Clearing the Fog: The Predictive Power of Weather for Employment Reports and their Asset Price Responses

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This paper exploits vast granular data – with over one million county-month observations – to estimate a dynamic panel data model of weather's local employment effects. The fitted county model is then aggregated and used to generate in-sample and rolling out-of-sample ("nowcast") estimates of the weather effect on national monthly employment. These nowcasts, which use only employment and weather data available prior to a given employment report, are significantly predictive not only of the surprise component of employment reports but also of stock and bond market returns on the days of employment reports.

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Weather is often cited by the media, financial analysts, and policymakers as a key factor behind short-run fluctuations in macroeconomic data. The role of weather in explaining such fluctuations has been well-documented.[2] A natural implication is that weather, if measurable in real-time, should be useful in predicting, or "nowcasting," contemporaneous macroeconomic data. Such predictive power obviously would be highly valuable to policymakers trying to discern the underlying strength of economic conditions as well as to financial market participants given the sensitivity of many asset prices to macroeconomic news. Surprisingly, there is little, if any, evidence one way or the other on the predictive power of real-time weather data for macroeconomic surprises and their asset price responses. This paper takes a step toward filling that void. It develops a methodology for using geographically granular real-time data to predict weather's impact on the latest month's national payroll employment growth prior to its release. These weather effect nowcasts have strong predictive power for payroll employment growth surprises – reported employment growth relative to pre-report forecasts – and equity and Treasury bond returns on the days of employment reports.

The first step of the methodology involves estimating a county-level dynamic panel data (DPD) model of monthly employment growth as a function of current and lagged values of temperature, precipitation, and snowfall, following Wilson (2017). The model is estimated using employment data from BLS administrative records and daily NOAA weather-station data aggregated to a monthly frequency. The full data set covers the period January 1980 through August 2016, amounting to over 1.3 million county-month observations, though the nowcasting exercise uses rolling subsamples of these data to simulate real-time predictions.

The combination of high-frequency and finely geographically-disaggregated data used in estimating the county DPD models offers considerable advantages. First, it yields precisely estimated marginal effects of each weather variable. Second, it allows for rich specifications. In particular, one can account for numerous weather variables, for lagged effects (to assess mean reversion and the permanence of weather effects), for heterogeneity in weather effects across key dimensions such as region and season, and for spatial spillovers. The vastness of the data set also allows one to control for high-dimensional fixed effects. Specifically, I include fixed effects for county*calendar-month*decade and time (sample-month) fixed effects. The former control for county-specific seasonal patterns and the latter control for national common factors such as business cycles, oil price shocks, etc.

[2] See Boldin and Wright (2015) and Bloesch & Gourio (2015) regarding nonfarm payroll employment; Lazo, et al. (2011) on GDP; Busse, et al. (2014) on auto sales; and Starr-McCluer (2000) on retail sales.

The estimates from the county DPD model show that contemporaneous local monthly employment growth is increasing in temperature – with the largest effect in the spring – decreasing in precipitation, and decreasing in snowfall. The estimates also indicate that the effects of temperature and snowfall are largely transitory, with near-zero cumulative effects over four months. Precipitation, on the other hand, is estimated to have a negative contemporaneous effect but a positive cumulative effect over four months. I also find negative contemporaneous and cumulative employment effects from the number of very hot days, where the daily high temperature is over 90° Fahrenheit (F) (32.2° Celsius (C)) in the month, holding mean daily high temperature fixed. The number of very cold days, where the daily low temperature is below 30°F (-1.1°C), has negative but insignificant contemporaneous and cumulative effects.

In the next step of the methodology, I use the fitted county DPD model to obtain estimates of weather's employment growth effects for every county in any given month. The fitted model is generated using the full sample (Jan. 1980 – Aug. 2016) for in-sample evaluations, and rolling subsamples for out-of-sample nowcasting evaluations. In the last step, the county-level estimates of weather's employment effect for a given month are aggregated to obtain estimates of weather's national employment effect. Because the national effect could differ from the sum of the local effects if there are spatial spillovers, I estimate and aggregate versions of the county DPD model that include spatial lags of weather, in addition to more parsimonious models without spatial lags.

After applying this methodology to obtain national weather effect estimates, I first evaluate their in-sample and out-of-sample explanatory power for national employment growth. The out-of-sample estimated weather effects are based on a rolling out-of-sample nowcasting exercise, which only uses data that would be available to an analyst prior to the corresponding employment report.[3] Other recent efforts, most notably Boldin and Wright (2015) and Bloesch and Gourio (2014), have sought to similarly estimate the real-time effects of weather on the national payroll employment growth using more aggregate data. However, the empirical models underlying their estimated national effects are much more parsimonious and less precisely estimated than the county DPD model.

I find that these weather effect nowcasts have better out-of-sample explanatory power for national employment growth than do nowcasts from a national time series model. Among the different versions of the county DPD model I consider – a parsimonious version without regional heterogeneity

[3] The data available to an analyst prior to a given reference month's employment report release, which typically occurs on the first Friday after the end of the reference month, are daily weather-station data for the reference month, national employment data through the prior month from the BLS Current Employment Statistics (CES), and county employment data through six to eight months prior from the BLS Quarterly Census of Employment and Wages (QCEW).

in the marginal effect of each weather variable and without spatial lags, a version with regional heterogeneity but without spatial lags, and a version without regional heterogeneity but with spatial lags – the most parsimonious yields the best in-sample and out-of-sample fit. Nonetheless, even the weather effect estimates from the parsimonious model explain a relatively small fraction of the variation in national employment growth. However, I find that these national weather effects have a strong positive association with the *surprise* component of employment data releases, both in-sample and out-of-sample. Surprises are measured by the difference between the real-time reported data and the median survey forecast from market participants prior to the release. In the full sample, the estimated weather effects explain roughly 8% of the variation in the monthly employment growth surprises. More importantly, the weather effect nowcasts, based on a rolling out-of-sample estimation, are strongly predictive of that month's employment release surprise. The nowcasts have a positive and statistically significant effect on the employment surprise and can explain nearly 20% of its monthly time series variation.

Given this finding, I then investigate the predictive power of the weather nowcasts on stock market returns and Treasury yield changes on employment report release days. The nowcasts have surprisingly strong predictive power for both stock market returns and Treasury yields.[4] The estimates from these regressions suggest that asset markets do not fully account for weather's effects on macroeconomic data news.

To illustrative the magnitude of weather's importance for explaining asset price movements on employment report days, I estimate the returns, Sharpe ratios and success rates, for equities and Treasury bonds, from a simple long-short trading strategy based on the sign of the weather effect nowcast. For both stocks and bonds, the weather nowcast correctly predicts the sign of the daily return about 60% of the time. For stocks, the trading strategy yields a Sharpe ratio around 0.7 and a cumulative annualized return (in excess of any investment returns on non-employment report days) of about 2.5%. For Treasury bonds, the results vary by maturity length. The highest Sharpe ratio is 0.8 for 5-year bonds, with a cumulative annualized return of close to 2%.

[4] Most prior work on the relationship between weather and asset prices has focused on the effect of weather on the *mood* of market participants and, in turn, market returns on days of favorable or unfavorable weather. For instance, Saunders (1993), Hirshleifer & Shumway (2003), and Goetzmann, et al. (2014) find that daily stock market returns are significantly affected by the degree of cloudiness on that day in the city in which the stock market exchange is located.

I. Data

A. Employment and Other Outcomes

Data on employment by county, industry, and month are available from the Quarterly Census of Employment and Wages (QCEW).[5] As of the time of this writing, the QCEW data for NAICS industries are available from January 1990 through December 2015. Data for SIC industries is available from January 1975 through December 2000. The QCEW is compiled by the Bureau of Labor Statistics based on state Unemployment Insurance administrative records. Nearly all private nonfarm employers in the U.S. are required to report monthly employment counts and quarterly total wages of their employees to their state's Unemployment Insurance agency. Employment covers "all full- and part-time workers who worked during or received pay (subject to Unemployment Insurance wages) for the pay period which includes the 12th day of the month."[6] Note that this is the same definition of employment used in the payroll survey underlying the monthly national payroll employment report (i.e., the BLS Current Employment Statistics (CES) report).[7]

The CES payroll survey does not cover agriculture, ranching, fishing, and hunting, which are included in the QCEW's all-industry employment total. Thus, to ensure full comparability between the CES and QCEW industry coverage, I construct an alternative QCEW "all-industry" sample that excludes these subsectors (which are a very small fraction of QCEW total employment).

I measure monthly surprises to total nonfarm employment growth by the difference between actual, real-time (as first reported) employment growth and the median forecast of employment growth from a survey of economists and market participants conducted in the few days prior to the employment report. The survey and real-time data, from January 1990 to present, come from Money Market Services (MMS)/Action Economics and have been used previously in event studies of the financial market responses to macroeconomic data releases (see, e.g., Gurkaynak, Sachs, and Swanson 2005).[8] Daily data (close-of-market) data on the Dow-Jones Industrial price index, S&P 500 price index, and Treasury bond yields were pulled from the FAME database.

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[5] http://www.bls.gov/cew/datatoc.htm.
[6] http://www.bls.gov/cew/cewproper.htm.
[7] http://www.bls.gov/web/empsit/cesfaq.htm#qc2.
[8] Unfortunately, the survey did not begin separately asking about *private* nonfarm employment until late 2011. Hence, I use total nonfarm employment here.

B. Weather

I use data on weather by county and month constructed by Wilson (2017) from the Global Historical Climatology Network Daily (GHCN-Daily) data set. The GHCN-Daily is a product of the U.S. National Climatic Data Center (part of the National Oceanic and Atmospheric Administration (NOAA)) and contains daily weather measurements from weather stations throughout the United States and around the world.[9] Using these records from individual weather stations, Wilson (2017) measures county-level weather as follows. First, the surface of the conterminous United States is divided into a 5-mile by 5-mile grid. Second, weather values for each grid point are estimated using inverse-distance-weighted averages of the weather values from weather stations within 50 miles of the grid point. These county-level *daily* weather measures are used to construct the following *monthly* variables: mean daily-high temperature, fraction of days in which the maximum temperature was above 90˚F (32.2°C), fraction of days in which the minimum temperature was below 30˚F (-1.1°C), mean daily precipitation, and mean daily snowfall.

As noted above, both the CES and QCEW aim to measure the number of individuals on employer payrolls as of the pay period containing the 12th of the month. This suggests that using all days of the calendar month may be suboptimal for the objective of nowcasting payroll employment growth. For a given firm, weather during the pay period containing the 12th of the month will matter much more than weather on other days for the employment counts they report to the BLS. Thus, aggregating over firms, the most relevant set of days depends on the distribution of pay period frequencies. The BLS reports that about one-third of businesses pay weekly and nearly 20% pay semimonthly (i.e., pay periods for the first half of the month and second half of the month)(Burgess 2014). Thus, for a little over half of employers, weather on days beyond the 12th is largely irrelevant. Moreover, weekly pay is especially common in the weather-sensitive industries of Construction (71% of employers), Mining (44%), and Manufacturing (51%). Another 37% of businesses pay biweekly, for which weather during the two weeks including the 12th matters most. Only a small share of employers pay monthly, for which all days of the month matter equally.

Given this feature of the employment data, my baseline monthly weather variables are constructed using just the first 12 days of the month, though I also have constructed alternative versions that use the full calendar month and, following Boldin and Wright (2016), versions that use

[9] http://www.ncdc.noaa.gov/oa/climate/ghcn-daily/.

the 30 days ending with the 12th of the month. The results reported in the paper use these baseline variables; results using the alternative measures are available upon request.[10]

II. Dynamic Panel-Data Model for Local Weather Effects

As mentioned earlier, the first step in the methodology for estimating national weather effect estimates entails estimating the effect of weather on monthly employment growth at the local level. To do so, I use the county-level dynamic panel data (DPD) model developed in Wilson (2017). The general regression specification is of the following form:

$$\Delta l_{ct} = \gamma_t + \alpha_{c,m(t),d(t)} + \sum_{k=1}^{K} \sum_{j=1}^{9} \sum_{i=1}^{4} \sum_{\tau=0}^{3} \beta_{ji\tau}^{k} \cdot 1[c \in R_j] \cdot 1[t \in S_i] \cdot w_{c,t-\tau}^{k} + \epsilon_{ct} \quad (1)$$

where Δl_{cst} is the change in log non-seasonally-adjusted private nonfarm employment in county *c* and month *t*. γ_{st} is an industry-specific time (month of sample) fixed effect, which absorbs all national common factors such as business cycles, oil price shocks, foreign economic shocks, monetary policy changes, and federal fiscal or regulatory policy changes. $\alpha_{c,m(t),d(t)}$ is a county-specific calendar-month*decade fixed effect. The inclusion of this fixed effect has the effect of seasonally adjusting employment growth, where seasonal patterns are specific to each county and are allowed to vary by decade.[11]

The $\beta_{ji\tau}^{k}$ are the key parameters to be estimated. They capture the effect of each weather variable (indexed by *k*), by season (*i*) and by region (*j*), on employment growth in the current month and up to three months ahead. $1[c \in R_j]$ is an indicator equal to 1 if county c is in region R_j; $1[t \in S_i]$ is an indicator variable equal to 1 if month *t* is in season S_i; and $w_{t-\tau}^{k}$ is one of K weather variables for the month $t - \tau$. Seasons are defined as follows: Winter = December, January, and February; Spring = March, April, and May; Summer = June, July, and August; and Fall = September, October, and November. The regions are the nine Census Bureau regions. I include five monthly weather variables: average daily precipitation (millimeters), average snowfall (centimeters), average daily high temperature (degrees Fahrenheit), the number of days in which the low temperature is below 30°F (-1.1°C), and the number of days in which the high temperature is above 90°F (32.2°C).

The model is estimated using weighted OLS, where the weights are log county employment. The weighting is done to mitigate the influence of sparsely populated counties. Measurement error in

[10] The county DPD regression results are qualitatively similar using these alternative measures, but their aggregated national weather effect estimates have somewhat lower predictive power for national employment surprises.
[11] The BLS does not provide seasonally-adjusted QCEW data at the county level.

the weather data is likely to be inversely proportional to population given that less populous counties generally have fewer or no weather stations and thus the weather data for these counties relies more heavily on spatial interpolation. In addition, to mitigate the influence of measurement error and outliers in the dependent variable, I winsorize employment growth at the 1st and 99th percentiles (i.e., values below the 1st and above the 99th percentiles are replaced with the 1st and 99th percentile values, respectively).

Without any constraints imposed, the above model contains 720 $\hat{\beta}^k_{ji\tau}$ parameters[12] – too many to be estimated with reasonable precision. To reduce this number while retaining the economically important sources of heterogeneity in weather effects, I impose some realistic constraints. First, note that there is already in equation (1) a constraint imposed by the number of lags included in the model. The model assumes that lags beyond 3 months have no effect, which is supported by a Wald test involving comparing the baseline model to a model with 4 lags. However, there are no constraints imposed on the lag structure within that lag length. This allows for the possibility of permanent (or at least persistent) weather effects and transitory (mean-reverting) weather effects. Second, I consider constraints on season heterogeneity. In particular, temperature seems likely to have different effects in the spring and winter, when warmer days may well boost economic activity, than in the summer, when warmer temperatures may have less positive, or even adverse, effects. Yet, a reasonable (and testable) constraint on the model might be to assume the other weather variables – snow, number of days below 30°F, number of days above 90°F, and precipitation – have approximately the same marginal effects on employment growth throughout the year.[13] Hence, I impose this joint constraint and test the constraint via a Wald test.

A priori, regional heterogeneity in weather effects seems important and it is largely absent from previous studies.[14] Weather is inherently a local phenomenon and its primary economic impacts

[12] 5 weather variables X 9 regions X 4 seasons X 4 lags.

[13] Note that this constraint on marginal effects (β^k) does not preclude these weather variables from having different predicted total effects ($\beta^k w^k_{cst}$) across seasons. For instance, though the effects of one centimeter of snowfall is assumed to be the same in all seasons, snowfall will typically be zero in summer months for most counties and hence will typically have no predicted effect on employment growth in those county-months while its predicted effect in winter months will typically be non-zero due to positive snowfall.

[14] Neither Boldin and Wright (2015) nor Bloesch and Gourio (2015) *explicitly* allow for regional heterogeneity in weather effects, however they do measure aggregate weather based on deviations-from-normal-weather at the city (Boldin and Wright) or state (Bloesch and Gourio) levels. Thus, the underlying assumption is *not* that all places respond the same to an inch of snow or an extra degree of temperature, but that all places respond the same to an inch of snow above *their* average or an extra degree of temperature above *their* average. It should also be noted that Boldin and Wright, in some specifications, include the Regional Snowfall Index (RSI) provided by the National Centers for Environmental Information (NCEI)(see Squires et al. 2014), which incorporates some regional heterogeneity in snowfall effects. The RSI rates snowstorms based on their "societal impact," where the latter is based on the severity of

are felt locally; national average effects may be of limited value. On the other hand, allowing for full regional heterogeneity could lead to overfitting. Hence, I estimate two versions of the DPD model: one version with full regional heterogeneity (RH), as in equation (1), and one version without regional heterogeneity (no-RH) – that is, with each $\hat{\beta}^k_{ji\tau}$ assumed to be equal across regions ($\hat{\beta}^k_{ji\tau} = \hat{\beta}^k_{i\tau}$). The RH model yields 288 $\hat{\beta}^k_{ji\tau}$ parameters while the no-RH model yields 32 $\hat{\beta}^k_{i\tau}$ parameters.

The RH and no-RH models capture the effects of local weather on local employment growth. It is possible that local employment growth is also affected by weather in other places through spatial spillovers of local economic shocks. There are a variety of potential channels for such spillovers, and spillovers can be positive and negative. For instance, a shock that boosts income in one county can positively affect economic activity in nearby counties, especially in non-tradable goods and services, due to cross-border shopping and commuting. On the other hand, such a shock could raise local and nearby-county wages and thus negatively affect labor demand in nearby counties. There's also the possibility that local shocks affect economic activity in faraway places. For example, vacation destinations across the country compete with one another. A negative weather shock in one destination can increase tourism in other destinations. In addition, a shock affecting the local tradable-goods sector can affect final goods prices faced by consumers and intermediate input costs faced by producers in other parts of the country.

If such spillovers exist, national aggregates of the local weather effects derived from the RH and no-RH models may be biased. Hence, I also consider a version of the no-RH model that incorporates spatial lags of each weather variables (and its three time lags). The spatial lag of a variable for a given county is simply a weighted average of that variable in other counties, where the weights measure the spatial linkage between the focal county and each other county. A common approach is to weight by the inverse of the geographic distance between population centroids (from U.S. Census Bureau data). This is the primary approach I follow for the spatial lag models used in the paper. However, I also obtained results from model where the spatial lags are constructed from an equal-weighted average of counties 1,000 or more miles away from the focal county (again based on distance between centroids).

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the storm, its spatial extent, and its nexus with population centers. However, the index only covers storms in the eastern two-thirds of the United States and only covers the subset of storms NCEI considers "major" (roughly 5 per year).

III. Estimated Models of Local Weather Effects

In this section, I briefly present the results from estimating three alternative county DPD models: (1) the model without regional heterogeneity in the marginal effects of weather (no-RH), (2) the model with regional heterogeneity (RH), and (3) the model accounting for potential spatial spillovers of weather in other counties affecting employment growth in the focal county (SL).

Each weather regressor is normalized by its full-sample standard deviation so that the coefficient magnitudes can be compared across the different weather variables. Each coefficient represents the effect on local employment growth of a one standard deviation change in that weather measure.

The coefficients and standard errors from estimating equation (1) for the version of the model without regional heterogeneity are shown in **Table 1**. Recall that the dependent variable is private nonfarm employment growth. The regression uses a balanced panel of 960,372 observations from 3,108 counties. The panel covers 309 months from January 1990 to December 2015.[15] The standard errors are robust to heteroskedasticity and allow for two-way clustering of the residuals. The first cluster group is county. Clustering by county allows for any form of within-county serial correlation. The second cluster group is state*sample-month, which allows for cross-sectional spatial correlation across counties within a state.[16] Allowing for this cross-sectional spatial correlation accounts for both the natural spatial correlation of weather across local areas but also any correlation introduced by the fact that neighboring counties may use data from the same weather station(s) in the process of constructing the weather variables for their county.

The first column of the table shows the estimated coefficients and their standard errors on the contemporaneous values of the weather variables. The second, third, and fourth columns show the coefficients and standard errors for the one-, two-, and three-month lagged values, respectively. The implied four-month cumulative effect is provided in the final column. The estimates indicate that higher temperatures have a positive and statistically significant contemporaneous effect on employment growth in all four seasons. The effects are economically significant as well. For instance, in spring months, a one standard deviation (18.1°F) increase in temperature is associated with 0.07 percentage point higher employment growth in the same month. Note that average monthly

[15] The results are similar using a longer sample from January 1980 to December 2015. I present results here using the 1990+ sample so that (1) the all-industry results can be compared to the industry-specific results and (2) the results without damages included in the model can be compared to those with damages included. Employment data by NAICS industries and comprehensive data on damages are not available before 1990.

[16] Recall that the regressions are estimated separately by industry, so in effect the cluster groups are really county*industry and state*sample-month*industry.

employment growth in the sample is 0.08 percentage point (see **Table 1**), so this spring temperature effect represents a near doubling relative to baseline employment growth.[17] The contemporaneous effect of temperature is largest in the spring and smallest in the fall. Precipitation and snowfall have modest negative contemporaneous effects; both are significant at below the 1% level. The percentage of days in the month in which the high temperature exceeded 90°F and the percentage of days in which the low temperature fell below 30°F, holding constant the average daily high temperature over the month, each have negative point estimates, though only the former is statistically significant.

The lagged effects tend to be of opposite sign to the contemporaneous effect and largest for the first two lags.[18] Over the course of four months, the implied cumulative effect is close to zero and statistically insignificant for average daily-high temperature. Precipitation has a negative contemporaneous effect but positive cumulative effect, while snowfall has an insignificant cumulative effect. The number of days above 90°F has a negative effect on employment growth in the current month and up to 3 months later, leading to a sizable negative cumulative effect. Though it is difficult to know the mechanisms underlying such effects, one possible explanation for this last effect is that very hot days increase business operating costs (e.g., air conditioning) which, if persistent over several months, can significantly dampen employment growth.

Due to the very large number of weather effect parameters (288, not counting implied cumulative effects), estimates of the model with regional heterogeneity are not shown here. The results are similar to those presented in detail in Wilson (2017), which uses the same empirical model and data except that the sample period is shorter (Jan. 1990 instead of Jan. 1980). The positive and significant contemporaneous temperature effects, especially in the spring, shown in **Table 1** are found to be broad-based across regions, though they tend to be largest in the Pacific region. The contemporaneous effect of the number of very hot days, which is negative, also is found to be largest in the Pacific region. The contemporaneous effect of precipitation is fairly broad-based, though the effect is largest in New England and the East North Central and the East South Central regions. Lastly, snowfall's negative effect appears to be most pronounced in the South Atlantic and East South Central, two of the three regions with the lowest average snowfall. Consistent with the findings from the no-RH model, the cumulative effects of weather are generally close to zero in all regions, with

[17] Note that monthly employment growth of 0.133 percentage points (p.p.) is equivalent to 1.6p.p. at an annual rate.
[18] This result is consistent with Bloesch and Gourio (2015), who estimate a state-level DPD model for winter employment growth and similarly find that, first, temperature has a positive contemporaneous effect but negative lagged effects and, second, that snowfall has a negative contemporaneous effect but positive lagged effects. His model does not include overall precipitation.

some exceptions. Notable exceptions are that higher temperatures in New England have persistent negative effects on employment growth in both the summer and the winter, and higher temperatures in the Pacific region have persistent positive effects on spring employment growth. Precipitation also has a cumulative negative effect in New England. The number of very cold days has negative cumulative effects in a few regions, especially in New England, the East North Central, and the Mountain region. Lastly, I find that the number of very hot days has negative cumulative effects in several regions and especially in the Pacific region (consistent with the negative contemporaneous effect in that region) and the South Atlantic.

The results from estimating a version of the panel data model without regional heterogeneity but with spatial lags (SL) are shown in **Table 2**. For each weather variable (contemporaneous and lagged values) included in the no-RH model (Table 1), the SL model includes that variable plus its spatial lag. The spatial lags here are based on inverse-distance weighting of other counties, where distance is measured between the population centroid of the focal county and each other county. Compared with the results in **Table 1**, the own-county effects are, in general, qualitatively similar but quantitatively smaller and less likely to be statistically significant. For instance, as in **Table 1**, the average daily high temperature has a large positive, but transitory, immediate effect on employment growth in the spring and the winter. Contrary to the results in **Table 1**, however, the own-county effects for temperature in the summer and fall from the SL model are near-zero contemporaneously but negative and significant over a four-month period.

The spatial lag effects – that is the effects of weather in nearby counties – are often large, though estimated somewhat imprecisely, and generally are in the same direction as the own-county effects. In particular, contemporaneous own-county employment growth is boosted when nearby counties experience higher spring and summer temperatures, lower winter temperatures, lower precipitation, and lower snowfall. Spatial lags of temperature in the spring, summer, and fall have positive cumulative effects while the spatial lag of the number of very hot days has a negative cumulative effect. These results potentially suggest that spatial spillovers of weather to nearby places tend to be positive (i.e., in the same direction as own-county effects). However, it is also possible that county level weather contains measurement error and that spatial lags of weather, by averaging weather measurements across nearby counties, provide a less noisy measure of own-county weather (in addition to picking up any spatial spillovers). I am agnostic here as to which interpretation is more

accurate. Either case implies that the SL model, when aggregated, could potentially provide a better in-sample and out-of-sample fit for national employment growth.[19]

IV. Estimating National Weather Effects, Historically and in Real-Time

The county panel models estimated above can potentially be useful in estimating the effects of weather on national economic activity, historically and in real-time. In this section, I show how these estimated county panel models can be used to obtain estimates of the overall weather effect on any given month's employment growth at the county level, which can then be aggregated to the national level. I then use this methodology to estimate national weather effects, and I evaluate the extent to which these weather effects can explain national payroll employment growth as well as employment data surprises and financial market returns on employment release days.

A. Methodology

The first step in obtaining the estimated overall weather effect for a given county and month is to obtain the fitted values of employment growth from estimating the county DPD model (equation (1)):

$$\hat{\Delta} l_{ct}(\mathbf{w_{ct}}) = \hat{\gamma}_t + \hat{\alpha}_{c,m(t),d(t)} + \sum_{k=1}^{K} \sum_{j=1}^{9} \sum_{i=1}^{4} \sum_{\tau=0}^{3} \hat{\beta}_{ji\tau}^{k} \cdot 1[c \in R_j] \cdot 1[t \in S_i] \cdot w_{c,t-\tau}^{k}$$

where $\mathbf{w_{ct}}$ is the vector of weather variables, $w_{c,t-\tau}^{k}$. Thus, $\hat{\Delta} l_{ct}(\mathbf{w_{ct}})$ is predicted local employment growth as a function of national factors (captured by the time fixed effect), seasonal factors (captured by the county*calendar-month*decade fixed effect), and actual weather in the current and past three months.

The second step is to obtain counterfactual estimates of employment growth had weather that month been equal to its historical average for that county, calendar month, and decade: $\hat{\Delta} l_{ct}(\bar{\mathbf{w}}_{\mathbf{c,m(t),d(t)}})$, where $\bar{\mathbf{w}}_{\mathbf{c,m(t),d(t)}}$ is the vector of weather variables where each is set equal to their county*calendar-month*decade mean. The difference between predicted employment growth given actual weather and predicted employment growth given average weather, $\Omega_{ct} = \hat{\Delta} l_{ct}(\mathbf{w_{ct}}) - \hat{\Delta} l_{ct}(\bar{\mathbf{w}}_{\mathbf{c,m(t),d(t)}})$, is an estimate of the overall weather effect for that county and

[19] I also have estimated a version of the SL model replacing the inverse-distance spatial lags with the 1,000-miles-plus distance spatial lags, as mentioned in the previous section. In general, the estimates suggest unfavorable weather in far-away counties tends to boost employment growth at home (see Wilson 2017 for further discussion). This model, however, yields aggregate weather effect estimates with a very weak fit for national payroll employment growth.

month. One can then sum these local growth effects, using employment weights, to get an estimate of the national weather effect on employment growth for a given month:

$$\Omega_t = \sum_c \left(\frac{L_{ct}}{L_t} \right) \Omega_{ct} \,,$$

where $L_t \equiv \sum_c L_{ct}$.

Because weather data is collected and made public by NOAA in nearly real-time – it is released with a one-day lag – such estimates of national weather effects can be produced both historically and concurrently with, or even a few days in advance of, the BLS' monthly release of national payroll employment growth, which leads the release of QCEW data by six to eight months. In other words, national aggregates of the fitted county DPD model can provide both "backcasts" (historical estimates) and "nowcasts" (real-time estimates) of weather's effect on national employment growth.

B. In-Sample and Out-of-Sample Fit for National Employment Growth

Policymakers and others often want to know the effect of weather in a given (typically the latest) month on national employment growth and other macroeconomic outcomes. A common approach is to estimate the historical relationship between weather, measured using national (cross-sectional) averages, and the national outcome in question using a time series regression, and then obtain weather effect estimates using a methodology similar to that described above. The rich heterogeneity of weather effects in the county DPD model and the precision of its estimates based on large degrees of freedom offer the potential of better explaining national weather effects.

However, there are two potential disadvantages. First, the county model is estimated using the QCEW data on employment. While the QCEW, being a census from administrative records rather than a survey, is likely a more accurate measure of employment than that from the CES payroll survey, the QCEW data are released with a several-month lag while the payroll survey's employment data is available in nearly real-time and hence is followed closely by policymakers and the public. Thus, estimates of the national weather effect based on the county DPD model using QCEW data may not be able to explain national CES employment growth as well as a simple national time series model based on CES data.[20] Second, though one can attempt to capture spatial spillover effects via spatial

[20] Note that the historical CES employment levels are annually benchmarked to the QCEW employment levels. However, the two series vary independently within the year. Also, the published CES data are seasonally adjusted using the Census X13 algorithm which is a different technique for seasonal adjustment than that which underlies our county-

lags in the county model, the true nature of spatial spillovers is unobserved. If these spillovers are quantitatively important and not fully captured by any spatial lags included in the county model, then the national effects obtained by aggregating across counties will be mismeasured.

To assess whether the advantages outweigh the disadvantages or vice-versa, I evaluate the in-sample and out-of-sample explanatory power of the national weather effect estimates derived from the county DPD model compared to estimates derived from a national time series model. The latter estimates are based on the same methodology as in the previous subsection – predicted values using actual weather minus predicted values using average weather – but using the following time series regression to obtain the fitted model:

$$\Delta l_t^{CES} = \sum_{k=1}^{K} \sum_{i=1}^{4} \sum_{\tau=0}^{3} \beta_{i\tau}^{k} \cdot 1[t \in S_i] \cdot \tilde{w}_{t-\tau}^{k} + \gamma_i \cdot 1[t \in S_i] + \epsilon_t \qquad (2)$$

where Δl_t^{CES} is *seasonally-adjusted* payroll employment growth from the official BLS Current Employment Situation (CES) series. This is the payroll employment series commonly reported on in the media each month and that is closely tracked by policymakers and the public. The regressor, $\tilde{w}_{t-\tau}^{k}$, for each weather variable *k*, is the national employment-weighted average of the county-level deviation of that variable from its county*calendar-month*decade average. That is, the regressor captures the extent to which weather across the county deviated from local seasonal norms in that month. γ_i is a season fixed effect (see text after equation (1) for season definitions), which is included to account for potential residual seasonality not captured by the BLS seasonal adjustment of employment.

This national model is estimated using the same sample period as that used for the county DPD model, January 1980 to December 2015. The estimated coefficients and standard errors are shown in **Table 3**. The effects of weather implied by the national time series regression are considerably different, and estimated much more imprecisely, than those obtained from the analogous county DPD model without regional heterogeneity (**Table 1**). In fact, none of the contemporaneous weather variables are statistically significant, though several have economically significant coefficients. For instance, the number of days in the month with minimum temperature below 30°F is estimated to have a large negative effect on employment growth, both contemporaneously and cumulatively, though only the cumulative effect is statistically significant.

DPD/QCEW estimates of weather effects. The latter relies on seasonal adjustment within the county DPD regressions via county*calendar-month*decade fixed effects.

In addition to the estimated national weather effects based on the fitted national model shown in **Table 3**, I calculate national weather effects based on three alternative versions of the county DPD model. The first is the county DPD model with regional heterogeneity (RH); the second is the county model without regional heterogeneity (no-RH), as in **Table 1**; and the third is same model but including inverse-distance-based spatial lag terms, as in **Table 2** (SL).

To assess the power of each model's estimated national weather effects for explaining/predicting national payroll employment growth, I regress private nonfarm employment growth (from the CES payroll survey) on that model's national weather-effect series. For in-sample evaluations, the county and national models are estimated using the sample described above, from January 1980 to December 2015.

The results from regressing payroll employment growth on each model's implied weather effects are shown in **Table 4**. Specifically, the table reports the estimated slope coefficient from each of these bivariate time series regressions – i.e., the coefficient on the weather effect – and its standard error, as well as the R^2. In sample, the national model yields the best fit (highest R^2). Moreover, the implied weather effect from that model is highly statistically significant. The full-sample R^2 is considerably lower for the county models, with the county spatial lag model having the worst fit, and their implied weather effects are statistically insignificant. Note that for the national model, this regression is in essence equivalent to the regression in **Table 3**, since that regression uses the same dependent variable and the same sample period, while the regressor in **Table 4** is just the predicted values from the regression in **Table 3**. Hence, the fact that the national model's implied weather effects give the best in-sample fit is not surprising; after all, that model is fitted to minimize the sum of squared errors (via OLS).

The more relevant question is which model yields the best fit *out of sample*. In particular, an analyst or policymaker would like to know which model specification would be most useful for estimating weather's effect on employment growth in the current month, even before that month's employment data is released. In other words, which model is best for "nowcasting"? A model with good out-of-sample/nowcasting properties could be useful to policymakers attempting to gauge the employment implications of weather in the current or most recent month, especially given that the NOAA weather data is released with only a one-day lag.

I construct rolling out-of-sample nowcasts of the national weather effects as follows. For the county models, I estimated the county DPD model iteratively over sample periods in which the first sample month is fixed at January 1980 and the end-month is iterated from May 2003 to December

2015. For each rolling sample, I calculate the implied county-level weather effect for the month eight months past the end-month and aggregate to the national level (as described in subsection A above). Using eight-month out-of-sample estimates mimics the best an analyst could do in real-time given that county-level QCEW data are released (at a quarterly frequency) with a lag of six to eight months. This process yields a time series of national weather effect nowcasts from January 2004 to August 2016.

For the national model, I estimate the model iteratively over sample periods in which the first month is fixed at January 1980 and the end-month is iterated from December 2003 to July 2016. For each rolling sample, I calculate the implied national weather effect for the month following the end-month. Using one-month out-of-sample estimates mimics the best an analyst could do in real-time given that the national CES data are released on the first Friday of the month following the reference month. As with the county-model based estimates, this process yields estimated national weather effects from January 2004 to August 2016.

The second row of **Table 4** shows the nowcasting/out-of-sample results, where actual payroll employment growth is regressed on the nowcasts of weather effects for each model. All three of the county models yield a better out-of-sample fit than the national model. The county models without spatial lags perform considerably better than the spatial lag model. The R^2's for the county models with and without regional heterogeneity are very similar, about 0.03. The weather effects from each of these two county models are statistically significant at below the 5% level.

In sum, the county models, despite being estimated using QCEW employment data instead of CES data and being estimated at the local rather than national level, yield national weather effect estimates with better out-of-sample explanatory power for national CES employment growth than does a national time series model estimated on national CES employment growth data. It is particularly interesting that the county model with no regional heterogeneity, which is exactly the same specification as the national model aside from fixed effects, yields a better out-of-sample fit than the national model. This suggests the advantage afforded by the large degrees of freedom in the county DPD regression outweigh the disadvantage of having to rely on a different employment data source at the local level.

C. Impact of National Weather Effects on Other National Labor Market Outcomes

Above I found that nowcasts of the national weather effect implied by the estimated county DPD model can help predict national payroll employment growth. Here I consider whether these

weather effect nowcasts also help predict other national labor market outcomes. As I did for payroll employment growth in **Table 4**, for each of several national labor market variables I regress the variable on the national weather effect nowcast from the county DPD model or the national model. For this exercise, I use the county DPD model with regional heterogeneity ("RH"); the results are very similar using the model without regional heterogeneity ("no RH").

The results are shown in **Table 5**. The results from **Table 4** for national CES employment growth are repeated in the first row for comparison. The right-most column shows the p-value on the Giacomini-White (GW) test that the mean squared errors of the two forecasts of employment growth are the same. I find that the county DPD model's weather effects have a statistically significant impact on national CES employment growth, national QCEW employment growth, the vacancy rate, the hires rate, and the quits rate.[21] Weather effects from the national model are statistically insignificant in all of these cases. Furthermore, the R^2 is higher using the county DPD model's weather effects in every case, though the GW test fails to reject the null that their predictive power is the same.

I also consider the predictive power of the weather effect nowcasts on payroll employment growth broken out by establishment size class (from national CES data).[22] The results are shown in rows 6-8 of **Table 5**. Interestingly, the county model's nowcast is most powerful at predicting employment growth at small establishments (less than 50 employees), while the national model is best at predicting employment growth at very large establishments (more than 500 employees). It is possible that small establishment employment growth is particularly sensitive to local weather (and insensitive to non-local weather), and hence the local model is particularly good at capturing those effects. Large establishment employment growth, on the other hand, may be less sensitive to local weather and more sensitive to non-local/nationwide weather, and hence the national model is somewhat better at predicting employment growth at large establishments.

Next, as a type of cross-validation exercise, I estimate the relationship between the weather effect nowcasts and the monthly change in the rate of self-reported work absences due to weather from the household survey portion of the employment report. In the household survey (i.e., the Current Population Survey), respondents are asked if they were employed but absent from work during the week containing the 12th of the month. Those that say yes are asked which of the following

[21] Like county level QCEW data, national QCEW data is not seasonally adjusted. For these regressions, I seasonally adjust QCEW employment growth by taking the residual from a regression of raw QCEW employment growth on calendar-month dummies.

[22] Unfortunately, the QCEW data only provide employment by size class for the first quarter of each year, so it is not possible to estimate a county DPD model for local employment growth by size class.

was the reason for the absence: vacation, illness, bad weather, labor dispute, or "other reasons"? The absence rate is the number of respondents reporting an absence divided by total household-survey employment. The penultimate row of **Table 5** shows that the weather effect nowcasts are strongly negatively related to the change in the weather-absences rate. That is, in months in which the nowcasts indicate that recent weather positively (negatively) affected employment growth, the rate of work absences due to bad weather tends to fall (rise). By contrast, the nowcasts from the national model are found to have virtually no correlation with reported work absences due to bad weather.

Lastly, as a falsification test, I evaluate whether the weather effect nowcasts are correlated with the monthly change in the rate of work absences for non-weather reasons. The final row of **Table 5** shows that, as expected, the nowcasts have no significant relationship with non-weather related absences.

The results in **Table 5** are also informative regarding the extent to which the county model's implied national weather effects capture the true effect of weather on national employment growth. That is, they are informative as to how well the county model is able to overcome the two challenges inherent in using county data to estimate national weather effects on CES payroll employment growth: (1) using QCEW data instead of CES data in the model estimation and (2) estimating at the county level and aggregating instead of estimating at the national level. If the model perfectly captured the true weather effect, we would expect a slope coefficient of one when the dependent variable is private nonfarm employment growth.[23] When this is measured using the aggregated QCEW data, we obtain a slope coefficient of 0.942. While this is not statistically significantly different from one, the fact that the point estimate is somewhat below one suggests some modest measurement error is introduced by the county-to-national mapping. When employment growth is measured using the CES data, the slope coefficient falls a bit further, to 0.783. While this is also not statistically significantly different from one, the drop in the point estimate further below one suggests there is some amount of additional measurement error introduced by the mismatch between the QCEW and CES. That mismatch could be due to differences between the two data sources in coverage, employment definition, and seasonal adjustment methods.

[23] Note that even with a slope coefficient of one, we might expect a low R^2. The low R^2 would simply reflect that a small fraction of the variation in employment growth is due to weather.

V. Predictive Power for Employment Report Surprises and Asset Prices

A. Predictive Power for Payroll Employment Report Surprises

While the R^2's for payroll employment growth in **Table 4** from the county-based models are greater than that for the national model, they are still fairly low. Even if one measured the employment growth weather effect perfectly, this R^2 likely would be quite low, indicating that a relatively small fraction of the variation in employment growth is due to weather as opposed to other factors. It is quite possible, however, that these other factors – e.g., strikes, financial conditions, and overall economic conditions – are largely observed and known to policymakers, market participants, and other analysts interested in tracking real-time employment growth (i.e., "nowcasting"). The national weather effect, on the other hand, may not be well observed given that it requires both a rich understanding of weather's local effects and real-time local weather data. In that case, one would expect the weather effect to predict the unanticipated, or "surprise," component of national employment data releases. Moreover, to the extent that the weather effect predicts employment surprises, one might also expect an effect on financial market asset prices on employment report release days given the strong sensitivity of asset prices to employment surprises.

I investigate these conjectures in **Table 6** and **Figure 1**. I measure monthly surprises to total nonfarm employment growth by the difference between actual, real-time (as first reported) employment growth and the median forecast of employment growth from a survey of economists and market participants conducted in the few days prior to the employment report. The survey and real-time data, from January 1990 to present, come from Money Market Services (MMS)/Action Economics and have been used previously in event studies of the financial market responses to macroeconomic data releases (see, e.g., Gurkaynak, Sachs, and Swanson 2005).

I regress employment growth surprises on estimated national weather effects. I consider this relationship both for the weather effect estimates derived from the full-sample county DPD estimation and the weather effect nowcasts derived from the rolling out-of-sample series of estimations (described in **Section IV.B**). The regression results are shown in the top row of each panel in **Table 6**. Panel A shows the results for the full-sample weather effects while Panel B shows the results for the weather effect nowcasts. In addition, these relationships are shown graphically via bin-scatter plots in the top two panels of **Figure 1**.[24] **Table 6** provides results for weather effects estimates based

[24] Each panel in **Figure 1** contains a bin-scatter plot showing the relationship between the indicated outcome variable (*y*-axis) and the national employment weather effect estimate (*x*-axis). Each point shows the mean *x* and *y* values within a bin. Bins are defined according to 30 quantiles of the *x* variable. The shown fit line is based on a linear regression of

on both the county model *without* regional heterogeneity (Columns 1-2) and the model *with* regional heterogeneity (Columns 3-4). The sample period for the employment growth surprise regressions in Panel A covers December 1989 to August 2016. (The MMS survey data necessary for constructing the surprises begins with December 1989.) The sample period for the regression in Panel B is January 2004 (the first month of the nowcasts) to August 2016.

The results in Panel A indicate that the estimated weather effects have a highly significant effect on the surprise component of employment growth, suggesting that, historically, market participants did not, or were unable to, fully account for the local effects of weather when forming their expectations of the latest month's employment growth. The R^2 is above 0.07 for both the no-RH and RH model based estimates, suggesting that weather is a significant, but not a dominant, factor in explaining unanticipated fluctuations in reported employment growth.

Panel B of **Table 6** and the right-hand side of **Figure 1** shows the analogous results based on the nowcasts. Recall that the nowcast of the weather effect for a given month uses only data that would be available to an analyst prior to that month's employment report. These nowcasts are able to explain between 16 and 19 percent of the variation in employment growth surprises. The slope coefficient in the regressions is around 0.5 and is highly statistically significant.

B. Predictive Power for Stock Market Returns and Treasury Bond Yield Changes on Report Days

Given this strong correlation between the estimated weather effects and employment growth surprises, and the well-known sensitivity of asset prices to macroeconomic data surprises, I evaluate the impact of the estimated weather employment effect on the stock market return and Treasury bond yield change on the day of the corresponding employment report release.[25] The asset price changes are calculated from the close of the prior market day to the close of the market day on which the

the outcome variable on the national employment weather effect, using the raw data (not the binned data). Thus, the fit lines match the regression results shown in **Table 6**.

[25] The employment reports are generally the dominant macroeconomic news on their release days. Possible exceptions are the eight observations (3/7/80, 12/5/80, 9/7/90, 12/7/90, 2/1/91, 3/8/91, 12/6/91, and 9/4/92) in which there was an unscheduled FOMC policy announcement made on the same day as the employment report. The full-sample results are virtually unchanged if these observations are dropped. The rolling out-of-sample results are unaffected because these dates are all prior to the rolling out-of-sample evaluation period. It is also possible that employment report releases coincide with other important macroeconomic or financial news. One approach to dealing with this issue would be to use intraday changes in asset prices for narrow windows of time around the employment report. However, intraday Treasury data is only available from June 1991 onward, so this would result in the loss of more than one decade's worth of observations for the full sample regressions.

employment report occurs.[26] For comparison, Column 5 of **Table 6** shows the slope coefficient and standard error from a regression of the indicated dependent variable for that row on the payroll employment growth surprise. Column 5 in Panel A shows that for this December 1989 to August 2016 sample period, employment growth surprises have no clear average effect on stock market returns (on the days of the employment report release) but have a strong positive effect on the Treasury bond yield change on those days. These results are consistent with prior empirical and theoretical research on the effect of macroeconomic data news on stock and bond returns.[27] Positive data news have ambiguous effects on stock returns but unambiguously positive effects on Treasury yields because positive news not only can signal higher future earnings, boosting stock prices today, but can also raise the discount rate, which both lowers current stock prices and raises current Treasury yields.

The full-sample results of regressing the stock market returns and yield changes on the estimated weather effects are shown in the remainder of **Table 6**, Panel A, and the lower three panels on the left side of **Figure 1**. The estimated weather effect has a positive but insignificant association with the S&P 500 index daily return. The impact on the Dow-Jones index return is significant at the 10% level for both county models. The weather effects appear to have a much stronger association with the Treasury bond yield changes, particularly for the medium-length maturities of two, five, and ten years. This mirrors the pattern of the effect of employment surprises themselves on Treasury yields (column 5).

The analogous nowcast results are shown in **Table 6**, Panel B and the right side of **Figure 1**. First, notice that during this sample period (Jan. 2004 – Aug. 2016), employment growth surprises have a strong positive effect on both Treasury yield changes *and* stock market returns on the days of the employment reports. Consistent with that effect, the weather effect nowcasts also have a positive and significant effect on the stock market returns and the change in Treasury bond yields on the days of employment report releases.[28] As with the full-sample, the Treasury yield effects are strongest for maturies between two and ten years. For stock returns, the nowcasts and the employment surprises

[26] The regressions for stock market returns exclude seven observations (four of which are in the rolling out-of-sample window) in which the employment report occurs on a "Good Friday" holiday because the NYSE is closed on those days.

[27] For instance, McQueen and Roley (1993), Boyd et al. (2005), and Andersen et al. (2007) all find that the response of stock prices to macroeconomic news is small on average and varies along the business cycle, with positive responses to "good" macroeconomic news during contractions and negative responses during expansions.

[28] The effect on the 30-year Treasury yield is positive but insignificant. The statistical insignificance may reflect the fact that there are fewer observations for these regressions because new issuances of 30-year Treasury bonds were suspended from late 2001 until February 2006.

themselves explain only a small share of the variation (2-4 percent), consistent with the somewhat ambiguous relationship in the literature between positive macroeconomic data news and stock returns mentioned above. For release-day changes in Treasury yields, though, employment surprises explain close to a third of the variation when looking at medium-term maturities. The weather effect nowcasts explain as much as 6.5% of the variation in yield changes, depending on the maturity.

Another way to assess the explanatory power of the weather effect nowcasts for asset price changes on employment report days is to compare the mean stock market return or Treasury bond yield change over all days to the return or yield change over days when the nowcast is positive and over days when the nowcast is negative. These means are shown in **Table 7**.[29] For all trading days from January 1, 2004 through August 31, 2016, the mean daily stock market return is just 0.02%, according to either index. The mean stock return over just employment report release days is also 0.02%. Yet, on release days in which the weather effect nowcast is positive, the mean stock return is an order of magnitude larger, at 0.26%. When the nowcast is negative, the mean return is of a similar magnitude but negative. A similar story arises looking at Treasury bond yield changes. Treasury yield changes in general tend to be close to zero on average, but across days in which the nowcast is positive the mean yield change is over 2 basis points for maturities above one year. When the nowcast is negative, the mean yield change is around -2 basis points for the 2-year, 5-year, and 10-year bonds and close to -1 basis points for the 1-year and 30-year bonds.

C. Illustration Based on a Simple Weather-Based Trading Strategy

To illustrate the *economic* significance of the predictive power of the weather effect nowcasts for asset prices, I evaluate the performance of a simple trading strategy based on the nowcasts. For simplicity and to compare across asset types, I implement the strategy separately for each asset type: the Dow-Jones Industrial index, the S&P 500 index, and 2-, 5-, 10- and 30-year Treasury bonds. The trading rule is straightforward: when the weather effect nowcast is positive, take a long position in equities or a short position in bonds; when the nowcast is negative, take a short position in equities or a long position in bonds. In other words, if the nowcast indicates employment growth last month was boosted by favorable weather, the strategy calls for buying stocks and selling bonds; if the nowcast indicates employment growth last month was constrained by unfavorable weather, the strategy calls for the opposite. Trades are assumed to be made at the close of the day before the employment report. The trade is unwound, and the balance put into cash, at the end of the day of the

[29] The nowcasts used to generate **Table 7** are based on the county model *with regional heterogeneity*.

report. The balance remains in cash until the day before the next employment report, which implies that the cumulative returns on the strategy can be interpreted as returns in excess of the return from whatever assets the balance is held in on non-report days.

I assume an initial trading balance of 100 in December 2003 and follow the trading rule from January 2004 to August 2016. The weather effect nowcasts are the rolling out-of-sample estimates based on the county model with regional heterogeneity (RH). The panels of **Figure 2** show the evolution of the balance from following this trading strategy for each asset type. The panels also provide the cumulative annualized return, the annualized Sharpe ratio, and the success rate over the period, where the success rate is defined as the percentage of trades yielding a positive daily return.[30][31] The success rates range from 59% to 63% across the asset types. For the stock market indices, the strategy would have earned a roughly 2.9% cumulative annualized return with a Sharpe ratio of about 0.8. For Treasury bonds, the cumulative annualized return increases with the maturity of the bond, ranging from 0.49% for 2-year bonds to 5.78% for 30-year bonds.[32] However, the standard deviation of the returns across the employment report days also increases with the maturity, so the Sharpe ratio is fairly stable across maturities, ranging from 0.78 to 0.95.

VI. Conclusion

Recent research has shown that weather has important short-run effects on economic activity, particularly employment growth, at the local level. This paper asks whether estimates of local weather effects, when aggregated to the national level, can be useful in explaining and predicting movements in aggregate payroll employment as well as asset price responses to payroll employment releases. Using a county-level dynamic panel data (DPD) model and monthly data from January 1980 to

[30] The return on a long position in Treasury bonds of maturity *M* on day *d* is calculated as: $-M(r_d - r_{d-1})$, where *r* is the yield on the bond at the close of day. The return on the short position is simply $M(r_d - r_{d-1})$. This expression comes from the relation between the price (p_d) of a zero-coupon bond to its face value (*F*), time to maturity (*M*), and yield to maturity (r_d): $p_d = F(1 + r_d)^{-M}$. The rate of return is then approximately:

$$log\frac{p_d}{p_{d-1}} = log\left[\frac{(1+r_d)}{(1+r_{d-1})}\right]^{-M} \approx -M(r_d - r_{d-1}).$$

[31] Because there are 12 employment reports a year, the annualized Sharpe ratio is calculated as the $\sqrt{12}$ times the mean return per report day divided by its standard deviation. The same formula, but with $\sqrt{8}$, is used in Lucca and Moensch (2015) for computing the annualized Sharpe ratio for returns on pre-FOMC announcement days, which occur 8 times a year.

[32] Note, however, that the performance of the strategy applied to 30-year bonds is not completely comparable to that for the other asset types because the sample periods differ; 30-year Treasury bonds were not issued between February 2002 and January 2006.

December 2015, I estimated the effects of temperature (by season), precipitation, snowfall, the frequency of very hot days, the frequency of very cold days, and storm property damages on private nonfarm employment growth. I then demonstrated how this county DPD model can be used to obtain local weather effects estimates that can be aggregated to the national level. Following this approach in a rolling out-of-sample nowcasting exercise, I found that the monthly national weather effect nowcasts have better explanatory power for the BLS's national payroll employment series than do nowcasts based on a national time series model fitted on that same employment growth data. In addition, the county DPD model's weather effect nowcasts were found to be useful in predicting other national labor market outcomes such as the vacancy rate, hires rate, and quits rate.

Lastly, I showed that these estimated weather effect nowcasts are predictive of the unanticipated, or surprise, component of real-time employment releases, explaining as much as 19% of their time-series variation. These nowcasts, in turn, were found to have predictive power for stock market returns and Treasury yield changes on employment report release days. A simple trading strategy based on the weather effect nowcasts was shown to yield a Sharpe ratio for equities of about 0.8 and for Treasuries bonds of about 1.0.

These are striking results. They suggest that financial markets do not, or are unable to, fully account for the effects of recent months' weather on current month's economic activity. This is likely due to some combination of the difficulty and complexities involved with processing the NOAA weather station data, processing the BLS QCEW county-level employment data, deriving a sufficiently rich empirical specification of weather's local employment effects, and properly estimating this specification. In particular, one can imagine market participants having fairly good information about average weather (temperature, snowfall, precipitation, etc.) across the country in a given month. However, understanding the geographic distribution of these weather data and how they correlate with the geographic distribution of employment may be more elusive. In addition, knowing how weather in prior months should affect current employment growth is difficult and arguably requires a precisely estimated empirical model. The vast geographical granularity and high frequency of the data employed in this paper allow for such precise estimation.

References

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold and Clara Vega. 2007. "Real-time price discovery in global stock, bond and foreign exchange markets." *Journal of International Economics* 73, pp. 251-77.

Bloesch, Justin and Francois Gourio. 2015. "The Effect of Winter Weather on U.S. Economic Activity." *Federal Reserve Bank of Chicago Economic Perspectives*.

Boldin, Michael, and Jonathan H. Wright. Fall 2015. "Weather adjusting economic data." *Brookings Papers on Economic Activity*.

Boyd, John H., Jian Hu and Ravi Jagannathan. 2005. "The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks," *Journal of Finance*, 60 (2), pp. 649-72.

Burgess, Matt. "How frequently do private businesses pay workers?" Beyond The Numbers, Bureau of Labor Statistics, May 2014, Vol. 3 (11). Url: http://www.bls.gov/opub/btn/volume-3/how-frequently-do-private-businesses-pay-workers.htm

Busse, Meghan R., Devin G. Pope, Jaren C. Pope, and Jorge Silva-Risso. 2015. "The Psychological Effect of Weather on Car Purchases." *Quarterly Journal of Economics*, pp. 371-414.

Goetzmann, William N., Dasol Kim, Alok Kumar, Qin Wang. "Weather-Induced Mood, Institutional Investors, and Stock Returns." *Review of Financial Studies* 28(1), pp. 73-111.

Gurkaynak, Refet S., Brian Sack, and Eric Swanson. "The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models." *American Economic Review* 95(1): 425-36.

Hirshleifer, David, and Tyler Shumway. 2003 "Good Day Sunshine: Stock Returns and the Weather." *Journal of Finance* 58(3): 1009-32.

Lazo, Jeffrey K., Megan Lawson, Peter H. Larsen, and Donald M. Waldman. (2011). "U.S. Economic Sensitivity to Weather Variability," *Bulletin of the American Meteorological Society*, June 2011, pp. 709-720.

Lucca, David O., and Emanuel Moensch. (2015). "The Pre-FOMC Announcement Drift," *Journal of Finance*, 70(1), pp. 329-71.

McQueen, Grant, and V. Vance Roley. 1993. "Stock Prices, News, and Business Conditions." *Review of Financial Studies*, 6(3), pp. 683-707.

Saunders, Edward M., Jr. 1993. "Stock Prices and Wall Street Weather." *American Economic Review*, 83(5), pp. 1337-45.

Squires, Michael F., Jay H. Lawrimore, Richard R. Heim, David A. Robinson, Mathieu R. Gerbush, Thomas W. Estilow, and Leejah Ross. (2014). "The Regional Snowfall Index," *Bulletin of the American Meteorological Society*, 95, 1835-1848.

Starr-McCluer, Martha. 2000. "The Effects of Weather on Retail Sales." Mimeo, Federal Reserve Board of Governors.

Table 1. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: All Private Industries

	(1)	(2)	(3)	(4)	(5)
	Contemporaneous	1st lag	2nd lag	3rd lag	Cumulative effect
Avg. daily high temp - Spring	0.071***	-0.058***	-0.025***	0.008	-0.004
	(0.007)	(0.007)	(0.006)	(0.007)	(0.011)
Avg. daily high temp - Summer	0.059***	-0.044***	-0.015**	-0.011	-0.012
	(0.010)	(0.008)	(0.007)	(0.007)	(0.014)
Avg. daily high temp - Fall	0.019**	-0.010	-0.026***	0.014	-0.003
	(0.008)	(0.009)	(0.010)	(0.010)	(0.016)
Avg. daily high temp - Winter	0.058***	-0.015*	-0.006	-0.018*	0.018
	(0.008)	(0.008)	(0.009)	(0.010)	(0.016)
Precipitation (mm)	-0.021***	0.023***	0.005*	0.010***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Snowfall (cm)	-0.033***	0.021***	0.006*	-0.002	-0.008
	(0.004)	(0.004)	(0.003)	(0.003)	(0.006)
% days high temp >90F	-0.023***	-0.006	-0.012*	-0.008	-0.049***
	(0.007)	(0.007)	(0.006)	(0.007)	(0.012)
% days low temp <30F	-0.011	-0.009	-0.004	0.003	-0.021
	(0.010)	(0.010)	(0.009)	(0.009)	(0.017)
N	1329900				
Counties	3100				
Months	429				
R2	0.553				

***p<0.01, **p<0.05, *p<0.10

Table 2: Model Including Spatial Lags (Inverse-Distance)

Panel A: Own-County Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.027**	-0.053***	-0.011	-0.003	-0.041**
	(0.012)	(0.012)	(0.011)	(0.011)	(0.019)
Avg. daily high temp - Summer	0.006	-0.041***	-0.034**	-0.004	-0.073***
	(0.016)	(0.014)	(0.013)	(0.012)	(0.023)
Avg. daily high temp - Fall	0.017	-0.030**	-0.041**	-0.008	-0.062**
	(0.015)	(0.015)	(0.017)	(0.016)	(0.025)
Avg. daily high temp - Winter	0.072***	-0.025*	-0.026*	0.013	0.033
	(0.014)	(0.014)	(0.016)	(0.016)	(0.025)
Precipitation (mm)	-0.006	0.009**	0.004	0.005	0.013*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Snowfall (cm)	0.001	-0.005	-0.005	-0.002	-0.010
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
% days high temp >90F	-0.021***	0.006	0.006	-0.008	-0.016
	(0.008)	(0.008)	(0.008)	(0.008)	(0.013)
% days low temp <30F	-0.016	0.002	-0.020*	0.007	-0.027
	(0.012)	(0.012)	(0.012)	(0.012)	(0.021)

Panel B: Spatial Lag Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.097**	0.025	-0.004	0.027	0.145**
	(0.038)	(0.035)	(0.035)	(0.036)	(0.059)
Avg. daily high temp - Summer	0.175***	0.009	0.076*	-0.024	0.236***
	(0.054)	(0.045)	(0.039)	(0.036)	(0.073)
Avg. daily high temp - Fall	-0.003	0.082*	0.101*	0.081	0.262***
	(0.043)	(0.046)	(0.057)	(0.056)	(0.085)
Avg. daily high temp - Winter	-0.106***	0.078*	0.082*	-0.098**	-0.043
	(0.040)	(0.042)	(0.044)	(0.045)	(0.081)
Precipitation (mm)	-0.039***	0.035***	0.003	0.012	0.011
	(0.009)	(0.010)	(0.010)	(0.009)	(0.017)
Snowfall (cm)	-0.148***	0.113***	0.047***	-0.000	0.011
	(0.016)	(0.015)	(0.013)	(0.013)	(0.025)
% days high temp >90F	-0.005	-0.043	-0.082***	0.001	-0.129***
	(0.029)	(0.029)	(0.030)	(0.030)	(0.048)
% days low temp <30F	0.040	-0.023	0.074	-0.035	0.055
	(0.055)	(0.052)	(0.052)	(0.052)	(0.092)
N	1329900				
Counties	3100				
Months	429				
R2	0.553				

***p<0.01, **p<0.05, *p<0.10

Table 3. Contemporaneous and Lagged Weather Effects on Nonfarm Payrolls

National Time Series Model

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.008	-0.004	-0.034	-0.050	-0.080
	(0.063)	(0.062)	(0.057)	(0.052)	(0.105)
Avg. daily high temp - Summer	0.079	-0.048	-0.087	-0.046	-0.101
	(0.131)	(0.088)	(0.071)	(0.062)	(0.167)
Avg. daily high temp - Fall	-0.065	0.079	-0.073	-0.074	-0.133
	(0.066)	(0.086)	(0.127)	(0.131)	(0.186)
Avg. daily high temp - Winter	-0.008	-0.017	-0.115*	-0.045	-0.185*
	(0.055)	(0.059)	(0.062)	(0.068)	(0.103)
Precipitation (mm)	-0.056	0.047	-0.046	-0.024	-0.079
	(0.049)	(0.049)	(0.050)	(0.051)	(0.102)
Snowfall (cm)	0.011	0.061	0.123**	0.070	0.265**
	(0.059)	(0.058)	(0.059)	(0.058)	(0.106)
% days high temp >90F	-0.012	0.058	0.169	0.087	0.301
	(0.119)	(0.098)	(0.116)	(0.118)	(0.203)
% days low temp <30F	-0.200	-0.152	-0.356**	-0.295**	-1.003***
	(0.148)	(0.155)	(0.154)	(0.148)	(0.296)
N	429				
R2	0.277				
RMSE	0.220				

***p<0.01, **p<0.05, *p<0.10

Table 4. In-Sample and Out-of-Sample Explanatory Power of Weather Effects for National Payroll Employment Growth

	County Model RH	R2	County Model no RH	R2	County Model SL	R2	National Model	R2
Full Sample	0.340	0.005	0.286	0.004	0.089	0.003	1.000***	0.089
	(0.241)		(0.218)		(0.081)		(0.155)	
Out of Sample	0.783**	0.029	0.724**	0.032	0.179	0.016	0.176	0.007
	(0.370)		(0.325)		(0.114)		(0.171)	

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Employment Growth is private nonfarm employment growth from the BLS CES payroll survey. For the full sample results, both the model estimation and fit evaluation use data from 1980m1 to 2015m12. For the Out-of-Sample results, models are estimated iteratively with first month fixed at 1980m1 and last month iterated from 2003m5 to 2015m12 for county models and from 2003m12 to 2016m7 for national model. The fitted models are then used to predict weather effects 8 months out of sample for county models (inline with the 8 month QCEW data lag) and 1 month out of sample for national model (inline with the 1 month CES data lag). County weather effects are then aggregated to national level. This process results in a time series, for each model, of out-of-sample national weather effect estimates from 2004m1 to 2016m8. The table shows the slope coefficient, standard error (in parentheses), and R^2 from bivariate regressions of each model's national weather effect estimates on payroll employment growth from 2004m1 to 2016m8. See text for further details.

Table 5. Out-of-Sample Explanatory Power of Weather Effects for Various National Labor Market Outcomes

	County Model (RH)	R2	National Model	R2	GW test
Employment Growth, Private Nonfarm, Payroll Survey	0.783**	0.029	0.176	0.007	0.298
	(0.370)		(0.171)		
Employment Growth, Private Nonfarm, QCEW (SA)	0.942**	0.026	0.161	0.004	0.356
	(0.466)		(0.216)		
Vacancy Rate (monthly change)	0.835***	0.046	0.085	0.002	0.101
	(0.312)		(0.146)		
Hires Rate (monthly change)	0.843***	0.065	-0.084	0.003	0.174
	(0.261)		(0.123)		
Quits Rate (monthly change)	0.355*	0.024	-0.065	0.004	0.471
	(0.183)		(0.085)		
Employment Growth, less than 50 employees	0.885*	0.041	0.328	0.015	0.575
	(0.494)		(0.288)		
Employment Growth, 50 to 499 employees	0.788	0.019	0.477	0.020	0.981
	(0.627)		(0.360)		
Employment Growth, 500 or more employees	0.556	0.020	0.488*	0.032	0.798
	(0.510)		(0.292)		
Weather Absences Rate (monthly change)	-0.683***	0.095	0.132	0.017	0.150
	(0.172)		(0.082)		
Non-weather Absences Rate (monthly change)	0.851	0.001	-1.346	0.012	0.543
	(2.312)		(1.017)		

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Standard errors in parentheses. Model is estimated iteratively with first month fixed at 1980m1 and last month iterated from 2003m5 to 2015m12 for county models and from 2003m12 to 2016m7 for national model. The fitted models are then used to predict weather effects 8 months out of sample for county models (inline with the 8 month QCEW data lag) and 1 month out of sample for national model (inline with the 1 month CES data lag). County weather effects are then aggregated to national level. This process results in a time series, for each model, of out-of-sample national weather effect estimates from 2004m1 to 2016m8. The table shows the slope coefficient, standard error (in parentheses), and R^2 from separate bivariate regressions of each model's national weather effect estimates on each of the indicated variables from 2004m1 to 2016m8. See text for further details.

Table 6: Weather Effect and Financial Markets on Employment Report Release Days

Panel A: Full Sample

	(1) County no RH	(2) R^2	(3) County RH	(4) R^2	(5) Payroll surprise	(6) R^2	(7) N
Real-Time Surprise in Payroll Employment Growth	0.434***	0.071	0.494***	0.076			321
	(0.088)		(0.097)				
S&P 500 daily return	2.108	0.007	1.968	0.005	-0.338	0.001	314
	(1.383)		(1.532)		(0.825)		
Dow Jones Ind. Avg daily return	2.511*	0.012	2.503*	0.01	0.635	0.002	314
	(1.297)		(1.437)		(0.775)		
3-month Treasury Bond daily change	0.226***	0.04	0.242***	0.038	0.321***	0.216	321
	(0.062)		(0.068)		(0.034)		
1-year Treasury Bond daily change	0.36***	0.054	0.415***	0.059	0.581***	0.372	321
	(0.085)		(0.093)		(0.042)		
2-year Treasury Bond daily change	0.468***	0.057	0.55***	0.065	0.71***	0.349	321
	(0.106)		(0.117)		(0.054)		
5-year Treasury Bond daily change	0.492***	0.056	0.588***	0.066	0.681***	0.285	321
	(0.113)		(0.124)		(0.06)		
10-year Treasury Bond daily change	0.419***	0.053	0.497***	0.061	0.536***	0.229	321
	(0.099)		(0.109)		(0.055)		
30-year Treasury Bond daily change	0.373***	0.058	0.432***	0.063	0.386***	0.173	273
	(0.091)		(0.101)		(0.051)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Rolling Out-of-Sample

	(1) County no RH	(2) R^2	(3) County RH	(4) R^2	(5) Payroll surprise	(6) R^2	(7) N
Real-Time Surprise in Payroll Employment Growth	0.472***	0.159	0.504***	0.19			152
	(0.089)		(0.085)				
S&P 500 daily return	4.237**	0.026	4.189**	0.028	3.432*	0.025	148
	(2.141)		(2.053)		(1.761)		
Dow Jones Ind. Avg daily return	4.313**	0.031	4.2**	0.032	3.937**	0.039	148
	(1.984)		(1.904)		(1.625)		
3-month Treasury Bond daily change	-0.004	0	0.019	0.001	0.104*	0.023	152
	(0.066)		(0.064)		(0.055)		
1-year Treasury Bond daily change	0.081	0.006	0.15*	0.02	0.483***	0.283	152
	(0.088)		(0.085)		(0.063)		
2-year Treasury Bond daily change	0.353**	0.04	0.403***	0.055	0.817***	0.302	152
	(0.141)		(0.136)		(0.101)		
5-year Treasury Bond daily change	0.496***	0.056	0.517***	0.064	0.982***	0.311	152
	(0.166)		(0.161)		(0.119)		
10-year Treasury Bond daily change	0.44***	0.057	0.455***	0.065	0.812***	0.274	152
	(0.146)		(0.142)		(0.108)		
30-year Treasury Bond daily change	0.39***	0.057	0.401***	0.063	0.62***	0.19	127
	(0.142)		(0.139)		(0.115)		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: In Panel A, the county model is estimated over 1980m1 to 2015m12. County weather effects are obtained from the fitted model and aggregated to the national level. The regressions in Panel A use a sample from 1989m12 (the earliest month of the payroll surprise data) to 2016m8. In Panel B, each model (county DPD model with or without regional heterogeneity) is estimated iteratively with first month fixed at 1980m1 and last month iterated from 2003m5 to 2015m12. The fitted models are then used to predict weather effects 8 months out of sample (inline with the 8 month QCEW data lag). County weather effects are then aggregated to national level. This process results in a time series, for each model, of national weather effect estimates from 2004m1 to 2016m8. The table shows the slope coefficient, standard error (in parentheses), and R^2 from separate bivariate regressions of each model's national weather effect estimates on each of the indicated variables from 2004m1 to 2016m8.The financial market variables are changes (or returns) from the market close of the prior day to the market close of the day of the employment report. See text for further details.

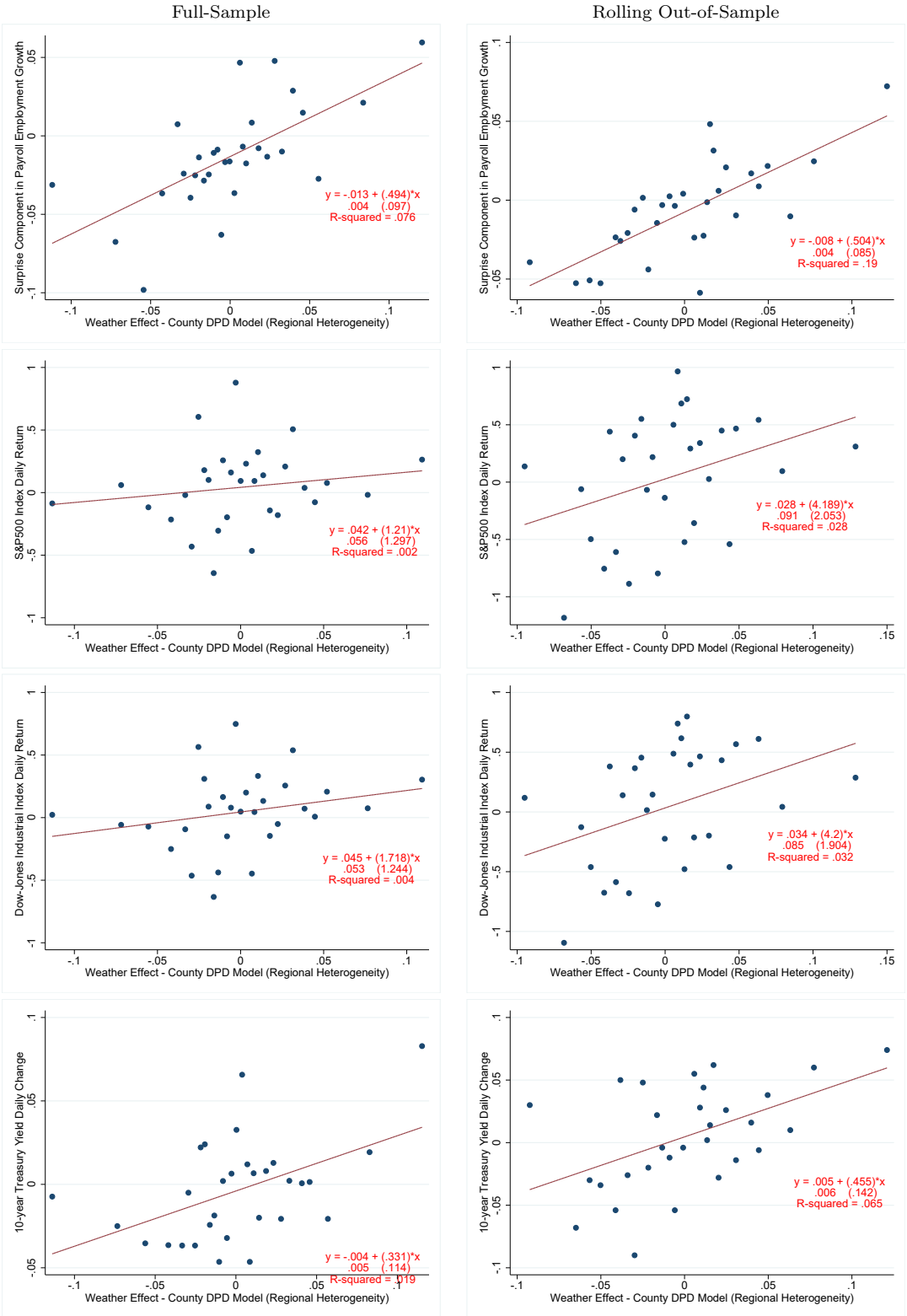
Table 7. Mean Daily Stock Returns and Treasury Yield Changes

Various Subsamples

	All Days (1/1/2004 to 8/31/2016)	All Release Days	Release Days, Nowcast >0	Release Days, Nowcast <0
Dow Jones (%)	0.02	0.02	0.26	-0.21
S&P 500 (%)	0.02	0.02	0.26	-0.22
1-yr Treasury (bps)	-0.01	-0.03	0.76	-0.74
2-yr Treasury (bps)	-0.02	0.26	2.38	-1.68
5-yr Treasury (bps)	-0.04	0.17	2.70	-2.15
10-yr Treasury (bps)	-0.06	0.32	2.52	-1.68
30-yr Treasury (bps)	-0.05	0.81	2.30	-0.83

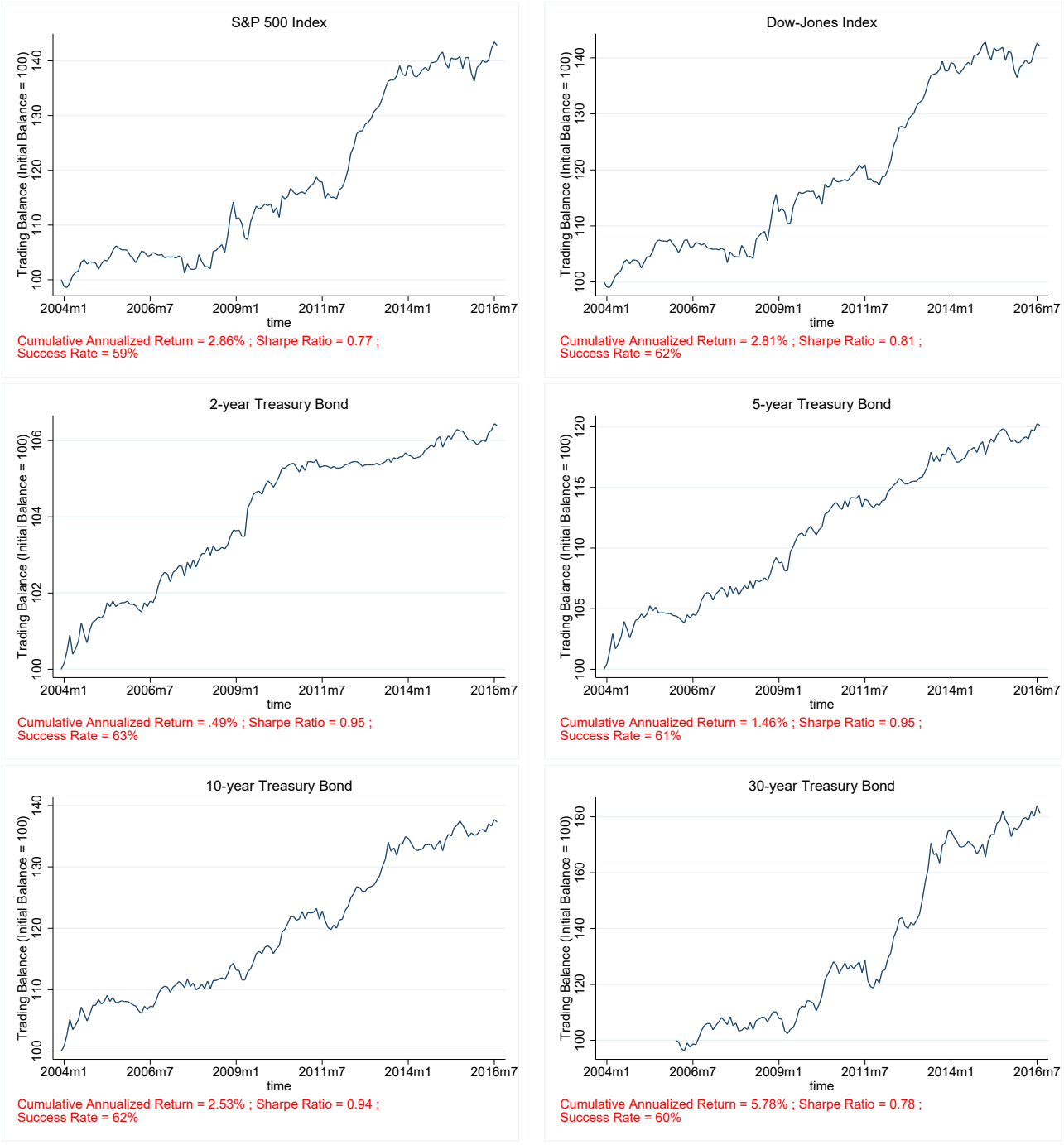
Notes: Stock returns are in percentage points; Treasury yield changes are in basis points. See text for details.

Figure 1. Relationship between Weather Effect and Financial Markets on Employment Report Release Days (Bin-scatter plots)



Notes: Each panel contains a bin-scatter plot showing the relationship between the indicated outcome variable (y-axis) and the national employment weather effect estimate (x-axis). Each point shows the mean x and y values within a bin. Bins are defined according to 30 quantiles of the x variable. The shown fit line is based on a linear regression of the outcome variable on the national employment weather effect, using the raw data (not the binned data). The weather effect estimate is derived from aggregating county-level weather effects, estimated using the county DPD model without regional heterogeneity. The left-side panels use weather effect estimates for which the county model is estimated using the full 1980m1 - 2016m8 sample; the right-side panels use estimates for which the county model is estimated using rolling (expanding) samples ending eight months prior to the observation month. See text for details.

Figure 2. Performance of Simple Trading Strategy Based on Weather Effect Nowcasts



Notes: Each panel shows the evolution of an investment balance, with an initial value of 100 in 2003m12, from following a simple trading strategy based on the weather effect nowcasts applied to the indicated asset type. Below each chart, the cumulative annualized return and the success rate (percentage of trades yielding a positive daily return) over the entire period are shown. The trading rule is as follows: when the weather effect nowcast is above ϵ, at the end of the day before the employment report take a long position if the asset type is stocks and a short position if the asset type is bonds; when the nowcast is below $-\epsilon$, take the opposite position. Positions are closed out at the end of the day of the report and held in cash until the day before the next employment report. The threshold ϵ is set equal to the 10th percentile of the absolute value of the nowcasts, which equals approximately 0.004 (i.e., a weather effect on employment growth for the month of 0.004 percentage points). See text for details.