errors.

To test this prediction, we use the earnings forecasts of sell-side analysts for investor earnings expectation. Sell-side analysts invest significant resources to formulate accurate earnings forecasts and have substantial influences over institutional and retail investors (e.g., Li, 2005; Emery and Li, 2009). Their earnings forecasts are widely studied by the academic literature and are often used as investor earnings expectations. Our hypothesis predicts that the nowcast differences are positively related with future earnings surprises as analysts who do not fully incorporate its information about future earnings until future periods.

We measure earnings surprises as the difference between the earnings per share forecasts and the realized earning per share announced by firms in our sample. Specifically, the standardized unexpected earnings ($SUE_{i,t+1}$) for firm i in month $t+1$ is defined as ($EPS^{actual}_{i,t+1}$-$u^{forecast}_{i,t}$)$/\sigma^{forecast}_{i,t}$, where $EPS^{actual}_{i,t+1}$ is the next EPS of firm i announced in month $t+1$, $u^{forecast}_{i,t}$ is the mean of financial analysts' forecast reported in month t, and $\sigma^{forecast}_{i,t}$ is the standard deviation of the forecasts made in month t.

We then run cross-sectional regressions of individual stocks' standardized unexpected earnings in month $t+1$ on the nowcast differences in month t and a number of control variables. Following So (2013), we include the following controls variables: earnings per share when earnings are positive and zero otherwise (E+), a binary variable indicating negative earnings (NEGE), negative and positive accruals per share (ACC-, ACC+), the percentage change in total assets (AG), a binary variable indicating zero dividends (DD), dividends per share (DIV), share price (PRICE), and book to market ratio (BE/ME).

Table XI reports the results. Column 1 shows that the coefficient estimate for the nowcast differences is positive and significant at the 5% level. After adding the control variables in column 2, the magnitude and statistical significance of the coefficient estimate for the nowcast differences are qualitatively the same.

The overall results in this section are consistent with our hypothesis that investors underreact to the information contained in the nowcast differences about future earnings and future stock returns.

5 Conclusion

We document that weather induced local employment growth surprises can predict the cross section of future local stock returns. We find that the county level weather induced employment growth surprises are positively related to the cross section of future local stock returns for up to three months without subsequent reversals. In comparison, neither weather nor reported employment growth, the inputs to obtain the weather induced employment growth surprises, can predict future returns. The return predictability is stronger in more weather sensitive industries, suggesting that it is weather related. The return predictability is also stronger when we use weather station data in a smaller radius from the county center to construct the weather induced employment growth surprises, indicating that it is local related. Lastly, the return predictability is stronger for firms with lower financial reporting transparency whose financial performance is more difficult for investors to discern. The weather induced employment growth surprises are also positively related to future earnings surprises, suggesting that investors have underestimated the impact of the weather induced employment growth surprises on the earnings of local firms. Overall, our results are consistent with the investor underreaction explanation.

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Table I: Weather's economic effects on local payroll employment growth

This table presents coefficient estimates and standard errors of key parameters from estimating the county-level panel data regression to construct the nowcast differences. The dependent variable is the monthly non-seasonally-adjusted nonfarm employment growth at the county-level. The key explanatory variables include the contemporaneous and the 3 lagged values of five county level weather variables. The five county level weather variables include the average daily high temperature, precipitation (mm), snowfall (cm), the fraction of days in a month with the maximum temperature being above 90°F, and the fraction of days with the minimum temperature being below 30°F. We allow the average maximum daily temperature to have differential effect on log employment growth across four seasons (Spring, Summer, Fall and Winter). Monthly fixed effects and a county-specific calendar-month-decade fixed effects are also included. *t*-statistics presented in parentheses are robust to heteroskedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 1980 to April 2018.

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag
Avg. daily high temp - Spring	0.0557***	-0.0424***	-0.087***	0.0003
	(13.37)	(-6.96)	(-8.60)	(0.05)
Avg. daily high temp - Summer	0.0506***	-0.0168***	-0.0113**	-0.0145***
	(6.67)	(-3.76)	(-2.58)	(-3.50)
Avg. daily high temp - Fall	0.0181***	-0.0034	0.0017	0.0122
	(3.48)	(-0.58)	(0.21)	(1.55)
Avg. daily high temp - Winter	0.0907***	-0.396***	-0.0320***	0.0036
	(16.99)	(-6.94)	(-6.21)	(0.67)
Precipitation (mm)	-0.0370***	0.0174***	0.0217***	0.0076***
	(-14.26)	(6.68)	(8.33)	(2.93)
Snowfall (cm)	-0.0102***	0.0036	0.0026	0.0038*
	(-4.52)	(1.59)	(1.13)	(1.68)
% days low temp $<$ 30°F	-0.0798***	-0.0036	0.0364***	0.0282***
	(-8.64)	(-0.38)	(3.87)	(3.06)
% days high temp $>$ 90°F	-0.0182***	-0.0208***	-0.0210***	-0.0084
	(-2.97)	(-3.60)	(-3.43)	(-1.37)
Adj. R^2	0.548			
N	1,254,201			

Table II: Sample statistics and correlations

This table reports summary statistics for the nowcast differences, nowcast variables that we construct to obtain the nowcast differences, and reported employment growth. Panel A presents the key statistics for these variables. Panel B shows the correlation between the nowcast differences with these variables and some stock characteristics. Stock characteristics include log of market capitalization from the previous month, book-to-market ratio, market beta, asset growth, return on asset, short term return reversal (past one-month return), one year return momentum (cumulative return on the stock from $t-12$ to $t-2$), and long term return reversal (cumulative return on the stock from $t-36$ to $t-13$). The sample period is from January 2004 to December 2018.

Panel A: Summary statistics

County-level employment growth variable	Mean	Std. Dev	AR(1)
Nowcast differences	-0.0009	0.0638	-0.0661
Nowcast based on actual weather	0.0407	0.2943	0.5218
Nowcast based on historical average weather	0.0416	0.2824	0.5769
Private nonfarm reported employment growth	0.0591	2.8927	0.1089

Panel B: Correlation table

	Nowcast differences
Reported employment growth	0.0145
Avg. daily high temp	0.1542
Precipitation (mm)	-0.1284
Snowfall (cm)	-0.0931
% days low temp $< 30°$F	0.1002
% days high temp $> 90°$F	-0.0552
Log of market capitalization	0.0000
Book-to-market ratio	-0.0036
Market beta	0.0003
Asset growth	-0.0019
Return on asset	-0.0028
R_{t-1}	-0.0060
$R_{t-2,t-12}$	0.0011
$R_{t-13,t-36}$	0.0002

Table III: The nowcast differences and future stock returns

This table presents results for the Fama-MacBeth regressions that study the impact of the nowcast differences on the cross-section of expected stock returns. We run cross-sectional regressions of the returns of individual stocks and county-level regional portfolios in month t on the nowcast differences in month t–1 every month with and without various control variables. Control variables in month $t-1$ include log of market capitalization, book-to-market ratio, market beta, asset growth, return on asset, short term return reversal (past one-month return), one year return momentum (cumulative return on the stock from $t-12$ to $t-2$), and long term return reversal (cumulative return on the stock from $t-36$ to $t-13$). We report the time-series average of the coefficient estimates and their associated time-series t-statistics computed using Newey-West standard errors (in parentheses). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

	Stocks			County portfolios		
	(1)	(2)	(3)	(4)	(5)	(6)
Nowcast differences	0.0509***	0.0412**	0.0323**	0.0790***	0.0616***	0.0495**
	(2.60)	(2.34)	(2.32)	(2.73)	(2.66)	(2.34)
Log of market capitalization		0.0006*	0.0002		-0.0002	-0.0003
		(1.72)	(0.55)		(-0.41)	(-0.79)
Book-to-market ratio		0.0005*	0.0001		-0.0013	-0.0007
		(1.88)	(0.18)		(-1.62)	(-0.76)
Market beta		-0.0008	-0.0011		-0.0061	-0.0047
		(-0.30)	(-0.51)		(-1.38)	(-1.19)
Asset growth			-0.0012*			-0.0034*
			(-1.88)			(-1.82)
Return on asset			0.0131***			0.0152
			(4.62)			(1.48)
R_{t-1}			0.0030			0.0014
			(0.55)			(0.11)
$R_{t-2,t-12}$			-0.0007			-0.0018*
			(-0.27)			(-0.46)
$R_{t-13,t-36}$			-0.0001			0.0004
			(-0.18)			(0.52)
Intercept	0.0072*	0.0033	0.0059	0.0075**	0.0157***	0.0135***
	(1.76)	(0.80)	(1.51)	(2.02)	(3.04)	(2.76)
Adj. R^2	0.0013	0.0312	0.050511	0.0078	0.0921	0.15989
Average observations	2987	2809	2342	126	122	111

Table IV: The nowcast differences and future stock returns: Longer horizons

This table presents results for the Fama-MacBeth regressions that study the impact of the nowcast differences on the cross-section of expected stock returns up to 6-month ahead. We run cross-sectional regressions of future returns of individual stocks and county-level regional portfolios on the nowcast differences and control variables in month t–1 every month. Control variables include log of market capitalization, book-to-market ratio, and market beta. We report the time-series average of the coefficient estimates and their associated time-series t-statistics computed using Newey-West standard errors (in parentheses). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

Month ahead (j)	Stocks	County portfolios
+1	0.0412**	0.0616***
	(2.34)	(2.66)
+2	0.0267*	0.0385
	(1.84)	(1.64)
+3	0.0324*	-0.0014
	(1.67)	(-0.08)
+4	0.0294	-0.001
	(1.23)	(-0.05)
+5	-0.0211	-0.0125
	(-1.4)	(-0.73)
+6	0.0024	0.0043
	(0.16)	(0.24)

Table V: Radius from county center

This table presents results for the Fama-MacBeth regressions that study how the radius from the county center affects the impact of the nowcast differences on the cross-section of expected stock returns. We construct the nowcast differences using data of weather stations within different radius from the county center. We run cross-sectional regressions of the returns of individual stocks and county-level regional portfolios in month t on the nowcast differences and control variables in month $t-1$ every month. Control variables include log of market capitalization, book-to-market ratio, and market beta. We report the time-series average of the coefficient estimates and their associated time-series t-statistics computed using Newey-West standard errors (in parentheses). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

	Stocks				County portfolios			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Radius $\leq$ 20 miles	0.0663*				0.1042*			
	(1.79)				(1.71)			
Radius $\leq$ 50 miles		0.0412**				0.0616***		
		(2.34)				(2.66)		
Radius $\leq$ 70 miles			0.0316*				0.0457**	
			(1.85)				(2.01)	
Radius $\leq$ 100 miles				0.0266*				0.0367**
				(1.90)				(2.02)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Adj R^2	0.0308	0.0312	0.0310	0.0034	0.0957	0.0921	0.0906	0.0907
Average observations	2753	2809	2809	2809	119	122	122	122

Table VI: Weather sensitivity

This table presents results for the Fama-MacBeth regressions that study nowcast difference's heterogeneous impact on the cross-section of expected stock returns across firms from high and low weather sensitivity industries. High weather sensitivity industries include construction, mining and logging, leisure and hospitality, retail trade, and manufacturing; low weather sensitivity industries include all the other industries. We regress stock returns in month t on the nowcast difference and control variables in month t–1 every month. Control variables include log of market capitalization, book-to-market ratio, and market beta. We report the time-series average of the coefficient estimates and their associated time-series t-statistics computed using Newey-West standard errors (in parentheses). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

	High weather sensitivity	Low weather sensitivity
Nowcast differences	0.0777***	0.0132
	(2.79)	(0.80)
Log of market capitalization	0.0005	0.0007**
	(1.24)	(2.02)
Book-to-market ratio	0.0008	0.0006
	(1.57)	(1.63)
Market beta	-0.001	-0.001
	(-0.34)	(-0.41)
Intercept	0.0044	0.0024
	(0.92)	(0.61)
Adj R^2	0.034	0.0324
Avg obs.	1131	1675

Table VII: Actual weather/employment-growth and future stock returns

This table presents results for the Fama-MacBeth regressions that study the impact of the variables used to construct the nowcast differences on the cross-section of expected stock returns. We consider the reported actual employment growth and the five county-level weather variables: average daily high temperature, precipitation, snowfall, the average fraction of month with high temperature above 90°F and the average fraction of a month with low temperature below 30°F. We run cross-sectional regressions of the returns of individual stocks and county-level regional portfolios in month t on the previous month's value of these variables while controlling for various stock characteristics every month. Control variables in month $t-1$ include log of market capitalization, book-to-market ratio, and market beta. We report the time-series average of the coefficient estimates and their associated time-series t-statistics computed using Newey-West standard errors (in parentheses). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

	Stocks							County portfolios						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Employment growth	0.0001							-0.0007						
	(0.23)							(-0.95)						
Avg. daily high temp		-0.0001					0.0000		0.0000					-0.0001
		(-1.10)					(-0.47)		(-0.50)					(-1.10)
Precipitation			-0.0002				-0.0001			-0.0003				-0.0001
			(-1.60)				(-0.62)			(-1.20)				(-0.44)
Snowfall				0.4476			-0.1757				-2.6992			-3.7379
				(0.40)			(-0.15)				(-1.30)			(-1.50)
% days high temp > 90°F					0.0000		0.0001					-0.0133		-0.0106
					(0.00)		(0.01)					(-0.84)		(-0.74)
% days low temp < 30°F						0.0072	0.0167						-0.0136	0.0211
						(1.14)	(2.13)						(-0.54)	(0.41)
Intercept	0.0034	0.0090	0.0037	0.0034	0.0036	0.0036	0.0078	0.0112	0.0196	0.0159	0.0152	0.0143	0.0161	0.0265
	(0.85)	(1.92)	(0.92)	(0.83)	(0.9)	(0.88)	(1.02)	(1.85)	(3.36)	(3.22)	(3.08)	(2.90)	(3.23)	(2.98)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.0304	0.0311	0.0311	0.0303	0.0310	0.0304	0.0331	0.0983	0.0961	0.0931	0.0892	0.0937	0.0930	0.1080
Average observations	2809	2809	2809	2809	2809	2809	2809	122	122	122	122	122	122	122

Table VIII: Relative importance of each weather variable

This table presents results that study how each county-level weather indicator used in constructing the nowcast differences affect the nowcast differences' impact on the cross-section of expected stock returns. We construct five alternative nowcast differences by omitting one of the five county-level weather variables at a time. The five county-level weather variables include the average daily high temperature, precipitation (mm), snowfall (cm), the fraction of days in a month with the maximum temperature being above 90°, and the fraction of days with the minimum temperature being below 30°. We run cross-sectional regressions of the returns of individual stocks and county-level regional portfolios in month t on each of the alternative nowcast difference and control variables in month $t-1$ every month. Control variables include log of market capitalization, book-to-market ratio, and market beta. We report the time-series average of the coefficient estimates and their associated time-series t-statistics computed using Newey-West standard errors (in parentheses). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

	Stocks						County portfolios					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Excl. none	0.0412**						0.0616***					
	(2.34)						(2.66)					
Excl. Avg. daily high temp		0.000017						-0.0025				
		(0.00)						(-0.36)				
Excl. Precipitation (mm)			0.0327**						0.0462**			
			(2.21)						(2.50)			
Excl. Snowfall (cm)				0.0355**						0.0506**		
				(2.15)						(2.39)		
Excl. % days low temp < 30°F					0.0287						0.0418*	
					(1.60)						(1.77)	
Excl. % days high temp > 90°F						0.0322**						0.0451**
						(2.23)						(2.38)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adj R^2	0.0312	0.0308	0.0310	0.0310	0.0309	0.3101	0.0157	0.0900	0.0902	0.0902	0.0905	0.0904
Observations	2809	2809	2809	2809	2809	2809	122	122	122	122	122	122

Table IX: Subsequent monthly returns of portfolios sorted by the nowcast differences

This table presents the performance of portfolios sorted by the nowcast differences. Test assets used to form these portfolios include individual stocks (Panel A) and county-level regional portfolios (Panel B). Equal-weighted quintile portfolios are formed monthly by assigning stocks (county portfolios) into quintiles (tertiles) based on the local county's nowcast differences. Low (high) corresponds to the quintile (tertile) portfolio of stocks or county portfolios with the lowest (highest) nowcast differences. $R_{High-Low}$ is the time-series-average returns of the zero investment portfolio between the lowest- and highest-ranked quintile (tertile) portfolios, or the quintile (tertile) spread portfolios. α_{FF3}, α_{FF5}, $\alpha_{FF5+Cahart}$ are the estimated alphas from regressing returns of the zero investment portfolios on the Fama-French three-factor model, the Fama-French five-factor model, and the Fama-French five-factor plus Cahart model. Heteroscedasticity-consistent t-statistics measuring the significance of excess returns and alphas are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

Panel A: Excess returns of portfolios formed with individual stocks

	Nowcast differences								
	Low	Q2	Q3	Q4	High	$R_{High-Low}$	α_{FF3}	α_{FF5}	$\alpha_{FF5+Cahart}$
Stocks	0.0061	0.0067	0.0066*	0.0074*	0.0083**	0.0022**	0.0022**	0.0024**	0.0024**
	(1.55)	(1.56)	(1.71)	(1.94)	(2.02)	(2.36)	(2.39)	(2.36)	(2.44)

Panel B: Excess returns of portfolios formed with county-level regional portfolios

	Nowcast differences						
	Low	T2	High	$R_{High-Low}$	α_{FF3}	α_{FF5}	$\alpha_{FF5+Cahart}$
County portfolios	0.0061	0.0072**	0.0084**	0.0023**	0.0027**	0.0028**	0.0028**
	(1.54)	(2.05)	(2.46)	(2.05)	(2.14)	(2.23)	(2.23)

Table X: Subsequent monthly returns of portfolios sorted by the nowcast differences with varying financial reporting quality

This table presents the performance of the equal-weighted portfolios sorted by the nowcast differences over subsets of stocks with common degrees of financial reporting quality. Following Leuz et al. (2003), we proxy for financial reporting quality by measuring the extent to which firms engage in earnings management. Earnings management is measured by the absolute value of a firm's accruals scaled by the absolute value of cash flow from operations. Each month, stocks are first sorted into terciles on degrees of financial reporting quality and then into equal-weighted quintile portfolios formed monthly by assigning stocks into quintiles based on the nowcast differences. Low (high) corresponds to the quintile stocks with the lowest (highest) nowcast differences. $R_{High-Low}$ are returns of the zero investment portfolios, or the quintile spread portfolios, between the lowest- and highest-ranked quintile portfolios. α_{FF3}, α_{FF5}, $\alpha_{FF5+Cahart}$ are the estimated alphas from regressing returns of the zero investment portfolios on the Fama-French three-factor model, the Fama-French five-factor model, and the Fama-French five-factor plus Cahart model. Heteroscedasticity-consistent t-statistics measuring the significance of excess returns and alphas are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

	Nowcast differences								
	Low	Q2	Q3	Q4	High	$R_{High-Low}$	α_{FF3}	α_{FF5}	$\alpha_{FF5+Cahart}$
Low quality	0.0056	0.0063	0.0057	0.0064	0.0096	0.0040**	0.0039**	0.0043**	0.0043**
	(1.22)	(1.21)	(1.17)	(1.36)	(2.04)	(2.58)	(2.63)	(2.43)	(2.43)
Medium quality	0.0085**	0.0096**	0.0082**	0.0098**	0.0098**	0.0013	0.0015	0.0018	0.0020
	(2.15)	(2.36)	(2.11)	(2.56)	(2.46)	(1.13)	(1.30)	(1.40)	(1.63)
High quality	0.0083**	0.0066	0.0076**	0.0090**	0.0084**	0.0001	0.0003	0.0003	0.0004
	(2.26)	(1.55)	(2.00)	(2.39)	(2.33)	(0.12)	(0.25)	(0.24)	(0.26)
High - Low						-0.0038	-0.0036	-0.0040	-0.0040
						(-2.36)	(-2.32)	(-2.40)	(-2.32)

Table XI: The nowcast differences and earnings surprises

This table reports estimated coefficients from the Fama-MacBeth regressions that study the impact of the nowcast differences on the cross-section of corporate earnings surprises. We run cross-sectional regressions of individual stocks' standardized unexpected earnings in month t on the nowcast differences and a number of control variables in month $t-1$. Standardized unexpected earnings ($SUE_{i,t}$) is defined as $(EPS_{i,t}^{actual} - u_{i,t-1}^{forecast})/\sigma_{i,t-1}^{forecast}$, where $EPS_{i,t}^{actual}$ is the EPS of firm i announced in month t, $u_{i,t-1}^{forecast}$ is the mean of financial analysts' forecast reported in month $t-1$, and $\sigma_{i,t-1}^{forecast}$ is the standard deviation of the forecasts made in month $t-1$. Following So (2013), we include the following controls: earnings per share when earnings are positive and zero otherwise (E^+), a binary variable indicating negative earnings ($NEGE$), negative and positive accruals per share (ACC^-, ACC^+), the percentage change in total assets (AG), a binary variable indicating zero dividends (DD), dividends per share (DIV), share price ($PRICE$) and book to market ratio. We report the time-series average of the coefficient estimates and their associated time-series t-statistics computed using Newey-West standard errors (in parentheses). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from January 2004 to December 2018.

	(1)	(2)
Nowcast differences	1.7269**	1.7284**
	(1.98)	(2.08)
E^+		0.021**
		(1.97)
$NEGE$		-0.452***
		(-11.00)
ACC^-		0.0415***
		(4.56)
ACC^+		-0.0087
		(-0.23)
AG		-0.3948***
		(-7.90)
DD		0.1966***
		(4.87)
DIV		-0.1193***
		(-2.80)
$PRICE$		0.0049***
		(9.06)
Book-to-market ratio		-0.2498***
		(-5.50)
Intercept	0.8955***	1.0852***
	(12.60)	(13.80)
Adj. R^2	0.01	0.01
Average observations	2128	1606

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