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

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*The views expressed in this paper are those of the authors should not be attributed to the Federal Reserve Bank of San Francisco or the Federal Reserve System.

Introduction

- Short-run fluctuations in macroeconomic data are often attributed to weather aberrations
  - **nonfarm payroll employment** [*Boldin & Wright 2015, Bloesch & Gourio 2015*], **GDP** [*Lazo et al 2011*], **retail sales** [*Starr-McCluer 2000*]
  - And many studies on weather's effects on **local** economic outcomes:
    - **annual crop yields** [*Deschênes & Greenstone 2007*], **annual income** [*Deryugina & Hsiang 2014*], **time use** [*Connolly 2008 and Graff-Zivin & Neidell 2014*]
- Implies weather, measurable in real-time, should be useful in "**nowcasting**" contemporaneous macroeconomic data
- Such predictive power would be highly valuable to:
  - policymakers, discerning strength of economic conditions
  - financial markets, given asset price sensitivity to macro data releases

Introduction

- Surprisingly, little if any evidence on predictive power of weather for macro data surprises and asset price responses

- This paper develops 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

- Evaluates how well such **nowcasts** predict actual employment growth, employment growth surprises, and stock and bond market reactions to employment reports

Preview of Findings

1. Nowcasts have strong positive association with employment growth *surprises* (actual minus median forecast)
   - Can explain ~15% of monthly variation

2. Nowcasts have strong predictive power for stock market returns and Treasury yield changes on employment report days

Outline of Talk

1. Intro
2. Methodology
3. Results
4. Conclusion

Overview of Methodology

1. Estimate county-level panel data model of monthly employment growth as function of weather
   - **temperature, precipitation, snowfall**
   - **current month plus 3 lags**
2. Use fitted county model to obtain estimates of weather's employment growth effects for every county in any given month
   - Generate weather effect estimates from both full 1980m1-2015m12 sample (***backcasts***) and rolling out-of-sample estimation (***nowcasts***)
3. Aggregate to national level

Step 1: Estimate County Panel Model

Data

County Employment

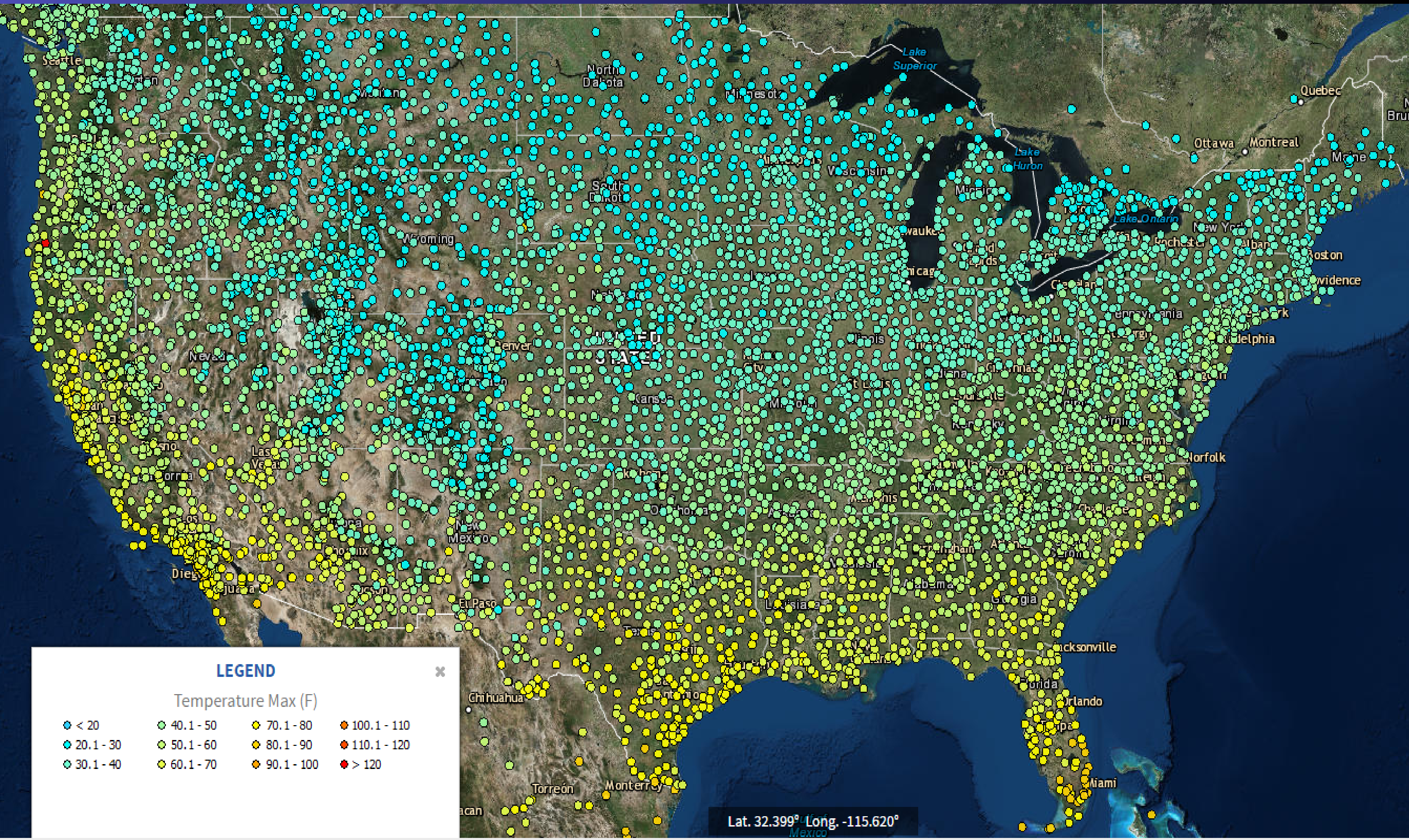
- BLS Quarterly Census of Employment and Wages (QCEW)
  - Based on state unemployment insurance administrative records
- Monthly Nonfarm Employment Counts by County
  - Number of workers for pay period including 12th of the month (same as BLS Payroll Survey)
- Not seasonally-adjusted
- Jan. 1980 – Dec. 2015

Data

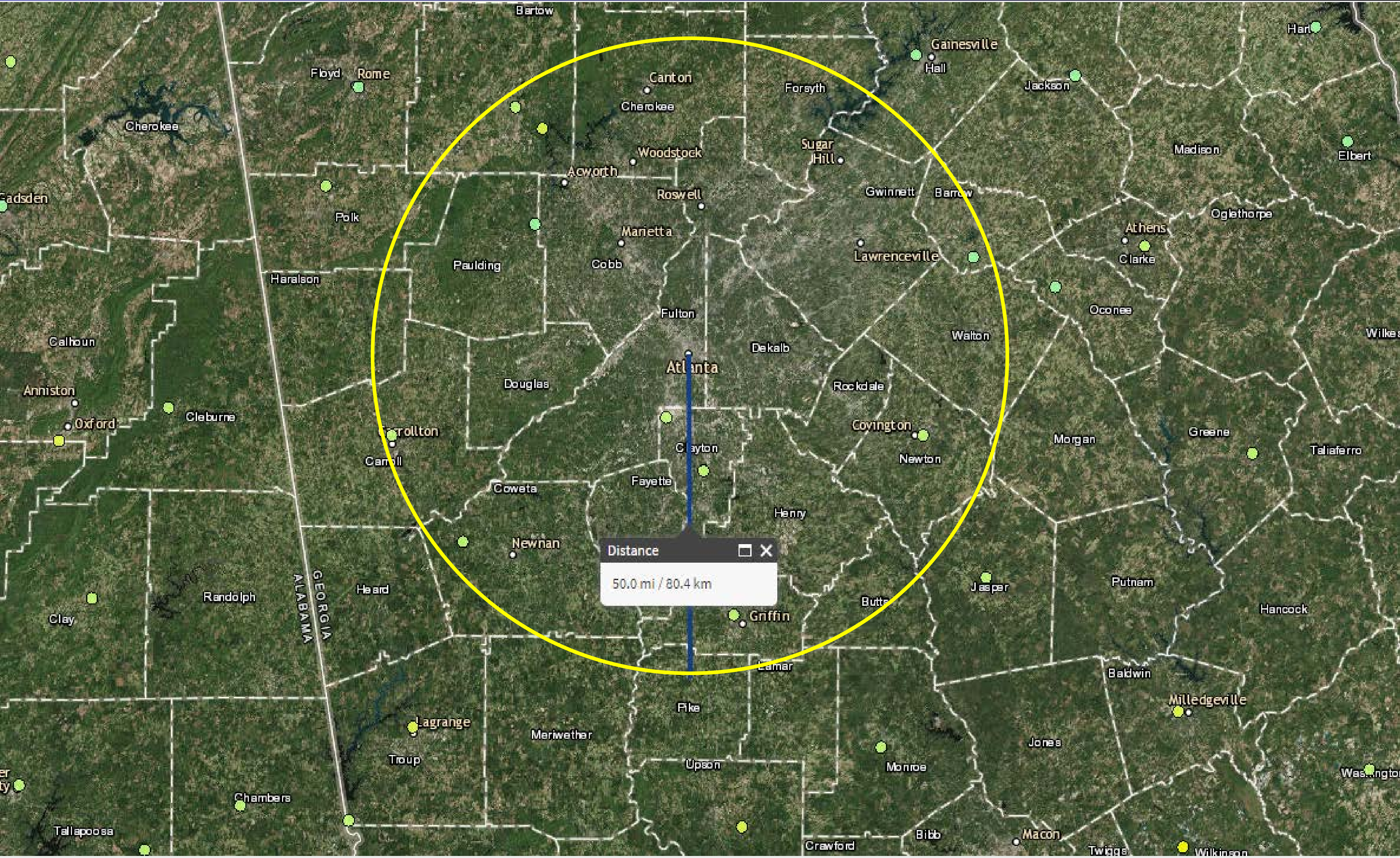
Weather

- NOAA/National Climatic Data Center, Global Historical Climate Network Daily Summaries (GHCN-Daily)(map)
- Daily weather variables by county measured by inverse-distance weighted average of measurements from weather stations within 50 miles (and 1000 feet elevation) (example)
- First, aggregate to weekly frequency:
  - Average Daily **Max Temperature**
  - Average Daily **Precipitation**
  - Average Daily **Snowfall**
  - # of Days with **Max Temp > 90**°F (32.2°C)
  - # of Days with **Min Temp < 30**°F (-1.1°C)
- Then, aggregate to monthly via weighted averages across weeks
  - Estimate weights on weeks 1-4 in first step of panel regression analysis

Locations of GHCN-Daily Weather Stations (1/1/2006)



GHCN-Daily Weather Stations near Atlanta (1/1/2006)



Estimating Weekly Weights

Baseline Dynamic Panel Data (DPD) Model:

$$\Delta l_{ct} = \sum_{k=1}^{K} \left(\delta_1^k w_{c,t,1}^k + \delta_2^k w_{c,t,2}^k + \delta_3^k w_{c,t,3}^k + \delta_4^k w_{c,t,4}^k\right) + \gamma_t + \alpha_{c,m(t),d(t)} + \epsilon_{ct}$$

for county (c) and month (t).

- where Δl_{ct} is employment growth (log-change)
- K = 5 weather variables
- $w_{c,t,i}^k$ is weather variable k in week i (i = 1, 2, 3, 4)
- Time (sample-month) fixed effects to absorb common global/national shocks
- Fixed effects by county*calendar-month*decade to capture county-specific seasonality

Estimated Weekly Weights

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***	-0.037***	-0.054**	-0.027	0.297
	(0.001)	(0.001)	(0.006)	(0.025)	(0.021)	
Week 2	0.007***	-0.004***	-0.040***	-0.102***	-0.007	0.341
	(0.001)	(0.001)	(0.006)	(0.025)	(0.022)	
Week 3	0.002***	-0.002**	-0.015**	-0.016	-0.020	0.152
	(0.001)	(0.001)	(0.006)	(0.026)	(0.021)	
Week 4	0.002**	-0.005***	-0.002	-0.049*	-0.032	0.211
	(0.001)	(0.001)	(0.006)	(0.027)	(0.023)	

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

Empirical Model

Baseline Dynamic Panel Data (DPD) Model:

$$\Delta l_{ct} = \sum_{k=1}^{K} \sum_{\tau=0}^{3} \beta_{\tau}^{k} w_{c,t-\tau}^{k} + \gamma_t + \alpha_{c,m(t),d(t)} + \epsilon_{ct}$$

for county (c) and month (t).

- where Δl_{ct} is employment growth (log-change)
- K = 5 weather variables, current + 3 lags of monthly weather ($w_{c,t,i}^{k}$)
- Time (sample-month) fixed effects to absorb common global/national shocks
- Fixed effects by county*calendar-month*decade to capture county-specific seasonality

Implementation

- Allow effects of average daily high temperature to vary by season
- Estimate 3 versions of model:
  - Baseline
  - Baseline plus **regional heterogeneity**
  - Baseline plus **spatial lags**
- Model estimated with weighted least squares (employment)

Baseline Results – All Private Industries

No Regional Heterogeneity

Contemporaneous and Lagged Weather Effects on Employment Growth
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

Summary of local weather effect estimates

- Average daily-high temperature has *positive* contemporaneous effect
  - Contemporaneous boost occurs in all seasons, but strongest in Spring:
- Very hot days, precipitation and snowfall have *negative* contemporaneous effects
- Lagged effects tend to be offsetting (mean reversion)
- Alternative models show:
  - Modest degree of regional heterogeneity
  - Spatially lagged weather tends to affect own-county employment growth similarly to own-county weather (amplifying effect)

Steps 2-3:
Generate County Weather Effect Backcasts & Nowcasts and Aggregate to National

Generate Implied National Weather Effects

- First, use fitted model(s) to get county weather effects:

$$\Omega_{ct} = \hat{\Delta} l_{ct}(\mathbf{w_{ct}}) - \hat{\Delta} l_{ct}(\bar{\mathbf{w}}_{\mathbf{c,m(t),d(t)}})$$

for county (c) and month (t); **w** is vector of weather variables.

- Aggregate county growth effects to national level:

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

- Can generate Ω_t using $\hat{\Delta} l_{ct}()$ estimated from:
  - full sample – Backcasts
  - Rolling end-month samples – Nowcasts (using real-time **w** data)

Evaluating Predictive Power of Weather Effect Estimates

Estimate National Model for Comparison

- First, for comparison I construct alternative weather effect estimates based on parallel national time series model:

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

  - where Δl_t^{CES} is log-change in seasonally adjusted nonfarm payroll employment from BLS payroll survey (CES),
  - includes same weather variables as county model, but averaged (population-weighted) across counties
  - includes season ($S(t)$) fixed effects (to account for residual seasonality)

National Time-Series Model – Results

Sample: 1980m1 – 2015m12

	(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

Assessing Predictive Power

- How well do weather effect estimates predict changes in national employment and other outcomes?

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Backcasts

- Estimate models and predict Weather Effects using 1980m1 – 2015m12 sample

Assessing Predictive Power

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Backcasts

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Nowcasts

- National model:
  - Estimate model iteratively on expanding window with end-month rolling from **2003m12-2016m7**
  - Each iteration, predict Weather Effect **1 month out of sample** (CES data lag)
- County models:
  - Estimate model iteratively on expanding window with end-month rolling from **2003m5 – 2015m12**
  - Each iteration, predict Weather Effect **8 months out of sample** (QCEW data lag)

Assessing Predictive Power

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Backcasts

- Estimate models and predict Weather Effects using 1980m1 – 2015m12 sample

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  - Estimate model iteratively on expanding window with end-month rolling from **2003m5 – 2015m12**
  - Each iteration, predict Weather Effect **8 months out of sample** (QCEW data lag)

➢ Yields Weather Effect Nowcasts for **2004m1 – 2016m8**

Predictive Power for Nonfarm Employment Growth

- Regress weather effect estimates on payroll employment growth:

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)	

Predictive Power for Nonfarm Employment Growth

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	(0.345)		(0.328)		(0.141)		(0.177)	

- In sample, national model wins
- Out of sample, county model wins

Other Labor Market Outcomes

- County DPD model also helps predict other labor market outcomes

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

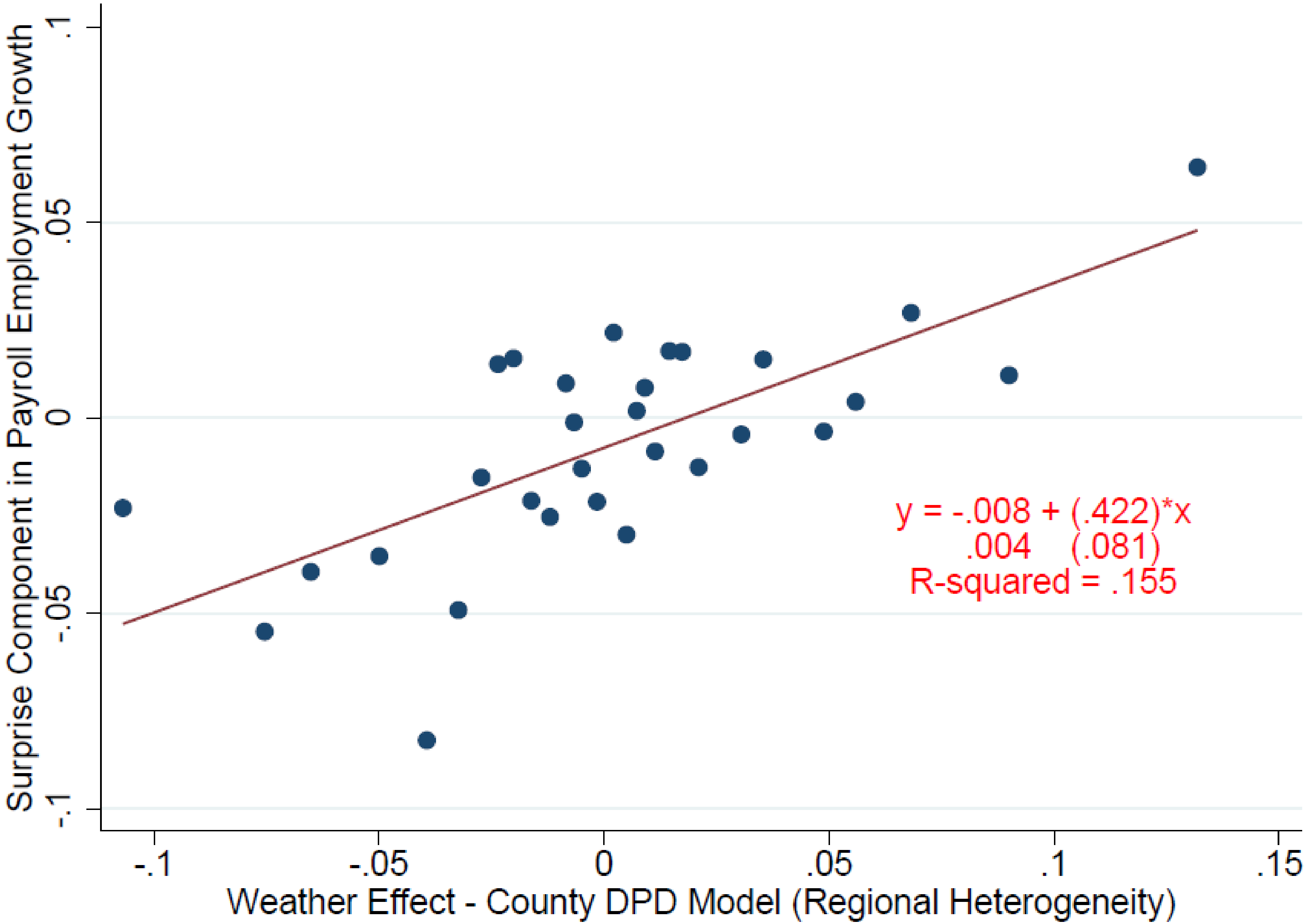
	County Model (RH)	R2	National Model	R2
Employment Growth, Private Nonfarm, Payroll Survey	0.899***	0.043	0.233	0.011
	(0.345)		(0.177	
Employment Growth, Private Nonfarm, QCEW (SA)	1.041***	0.037	0.200	0.005
	(0.437)		(0.224)	
Vacancy Rate (monthly change)	0.712***	0.037	0.138	0.006
	(0.295)		(0.151)	
Hires Rate (monthly change)	0.862***	0.077	0.076	0.002
	(0.244)		(0.128)	
Quits Rate (monthly change)	0.222	0.011	0.000	0.000
	(0.174)		(0.088)	
Employment Growth, less than 50 employees	1.059***	0.050	0.572	0.042
	(0.485)		(0.295)	
Employment Growth, 50 to 499 employees	0.869	0.026	0.854	0.060
	(0.616)		(0.367)	
Employment Growth, 500 or more employees	0.567	0.020	0.681***	0.058
	(0.504)		(0.299)	
Weather Absences Rate (monthly change)	-0.683***	0.107	0.017	0.000
	(0.161)		(0.086)	
Non-weather Absences Rate (monthly change)	0.100	0.000	-1.449	0.012
	(2.131)		(1.065)	

Predictive Power for Employment *Surprises*

- Weather effect **nowcasts** still can only explain about **4%** of monthly employment growth
  - Suggests other factors (e.g., strikes, financial conditions, overall macro conditions) are primary drivers of fluctuations
  - But other factors may be easily observable/predictable

- Do weather effect nowcasts help predict **surprise** component of employment reports?
  - If market participants do not/cannot fully incorporate real-time weather effects into expectations of macro data releases, weather effects will affect surprises
  - Measure **surprise** to nonfarm employment growth as difference between:
    - **actual, real-time (as first reported) employment growth, and**
    - **median forecast from survey of economists and market participants conducted in days leading up to employment report**
  - Data from January 1990+ from Money Market Services (MMS)/Action Economics

Predictive Power for Employment *Surprises*



Predictive Power of Weather Effect Nowcasts

Rolling Out-of-Sample (8 months)

	(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	.375***	.136	.422***	.155			152
	(.077)		(.081)				

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

Predictive Power of Weather Effect Nowcasts

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Real-Time Surprise in Payroll Employment Growth	.375***	.136	.422***	.155			152
	(.077)		(.081)				
S&P 500 daily return	3.075*	.019	3.276*	.02	3.432*	.025	148
	(1.838)		(1.912)		(1.761)		
Dow Jones Ind. Avg daily return	3.223*	.024	3.307*	.023	3.937**	.039	148
	(1.703)		(1.773)		(1.625)		

Standard errors in parentheses
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Predictive Power of Weather Effect Nowcasts

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	(.077)		(.081)				
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	(1.838)		(1.912)		(1.761)		
Dow Jones Ind. Avg daily return	3.223*	.024	3.307*	.023	3.937**	.039	148
	(1.703)		(1.773)		(1.625)		
3-month Treasury Bond daily change	-.004	0	.013	0	.104*	.023	152
	(.056)		(.059)		(.055)		
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
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Weather Effect Nowcasts and Market Returns

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
Payroll Surprises (%)	--	-0.78	0.87	-2.29
S&P 500 (%)	0.02	0.02	0.21	-0.14

Notes: The payroll employment surprise and stock returns are in percentage points; Treasury yield changes are in basis points.

Weather Effects and Employment Surprises

Mean Daily Stock Returns and Treasury Yield Changes

Various Subsamples

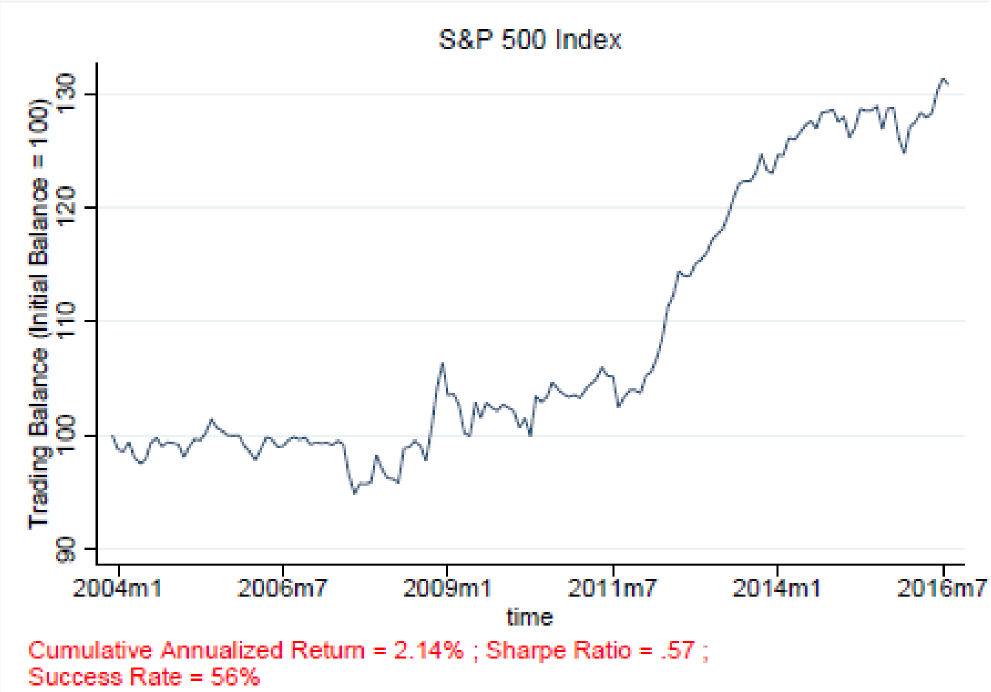
	All Days (1/1/2004 to 8/31/2016)	All Release Days	Release Days, Nowcast >0	Release Days, Nowcast <0
Payroll Surprises (%)	--	-0.78	0.87	-2.29
S&P 500 (%)	0.02	0.02	0.21	-0.14
Dow Jones (%)	0.02	0.02	0.21	-0.15
1-yr Treasury (bps)	-0.01	-0.03	0.72	-0.64
2-yr Treasury (bps)	-0.02	0.26	2.50	-1.64
5-yr Treasury (bps)	-0.04	0.17	2.95	-2.21
10-yr Treasury (bps)	-0.06	0.32	2.57	-1.57
30-yr Treasury (bps)	-0.05	0.81	2.14	-0.41

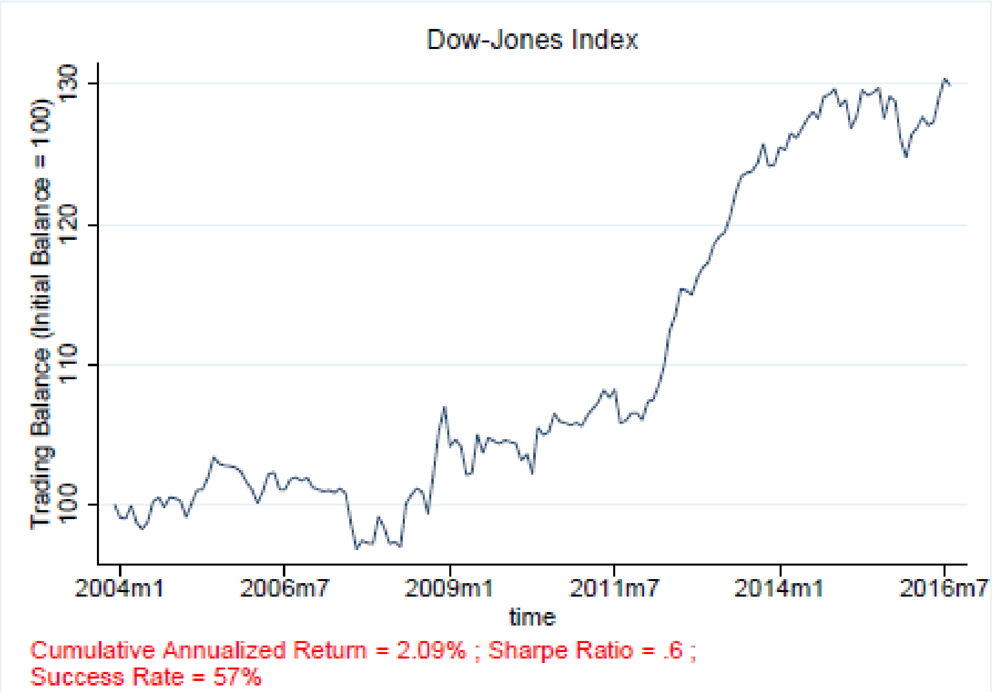
Notes: The payroll employment surprise and stock returns are in percentage points; Treasury yield changes are in basis points.

Illustration Based on Simple Trading Strategy

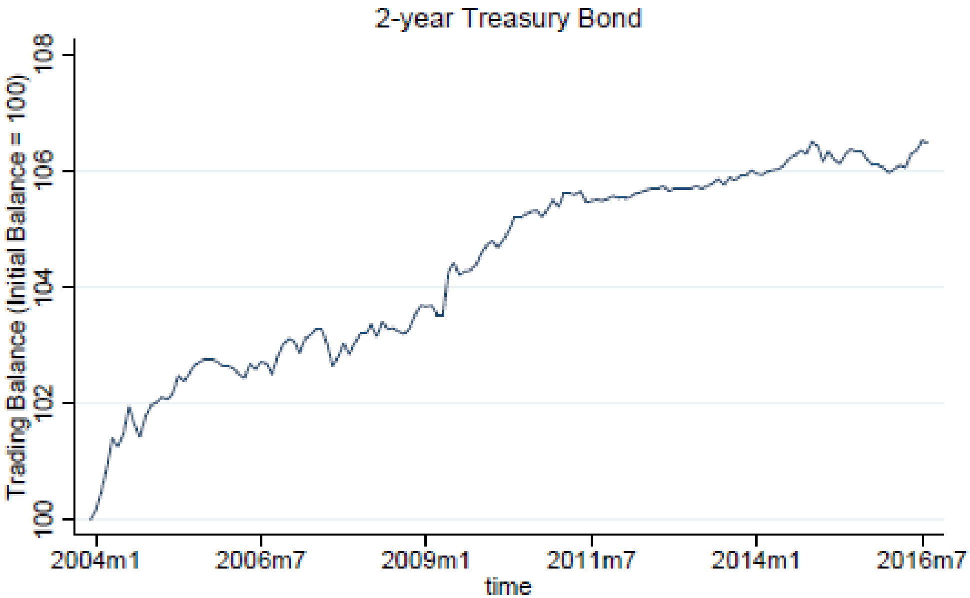
- Another way to illustrate predictive power of weather effect nowcasts is to consider performance of simple weather-based trading strategy:
- Trading Rule:
  - Nowcast > 0, take a long position in equities or short position in bonds
  - Nowcast < 0; take a short position in equities or long position in bonds
- Start with balance of 100 (on 2003m12),
  - trade at end of day prior to employment report
  - Unwind trade (put in cash) at end of day of employment report
- Calculate:
  - Success rate: % of trades earning positive return
  - Cumulative return (annualized)
  - Sharpe Ratio (annualized): mean return divided by std deviation

Performance of Nowcast-Based Trading Strategy

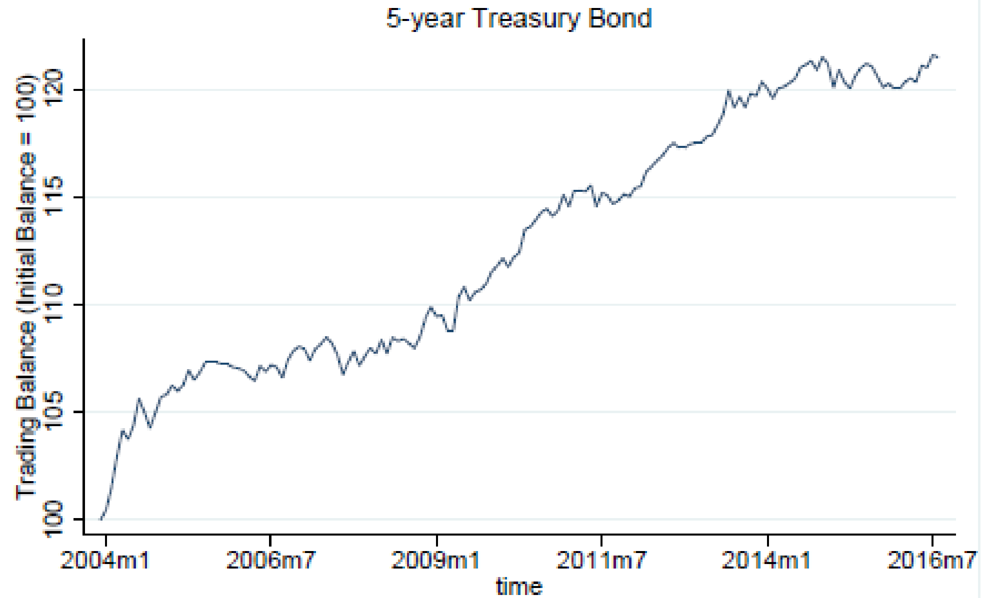




Performance of Nowcast-Based Trading Strategy



Cumulative Annualized Return = .5% ; Sharpe Ratio = .96 ;
Success Rate = 64%



Cumulative Annualized Return = 1.55% ; Sharpe Ratio = 1.01 ;
Success Rate = 63%

Cumulative Annualized Return = 2.47% ; Sharpe Ratio = .91 ;
Success Rate = 62%

Cumulative Annualized Return = 4.47% ; Sharpe Ratio = .61 ;
Success Rate = 57%

Conclusion

- Weather effect nowcasts of national payroll employment growth, based on estimated county panel data model:
  - Explains small share of monthly variation in employment growth
  - Explains large share (~15%) of monthly variation in employment growth surprises
  - Helps predict stock market returns and Treasury bond yield changes on employment report days
- Future research could refine county model to maximize predictive power
  - non-linear temperature effects, weekend vs weekday weather, extreme weather effects, etc.
  - Machine learning techniques for variable selection