On the Evolution of
U.S. Temperature Dynamics

Francis X. Diebold              Glenn D. Rudebusch
University of Pennsylvania      FRB San Francisco

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Abstract: Climate change is a multidimensional shift. While much research has documented rising mean temperature levels, we also examine range-based measures of daily temperature volatility. Specifically, using data for select U.S. cities over the past half-century, we compare the evolving time series dynamics of the average temperature level, AVG, and the diurnal temperature range, DTR (the difference between the daily maximum and minimum temperatures at a given location). We characterize trend and seasonality in these two series using linear models with time-varying coefficients. These straightforward yet flexible approximations provide evidence of evolving DTR seasonality, stable AVG seasonality, and conditionally Gaussian but heteroskedastic innovations for both DTR and AVG.

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Contact: fdiebold@upenn.edu, glenn.rudebusch@sf.frb.org
1 Introduction

Climate change can be defined as the variation in the joint probability distribution describing the state of the atmosphere, oceans, and fresh water including ice (Hsiang and Kopp, 2018). These are complex, multidimensional physical systems, and the various features of climate change have been described using a diverse set of summary statistics. One of the most important aspects of climate change is the evolving distribution of temperature, and many subsidiary indicators have been used to measure this variation, including, for example, mean temperature, temperature range, hot and cold spell duration, frost days, growing season length, ice days, heating and cooling degree days, and start of spring dates (Masson-Delmotte et al., 2018; Reidmiller et al., 2018). Of course, the level of temperature – the central tendency of the distribution – has attracted the most attention, in particular, regarding the upward trend in the average daily temperature (AVG). In contrast, less attention has been given to temperature volatility, which can be measured by the diurnal temperature range (DTR), which is the difference between the daily maximum temperature (MAX) and minimum temperature (MIN) at a given location.

Similar to changes in temperature averages, changes in temperature ranges and variability can also have important effects on environmental and human health (Davy et al., 2017). For example, the incidence of temperature extremes such as heat waves depends critically on how the whole distribution of temperature is shifting – including both the central tendency and variability. Of course, such temperature extremes can have notable adverse effects on society and the economy. Temperature variability can stress workers and lower labor productivity, but it can also have direct effects on output. A salient example is agriculture, whose output is a function of capital, labor, and weather inputs. Indeed, the very viability of certain agricultural sub-industries, notably wine or maple syrup production, is crucially dependent on temperature ranges. For example, Robinson (2006) notes that

Diurnal temperature variation is of particular importance in viticulture. Wine regions situated in areas of high altitude experience the most dramatic swing in temperature variation during the course of a day. In grapes, this variation has the effect of producing high acid and high sugar content as the grapes’ exposure to sunlight increases the ripening qualities while the sudden drop in temperature at night preserves the balance of natural acids in the grape. (p. 691)

Wigglesworth (2019) finds an important role of DTR in a panel study of U.S. state-level agricultural production over and above standard covariates like capital, labor, and AVG.
To better understand the full nature of the changing distribution of temperature, we examine DTR in select cities in the United States over the past half-century, quantifying both conditional-mean and conditional-variance dynamics. Our contribution is importantly methodological as we characterize the trend and seasonality in DTR using linear models that are easy to interpret but also quite adept at accounting for variation in the temperature distribution. We allow for time-varying coefficients, which provide a straightforward yet flexible approximation to more general nonlinear effects. Although our focus is on DTR, we also provide a parallel analysis for AVG, which allows valuable interpretive context and contrast. Our work reveals an evolving DTR conditional mean seasonal pattern, in contrast to the fixed AVG conditional mean seasonal pattern. In addition, our work reveals clear seasonality in conditional variance dynamics, both for DTR and AVG, although the evidence is weaker as to their evolution.

The previous research literature that examined DTR struggled for some time to develop firm conclusions about the dynamics of temperature variability. Even the direction of the trend in DTR has been somewhat contentious (Alexander and Perkins, 2013). Recent work has established that the downward trend in DTR in many locations reflects a more rapid warming of MIN than MAX – generally the result of nighttime lows rising faster than daytime highs (Davy et al., 2017). However, this differential trending of MIN and MAX, or “diurnal asymmetry,” is not geographically uniform because of variation in vegetation, cloud cover, and other factors (Jackson and Forster, 2010; Sun and Pinker, 2014). Along with this trend in temperature variability, seasonal variation in DTR has also been considered by a few authors, including Ruschy et al. (1991) and Durre and Wallace (2001), who describe a lower temperature range in winter than at other times. Qu et al. (2014) also provide some evidence that the seasonality of DTR in the United States may be changing over time. To capture as much variation as possible in the distribution of DTR – including trend and seasonal – we use linear time series models with time-varying coefficients to provide simple yet powerful representations.

We proceed as follows. In section 2, we provide an introductory analysis for a representative city, Philadelphia. Then, in section 3, we broaden the analysis to include fifteen geographically dispersed U.S. cities, characterizing both conditional-mean and conditional-variance dynamics. We conclude in section 4.
We introduce and illustrate our approach by studying temperature data measured at the Philadelphia airport (PHL) in a step-by-step fashion. We present most results graphically, while regression results on which these graphs are based appear in Appendix A. 2. The underlying data are the daily MAX and MIN measured in degrees Fahrenheit, obtained from the U.S. National Ocean and Atmospheric Administration’s Global Historical Climate Network database (GHCN-daily). 3 Our sample period is from 01/01/1960 to 12/31/2017, which covers the period of almost all recent climate change.

2.1 Distributions

The daily MAX and MIN are informative of both the central tendency and variability of the daily continuous-time temperature record. In particular, the daily average temperature, $\text{AVG}=(\text{MAX}+\text{MIN})/2$, is a natural measure of central tendency, and the daily temperature range, $\text{DTR}=$ MAX-MIN, is a natural measure of volatility or variability. DTR is not only a natural and intuitive estimator of daily volatility, but it is also highly efficient statistically. The “daily range” has a long and distinguished tradition of use in econometrics due to its good properties in estimating underlying quadratic variation from discretely-sampled data (Alizadeh et al., 2002). AVG has been studied and modeled extensively (Raftery et al.,

\footnote{EViews code is available at \url{https://www.sas.upenn.edu/~fdiebold/papers/paper122/DTRcode.txt}}\footnote{The data are available at \url{https://www.ncdc.noaa.gov/ghcn-daily-description}. For details, see Menne et al. (2012) and Jaffres (2019).}
In Figure 1, we show kernel estimates of the unconditional densities of AVG and DTR. The bimodal shape of the AVG density reflects the strong seasonality in AVG. The “winter mode” is around 40°F, and the “summer mode” is around 75°F. The AVG density contrasts sharply with the unimodal approximately-symmetric density of DTR, which is centered around 19°F and much less dispersed.

2.2 Trend

In Figure 2, we display time series plots of the entire data sample of AVG and DTR with fitted linear trends superimposed. The regression is

\[ Y \rightarrow c, TIME, \]

where \( Y \) is AVG or DTR, \( c \) is a constant, and \( TIME \) is a time trend (that is, \( TIME_t = t \) and \( t = 1, ..., T \)). Here and throughout, we use Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors to assess statistical significance.

The AVG trend slopes upward and is statistically significant, which is consistent with the overall global warming during this period. The steepness of this trend is surprising, as the AVG trend grows by nearly five degrees Fahrenheit over the course of the 57-year 1960-2017 period.
sample. This increment is a bit more than twice as much as the average global increase over the same period (Rudebusch, 2019). The faster upward trend in the Philadelphia airport average temperature likely reflects two key factors: (1) average temperatures in growing cities tend to rise more quickly due to an increasing urban heat island effect and (2) average land temperatures generally grow more quickly than the global average, which includes ocean areas that are slow to warm.

As for Philadelphia temperature variability, DTR also has a significant trend, and it slopes downward, dropping by more than two degrees over the course of the sample – a diurnal asymmetry. The downward DTR trend arises from different trends in the underlying MAX and MIN. Both trend upward, but MIN is on a steeper incline as evening temperatures warm more quickly. Hence, the spread between MAX and MIN tends to shrink, and DTR decreases over time. As noted by Dai et al. (1999), Davy et al. (2017), and Vinnarasi et al. (2017), such a downward trend is not found at all locations; however, the relatively muted upward trend in MAX can generally be ascribed to increased cloud cover, soil moisture, and precipitation, which lead to decreased surface solar radiation and increased daytime surface evaporative cooling.

The overall picture, then, involves not only an upward trend in AVG, but also a gradual tightening of daily fluctuations around that trend. Warming is not only happening, but progressively less volatility as well. As a result, the increases in heat are becoming harder to avoid at night, with potentially adverse consequences that likely fall disproportionately on the poor and vulnerable.

2.3 Fixed Seasonality

In Figure 3, we show the actual and fitted values from regressions of de-trended AVG and DTR on 12 monthly seasonal dummies,

\[ \tilde{Y} \rightarrow D_1, \ldots, D_{12}, \]  

where \( \tilde{Y} \) is de-trended AVG or DTR – the residuals from regression (1) – and \( D_{it} = 1 \) if day \( t \) is in month \( i \), and 0 otherwise.\(^4\) This model is effectively an intercept regression for deviations from trend, allowing for a different intercept each month.

As shown in the top panel of Figure 3, AVG displays pronounced seasonality. The

\(^4\)There is of course no need for an intercept, which would be completely redundant and hence cause perfect multicollinearity.
seasonality is highly significant and is responsible for a large amount AVG variation. The $R^2$ of the seasonal AVG regression (2) is .81. As with the upward trend in AVG, strong seasonality in deviations of AVG from its trend is hardly surprising – it’s cold in the winter and hot in the summer.

There is also significant seasonality in DTR, as shown in the bottom panel of Figure 3. The DTR seasonality was hard to detect visually in the time series plot of Figure 2, because it is buried in much more noise than that of AVG. The $R^2$ of the seasonal DTR regression (2) is only .07.

In Figure 4, we show the estimated monthly seasonal factors for AVG (left panel) and DTR (right panel). They are simply the 12 estimated coefficients on the 12 monthly dummies in the seasonal regression (2). The seasonal pattern for AVG is as expected – smooth and unimodal, high in the summer and low in the winter, achieving its maximum in July and its minimum in January. In contrast, the seasonal pattern for DTR is clearly bi-modal, with one mode in April-May and one in October. DTR’s two annual peaks (spring and fall) and two annual troughs (winter and summer) contrast sharply with AVG’s single annual peak (summer) and single annual trough (winter). This “twin-peaks” or “M-shaped” DTR
Notes to figure: We show estimated fixed twelve-month seasonal patterns for AVG and DTR, based on regressions of daily linearly de-trended data on 12 monthly seasonal dummies, 1960-2017. The vertical axes are scaled differently in the left and right panels, and they are in degrees Fahrenheit.

pattern is common across many U.S. cites. Moreover, as we shall show, in many locations, the DTR seasonal pattern has evolved noticeably over time with climate change.

2.4 Evolving Seasonality

The AVG and DTR trends documented thus far are trends in level. More subtle are trends in seasonality – that is, trends in the tent-shaped AVG seasonal pattern and the M-shaped DTR seasonal pattern. In that case, the seasonal patterns shown in Figure 4, estimated over the full sample 1960-2017, would be the sample averages that would not capture the evolution of the distribution over time.

We now explore the possibility of evolving seasonality by allowing for trends in the seasonal factors. Mechanically, this involves regressing de-trended AVG or DTR not only on 12 monthly dummies, but also those same 12 dummies interacted with time,

$$\tilde{Y} \rightarrow D_1, \ldots, D_{12}, \ D_1 \cdot \text{TIME}, \ldots, D_{12} \cdot \text{TIME},$$

where $\tilde{Y}$ is de-trended AVG or DTR, $D_{it} = 1$ if day $t$ is in month $i$ and 0 otherwise, and $\text{TIME}_t = t$. Regression (3) can capture linearly-trending seasonal deviations from a linear trend. Effectively, it allows for a different intercept each month, with those intercepts themselves potentially trending at different rates. In the special case where all interaction
Note to figure: We show the estimated twelve-month seasonal patterns of AVG and DTR, based on regressions of daily linearly de-trended data on 12 monthly seasonal dummies, and those same dummies interacted with time, 1960-2017. 1960 is blue, and 2017 is red. The vertical axes are scaled differently in the left and right panels, and they are in degrees Fahrenheit.

Coefficients are zero, it collapses to fixed seasonal deviations from linear trend, as explored in section 2.3.

For AVG, there are no gains from estimating the more flexible seasonal specification (3). The interaction terms are universally insignificantly different from zero, clearly indicating no change over time in the AVG seasonal pattern. In the left panel of Figure 5, we show the estimated seasonal factors for AVG for the first year (1960) and last year (2017) of our sample. This range provides the maximum contrast, but the two seasonal patterns are nevertheless essentially identical.

The results for DTR, however, are very different. Unlike the AVG seasonal, which does not evolve, the DTR seasonal changes significantly over time. The January-through-March DTR interaction coefficients are significantly positive, indicating that the winter DTR low is increasing. In addition, all May-through-October interaction coefficients are negative, and the October coefficient is large and highly significantly negative. This corresponds to progressively lower DTR highs in Octobers, so that the fall DTR peak is gradually vanishing. Both effects (higher winter DTR lows, and lower fall DTR highs) are visually apparent in the right panel of Figure 5, in which we contrast the estimated DTR M-shaped seasonal pattern in the first year (1960) and last year (2017) of our sample.
3 Fifteen Cities

We now expand our analysis to include data from the airports of the fifteen U.S. cities shown in Figure 6. As with the Philadelphia case study in section 2, we obtain the underlying daily MAX and MIN data, from which we construct daily AVG and DTR, from the U.S. National Ocean and Atmospheric Administration’s GHCN-daily, https://www.ncdc.noaa.gov/ghcn-daily-description. Our sample period is 01/01/1960-12/31/2017.\(^5\)

We choose these city weather reporting stations because all of them have had temperature derivatives traded on the Chicago Merchantile Exchange (CME). Consideration of such CME cities is of interest for several reasons. First, these locations cover a diverse set of climates, so they can provide a check of the robustness of our Philadelphia results. Second, they are urban locations that represent large numbers of people and a sizable share of economic activity – one reason that their CME contracts are traded. Finally, the valuations of weather derivatives traded in financial markets depend on the evolution of the stochastic structure of

\(^5\)There were a (very) few missing observations, in which case we interpolated using an average of the immediately previous and subsequent days’ values, rounded to the nearest integer. The missing observations are: BWI max: 1/7/04, min: 1/6/04, DSM max: 9/15/96, min: 9/15/96, and TUS max: 5/10/10, 8/18/17, 8/19/17, min: 5/11/10, 8/18/17, 8/19/17.
temperature dynamics, which is precisely the focus of our modeling efforts and so naturally paired with the CME cities.

The full set of historically-traded cities includes: Atlanta, ATL; Boston, BOS; Baltimore Washington, BWI; Chicago, ORD; Cincinnati, CVG; Dallas Fort Worth, DFW; Des Moines, DSM; Detroit, DTW; Houston, IAH; Kansas City, MCI; Las Vegas, LAS; Minneapolis St Paul, MSP; New York, LGA; Portland, PDX; Philadelphia, PHL; Sacramento, SAC; Salt Lake City, SLC, and Tuscon, TUS.\(^6\) We exclude Houston, Kansas City, and Sacramento, however, due to large amounts of missing data, leaving fifteen cities. Presently eight cities are traded (Atlanta, Chicago, Cincinnati, Dallas, Las Vegas, Minneapolis, New York, and Sacramento), and all but Sacramento are in our fifteen.\(^7\)

In addition to expanding our analysis to include more cities, we also employ a more sophisticated modeling approach that jointly captures trend, seasonality, and serial correlation, and we implement it for both conditional-mean and conditional-variance dynamics. Our approach builds on Campbell and Diebold (2005), but with several important differences. We study the variability as well as the central tendency of temperature, explore time-varying seasonality, and consider more cities and a longer data sample.

### 3.1 Conditional Mean Dynamics

We view the sequential approach employed in section 2 – fitting a trend and then characterizing seasonality in the de-trended data – as intuitive and transparent. We now consolidate and extend various aspects of that approach, to arrive at a simple yet powerful joint model. Regarding consolidation, we move from a multi-step sequential conditional mean modeling approach to a single-step joint approach with a single conditional mean estimation. Regarding extension, we now include an autoregressive lag in the model. The single autoregressive lag facilitates simple assessment of the strength of serial correlation in the deviations from the trend/seasonal, and it also provides potentially valuable pre-whitening for HAC covariance matrix estimation, as emphasized in Andrews and Monahan (1992).

We proceed by regressing AVG or DTR on an intercept and 11 monthly seasonal dummies to capture seasonal intercept variation (we drop July, so the included constant captures July and all estimated seasonal effects are relative to July), a linear trend and 11 seasonal dummies interacted with it to capture seasonal trend slope variation (we drop the July interaction),

\(^6\)See ftp://ftp.cmegroup.com/weather/usa/temperature/historical/daily.
\(^7\)See https://www.cmegroup.com/trading/weather/temperature-based-indexes.html.
Table 1: AVG, Conditional Mean Dynamics, Fifteen Cities

| station | Δtrend | p(nt) | p(ns) | p(nts) | ρ | R² |
|---------|--------|-------|-------|--------|---|----|
| ATL     | 4.36   | 0.00  | 0.00  | 0.00   | 0.76⁺ | 0.90 |
| BOS     | 2.06   | 0.00  | 0.00  | 0.73   | 0.67⁺ | 0.89 |
| BWI     | 2.25   | 0.00  | 0.00  | 0.80   | 0.71⁺ | 0.90 |
| CVG     | 2.53   | 0.04  | 0.00  | 0.94   | 0.74⁺ | 0.89 |
| DFW     | 3.44   | 0.00  | 0.00  | 0.55   | 0.72⁺ | 0.89 |
| DSM     | 3.93   | 0.00  | 0.00  | 0.17   | 0.76⁺ | 0.91 |
| DTW     | 4.09   | 0.00  | 0.00  | 0.99   | 0.74⁺ | 0.91 |
| LAS     | 6.05   | 0.00  | 0.00  | 0.41   | 0.82⁺ | 0.96 |
| LGA     | 4.03   | 0.00  | 0.00  | 0.97   | 0.71⁺ | 0.91 |
| MSP     | 4.72   | 0.00  | 0.00  | 0.18   | 0.77⁺ | 0.93 |
| ORD     | 2.86   | 0.00  | 0.00  | 0.78   | 0.74⁺ | 0.90 |
| PDX     | 2.55   | 0.00  | 0.00  | 0.26   | 0.76⁺ | 0.90 |
| PHL     | 4.78   | 0.00  | 0.00  | 0.95   | 0.72⁺ | 0.91 |
| SLC     | 3.92   | 0.00  | 0.00  | 0.67   | 0.77⁺ | 0.93 |
| TUS     | 4.89   | 0.00  | 0.00  | 0.33   | 0.79⁺ | 0.93 |
| Median  | 3.93   | 0.00  | 0.00  | 0.67   | 0.74  | 0.91 |

Notes to table: All results are based on daily data, 1960-2017. Column 1 reports measurement station by airport code. Column 2 reports the estimated trend movement over the entire 57-year sample in degrees Fahrenheit, using a simple regression on linear trend. The remaining columns report results from the conditional-mean regression (4). p(nt) is the robust p-value for a Wald test of no trend (all coefficients on TIME and D·TIME interactions are 0), p(ns) is the robust p-value for a Wald test of no seasonality (all coefficients on D’s and D·TIME interactions are 0), and p(nts) is the robust p-value for Wald a test of no trend in seasonality (all coefficients on D·TIME interactions are 0). ρ is the estimated autoregressive coefficient, and R² is the coefficient of determination. Asterisks denote significance at the one percent level. See text for details.
Table 2: DTR, Conditional Mean Dynamics, Fifteen Cities

| station | ∆trend | p(nt) | p(ns) | p(nts) | ρ     | R²   |
|---------|--------|-------|-------|--------|-------|------|
| ATL     | -1.65* | 0.00  | 0.00  | 0.14   | 0.38* | 0.18 |
| BOS     | -0.48* | 0.00  | 0.00  | 0.00   | 0.25* | 0.10 |
| BWI     | -0.43  | 0.34  | 0.00  | 0.50   | 0.38* | 0.19 |
| CVG     | -1.31* | 0.00  | 0.00  | 0.04   | 0.32* | 0.17 |
| DFW     | -1.31* | 0.00  | 0.00  | 0.64   | 0.40* | 0.17 |
| DSM     | -0.51* | 0.00  | 0.00  | 0.03   | 0.32* | 0.15 |
| DTW     | -2.88* | 0.00  | 0.00  | 0.03   | 0.33* | 0.27 |
| LAS     | -7.02* | 0.00  | 0.00  | 0.13   | 0.46* | 0.37 |
| LGA     | 0.03*  | 0.00  | 0.00  | 0.00   | 0.23* | 0.14 |
| MSP     | -3.07* | 0.00  | 0.00  | 0.00   | 0.31* | 0.18 |
| ORD     | -2.03* | 0.00  | 0.00  | 0.00   | 0.30* | 0.20 |
| PDX     | -1.68* | 0.00  | 0.00  | 0.63   | 0.50* | 0.45 |
| PHL     | -2.13* | 0.00  | 0.00  | 0.00   | 0.34* | 0.19 |
| SLC     | -4.21* | 0.00  | 0.00  | 0.00   | 0.44* | 0.47 |
| TUS     | 0.48   | 0.05  | 0.00  | 0.03   | 0.51* | 0.35 |

Median -1.65 0.00 0.00 0.03 0.34 0.19

Notes to table: See Table 1.

and a first-order autoregressive lag: \(^8\)

\[
Y \rightarrow c, TIME, Y(-1), D_1, ..., D_6, D_8, ..., D_{12}, D_1 \cdot TIME, ..., D_6 \cdot TIME, D_8 \cdot TIME, ..., D_{12} \cdot TIME, \ (4)
\]

where \(Y\) is AVG or DTR, \(TIME_t = t\), \(Y(-1)\) denotes a 1-day lag, and \(D_i = 1\) if day \(t\) is in month \(i\) and 0 otherwise. The joint model (4) allows for different intercepts each month, with the different intercepts potentially trending linearly at different rates, and for serially correlated deviations from the trend/seasonal.\(^9\) We summarize the estimation results in Tables 1 and 2, in which we show the weather station identifier (airport code) in column 1, and various aspects of the estimation results in subsequent columns.\(^10\)

\(^8\)We continue to use HAC standard errors despite the inclusion of a first-order autoregressive lag, both because we view the autoregressive lag as a simple pre-whitening strategy rather than a definitive model of serial correlation, and to maintain robustness to heteroskedasticity in temperature shocks.

\(^9\)We have explored – and generally confirmed – the robustness of our results by comparing them to those obtained from a more flexible model with quadratic terms as well as assessing the structural stability of regressions.

\(^10\)Detailed regression results for all cities are in the online Appendix B (https://www.sas.upenn.edu/~fdiebold/papers/paper122/OnlineAppendix.pdf.txt), and underlying EViews code is at https://www.sas.upenn.edu/~fdiebold/papers/paper122/DTRcode.txt.
3.1.1 Trend

As shown in column 2 of Table 1, the estimated AVG trend movements over the full sample are large and positive in each city. They are also all highly statistically significant (column 3), with a median $p$-value of 0.00 for Wald tests of the null hypothesis of no trend. These $p$-values are denoted $p(nt)$, where “nt” stands for “no trend”, which corresponds to zero coefficients on TIME and all TIME interactions in regression (4) (in which case it collapses to seasonal intercepts with serial correlation). The median estimated trend movement is 3.38°F, greater than the consensus estimate of the increase in the mean global temperature over the same period, as U.S. airports have warmed more quickly than the global average.

Similarly, in column 2 of Table 2, we report the estimated full-sample trend movements for DTR. All but one are negative, and most are significant at the one percent level. The median estimated trend movement is -1.45°F, with a median $p$-value, $p(nt)$, of 0.00 for the no-trend null hypothesis (column 3). Interestingly, LAS, which has the largest upward AVG trend, also has the largest downward DTR trend.

3.1.2 Seasonality

In column 4 of Tables 1 and 2, we report $p$-values for Wald tests of the hypothesis of no AVG and DTR seasonality, respectively. These $p$-values are denoted $p(ns)$, where “ns” stands for “no seasonality”, which corresponds to zero coefficients on all included seasonal dummies and dummy interactions in regression (4) (in which case it collapses to linear trend with serial correlation). There is of course strong evidence of seasonality in AVG with all $p(ns)$’s equal to 0.00. Less well known is the similarly strong seasonality in DTR with all $p(ns)$’s again equal to 0.00.

In column 5 of Tables 1 and 2, we report $p$-values for Wald tests of the hypothesis of no evolving (i.e., trending) AVG and DTR seasonality, respectively. These $p$-values are denoted $p(nts)$, where “nts” stands for “no trending seasonality”, which corresponds to zero coefficients on all seasonal dummy interactions in regression (4) (in which case it collapses to linear trend and fixed seasonal dummies with serial correlation). The results are striking. There is no evidence for evolving seasonality in AVG; the median AVG $p(nts)$ is 0.67. In contrast, there is strong evidence of evolving seasonality in DTR; the median DTR $p(nts)$ is 0.03.
3.1.3 Serial Correlation

Estimated AVG and DTR serial correlation coefficients appear in column 6 of Tables 1 and 2, respectively. All are positive and significant at the one percent level. Their magnitudes, however, are very different. All those for AVG are around 0.75, whereas all those for DTR are around 0.35.

It is interesting to note that, although the signal in both AVG and DTR is clearly driven by trend, seasonal, and cyclical components, the AVG signal is buried in much less noise. As shown in column 7 of Tables 1 and 2, respectively, all AVG regression $R^2$ values are around 0.9, whereas all those for DTR are around 0.2.

3.2 Conditional Variance Dynamics

To allow for residual heteroskedasticity, we proceed exactly as in the conditional mean regression, whether for AVG or DTR, except that the left-hand-side variable is now a squared residual from the conditional mean regression:

$$e^2 \rightarrow c, TIME, e^2(-1), D_1, ..., D_6, D_8, ..., D_{11}, D_1 \cdot TIME, ..., D_6 \cdot TIME, D_8 \cdot TIME, ..., D_{11} \cdot TIME.$$ (5)

The key point is that residual signs don’t matter in the conditional-variance regression (5), because the residuals are squared. Instead the regression explains the squared variation in the residuals, which is their volatility, or more precisely (in conditional expectation) their conditional variance. The conditional-variance regression results appear in Tables 3 and 4, which are in precisely the same format as our earlier conditional-mean Tables 1 and 2.

Interestingly, AVG and DTR conditional variance $e^2$ dynamics display the same component structure as did the conditional mean dynamics, although the patterns of trend and seasonality differ. The trend patterns are similarly downward for both AVG and DTR. The seasonal patterns are similarly high in the winter for both AVG and DTR. The conditional variance trend and seasonal effects tend to be significant, but the conditional variance regressions are noisy, with $R^2$’s around 0.05.

3.3 Shock Distributions

Armed with estimates of residual conditional standard deviations (the square roots of the fitted values from regression (5)), we can examine the densities of standardized residuals, that is the densities of the ultimate underlying AVG and DTR shocks. We show their skewness and kurtosis in Table 5. For each station, skewness is approximately 0 and kurtosis
| station | Δtrend | p(nt) | p(ns) | p(nts) | ρ   | R² |
|---------|--------|-------|-------|--------|-----|----|
| ATL     | -0.29  | 0.23  | 0.00  | 0.34   | 0.07*| 0.11|
| BOS     | -0.01  | 0.02  | 0.00  | 0.02   | 0.07*| 0.04|
| BWI     | -0.03  | 0.44  | 0.00  | 0.54   | 0.05*| 0.06|
| CVG     | -0.43* | 0.00  | 0.00  | 0.52   | 0.04*| 0.10|
| DFW     | -0.11  | 0.82  | 0.00  | 0.77   | 0.09*| 0.11|
| DSM     | -0.34* | 0.00  | 0.00  | 0.25   | 0.05 | 0.08|
| DTW     | -0.53* | 0.00  | 0.00  | 0.07   | 0.05*| 0.05|
| LAS     | -0.61  | 0.46  | 0.00  | 0.39   | 0.09*| 0.03|
| LGA     | -0.04  | 0.36  | 0.00  | 0.52   | 0.06*| 0.05|
| MSP     | -0.79* | 0.00  | 0.00  | 0.00   | 0.04*| 0.08|
| ORD     | -0.79* | 0.00  | 0.00  | 0.40   | 0.04*| 0.05|
| PDX     | -0.03  | 0.38  | 0.00  | 0.30   | 0.10*| 0.02|
| PHL     | -0.25* | 0.00  | 0.00  | 0.29   | 0.05*| 0.06|
| SLC     | -0.14  | 0.05  | 0.00  | 0.04   | 0.08*| 0.02|
| TUS     | 0.02   | 0.03  | 0.00  | 0.03   | 0.03*| 0.04|

Median: -0.25  0.03  0.00  0.30  0.05  0.05

Notes to table: All results are based on daily data, 1960-2017. Column 1 reports measurement station by airport code. Column 2 reports the estimated trend movement over the entire 57-year sample in degrees Fahrenheit, using a regression of absolute residuals from conditional-mean regression (4) on linear trend. (We use absolute rather than squared residuals for the column 2 regression to keep the units in degrees Fahrenheit.) The remaining columns report results from the conditional-variance regression (5). p(nt) is the robust p-value for a Wald test of no trend (all coefficients on TIME and D·TIME interactions are 0), p(ns) is the robust p-value for a Wald test of no seasonality (all coefficients on D’s and D·TIME interactions are 0), and p(nts) is the robust p-value for Wald a test of no trend in seasonality (all coefficients on D·TIME interactions are 0). ρ is the estimated autoregressive coefficient, and R² is the coefficient of determination. Asterisks denote significance at the one percent level. See text for details.
Table 4: DTR, Conditional Variance Dynamics, Fifteen Cities

| station | $\Delta \text{trend}$ | $p(\text{nt})$ | $p(\text{ns})$ | $p(\text{nts})$ | $\rho$ | $R^2$ |
|---------|----------------------|----------------|----------------|----------------|-------|------|
| ATL     | -0.86*               | 0.00           | 0.00           | 0.00           | 0.01  | 0.10 |
| BOS     | -0.28                | 0.13           | 0.00           | 0.65           | 0.07* | 0.03 |
| BWI     | -0.32                | 0.31           | 0.00           | 0.90           | 0.04* | 0.04 |
| CVG     | -0.64*               | 0.00           | 0.00           | 0.72           | 0.03* | 0.05 |
| DFW     | -0.44                | 0.12           | 0.00           | 0.91           | 0.03* | 0.11 |
| DSM     | -0.50*               | 0.01           | 0.00           | 0.87           | 0.01  | 0.06 |
| DTW     | -1.14*               | 0.00           | 0.00           | 0.00           | 0.05* | 0.03 |
| LAS     | -1.23*               | 0.00           | 0.00           | 0.00           | 0.04* | 0.04 |
| LGA     | -0.47*               | 0.00           | 0.00           | 0.14           | 0.06* | 0.03 |
| MSP     | -1.44*               | 0.00           | 0.00           | 0.26           | 0.04* | 0.03 |
| ORD     | -1.05*               | 0.00           | 0.00           | 0.02           | 0.04* | 0.03 |
| PDX     | -0.79*               | 0.00           | 0.00           | 0.01           | 0.00  | 0.05 |
| PHL     | -0.89*               | 0.00           | 0.00           | 0.02           | 0.07* | 0.05 |
| SLC     | -0.77*               | 0.00           | 0.00           | 0.02           | 0.05* | 0.02 |
| TUS     | 0.21                 | 0.15           | 0.00           | 0.63           | 0.01  | 0.04 |

Median: -0.77 0.00 0.00 0.14 0.04 0.04

Notes to table: See Table 3.

is approximately 3, corresponding to conditional normality. Indeed for DTR the median skewness and kurtosis are 0.00 and 3.00, respectively.

4 Concluding Remarks

Climate change is one of the most consequential and pressing issues of our time. We have focused on DTR as an important summary statistic for characterizing climate change. We have provided new stochastic time series representations of DTR that can capture in particular its evolving seasonality. Throughout we have also provided parallel contrasting results for AVG. Indeed the results in Tables 1-5 provide a detailed summary of both DTR and AVG stochastic structure.

Our results may prove useful for assessing and improving structural climate models. In previous research, Braganza et al. (2010), Zhou et al. (2010), Lewis and Karoly (2013), and Rader et al. (2018) show that DTR is a useful metric to help assess the accuracy and degree of fit of global climate models. They generally found that these models persistently
Table 5: Skewness and Kurtosis, Standardized Residuals, Fifteen Cities

| station | AVG skew | AVG kurt | DTR skew | DTR kurt |
|---------|----------|----------|----------|----------|
| ATL     | -0.68    | 3.74     | -0.32    | 3.19     |
| BOS     | 0.06     | 2.96     | 0.43     | 3.23     |
| BWI     | -0.13    | 3.15     | -0.09    | 2.92     |
| CVG     | -0.31    | 3.23     | 0        | 2.86     |
| DFW     | -0.64    | 4.10     | -0.08    | 3.25     |
| DSM     | -0.18    | 3.17     | 0.13     | 2.96     |
| DTW     | -0.07    | 3.14     | 0.09     | 2.98     |
| LAS     | -0.76    | 4.51     | -0.44    | 3.07     |
| LGA     | -0.14    | 3.02     | 0.43     | 3.55     |
| MSP     | -0.12    | 3.17     | 0.22     | 3.00     |
| ORD     | -0.13    | 3.24     | 0.16     | 2.90     |
| PDX     | 0.04     | 3.14     | 0.11     | 2.80     |
| PHL     | -0.20    | 3.09     | -0.06    | 3.02     |
| SLC     | -0.50    | 3.77     | -0.28    | 2.98     |
| TUS     | -0.69    | 4.16     | -0.53    | 3.37     |
| Median  | -0.18    | 3.17     | 0.00     | 3.00     |

Notes to table: We show sample skewness and kurtosis of residuals from the conditional-mean regression (4) divided by square roots of fitted values from the conditional-variance regression (5). See text for details.

underestimated the trend in DTR, which was likely related to deficiencies in modeling water vapor and cloud cover processes. Our new results on the evolving seasonality of DTR may provide an additional, more refined, benchmark for such evaluations.

Our results may also prove useful for assessing financial market efficiency, that is, for assessing whether the temperature forecasts embedded in financial asset prices accurately reflect temperature’s underlying dynamics. Schlenker and Taylor (2019) address this issue focusing on AVG, and it may be of interest to extend their analysis to incorporate our more complete model of AVG dynamics, or to consider a multivariate modeling of AVG and DTR extending the univariate approach undertaken in this paper.
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Appendices

A  Sequential and Joint Regression Results for Philadelphia

Figure A1: PHL Trend Regression, AVG

| Variable  | Coefficient | Std. Error | t-Statistic | Prob.   |
|-----------|-------------|------------|-------------|---------|
| C         | 53.02047    | 0.860367   | 61.62542    | 0.0000  |
| TIME      | 0.000226    | 6.97E-05   | 3.237848    | 0.0012  |

Dependent Variable: AVG_PHL
Method: Least Squares
Date: 07/09/19  Time: 13:46
Sample: 01/01/1960 12/31/2017
Included observations: 21185
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 14.0000)

R-squared 0.006068  Mean dependent var 55.41086
Adjusted R-squared 0.006021  S.D. dependent var 17.71674
S.E. of regression 17.66333  Akaike info criterion 8.580953
Sum squared resid 6608952.  Schwarz criterion 8.581704
Log likelihood -90891.74  Hannan-Quinn criter. 8.581198
F-statistic 129.3170  Durbin-Watson stat 0.107062
Prob(F-statistic) 0.000000  Wald F-statistic 10.48366
Prob(Wald F-statistic) 0.001206
Figure A2: PHL Trend Regression, DTR

| Variable   | Coefficient | Std. Error | t-Statistic | Prob. |
|------------|-------------|------------|-------------|-------|
| C          | 18.81577    | 0.171811   | 109.5146    | 0.0000|
| TIME       | -0.000100   | 1.30E-05   | -7.722985   | 0.0000|

R-squared: 0.009040
Adjusted R-squared: 0.008993
S.E. of regression: 6.432020
Sum squared resid: 876359.4
Log likelihood: -69490.61
F-statistic: 193.2414
Prob(F-statistic): 0.000000
Prob(Wald F-statistic): 0.000000
Figure A3: PHL Fixed Seasonal Regression, AVG

| Variable | Coefficient | Std. Error | t-Statistic | Prob.  |
|----------|-------------|------------|-------------|--------|
| D1       | -23.30393   | 0.501435   | -46.47449   | 0.0000 |
| D2       | -21.02927   | 0.482270   | -43.60480   | 0.0000 |
| D3       | -12.45912   | 0.432459   | -28.80997   | 0.0000 |
| D4       | -1.758657   | 0.360955   | -4.617651   | 0.0000 |
| D5       | 8.244852    | 0.350938   | 23.49374    | 0.0000 |
| D6       | 17.32183    | 0.273401   | 63.35694    | 0.0000 |
| D7       | 22.24082    | 0.218207   | 101.9252    | 0.0000 |
| D8       | 20.79500    | 0.240577   | 86.43813    | 0.0000 |
| D9       | 13.65797    | 0.337038   | 40.52355    | 0.0000 |
| D10      | 1.849370    | 0.382281   | 4.837729    | 0.0000 |
| D11      | -8.365280   | 0.381983   | -21.89963   | 0.0000 |
| D12      | -18.38047   | 0.453931   | -40.49180   | 0.0000 |

R-squared 0.810549 Mean dependent var -4.09E-16
Adjusted R-squared 0.810451 S.D. dependent var 17.66291
S.E. of regression 7.899949 Akaike info criterion 6.918272
Sum squared resid 1252072. Schwarz criterion 6.922781
Log likelihood -73269.79 Hannan-Quinn criter. 6.919743
Durbin-Watson stat 0.599680

Notes: The regression is based on de-trended data. See text for details.
Figure A4: PHL Fixed Seasonal Regression, DTR

The regression is based on de-trended data. See text for details.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| D1       | -2.991512   | 0.192368   | -15.55099   | 0.0000|
| D2       | -1.635110   | 0.231828   | -7.053111   | 0.0000|
| D3       | 0.330347    | 0.259911   | 1.271004    | 0.2037|
| D4       | 2.503174    | 0.249080   | 10.04967    | 0.0000|
| D5       | 2.176853    | 0.224701   | 9.687776    | 0.0000|
| D6       | 1.552979    | 0.203088   | 7.646812    | 0.0000|
| D7       | 0.481646    | 0.176516   | 2.728617    | 0.0064|
| D8       | -0.018021   | 0.161591   | -0.111525   | 0.9112|
| D9       | 0.301301    | 0.198622   | 1.516957    | 0.1293|
| D10      | 0.977539    | 0.232409   | 4.206109    | 0.0000|
| D11      | -0.717284   | 0.227973   | -3.146351   | 0.0017|
| D12      | -2.989081   | 0.189615   | -15.76399   | 0.0000|

The regression is based on de-trended data. See text for details.
Figure A5: PHL Evolving Seasonal Regression, AVG

The regression is based on de-trended data. See text for details.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| D1       | -23.64611   | 0.917908   | -25.76088   | 0.0000|
| D2       | -21.28787   | 0.914906   | -23.26781   | 0.0000|
| D3       | -12.23296   | 0.909260   | -13.45376   | 0.0000|
| D4       | -1.811997   | 0.788622   | -2.044069   | 0.0410|
| D5       | 8.723673    | 0.694282   | 12.56503    | 0.0000|
| D6       | 17.74138    | 0.472155   | 37.57531    | 0.0000|
| D7       | 22.28663    | 0.396004   | 56.22834    | 0.0000|
| D8       | 21.46530    | 0.458948   | 46.77065    | 0.0000|
| D9       | 14.03163    | 0.725289   | 19.34628    | 0.0000|
| D10      | 2.092955    | 0.757859   | 2.761666    | 0.0058|
| D11      | -7.665536   | 0.745087   | -10.28839   | 0.0000|
| D12      | -19.43088   | 0.896796   | -21.66700   | 0.0000|
| D1*TIME  | 3.28E-05    | 7.58E-05   | 0.433257    | 0.6648|
| D2*TIME  | 2.47E-05    | 7.77E-05   | 0.318247    | 0.7503|
| D3*TIME  | -2.16E-05   | 7.55E-05   | -0.285878   | 0.7750|
| D4*TIME  | -1.39E-05   | 6.18E-05   | -0.225743   | 0.8214|
| D5*TIME  | -4.54E-05   | 5.85E-05   | -0.775604   | 0.4380|
| D6*TIME  | -3.97E-05   | 4.00E-05   | -0.992529   | 0.3210|
| D7*TIME  | -2.43E-06   | 3.33E-05   | -0.730364   | 0.9417|
| D8*TIME  | -6.30E-05   | 3.76E-05   | -1.673848   | 0.0942|
| D9*TIME  | -3.50E-05   | 5.66E-05   | -0.618641   | 0.5362|
| D10*TIME | -2.28E-05   | 6.08E-05   | -0.374342   | 0.7082|
| D11*TIME | -6.62E-05   | 5.89E-05   | -1.107436   | 0.2681|
| D12*TIME | 9.76E-05    | 7.39E-05   | 1.320912    | 0.1865|

- R-squared: 0.810805
- Mean dependent var: -4.08E-16
- Adjusted R-squared: 0.810600
- S.D. dependent var: 17.66291
- Akaike info criterion: 6.918051
- Schwarz criterion: 6.927070
- Hannan-Quinn crit.: 6.920993
- Durbin-Watson stat: 0.600496

The regression is based on de-trended data. See text for details.
The regression is based on de-trended data. See text for details.
Figure A7: PHL Joint Conditional Mean Regression, AVG

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 21.20203    | 0.406242   | 52.19058    | 0.0000|
| TIME     | 6.68E-05    | 1.13E-05   | 5.890710    | 0.0000|
| D1       | -13.00377   | 0.398518   | -32.63032   | 0.0000|
| D2       | -12.01654   | 0.399985   | -30.04244   | 0.0000|
| D3       | -9.477612   | 0.366252   | -25.87730   | 0.0000|
| D4       | -6.497795   | 0.316712   | -20.51640   | 0.0000|
| D5       | -3.590633   | 0.271226   | -13.23852   | 0.0000|
| D6       | -1.031422   | 0.224911   | -4.585914   | 0.0000|
| D8       | -0.281529   | 0.207881   | -1.354279   | 0.1757|
| D9       | -2.623407   | 0.270530   | -9.697284   | 0.0000|
| D10      | -5.887328   | 0.305137   | -19.29406   | 0.0000|
| D11      | -8.778265   | 0.325337   | -26.98210   | 0.0000|
| D12      | -11.86465   | 0.382181   | -31.04459   | 0.0000|
| D1 TIME  | 7.51E-06    | 2.78E-05   | 0.270704    | 0.7866|
| D2 TIME  | -5.17E-06   | 2.81E-05   | -0.183774   | 0.8542|
| D3 TIME  | -7.90E-06   | 2.69E-05   | -0.293868   | 0.7689|
| D4 TIME  | -6.22E-06   | 2.30E-05   | -0.270271   | 0.7870|
| D5 TIME  | -1.02E-05   | 2.24E-05   | -0.455154   | 0.6490|
| D6 TIME  | -2.41E-05   | 1.84E-05   | -1.313423   | 0.1891|
| D8 TIME  | -2.11E-05   | 1.68E-05   | -1.254882   | 0.2095|
| D9 TIME  | -1.35E-05   | 2.12E-05   | -0.637214   | 0.5240|
| D10 TIME | -1.09E-05   | 2.32E-05   | -0.470157   | 0.6382|
| D11 TIME | -1.16E-05   | 2.28E-05   | -0.515052   | 0.6065|
| D12 TIME | 1.82E-05    | 2.72E-05   | 0.668393    | 0.5039|
| AVG_PHL(-1) | 0.718329  | 0.005105   | 140.7124    | 0.0000|

- R-squared: 0.908718
- Adjusted R-squared: 0.908614
- S.E. of regression: 5.355669
- Sum squared resid: 606907.6
- Log likelihood: -65596.33
- F-statistic: 8776.620
- Prob(F-statistic): 0.000000
- Prob(Wald F-statistic): 0.000000
Figure A8: PHL Joint Conditional Mean Regression, DTR

| Variable  | Coefficient | Std. Error | t-Statistic | Prob.  |
|-----------|-------------|------------|-------------|--------|
| C         | 12.95271    | 0.302723   | 42.78740    | 0.0000 |
| TIME      | -8.61E-05   | 1.93E-05   | -4.453194   | 0.0000 |
| D1        | -2.922818   | 0.369270   | -7.915131   | 0.0000 |
| D2        | -2.173920   | 0.412045   | -5.275928   | 0.0000 |
| D3        | -1.035858   | 0.441871   | -2.344253   | 0.0191 |
| D4        | 0.964259    | 0.481586   | 2.002259    | 0.0453 |
| D5        | 0.990373    | 0.408136   | 2.426577    | 0.0153 |
| D6        | 0.804887    | 0.403563   | 1.994453    | 0.0461 |
| D8        | -0.301248   | 0.360100   | -0.836567   | 0.4028 |
| D9        | -0.093547   | 0.418881   | -0.223433   | 0.8232 |
| D10       | 1.209749    | 0.443337   | 2.728733    | 0.0064 |
| D11       | -1.082676   | 0.440556   | -2.457523   | 0.0140 |
| D12       | -2.615967   | 0.393432   | -6.649102   | 0.0000 |
| D1*TIME   | 6.07E-05    | 2.91E-05   | 2.088017    | 0.0368 |
| D2*TIME   | 7.69E-05    | 3.20E-05   | 2.406160    | 0.0161 |
| D3*TIME   | 9.12E-05    | 3.15E-05   | 2.895508    | 0.0038 |
| D4*TIME   | 3.91E-05    | 3.58E-05   | 1.097937    | 0.2722 |
| D5*TIME   | 1.28E-05    | 3.16E-05   | 0.398334    | 0.6904 |
| D6*TIME   | -9.59E-06   | 2.88E-05   | -0.333302   | 0.7389 |
| D8*TIME   | -1.36E-06   | 2.63E-05   | -0.51623    | 0.9588 |
| D9*TIME   | -2.09E-06   | 3.02E-05   | -0.69050    | 0.9450 |
| D10*TIME  | -8.02E-05   | 3.22E-05   | -2.489722   | 0.0128 |
| D11*TIME  | 2.43E-05    | 3.23E-05   | 0.753026    | 0.4514 |
| D12*TIME  | 3.13E-05    | 2.92E-05   | 1.070849    | 0.2842 |
| DTR_PHL(-1) | 0.339047   | 0.007669  | 44.20912    | 0.0000 |

| Statistic          | Value       | Description                        | p-value  |
|--------------------|-------------|------------------------------------|----------|
| R-squared          | 0.190049    | Mean dependent var                  | 17.75151 |
| Adjusted R-squared | 0.189130    | S.D. dependent var                  | 6.461226 |
| S.E. of regression | 5.818225    | Akaike info criterion               | 6.361047 |
| Sum squared resid  | 716268.9    | Schwarz criterion                   | 6.370442 |
| Log likelihood     | -67351.21   | Hannan-Quinn criter.                | 6.364112 |
| F-statistic        | 206.8665    | Durbin-Watson stat                  | 1.997036 |
| Prob(F-statistic)  | 0.0000000   | Wald F-statistic                    | 149.6270 |
| Prob(Wald F-statistic) | 0.0000000 |                                 |          |
Figure A9: PHL Joint Conditional Variance Regression, AVG

| Variable   | Coefficient | Std. Error | t-Statistic | Prob.     |
|------------|-------------|------------|-------------|-----------|
| C          | 12.53425    | 0.856703   | 14.63081    | 0.0000    |
| TIME       | -8.55E-05   | 6.71E-05   | -1.274025   | 0.2027    |
| D1         | 27.95462    | 3.314398   | 8.434298    | 0.0000    |
| D2         | 27.40326    | 3.694701   | 7.416908    | 0.0000    |
| D3         | 19.65243    | 3.217091   | 6.108760    | 0.0000    |
| D4         | 16.33077    | 2.814383   | 5.802609    | 0.0000    |
| D5         | 15.64959    | 2.275588   | 6.877178    | 0.0000    |
| D6         | 7.851489    | 1.614614   | 4.862766    | 0.0000    |
| D8         | 1.684095    | 1.451363   | 1.160355    | 0.2459    |
| D9         | 10.15016    | 1.696774   | 5.982032    | 0.0000    |
| D10        | 15.41559    | 1.868326   | 8.251017    | 0.0000    |
| D11        | 21.81678    | 2.580458   | 8.454616    | 0.0000    |
| D12        | 25.32869    | 2.912168   | 8.697454    | 0.0000    |
| D1*TIME    | 0.000147    | 0.000289   | 0.508400    | 0.6112    |
| D2*TIME    | 2.29E-05    | 0.000311   | 0.073498    | 0.9414    |
| D3*TIME    | 0.000468    | 0.000278   | 1.683618    | 0.0923    |
| D4*TIME    | 0.000376    | 0.000229   | 1.646811    | 0.0996    |
| D5*TIME    | -0.000170   | 0.000179   | -1.000579   | 0.3170    |
| D6*TIME    | -0.000154   | 0.000129   | -1.191914   | 0.2333    |
| D8*TIME    | -0.000147   | 0.000104   | -1.409849   | 0.1586    |
| D9*TIME    | -0.000204   | 0.000130   | -1.572636   | 0.1158    |
| D10*TIME   | -0.000131   | 0.000160   | -0.870783   | 0.3839    |
| D11*TIME   | -5.66E-05   | 0.000223   | -0.253438   | 0.7999    |
| D12*TIME   | -0.000102   | 0.000226   | -0.449544   | 0.6530    |
| E2_AVG_PHL(-1) | 0.045064 | 0.0008634 | 5.219394 | 0.0000 |

- **R-squared**: 0.056834
- **Adjusted R-squared**: 0.055765
- **S.E. of regression**: 43.53862
- **Sum squared resid**: 40107347
- **Log likelihood**: -109982.1
- **F-statistic**: 53.12346
- **Prob(F-statistic)**: 0.000000
- **Prob(Wald F-statistic)**: 0.000000

- Mean dependent var: 28.65058
- S.D. dependent var: 44.80583
- Akaike info criterion: 10.38635
- Schwarz criterion: 10.39575
- Hannan-Quinn criter.: 10.38942
- Durbin-Watson stat: 2.002735
- Wald F-statistic: 71.11827
Figure A10: PHL Joint Conditional Variance Regression, DTR

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| C        | 22.37441    | 2.025807   | 11.04469    | 0.0000|
| TIME     | -0.000393   | 0.000143   | -2.754483   | 0.0059|
| D1       | 10.66203    | 3.499646   | 3.046602    | 0.0023|
| D2       | 15.43329    | 3.251396   | 4.746665    | 0.0000|
| D3       | 23.89886    | 3.584542   | 6.667200    | 0.0000|
| D4       | 27.07562    | 3.612763   | 7.494436    | 0.0000|
| D5       | 23.21550    | 3.713078   | 6.252359    | 0.0000|
| D6       | 10.56819    | 2.869652   | 3.682741    | 0.0002|
| D9       | -0.077822   | 2.467053   | -0.031545   | 0.9748|
| D9       | 11.83351    | 3.131250   | 3.779164    | 0.0002|
| D10      | 15.76030    | 3.429174   | 4.595946    | 0.0000|
| D11      | 12.79291    | 3.141156   | 4.072675    | 0.0000|
| D12      | 11.53788    | 2.921364   | 3.949484    | 0.0001|
| D1*TIME  | 0.000435    | 0.000282   | 1.542890    | 0.1229|
| D2*TIME  | 0.000121    | 0.000256   | 0.471372    | 0.6374|
| D3*TIME  | 0.000287    | 0.000279   | 1.029384    | 0.3033|
| D4*TIME  | 0.000150    | 0.000283   | 0.531146    | 0.5963|
| D5*TIME  | -0.000227   | 0.000269   | -0.845246   | 0.3980|
| D6*TIME  | -0.000307   | 0.000211   | -1.455570   | 0.1455|
| D8*TIME  | -9.88E-05   | 0.000176   | -0.560119   | 0.5754|
| D9*TIME  | -0.000565   | 0.000219   | -2.586589   | 0.0097|
| D10*TIME | -0.000220   | 0.000244   | -0.893320   | 0.3890|
| D11*TIME | 0.000126    | 0.000236   | 0.535258    | 0.5925|
| D12*TIME | 6.74E-05    | 0.000211   | 0.319497    | 0.7494|
| E2_DTR_PHL(-1) | 0.067617 | 0.011837 | 5.712522 | 0.0000 |

| Statistic          | Value                  | Description                        | Prob. |
|--------------------|------------------------|------------------------------------|-------|
| R-squared          | 0.046411               | Mean dependent var                 | 33.80817 |
| Adjusted R-squared | 0.045329               | S.D. dependent var                 | 49.85206 |
| S.E. of regression | 48.70908               | Akaike info criterion              | 10.61079 |
| Sum squared resid  | 50198927               | Schwarz criterion                  | 10.62018 |
| Log likelihood     | -112359.2              | Hannan-Quinn criter.               | 10.61385 |
| F-statistic        | 42.90654               | Durbin-Watson stat                 | 2.001013 |
| Prob(F-statistic)  | 0.000000               | Wald F-statistic                  | 56.51759 |
| Prob(Wald F-statistic) | 0.000000 |                      |       |