Online Appendix

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

By Daniel J. Wilson

I. Aggregation of Weather Data from Daily to Monthly Frequency

Both the CES and QCEW define monthly employment as the number of individuals on employer payrolls as of the pay period containing the 12th of the month. This suggests that 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 that they report to the BLS. Thus, aggregating over firms, the most relevant set of weather days depends on the distribution of pay period frequencies. For instance, for firms paying weekly, weather during weeks beyond the 12th should not matter for their reported counts, while for firms paying monthly, weather throughout the month may matter. 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 first two is largely irrelevant. 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 weeks of the month are relevant.

To assess more formally which weeks of weather are most relevant for reported employment counts, I estimate a variant of the panel fixed effects regression discussed in Section II of the paper. In this variant, I regress monthly county employment growth on weather variables for each of the weeks within the month (where the fourth "week" is day 22 through the end of the month). The weekly weather variables are average daily-maximum temperature, average daily precipitation, average daily snowfall, fraction of days with maximum temperature above 90˚F (32.2°C), and fraction of days with minimum temperature below 30˚F (-1.1°C). The regressions include fixed effects for time (sample-month) and county-by-calendar-month-by-decade to absorb county-specific, decade-varying seasonality.

The results are shown in **Table A1**. Though the exact pattern of effects over the four weeks varies somewhat by variable, the impact of weather in the first two weeks of the month tends to be roughly double that of weather in the last two weeks. To be precise, the implied weights averaged over the five variables are 0.28 on week 1, 0.39 on week 2, 0.12 on week 3, and 0.20 on week 4.[1] Thus, both the distribution of pay period frequencies reported by the BLS and these empirical estimates suggest giving roughly double weight to weather in the first two weeks relative to the last two weeks when constructing monthly weather variables. For the baseline monthly weather variables used in the analyses below, weather from the first two weeks is given double weight relative to the remainder of the month in constructing the monthly variables. Alternative results based on using equal weights, zero weight on the last two weeks, or the average implied weights from **Table A1** are all qualitatively similar and are available upon request.

II. Additional Results

A. Regression Results for Baseline County Panel Model

The results of estimating the no-RH model using the full sample are provided in **Table A2**.[2] Each coefficient represents the effect on local employment growth of a one standard deviation change in that weather measure. Recall that the dependent variable is private nonfarm employment growth. The regression uses a balanced panel of 1,329,900 observations from 3,100 counties. The panel covers 429 months from January 1980 to December 2015. The standard errors are robust to heteroskedasticity and allow for two-way clustering of the residuals by county (allowing for serial correlation) and by state*time (allowing for within-state spatial correlation).

The first column of the table shows the estimated coefficients and standard errors on contemporaneous values of the weather variables. The second, third, and fourth columns show those 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, with the largest effect in the spring. 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 0.11 percentage point higher employment growth in the same month. Note that average monthly employment growth in the sample is 0.08 percentage point, so this spring temperature effect

[1] The implied weekly weights for a given variable are the coefficient for that week divided by the sum of the coefficients over the four weeks.
[2] Due to the very large number of weather effect parameters, estimates of the model with regional heterogeneity are not shown.

represents more than a doubling relative to baseline employment growth. 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 the latter is only weakly statistically significant.

The lagged effects tend to be of opposite sign to the contemporaneous effect and largest for the first two lags. Over the course of four months, the implied cumulative effect is close to zero and statistically insignificant for average daily-high temperature, with the exception of a small and weakly significant effect in the winter. Precipitation has positive cumulative effect, while snowfall has a negative cumulative effect. The number of days above 90°F has a sizable negative cumulative effect.

B. Backcasts and Nowcasts Based on Alternative Models

The rich heterogeneity of weather effects in the county panel model and the precision of its estimates based on large degrees of freedom offer many benefits for explaining weather's impact on national payroll employment. However, there are two potential disadvantages. First, the county model can only be 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, it is possible that estimates of the national weather effect based on the county panel 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.[3] Second, though one can attempt to capture spatial spillover effects via spatial lags in the county model, the true nature of spatial spillovers is unobserved. If these spillovers are

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

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 panel model compared to estimates derived from a national time series model. The latter estimates are based on the same methodology as in Section III of the paper – predicted values using actual weather minus predicted values using average weather – but using the following time series regression to obtain the fitted model:

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

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. $\alpha_{S(t)}$ 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 panel model, January 1980 to December 2015. The estimated coefficients and standard errors are shown in **Table A3**. 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 panel model without regional heterogeneity (**Table 2**). 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.

In addition to the estimated national weather effects based on the fitted national model shown in **Table A3**, I calculate national weather effects based on three versions of the county panel model. The first is the county panel model with regional heterogeneity (RH); the second is the county model without regional heterogeneity (no-RH), as in **Table 2**; and the third is same model but including inverse-distance-based spatial lag terms (SL).[4]

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, backcasting 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 A4**. 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. Nonetheless, the weather effect estimates from the RH and no-RH versions of the county model are statistically significant. Note that for the national model, this regression is in essence equivalent to the regression in **Table A3**, since that regression uses the same dependent variable and the same sample period, while the regressor in **Table A4** is just the predicted values from the regression in **Table A3**. 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 and market participants

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[4] The SL model is motivated by the possibility that local employment growth is also affected by weather in other places through spatial spillovers of local economic shocks. If such spillovers exist, national aggregates of the local weather effects derived from the RH and no-RH models may be biased. For each weather variable (contemporaneous and lagged values) included in the no-RH model (**Table 2**), 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.

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 panel 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 A4** 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.

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 nowcasting 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 panel regression outweigh the disadvantage of having to rely on a different employment data source at the local level.

C. Other Potential Predictors of Payroll Surprises and Treasury Yield Responses

I also compared the explanatory power of the county panel model weather effect backcasts and nowcasts to a couple of other potential predictors. First, given the weather sensitivity of the construction sector, it is possible that financial market participants might, in their assessment/reaction to a given payroll report surprise, down-weight construction's contribution to that surprise. To address this question, I calculated the NFP growth surprise net of construction employment growth (times construction's share of nonfarm payroll). This is the extreme of "down-weighting" construction. Note that this is an imperfect measure because data is not available on either market expectations of construction employment growth or real-time data on payroll employment for the construction sector. With that caveat in mind, I regressed Treasury bond yield changes (on report days) on this measure of the NFP growth surprise outside of construction (for the 2004m1 - 2016m8 sample). The explanatory power (R^2) of this measure is nearly identical (in fact, slightly worse) to the total NFP growth surprise. For example, for the 5-year Treasury yield change, the total NFP growth surprise explains 31.08% of the variation while the surprise net of construction explains 30.92%. I also tried regressing yield changes on both the total surprise and construction employment growth to assess whether knowing construction employment growth in addition to the payroll surprise helps predict Treasury yield changes. Construction employment growth does have a weakly significant negative effect on yield changes (as one would expect if traders down-weight construction's contribution to total employment growth surprises), but the increase in explanatory power is very small. For instance, in the case of the 5-year Treasury yield change, the R^2 increases to 32.67%. (The increase in adjusted R^2 is smaller.)

Second, there is a literature in finance showing that weather in NYC or, more generally, the city in which the financial market is based, can affect asset prices in that market, presumably by affecting the mood of traders. See, e.g., Saunders (1993 AER), Hirshleifer & Shumway (2003 JF), Goetzmann, Kim, Kumar, & Wang (2014 RFS), and Bassi, Colacito, & Fulghieri (2013 RFS). Therefore, I check whether weather in NYC could potentially affect NFP surprises and Treasury yield changes as much as the nationwide aggregated weather effects that I estimate. Specifically, I regressed payroll surprises and Treasury bond yield changes (on employment report days) on numerous measures of NYC weather – current and 3 lags of snowfall, precipitation, and maximum daily temperature. I find these NYC weather variables have essentially zero explanatory power (individually or collectively) for NFP, NFP surprises, and Treasury yield changes on employment report days.

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

As shown in the paper, nowcasts of the national weather effect implied by the estimated county panel 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 1** of the paper, for each of several national labor market variables I regress the variable on the national weather effect nowcast from the county panel model or the national model. For this exercise, I use the county panel model with regional heterogeneity ("RH"); the results are very similar using the model without regional heterogeneity ("no RH").

The results are shown in **Table A5**. 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 panel model's weather effects have a statistically significant impact on national CES employment growth (current-vintage), national QCEW employment growth, the vacancy rate, and the hires rate.[5] Weather effects from the national model are statistically insignificant in all of these cases. Furthermore, the R^2 is higher using the county panel model's weather effects than the national 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).[6] The results are shown in rows 6-8 of **Table A5**. 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

[5] 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.

[6] 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 panel model for local employment growth by size class.

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 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 A5** 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 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 A5** shows that, as expected, the nowcasts have no significant relationship with non-weather related absences.

The results in **Table A5** 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, one would expect a slope coefficient of one when the dependent variable is private nonfarm employment growth.[7] When this is measured using the aggregated QCEW data, we obtain a slope coefficient of 1.041, suggesting little if any measurement error is introduced by the county-to-national mapping. When employment growth is

[7] 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.

measured using the CES data, the slope coefficient falls a bit, to 0.899. While this is not statistically significantly different from one, the drop in the point estimate below one suggests there is some amount of 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.

D. Predictive Power of Weather Effects for Stock Market Return on Report Days

Table 1 of the paper shows the predictive power of the weather effect backcasts and nowcasts for Treasury bond yield changes on the days of employment report releases. **Table A6** provides an extended version of the table that includes results for the stock market return on those same days. I find that the backcasts over the longer sample period have very little association with stock returns, measured using either the S&P 500 index or the Dow-Jones Industrial index. However, this is not surprising given that payroll surprises also had essentially no association with stock returns on average over that period (see column 5).

Payroll surprises over the more recent sample period, on the other hand, are found to have a modest positive association with stock market returns, as shown in Panel B. In turn, the weather effect nowcasts are also found to have a modest positive association with stock market returns on those same days.

Table A1. Effects of Weather by Week on Monthly Employment Growth

	(1) Daily-High Temp	(2) Precipitation	(3) Snowfall	(4) % days > 90F	(5) % days < 30F	(6) Average Implied Weight
Week 1	0.004***	-0.004***	-0.039***	-0.042*	-0.028	0.284
	(0.001)	(0.001)	(0.006)	(0.023)	(0.020)	
Week 2	0.006***	-0.005***	-0.043***	-0.109***	-0.028	0.391
	(0.001)	(0.001)	(0.006)	(0.022)	(0.022)	
Week 3	0.002***	-0.002*	-0.013**	-0.010	-0.015	0.121
	(0.001)	(0.001)	(0.006)	(0.023)	(0.021)	
Week 4	0.003***	-0.005***	-0.003	-0.055**	-0.023	0.204
	(0.001)	(0.001)	(0.006)	(0.024)	(0.023)	

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

Table A2. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: All Private Industries

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.109***	-0.068***	-0.046***	0.005	0.001
	(0.009)	(0.009)	(0.008)	(0.008)	(0.013)
Avg. daily high temp - Summer	0.081***	-0.049***	-0.022**	-0.014	-0.004
	(0.013)	(0.011)	(0.010)	(0.009)	(0.017)
Avg. daily high temp - Fall	0.032***	-0.012	-0.028**	0.018	0.010
	(0.010)	(0.011)	(0.012)	(0.013)	(0.019)
Avg. daily high temp - Winter	0.085***	-0.021**	-0.016	-0.017	0.031*
	(0.010)	(0.011)	(0.011)	(0.011)	(0.018)
Precipitation (mm)	-0.025***	0.025***	0.011***	0.011***	0.021***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.006)
Snowfall (cm)	-0.035***	0.016***	0.007**	-0.003	-0.014**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.006)
% days high temp >90F	-0.024***	-0.010	-0.013	-0.006	-0.053***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.014)
% days low temp <30F	-0.024*	-0.021	0.006	0.012	-0.027
	(0.013)	(0.013)	(0.013)	(0.012)	(0.021)
N	1329900				
Counties	3100				
Months	429				
R2	0.553				

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

Table A3. 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	0.017	-0.040	-0.012	-0.046	-0.081
	(0.056)	(0.054)	(0.051)	(0.049)	(0.094)
Avg. daily high temp - Summer	0.084	-0.068	-0.048	-0.044	-0.076
	(0.111)	(0.075)	(0.060)	(0.056)	(0.144)
Avg. daily high temp - Fall	-0.027	0.031	-0.110	-0.066	-0.172
	(0.059)	(0.083)	(0.126)	(0.109)	(0.172)
Avg. daily high temp - Winter	0.007	-0.064	-0.090	-0.045	-0.192**
	(0.050)	(0.055)	(0.057)	(0.062)	(0.096)
Precipitation (mm)	-0.064	0.010	-0.062	-0.043	-0.158*
	(0.045)	(0.044)	(0.046)	(0.045)	(0.092)
Snowfall (cm)	0.003	0.097*	0.145***	0.092*	0.337***
	(0.056)	(0.054)	(0.055)	(0.054)	(0.102)
% days high temp >90F	-0.032	0.051	0.167	0.086	0.273
	(0.105)	(0.096)	(0.119)	(0.106)	(0.183)
% days low temp <30F	-0.178	-0.288*	-0.336**	-0.360**	-1.162***
	(0.140)	(0.150)	(0.147)	(0.143)	(0.287)
N	429				
R2	0.287				
RMSE	0.218				

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

Table A4. 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
Backcast	0.457**	0.009	0.414**	0.008	0.091	0.002	1.000***	0.102
	(0.238)		(0.225)		(0.099)		(0.144)	
Nowcast	0.899***	0.043	0.847***	0.043	0.248**	0.020	0.233	0.011
	(0.345)		(0.328)		(0.141)		(0.177)	

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 backcast results, both the model estimation and fit evaluation use data from 1980m1 to 2015m12. For the nowcast 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 national weather effect nowcasts 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 A5. 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	0.899***	0.043	0.233	0.011	0.201
	(0.345)		(0.177		
Employment Growth, Private Nonfarm, QCEW (SA)	1.041***	0.037	0.200	0.005	0.258
	(0.437)		(0.224)		
Vacancy Rate (monthly change)	0.712***	0.037	0.138	0.006	0.228
	(0.295)		(0.151)		
Hires Rate (monthly change)	0.862***	0.077	0.076	0.002	0.164
	(0.244)		(0.128)		
Quits Rate (monthly change)	0.222	0.011	0.000	0.000	0.574
	(0.174)		(0.088)		
Employment Growth, less than 50 employees	1.059***	0.050	0.572	0.042	0.900
	(0.485)		(0.295)		
Employment Growth, 50 to 499 employees	0.869	0.026	0.854	0.060	0.617
	(0.616)		(0.367)		
Employment Growth, 500 or more employees	0.567	0.020	0.681***	0.058	0.552
	(0.504)		(0.299)		
Weather Absences Rate (monthly change)	-0.683***	0.107	0.017	0.000	0.174
	(0.161)		(0.086)		
Non-weather Absences Rate (monthly change)	0.100	0.000	-1.449	0.012	0.500
	(2.131)		(1.065)		

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 national weather effect nowcasts 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 A6: Weather Effects and Asset Price Responses on Employment Report Release Days
Including Stock Market Responses

Panel A: Backcasts, Sample: 1989m12 - 2016m8

	(1) County no RH	(2) R^2	(3) County RH	(4) R^2	(5) Payroll surprise	(6) R^2	(7) N
Payroll Employment Growth (Current Vintage)	.657***	.024	.767***	.03			313
	(.236)		(.248)				
Payroll Employment Growth (Real-Time)	.628***	.029	.731***	.036			313
	(.205)		(.215)				
Real-Time Surprise in Payroll Employment Growth	.527***	.091	.589***	.103			313
	(.094)		(.099)				
S&P 500 daily return	2.34	.009	1.385	.003	-.77	.003	313
	(1.428)		(1.506)		(.82)		
Dow Jones Ind. Avg daily return	2.946**	.015	2.11	.007	.249	0	313
	(1.335)		(1.41)		(.771)		
1-year Treasury Bond daily change	.357***	.046	.416***	.056	.581***	.371	313
	(.092)		(.097)		(.043)		
2-year Treasury Bond daily change	.529***	.063	.609***	.076	.709***	.347	313
	(.115)		(.12)		(.055)		
5-year Treasury Bond daily change	.581***	.068	.669***	.082	.68***	.284	313
	(.122)		(.127)		(.061)		
10-year Treasury Bond daily change	.494***	.064	.567***	.076	.536***	.228	313
	(.107)		(.112)		(.056)		
30-year Treasury Bond daily change	.455***	.075	.531***	.09	.386***	.173	265
	(.099)		(.104)		(.052)		

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

Panel B: Nowcasts, Sample: 2004m1 - 2016m8

	(1) County no RH	(2) R^2	(3) County RH	(4) R^2	(5) Payroll surprise	(6) R^2	(7) N
Payroll Employment Growth (Current Vintage)	.856***	.044	.903***	.044			152
	(.327)		(.345)				
Payroll Employment Growth (Real-Time)	.632**	.038	.703**	.042			152
	(.261)		(.274)				
Real-Time Surprise in Payroll Employment Growth	.375***	.136	.422***	.155			152
	(.077)		(.081)				
S&P 500 daily return	3.11*	.021	3.372*	.022	3.341*	.024	152
	(1.755)		(1.85)		(1.722)		
Dow Jones Ind. Avg daily return	3.142*	.024	3.303*	.024	3.833**	.037	152
	(1.625)		(1.714)		(1.588)		
1-year Treasury Bond daily change	.064	.005	.14*	.021	.483***	.283	152
	(.075)		(.079)		(.063)		
2-year Treasury Bond daily change	.27**	.032	.366***	.053	.817***	.302	152
	(.121)		(.127)		(.101)		
5-year Treasury Bond daily change	.377***	.044	.465***	.061	.982***	.311	152
	(.143)		(.15)		(.119)		
10-year Treasury Bond daily change	.323**	.042	.382***	.053	.812***	.274	152
	(.126)		(.132)		(.108)		
30-year Treasury Bond daily change	.243*	.03	.269**	.032	.62***	.19	127
	(.123)		(.132)		(.115)		

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

Notes: In Panel A, the county panel models (RH and noRH) are estimated over 1980m1 to 2015m12. County weather effect "backcasts" 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, the county panel models are 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 nowcasts 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 nowcasts 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.