On the Relationship between Climate and Homelessness

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Abstract

It is well understood that unsheltered homelessness is on average more common in communities with warmer climates. In this paper, we show that cold places uniformly have low rates of unsheltered homelessness, while warm places display wide variation. For example, among communities with an average daily low January temperature of 10 degrees, the 10th and 90th percentile unsheltered homelessness rates per 10,000 people are 0.2 and 3.9 respectively. When the temperature is 40 degrees, these rates are 2.1 and 38.9. Using data on homeless counts within communities over time, we find that at most 41 percent of the cross sectional 90/10 gap in warm places is due to non-persistent measurement error. Finally, we show that accounting for variation over climate is important in determining the importance of other factors in predicting unsheltered homelessness. We find that precipitation, housing prices, poverty rates, racial demographics and religious affiliations of the population are important.

JEL classification: I32; I38; R12; R28
Keywords: Homelessness; Climate; Measurement; Religion

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1 Introduction

Climate is an important amenity. It helps explain why housing is much more expensive in San Diego than Minneapolis. For the homeless population, climate is especially important, as lack of shelter in cold places can have serious consequences for health or potentially mortality (Hwang 2011). But climate is not directly capitalized into the cost of living for the homeless, who do not pay rent or mortgages. Thus, we would expect their populations to be much larger in places with warm climates. Indeed, 48 percent of the unsheltered homeless population is found in California and Florida alone, while just 15 percent of the United States population lives in these two states. A number of studies point to climate as among the most important factors that determine homeless population sizes (see Byrne et al. 2013 for a review). Conventional wisdom among local officials and others in cities with warm climates is that warm temperatures are major draws for the homeless.[1]

We move beyond the focus on averages to study the distribution of homelessness over temperature. Using cross-sectional homeless counts from communities across the United States, we reject the notion that warm climates automatically produce large unsheltered homeless populations. While unsheltered homelessness rates are uniformly low in cold climates, there is wide variation in unsheltered homeless rates in warm communities. In a community where the average daily low temperature in January is 10 degrees, the predicted unsheltered rate is 0.2 per 10,000 for the 10th percentile community, and 3.9 per 10,000 for the 90th percentile. But in communities where the temperature is 40 degrees, the predicted unsheltered rates in the 10th and 90th percentile communities are 2.1 and 38.9 per 10,000 people.

What explains these findings? The result that cold climate places have uniformly low unsheltered rates is unsurprising; extremely harsh conditions presumably lead otherwise unsheltered individuals to sleep in shelter, find housing (possibly with friends or relatives), or move (at least during the winter when homeless counts are conducted). The result that warm places exhibit wide

[1] For example, Vancouver's mayor stated in 2015 that "B.C. faces a bigger challenge because it's warmer than the rest of Canada" (Hopper 2015). A homelessness consultant states, "Where there are palm trees and golf courses, there will always be homeless individuals because of the moderate climate" (Marbut 2011).

variation in unsheltered rates after controlling for community level factors is less obvious. Rates of homeless shelter use are uniformly low in warm weather places, suggesting that shelter usage does not explain this variation.

One explanation could be multiplicative measurement error in unsheltered homelessness rates. In other words, places with high average rates of homelessness—which also have warm climates—may have larger errors in counting their homeless populations. Fortunately, we have panel data on homeless counts over eight years that allow us to bound the impact of non-persistent measurement error on our results. Intuitively, if homeless counts vary substantially over time within a given community, then non-persistent measurement error could be an important source of variation in homeless counts in our cross section during a given year. In order to bound the effect of non-persistent measurement error on our results, we first estimate a fixed effects regression explaining within community variation in unsheltered homelessness rates over time, controlling for observable community factors. We then use the unexplained variation in unsheltered homelessness rates over time to form an upper bound estimate of cross-sectional variation in unsheltered rates caused by non-persistent measurement error. We find that at most 41 percent of the gap between the 90th and 10th percentile in unsheltered rates when the average daily low temperature in January is 40 degrees can be explained by measurement error.

The result that rates of unsheltered homelessness vary much more widely in warm places than cold places, after accounting for measurement error, has important implications for modeling the determinants of unsheltered homelessness. Specifically, including cold places in regressions of rates of unsheltered homelessness on community characteristics will mask associations in warm places. One remedy is to separate the sample on the basis of temperature. An alternative remedy is to take logarithmic transformations of unsheltered homelessness rates, which we show to be more uniformly distributed over temperature. We estimate the determinants of unsheltered homelessness using both approaches and find that doing so has important consequences. We find that housing prices and poverty rates significantly increase unsheltered homelessness in rates in the warm climate sample and in percentage terms in the full sample. Also, the percent of the population that is

an adherent to Catholic churches is significantly and negatively associated with unsheltered homelessness. These religious measures could proxy for broader cultural forces that affect unsheltered population sizes or they may be related to the types of efforts utilized to address homelessness.

This paper contributes to an extensive literature on the determinants of homeless population sizes across the United States. The quality of measures of homelessness has varied significantly across this literature, with earlier studies relying on counts with methodological flaws, counts that omit unsheltered homeless populations altogether, or personal estimates by local experts of their homeless populations (Appelbaum et al. 1991; Grimes and Chressanthis 1997; Honig and Filer 1993; Quigley et al. 2001; Early and Olsen 2002; Lee et al. 2003). More recent studies have relied on homeless counts conducted by Continuums of Care that span the United States and are considered significantly more reliable, though still highly imperfect (e.g., Raphael 2010; Byrne et al. 2014; Lucas 2017). Cross-sectional studies typically conclude that housing prices and climate are among the most important predictors of homeless populations. Time-series and panel data have occasionally been employed as well, and have found that macroeconomic conditions, as well as housing prices, are associated with larger homeless populations (Cragg and O'Flaherty 1999; Culhane et al. 2003; O'Flaherty and Wu 2006; O'Flaherty and Wu 2008; Hanratty 2017). Some have sought to identify the effects of policy on homeless populations as well—findings of the effect of federal funding for homeless assistance have been mixed (Moulton 2013, Lucas 2017); permanent housing targeted to homeless families reduces homeless populations (Cragg and O'Flaherty 1999; O'Flaherty and Wu 2006); permanent supportive housing has small to modest effects on homeless populations (Byrne et al. 2014, Corinth 2017); and higher shelter quality increases the number of people sleeping in shelters (Cragg and O'Flaherty 1999).

Findings on climate have been largely consistent. For example, Appelbaum et al. (1991) find that warmer temperatures are associated with larger homeless populations in HUD's 1984 report on homeless estimates in a number of cities. Grimes and Chressanthis (1997) find the same pattern: colder climates are associated with smaller street populations but do not predict variation in sheltered populations. Lee et al. (2003) find that precipitation is inversely related to 1990 S-night

homeless counts. Quigley et al. (2001) find milder climate to correspond to significantly higher incidences of homelessness using the S-night counts and data reported by Burt and Cohen (1989). Despite data limitations, the effects of climate on homelessness have proven robust. In an extensive review, Byrne et al. (2013) summarize the persistent pattern: "[a]mong these studies, most have found climate to have a significant relationship with rates of homelessness, and in the expected direction, with higher temperatures and less precipitation associated with higher rates of homelessness, and higher proportions of persons experiencing homelessness in unsheltered locations" (p. 613).

While largely consistent in its findings, prior research has focused exclusively on average climate effects. This approach masks a nuanced relationship between climate and homelessness: unsheltered homelessness is uniformly rare in cold places and exhibits wide variation in warm places. We identify this relationship by exploring how climate affects the distribution of rates of homelessness. We also show that accounting for this relationship is important for estimating the importance of other determinants of homelessness. Moreover, we bound the extent to which measurement error and short-term weather fluctuations affect our cross-sectional results using panel data on homeless counts over time.

It is important to emphasize that the focus of this paper is on climate and the implications for cross-sectional variation in unsheltered homelessness. Thus, we do not seek to identify the impact of weather—day-to-day fluctuations in temperature or precipitation—on homeless counts over time. Some studies have used time-series or panel data to study weather. O'Flaherty and Wu (2008) use monthly time series data in New York City to estimate the determinants of shelter populations for single adults, finding that increases in temperature reduce shelter populations. However, using annual, nation-wide data, Corinth (2017) does not find a significant association between day-of-count temperature or precipitation on total homeless counts using panel data between 2007 and 2014. In this paper, we use panel data on homeless counts to estimate the extent to which year-to-year variation in homeless counts drives the variation we observe in the cross-section. While we use this estimate to bound the effect of measurement error, it also bounds the effect of other

time-varying factors—including weather on the days when homeless counts are conducted. This affirms the notion that the patterns we identify are primarily due to climate rather than weather.

The paper proceeds as follows. We discuss our data and methodology in section 2. We present our results in section 3. We discuss our findings with implications for policy and future research in section 4. Section 5 concludes.

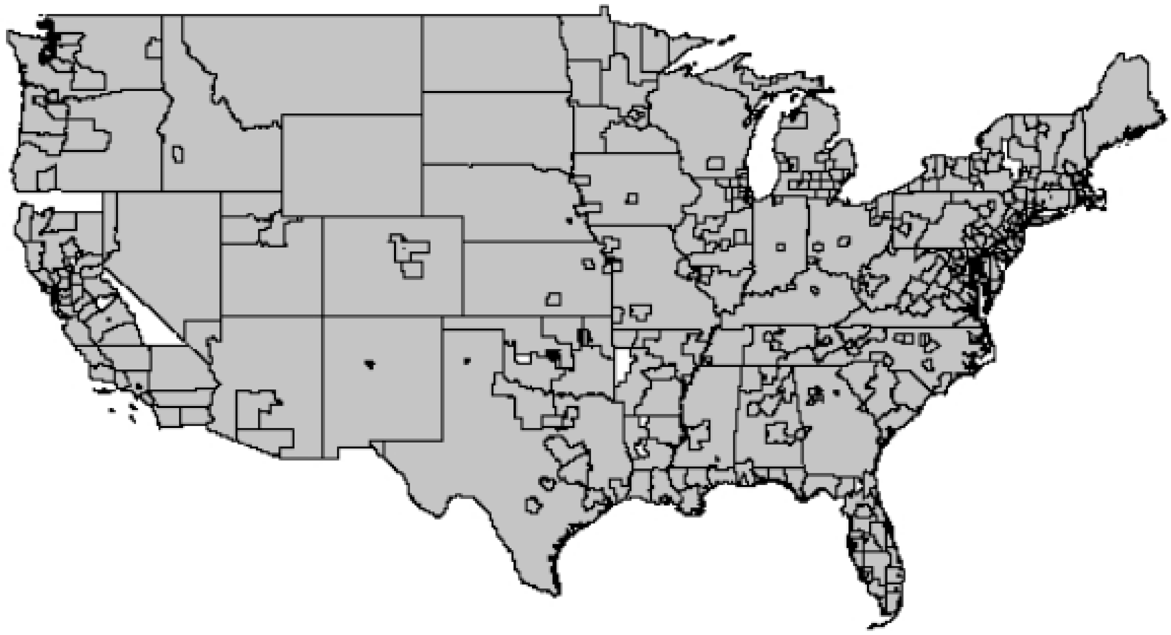
2 Data and Methodology

To explore the relationship between climate and homelessness, we use cross-sectional data for the year 2013 from communities that span the United States. Our measures of homelessness come from the Department of Housing and Urban Development's (HUD's) annual Point in Time (PIT) counts. Unsheltered counts are carried out by volunteers and social workers who identify local homeless populations during a single night in January. Emergency shelters and transitional housing programs provide sheltered counts for the same night. The PIT counts are reported at the Continuum of Care (CoC) level. CoCs are geographies created by HUD to facilitate the coordination of homeless services. Each CoC may comprise one county, multiple counties, or a portion of a county. CoC geographies as of 2013 are shown in Figure 1.

Climate variables are obtained from the United States Historical Climate Network (USHCN). Following the literature, we capture two key measures of climate: long-term temperature and precipitation. For temperature, we use the mean daily low temperature for the month of January averaged over the five year period 2009 to 2013 in degrees Fahrenheit. For precipitation, we use the average monthly precipitation in January over the same five year period. Temperature and precipitation for each CoC are based on readings from the weather station nearest to its centroid. Poverty rates and racial demographics are drawn from the American Community Survey.[2] Median rent comes from HUD's annual 50th percentile rent estimates by county. For these variables, CoCs composed of multiple counties are attributed a population-weighted average. We also use the U.S.

[2] We use the 2013 five-year pooled estimates.

Figure 1: Map of Continuum of Care Boundaries, 2013



Source: HUD CoC Shapefile for 2013

Department of Agriculture's "rural-urban continuum" score, which assigns each county a score ranging from one (most urban) to nine (most rural). We create a set of indicator variables based on the county population-weighted average score in the CoC.

In regressions that estimate the determinants of unsheltered homelessness, accounting for the climate patterns observed, we sometimes include additional explanatory variables. Rates of adherents of churches are obtained from the Association of Religion Data Archives 2010 U.S. Religion Census: Religious Congregations & Membership Study (RCMS). These data are available at the county level and are merged into our CoCs. It should be noted that these data are based on the number of adherents documented by churches themselves, not the number of people identifying under a particular denomination or religion. We include measures of Catholic, Evangelical and Protestant adherence; other denominations and religions have few or no adherents documented in a number of counties. Some of our specifications include inventories of emergency shelter, transitional housing, and permanent supportive housing beds. These data are obtained from HUD's annual inventory of homeless assistance beds. One other important factor is the degree to which communities pass

and enforce ordinances that affect the ability to sleep unhindered in unsheltered locations. These include restrictions on sleeping and camping in public, loitering, and homeless feeding programs. Unfortunately, quality community level data on these ordinances are not available.[3]

Table 1: Summary Statistics

Variable	Median	Mean	Standard Deviation
Unsheltered Homeless per 10,000 residents	2.16	7.07	15.96
Sheltered Homeless per 10,000 residents	9.79	12.64	12.17
Emergency shelter beds per 10,000 residents	5.45	6.98	7.38
Transitional housing beds per 10,000 residents	4.82	6.15	5.05
PSH beds per 10,000 residents	6.65	9.36	11.10
January temperature (degrees Fahrenheit)	24.48	25.57	11.62
January total precipitation (inches)	2.48	2.64	1.61
Median rent (dollars)	837	890	234
Poverty rate	.143	.143	.044
Rural score = 1	0	.346	.476
Rural score = 2	0	.261	.440
Rural score = 3	0	.161	.368
Rural score = 4	0	.108	.311
Rural score = 5	0	.063	.244
Rural score = 6	0	.061	.239
Percent black	.083	.120	.121
Percent Hispanic	.073	.119	.128
Percent Evangelical	.122	.158	.114
Percent Catholic	.156	.177	.119
Percent Protestant	.074	.083	.052

Note: All variables are based on the year 2013. Homeless variables come from the 2013 HUD PIT counts, climate variables come from the USHCN, economic and demographic variables come from the American Community Survey, median rent comes from the HUD 50th percentile rent estimates, rural scores come from the U.S. Department of Agriculture, and religious variables come from the Association of Religion Data Archives.

In order to determine the relationship between homelessness and climate, we estimate cross-sectional regressions of the form

$$H_c = p(T_c) + \beta X_c + \epsilon_c \tag{1}$$

[3]The National Law Center on Homelessness and Poverty publishes a regular report documenting ordinances in a number of cities. However, only 147 of our 379 CoCs include at least one city that it including in the 2014 report (National Law Center on Homelessness and Poverty 2014). Moreover, substantial variation in ordinances across reports suggests there may be inconsistencies in classification.

where c indexes a CoC, H is the rate of homelessness per 10,000 residents, $p(T)$ is a polynomial of the average daily low January temperature over the past five years, and X is a vector of control variables. We estimate equation (1) with both the unsheltered homelessness rate and sheltered homelessness rate as dependent variables. Given that we are interested in the distribution of effects of temperature on rates of homelessness, we estimate quantile regressions that uncover the effect at any point in the distribution.

As described above and argued elsewhere (e.g., Lucas 2016), homeless counts remain imperfect. Thus, one potential explanation for wide variation in unsheltered homelessness rates in warm climates is mismeasurement. While an additive error in measurement that has constant variance over rates of unsheltered homelessness would simply produce constant dispersion over climate, an error term that is larger in CoCs with higher rates of unsheltered homelessness would generate larger observed variation when unsheltered rates are higher—and, thus, when temperatures are warmer.

Fortunately, we have access to panel data on homeless counts that allow us to determine the extent to which year-to-year variation in counted rates of homelessness are larger for CoCs with higher rates of unsheltered homelessness. This allows us to bound the extent to which non-persistent measurement error can explain our results.[4] The methodology for estimating an upper bound of the impact of measurement error on dispersion in unsheltered homelessness rates is included in the appendix. The basic intuition is that year-to-year variation in homeless counts within a community that cannot be explained by observed factors reflects a combination of measurement error in each year and changing unobserved factors (such as weather on the night of the count or policy changes). Thus, measurement error is bounded by this unexplained dispersion in homeless counts over time within communities.

Once we document the relationship between climate and unsheltered homelessness (and whether greater variation in unsheltered homelessness rates in warm places can be explained by measurement error), we assess the cross-sectional determinants of unsheltered homelessness in ways that

[4]However, we are unable to rule out persistent bias in homeless counts that is larger in CoCs with higher rates of unsheltered homelessness.

account for the relationship we document. Here we estimate ordinary least squares regressions of the form

$$H_c = \alpha T_c + \beta X_c + \epsilon_c \tag{2}$$

Given wider variation in rates of unsheltered homelessness in warm places, one approach to estimating equation (2) is to split the cross-section into separate samples on the basis of temperature. Alternatively, we show that the logarithm of unsheltered rates of homelessness exhibits more uniform levels of variation over temperature. Thus, we also estimate equation (2) on the full sample using the logarithm of unsheltered homelessness rates as our dependent variable. Along with control variables used previously, we also include religious adherents of particular denominations of the population, as well as inventories of homeless assistance beds.

3 Results

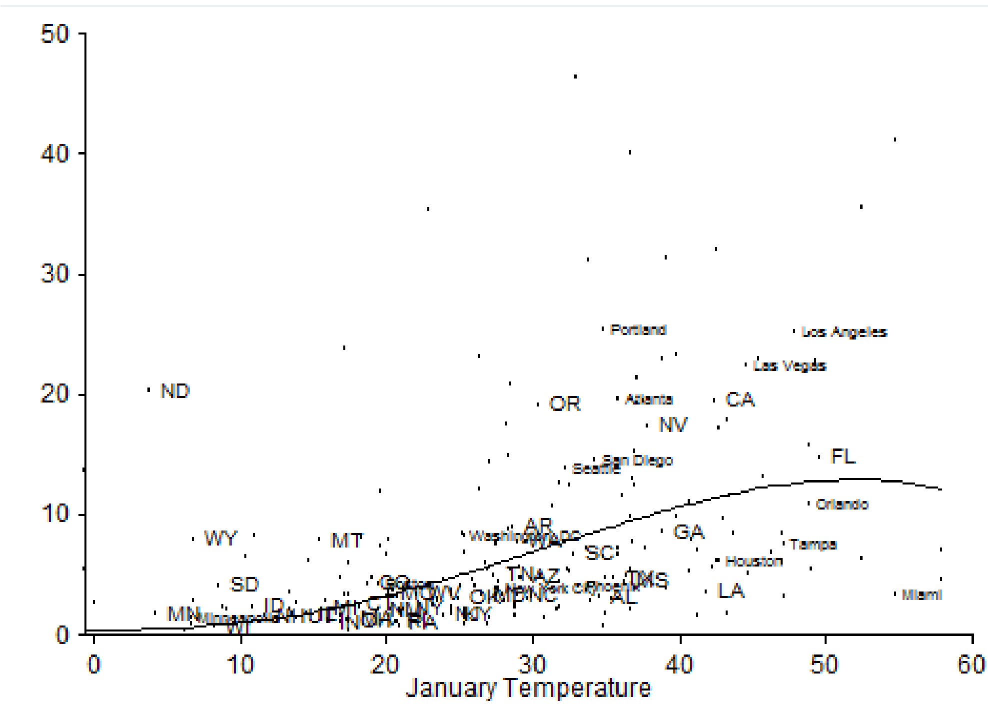
Figure 2 shows a histogram of unsheltered homelessness rates by January temperature. Entire states (based on average temperatures) and selected CoCs are shown as well. It is clear that essentially all CoCs with low temperatures have very low rates of unsheltered homelessness, while there is substantial variation in CoCs with modest and warm temperatures. For example, Miami, FL reports 3 unsheltered homeless individuals per 10,000, Houston, TX reports 6, Las Vegas, NV reports 23, and Los Angeles, CA reports 25.

Figure 3 shows sheltered homelessness rates by January temperature. Here, there is no discernible relationship with temperature. Three CoCs including New York City, Washington, DC and Boston, MA each have sheltered homelessness rates that far exceed all others. Aside from high housing costs, these cities have in common a legal right-to-shelter for all who need it.[5]

Quantile regression estimates are presented in Table 2, including estimates of the effect of

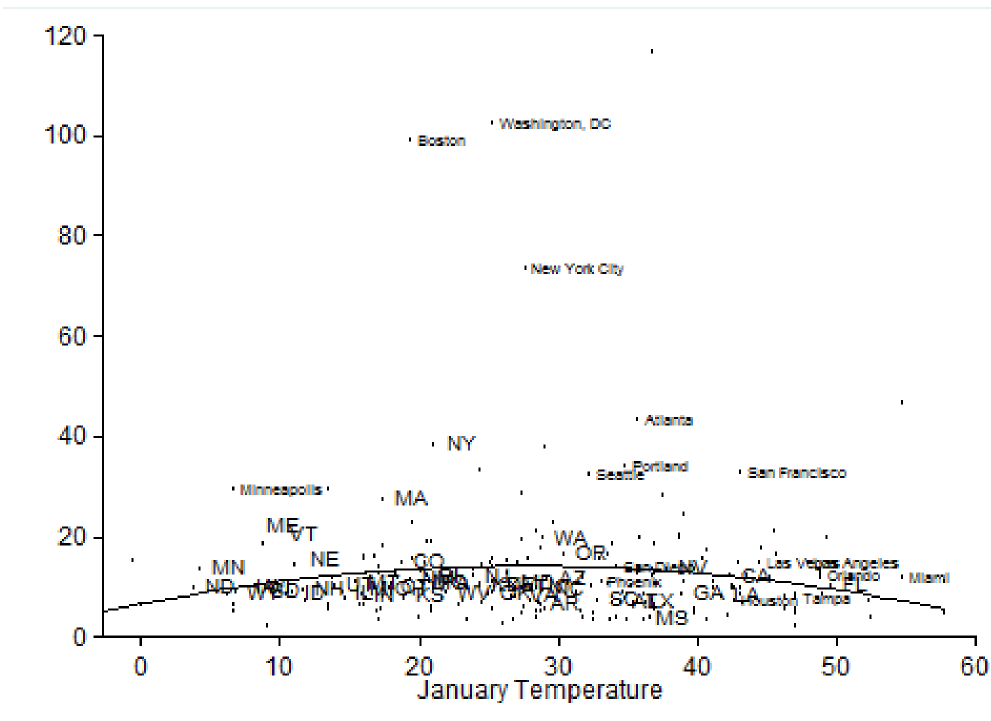
[5] Leopold (2014) identifies Washington DC, New York City, Columbus, OH, Hennepin County, MN, Montgomery County, MD and the state of Massachusetts as those with a legal right to shelter.

Figure 2: Unsheltered Homeless Rate per 10,000 Residents by Temperature



Note: Temperature is average daily low in January between 2009 and 2013 measured at the weather station nearest to the centroid of each CoC. State temperatures and homelessness rates are based on the population-weighted average.

Figure 3: Sheltered Homeless Rate per 10,000 Residents by Temperature



Note: Temperature is average daily low in January between 2009 and 2013 measured at the weather station nearest to the centroid of each CoC. State temperatures and homelessness rates are based on the population-weighted average.

temperature at the 10th percentile, 25th percentile, 50th percentile, 75th percentile and 90th percentile. Specifications with and without controls are shown, as are specifications with the unsheltered homelessness rate and sheltered homelessness rate as dependent variables. All specifications include precipitation, and they exclude higher order polynomial terms in temperature. Estimated temperature effects for unsheltered homelessness rates are much higher at the upper end of the distribution, and controlling for non-climate factors does little to explain the variation in temperature effects. At the 10th, 25th, 50th, 75th and 90th percentile, a one degree increase in temperature leads to a 0.04, 0.10, 0.17, 0.36 and 0.74 person increase in the rate of unsheltered homelessness. Estimates at all points of the distribution are statistically significant.

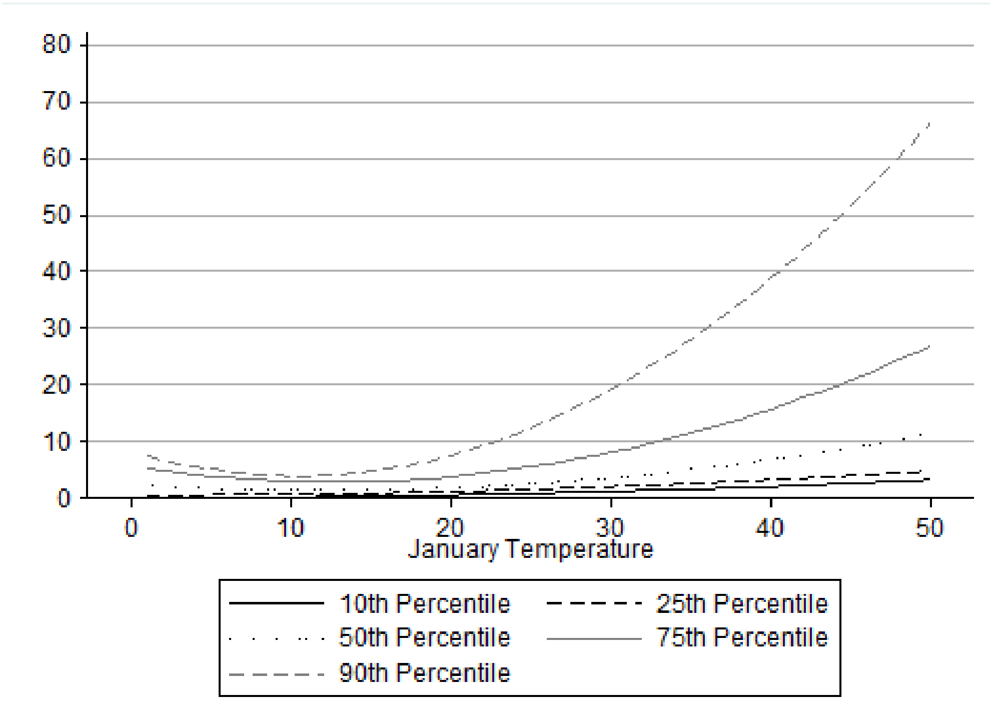
Effects of temperature on sheltered homelessness rates are not statistically different from zero when excluding control variables, but a significant negative relationship emerges when controls are added. Effect sizes are larger in absolute value (more negative) at higher points in the distribution. In contrast to the unsheltered results, in which variation increases with temperature, variation in sheltered rates decreases with temperature. This suggests that variation in unsheltered homelessness rates in warm places is not explained by variation in sheltered homelessness rates.

Table 2: Quantile Regression Estimates: Distribution of Temperature Effects

	Unsheltered	Unsheltered	Sheltered	Sheltered
10th percentile	0.0387***	0.0554***	-0.0164	-0.0642
	(0.00979)	(0.0198)	(0.0255)	(0.0512)
25th percentile	0.0950***	0.0866***	-0.0300	-0.110***
	(0.0217)	(0.0228)	(0.0249)	(0.0280)
50th percentile	0.173***	0.150***	0.00850	-0.178***
	(0.0224)	(0.0448)	(0.0313)	(0.0564)
75th percentile	0.364***	0.385***	-0.0875	-0.302***
	(0.0955)	(0.0951)	(0.0588)	(0.0562)
90th percentile	0.735***	0.734***	-0.0555	-0.469**
	(0.149)	(0.247)	(0.129)	(0.184)
Controls		X		X
Observations	379	379	379	379

Note: Dependent variable is homeless persons, either unsheltered or sheltered as indicated in column headings, per 10,000 residents. Estimates shown are for average daily low temperature in January between 2009 and 2013. Control variables include precipitation, logarithm of median rent, poverty rate, rural score indicator variables, percent black, and percent Hispanic. Bootstrapped standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Figure 4: Predicted Unsheltered Homeless Rate per 10,000 Residents by Temperature (with Controls)



Note: Predicted homelessness rates are based on regression estimates in Table 3. Average values of controls are assumed.

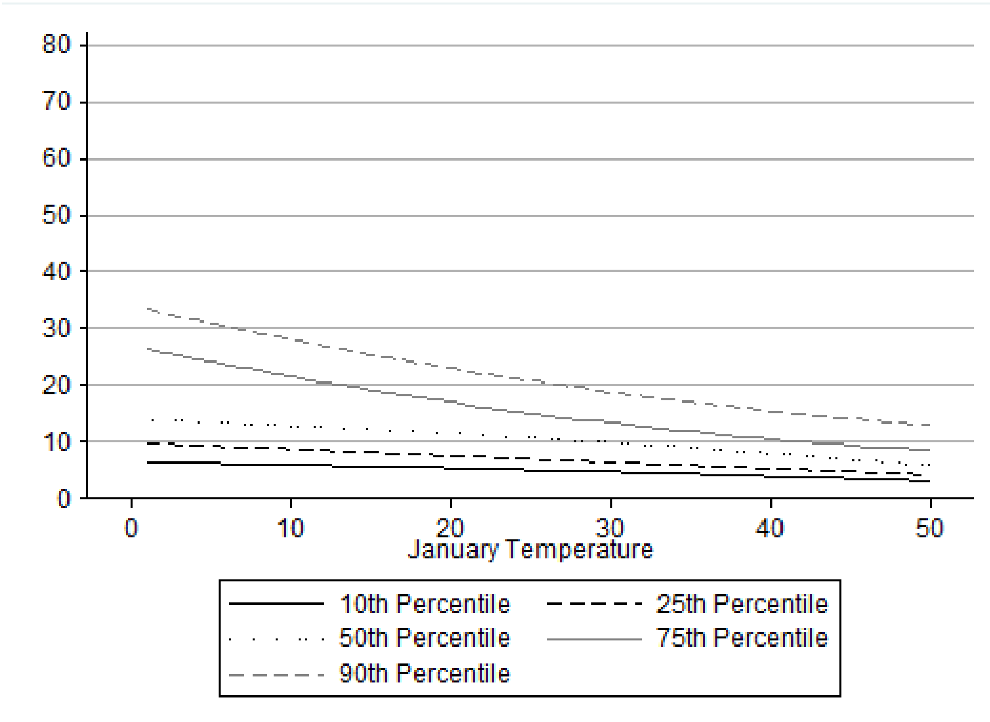
Table 3 presents quantile regression results incorporating a squared temperature term to allow for a nonlinear relationship between temperature and the homelessness rate. Figure 4 shows how estimates translate into predicted unsheltered rates, while Figure 5 show predicted sheltered rates. It is apparent from these figures that the relationship that imposes linear effects is preserved in the case of a second order polynomial in temperature. The effect of temperature on unsheltered homelessness is small at the low ends of the distribution and much larger at the upper ends of the distribution. Higher temperatures lead to lower rates of sheltered homelessness, particularly at the upper ends of the distribution. Figures based on higher order polynomials in temperature are shown in the appendix, with these same basic results. Table 4 summarizes predicted rates of unsheltered homelessness at various points in the distribution. Sizable differences between the highest and lowest percentiles are observed across the distribution, and these differences persist with the inclusion of relevant covariates.

Table 3: Quantile Regression Estimates: Distribution of Temperature and Squared Temperature Effects

	Unsheltered	Unsheltered	Sheltered	Sheltered
10th percentile				
Temperature	-0.0375	-0.000533	-0.0744	-0.0407
	(0.0259)	(0.0349)	(0.0977)	(0.128)
Temperature squared	0.00154**	0.00126	0.000785	-0.000515
	(0.000737)	(0.000772)	(0.00171)	(0.00211)
25th percentile				
Temperature	-0.0460	-0.00628	0.0148	-0.118
	(0.0517)	(0.0429)	(0.0812)	(0.102)
Temperature squared	0.00297**	0.00183**	-0.000747	0.0000996
	(0.00135)	(0.000859)	(0.00155)	(0.00165)
50th percentile				
Temperature	-0.172*	-0.164	0.150	-0.0939
	(0.0909)	(0.115)	(0.144)	(0.158)
Temperature squared	0.00728***	0.00693*	-0.00263	-0.00137
	(0.00265)	(0.00365)	(0.00247)	(0.00200)
75th percentile				
Temperature	-0.629**	-0.432***	0.0747	-0.584**
	(0.257)	(0.152)	(0.198)	(0.243)
Temperature squared	0.0220***	0.0172***	-0.00246	0.00428
	(0.00630)	(0.00334)	(0.00288)	(0.00391)
90th percentile				
Temperature	-1.960**	-0.835*	0.482	-0.635*
	(0.848)	(0.456)	(0.421)	(0.378)
Temperature squared	0.0640***	0.0401***	-0.00889	0.00427
	(0.0223)	(0.0143)	(0.00964)	(0.00621)
Controls		X		X
Observations	379	379	379	379

Note: Dependent variable is homeless persons, either unsheltered or sheltered as indicated in column headings, per 10,000 residents. Estimates shown are for average daily low temperature in January between 2009 and 2013. Control variables include precipitation, logarithm of median rent, poverty rate, rural score indicator variables, percent black, and percent Hispanic. Bootstrapped standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Figure 5: Predicted Sheltered Homeless Rate per 10,000 Residents by Temperature (with Controls)



Note: Predicted homelessness rates are based on regression estimates in Table 3. Average values of controls are assumed.

Table 4: Predicted Rates of Unsheltered Homelessness by Temperature and Specification

	Percentiles					Differences	
Specification/Temperature	10th	25th	50th	75th	90th	75th – 25th	90th – 10th
Temperature = 10							
No controls	0.21	0.31	0.87	2.09	5.16	1.77	4.95
Controls	0.18	0.68	1.36	2.94	3.88	2.26	3.71
Temperature = 25							
No controls	0.45	1.18	2.12	4.23	9.37	3.04	8.91
Controls	0.83	1.55	2.53	5.49	12.39	3.94	11.56
Temperature = 40							
No controls	1.39	3.39	6.64	16.28	42.39	12.98	40.99
Controls	2.05	3.23	6.82	15.77	38.92	12.54	36.87

Note: Predicted homelessness rates are based on regression estimates in Table 3. Average values of controls are assumed. Temperature is measured in degrees Fahrenheit.

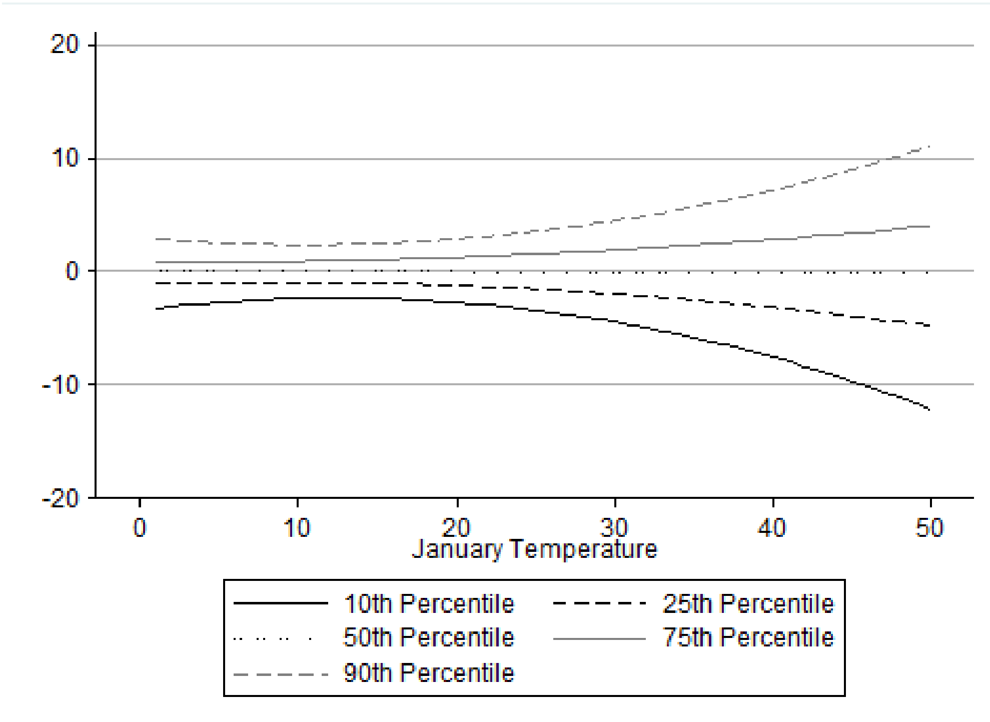
Bounding Measurement Error

One potential explanation for wide variation in unsheltered homelessness rates in warm climates is measurement error. CoCs with higher unsheltered rates may plausibly have larger measurement error, and given that higher temperatures are associated with higher unsheltered rates, this could explain the variation we observe. On the basis of a fixed effects regression using 2007–2014 panel data, we use the squared residuals to predict the variance in within-CoC rates of unsheltered homelessness over levels of unsheltered rates. Specifically, we regress squared residuals on unsheltered rates and unsheltered rates squared in our panel data. The square root of the estimated function provides an estimate of the standard deviation for any given level of unsheltered rate. Figure A5 plots this function. (In the appendix, Table A1 shows estimates from the fixed effects regression, and Table A2 shows estimates of the association between unsheltered rates and squared residuals.)

The standard deviation of within-CoC counts is indeed larger in CoCs with higher rates of unsheltered homelessness. It is important to recognize, however, that this variation is not solely due to measurement error, but to all time-varying, unobserved factors in a CoC that affect counts, including weather on the day of the count and local policy changes. Thus, this estimate is an upper bound estimate of the variation in homeless counts attributed to year-to-year measurement error. Furthermore, it is likely that homeless counts have improved over time, and so our cross-sectional data from 2013 may suffer less from measurement error than that found over the entire period of our panel.

Figure 6 shows the estimated distribution of predicted unsheltered rates over temperature that can be attributed to within-CoC variation in unsheltered rates. If measurement error were the only reason unsheltered rates vary in CoCs over time, these estimates indicate the extent to which the variation we observe cross-sectionally in unsheltered rates is attributed to measurement error. The difference in unsheltered rates between the 90th and 10th percentile when the temperature is 40 degrees Fahrenheit (including controls), for example, is 38.7 people per 10,000 in a CoC. Given that the gap between the 90th and 10th percentile due to unexplained within-CoC variation at 40 degrees is 15.1 people, measurement error could explain at most 41 percent of the gap. Since many

Figure 6: Estimated distribution of predicted unsheltered homelessness rates attributed to year-to-year variation in unsheltered rates



Note: Percentiles for each temperature are predicted based on quantile regressions using randomly generated deviations in unsheltered homelessness rates. We show the average prediction over 10,000 trials.

other factors beyond measurement error likely drive within-CoC variation in unsheltered rates over time, measurement error is likely less important than this implies.

Application to the Determinants of Homelessness

We have shown above that rates of unsheltered homelessness exhibit substantially more variation in warmer places, and that measurement error is at most a partial explanation. This has important implications for assessing the determinants of unsheltered homelessness. In particular, inclusion of cold places in regressions where the dependent variable is the rate of unsheltered homelessness will mask potentially important relationships in warm places. For example, the price of housing can vary substantially across cold places. But because all cold places have uniformly low rates of unsheltered homelessness, the association between housing prices and unsheltered homelessness will

be diminished in the full sample, even if housing prices are important predictors of homelessness in warm places. One approach is to account for nonlinearity by using the logarithm of unsheltered homeless rates. Table 5 shows quantile regression estimates predicting the logarithm of unsheltered homelessness rates in the 2013 cross section. Temperature effects across the distribution are much more condensed than when the dependent variable is expressed as a rate.

Table 5: Quantile regression estimates, logarithm of unsheltered homelessness rate

	10th pct.	25th pct.	50th pct.	75th pct.	90th pct.
Temperature	0.0471***	0.0495***	0.0639***	0.0540***	0.0814***
	(0.0122)	(0.00877)	(0.00796)	(0.00582)	(0.0186)
Log precipitation	-0.599***	-0.292*	-0.268	-0.273***	-0.453**
	(0.144)	(0.161)	(0.181)	(0.0830)	(0.225)
Log median rent	3.188***	2.951***	2.959***	3.284***	2.666***
	(1.043)	(0.560)	(0.499)	(0.371)	(1.024)
Poverty rate	21.47***	20.14***	20.04***	19.72***	17.13**
	(5.511)	(3.506)	(3.311)	(2.635)	(6.928)
Percent black	-2.834*	-3.587**	-3.849***	-3.425***	-4.427***
	(1.599)	(1.419)	(0.984)	(0.522)	(1.016)
Percent Hispanic	-2.754**	-2.636**	-3.121***	-3.280***	-4.326**
	(1.131)	(1.051)	(0.686)	(0.647)	(1.725)
Observations	377	377	377	377	377

Note: Dependent variable is logarithm of unsheltered homeless persons per 10,000 residents. Bootstrapped standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Another approach is to split the sample to assess the effects in different subsets of the CoC population. Table 6 shows regression estimates that split the sample on the basis of January temperature (whether below or above the median), using both rates of unsheltered homelessness and its logarithm. We find that splitting the sample is important when the dependent variable is expressed as a rate. For example, the association between rent and unsheltered homelessness is much stronger in the warm sample. Meanwhile, splitting the sample is not important when taking the logarithm of the unsheltered homelessness rate.

Finally, we explore whether other factors can help explain the variation in the logarithm of unsheltered homelessness. Table 7 includes the religious affiliation of the population and homeless

Table 6: Ordinary least squares estimates of the determinants of homelessness, split sample

	Rate Cold	Rate Warm	Rate All	Log Cold	Log Warm	Log All
Temperature	0.00898	0.674***	0.491***	0.0240	0.0512***	0.0570***
	(0.0618)	(0.181)	(0.106)	(0.0175)	(0.0117)	(0.00722)
Log precipitation	-0.870	2.648	-0.912	-0.632***	0.0297	-0.337***
	(0.562)	(2.489)	(1.160)	(0.138)	(0.141)	(0.103)
Log median rent	5.736**	34.90***	23.24***	3.055***	3.242***	3.043***
	(2.521)	(10.06)	(5.655)	(0.834)	(0.576)	(0.464)
Poverty rate	47.32**	207.0***	149.5***	19.25***	19.25***	19.52***
	(23.51)	(69.22)	(36.98)	(4.543)	(3.778)	(2.675)
Percent black	-10.21	-53.34***	-46.96***	-3.287**	-3.804***	-3.670***
	(7.665)	(12.86)	(10.24)	(1.400)	(0.736)	(0.666)
Percent Hispanic	-9.425**	-31.41***	-27.04***	-4.231***	-2.251***	-3.020***
	(3.878)	(11.46)	(7.862)	(1.224)	(0.739)	(0.650)
Observations	188	191	379	186	191	377
R^2	0.093	0.227	0.247	0.191	0.364	0.419

Note: Dependent variable is rate or logarithm of unsheltered homeless persons per 10,000 residents. Cold places are those with temperature below the median and warm places are those with temperatures above the median. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

assistance beds. The percent of the population that are adherents of the Catholic Church is significantly and negatively associated with unsheltered homelessness. Beds in emergency shelters, transitional housing programs and permanent supportive housing programs are not significant. Of course, homeless assistance beds are clearly endogenous to homeless counts; this result merely suggests that variation in homeless assistance programs do not help explain observed variation in homeless counts.[6]

4 Discussion

Just under 200,000 people were found sleeping on the streets across the United States on a single night in January of 2013. Unsurprisingly, they were overwhelmingly found in warm places. However, we document that rates of unsheltered homelessness vary substantially in warm places. For a community with an average January temperature of 40 degrees Fahrenheit, moving from the 10th to the 90th percentile means a rate of unsheltered population per 10,000 people that moves from 2.1 to 38.9.

This finding has important implications for modeling the determinants of unsheltered homelessness. The lack of variation in cold places will tend to mask potentially important associations with covariates in warm places. We show that accounting for this relationship by splitting the sample based on temperature or using logarithms of unsheltered rates of homelessness has important implications for results. For example, the associations of median rent and poverty rates with rates of unsheltered homelessness is much larger in warm places than cold places. We also provide new evidence that religiosity is significantly associated with unsheltered homelessness. Whether this reflects differences in efforts to assist the homeless, different expectations and possibly ordinances surrounding sleeping outdoors, or other factors is unclear. Data limitations mitigate our ability to parse these mechanisms, but this is an important question for future research.

While we do not identify the impact of policies on unsheltered homelessness, the results

[6] See Corinth (2017) and Lucas (2017) for causal evidence on homeless assistance programs.

Table 7: Ordinary least squares estimates of the determinants of homelessness, other factors

	(1)	(2)
Temperature	0.0442***	0.0619***
	(0.00848)	(0.00786)
Log precipitation	-0.322***	-0.313***
	(0.101)	(0.102)
Log median rent	3.310***	2.685***
	(0.517)	(0.483)
Poverty rate	18.02***	17.25***
	(2.695)	(2.888)
Percent black	-3.632***	-3.883***
	(0.708)	(0.680)
Percent Hispanic	-2.657***	-2.977***
	(0.758)	(0.688)
Log percent Evangelical	0.131	
	(0.127)	
Log percent Protestant	-0.197	
	(0.129)	
Log percent Catholic	-0.231**	
	(0.115)	
Log rate of emergency shelter beds		0.128
		(0.110)
Log rate of transitional housing beds		0.139
		(0.0975)
Log rate of PSH beds		0.0854
		(0.0805)
Observations	377	366
R^2	0.438	0.441

Note: Dependent variable is the logarithm of unsheltered homeless persons per 10,000 residents. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

nonetheless have important implications for policies that seek to reduce unsheltered homelessness. In our models that account for greater dispersion in warm places, the majority of variation in unsheltered homelessness is left unexplained. Furthermore, differences in rates of sheltered homelessness do not appear to be the reason. After controlling for community level factors, the distribution of sheltered rates is relatively tight in warm places and rates are low. For a community with an average January temperature of 40 degrees Fahrenheit, the rate of sheltered homelessness per 10,000 people is 4.0 at the 10th percentile and 21.1 at the 90th percentile. This suggests that communities with low rates of unsheltered homeless people are not simply sheltering otherwise unsheltered people.

Our work does not rule out the importance of policies in affecting unsheltered homelessness. While we find that homeless assistance beds are not associated with unsheltered homelessness, we do not identify causal effects for these measures. However, our results are consistent with recent causal estimates of policy effects. For instance, Lucas (2017) finds that federal funding has little to no effect on unsheltered populations, and Corinth (2017) finds that adding permanent supportive housing leads to relatively minor changes in homeless population sizes.

Why then do some warm places have much greater rates of unsheltered homelessness than others? The fact that our religiosity measures help explain some of variation could suggest that cultural factors are important. Meanwhile, variation in local ordinances that make sleeping outdoors more difficult could drive difference in unsheltered rates. Florida, for instance, is often alleged to have stricter ordinances regarding activities such as public feeding efforts and sitting, lying and camping in public than many west coast cities which are perceived to adopt more lenient attitudes.[7] Moreover, some research has shown negative impacts of homeless-related ordinances on crime—it is possible that they reduce unsheltered homelessness within a particular city as well (Berk and MacDonald 2010). Without comparable data on local ordinances (and their enforcement), we are unable to assess this factor in the present paper.

A final potential explanation for variation in rates of unsheltered homelessness in warm places

[7] According to one homeless advocate, "Florida leads the pack" on these types of ordinances (Alvarez and Robles 2014).

is agglomeration. This could be a result of service concentration in a particular area, in which street feeding programs, outreach, shelter and other services can attain greater scale and efficiency when unsheltered populations are more concentrated. Additionally, unsheltered individuals may form strong communal bonds with one another or offer shared security, decreasing the severity of sleeping on the streets. Within cities, Lee and Price-Spratlen (2004) find that homeless individuals are often concentrated in specific neighborhoods. As an extreme example, Skid Row in Los Angeles is home to the most well known concentration of homeless individuals in the United States. Culhane (2010) argues that "people are living in the streets of Skid Row *en masse* because of the spatial concentration there of large shelters, meal programs, and other social services that target people who are homeless" (p. 853). Without more fine-grained measures of unsheltered homeless populations, we are unable to assess the role of agglomeration.

Finally, an important caveat for our results is that they are based on homeless counts conducted in January. Rates of unsheltered homelessness are likely higher in summer months in places with cold winter climates. It is unclear, however, how the distribution of summer rates would vary in places with warm winter climates. One possibility is that warm places with high concentrations of unsheltered homelessness in the winter months experience larger summer outflows of homeless individuals to places that are cold in the winter. Research has indicated, however, that homeless migration among veterans who access veteran services is relatively infrequent (Metraux et al. 2016). If this is the case more generally, we may expect wide variation in unsheltered homelessness across places with warm winter climates to be maintained throughout the year.

5 Conclusion

Places with warmer climates have on average higher rates of unsheltered homelessness. But average effects mask a more nuanced relationship. Cold places uniformly have low rates of unsheltered homelessness, while warm places exhibit substantial variation. Measurement error is at most a partial explanation. Furthermore, rates of sheltered homelessness are low or modest in warm places,

implying that variation in unsheltered homelessness cannot be explained by some warm places simply sheltering their homeless population. Accounting for this pattern is important in modeling the determinants of unsheltered homelessness. We also find that measures of religiosity can help explain significant variation in unsheltered homelessness in warm places, suggesting that culture may play an important role.

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A Methodology for bounding measurement error

Let $H_{c,t}$ denote the true (unsheltered) homeless rate in community c at time t, and let $\hat{H}_{c,t}$ denote the counted rate. Letting $\eta_{c,t}$ denote counting error, we have

$$\hat{H}_{c,t} = H_{c,t} + \eta_{c,t} \tag{A1}$$

We assume that the counting error is normally distributed with mean zero so that $\eta_{c,t} \sim N(0, \sigma_c^2)$. If we observed σ_c^2 for each community c, we could then estimate the extent to which measurement error drives the dispersion in unsheltered rates.

We instead estimate an upper bound for the standard deviation of measurement error using within-community variation in unsheltered homeless rates over time that is unexplained by observable factors. To this end, suppose the true homeless rate is a function of CoC-level covariates $X_{c,t}$, time-invariant CoC characteristics δ_c, and an error term $\epsilon_{c,t}$ that incorporates shocks due to time-varying unobservable CoC factors aside from measurement error. Thus we have

$$H_{c,t} = \beta X_{c,t} + \delta_c + \epsilon_{c,t} \tag{A2}$$

Combining equations (2) and (3) subtracting the average homeless count in the community over all time periods, we have

$$\hat{H}_{c,t} - \bar{\hat{H}}_{c,t} = \beta(X_{c,t} - \bar{X}_{c,t}) + \epsilon_{c,t} + \eta_{c,t} - (\bar{\epsilon}_{c,t} + \bar{\eta}_{c,t}) \tag{A3}$$

Using a panel of annual point-in-time unsheltered homeless counts from 2007 through 2014, we estimate equation (4) using ordinary least squares, and we use the residuals to form an estimate of the variance of the within-community composite error term (including shocks due to unobserved CoC factors and measurement error) as a function of homeless rates. The variance of this composite error term will overstate the variance of $\eta_{c,t}$. We estimate the variance of the composite error term by regressing the squared residuals of the fixed effects regression on a polynomial in the unsheltered homeless rates using our panel data.

We next simulate the distribution in unsheltered rates over temperature due solely to within-CoC variation that is unexplained by observed CoC-level factors. Using our cross section of data, we conduct 10,000 trials in which we generate for each observation a random shock to its unsheltered rate from a normal distribution with mean zero and the variance of the composite error term estimated in the previous step. For each trial, we estimate the distribution of random shocks to unsheltered rates over temperature. The average distribution of unsheltered rates across all trials is our estimate of the distribution in unsheltered rates attributed to year-to-year variation in unsheltered rates, which is an upper bound estimate of the variation due to non-persistent measurement error.

B Supplemental tables and figures

Table A1: Fixed Effects Regression Estimates

	Unsheltered
Unemployment rate	0.0346
	(0.318)
Log median rent	-1.119
	(3.905)
Observations	2,367
R^2	0.016

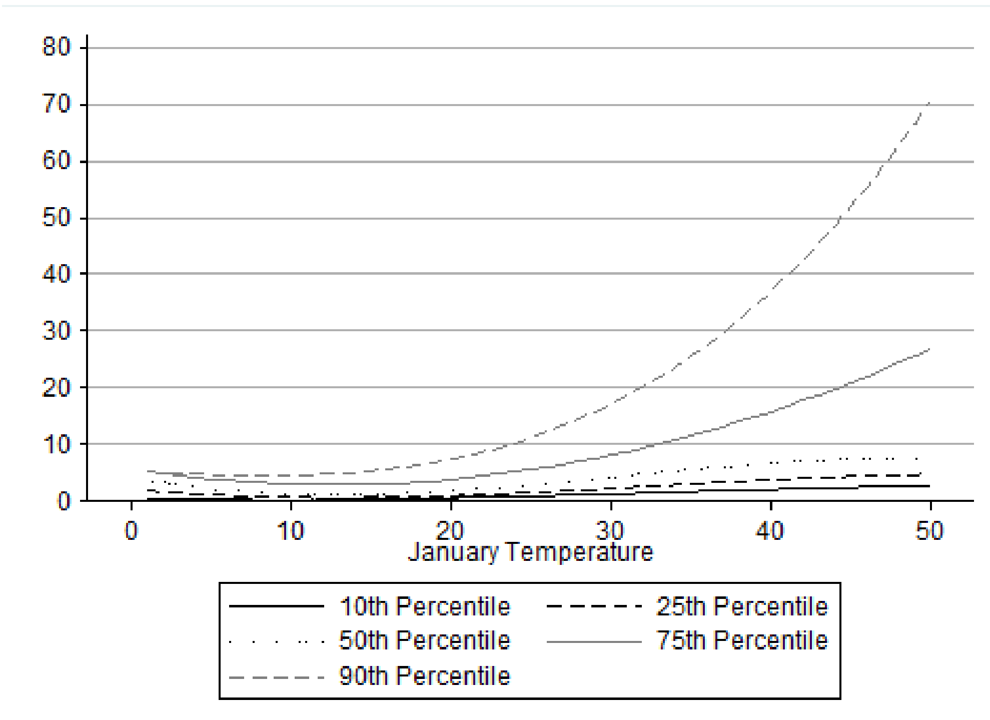
Note: Dependent variable is unsheltered homeless persons per 10,000 residents. The period is 2007 through 2014. During odd years, unsheltered estimates are not available for some CoCs. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table A2: Regression Estimates for Variance Function

	Squared residuals
Unsheltered homeless per 10,000 residents	2.817^{***}
	(0.534)
(Unsheltered homeless per 10,000 residents)^2	0.0407^{***}
	(0.00536)
Observations	2,367
R^2	0.243

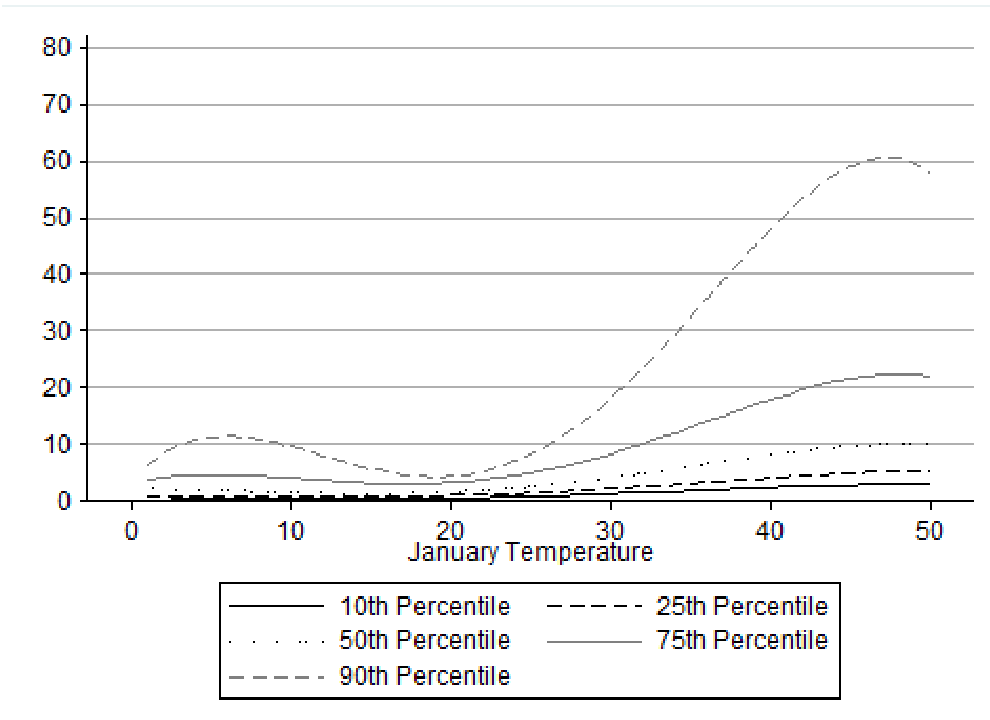
Note: Dependent variable is squared residual from fixed effects regression. The period is 2007 through 2014. During odd years, unsheltered estimates and thus squared residuals are not available for some CoCs. Standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Figure A1: Predicted Unsheltered Homeless Rate per 10,000 Residents by Temperature (With Controls): Polynomial of degree 3



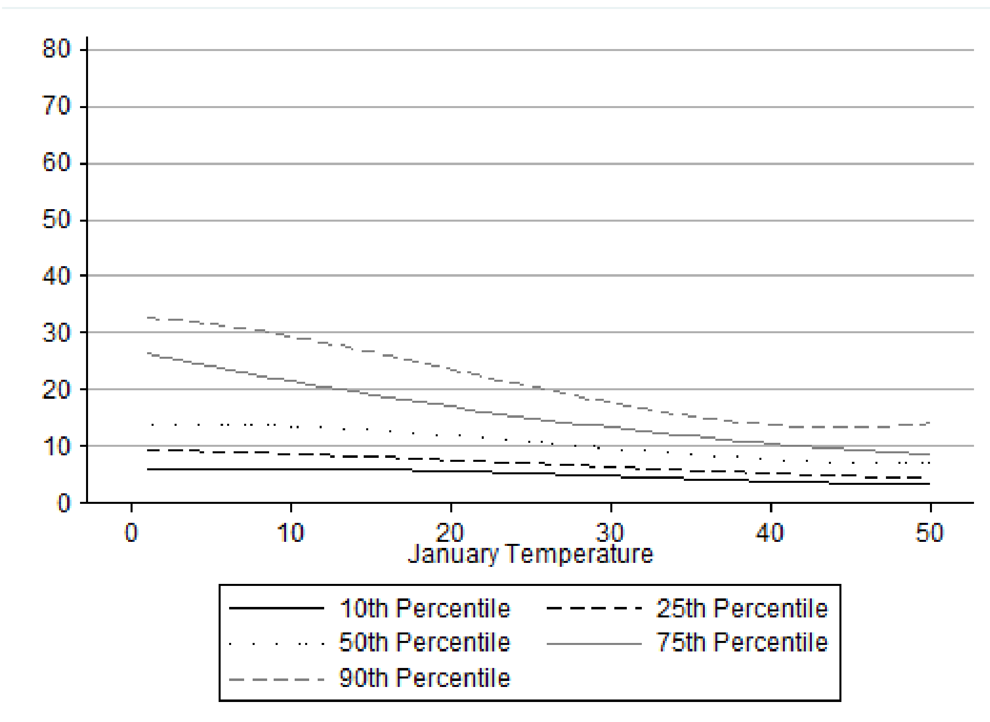
Note: Predicted homelessness rates are based on quantile regression estimates. Estimates available by request from authors.

Figure A2: Predicted Unsheltered Homeless Rate per 10,000 Residents by Temperature (With Controls): Polynomial of degree 4



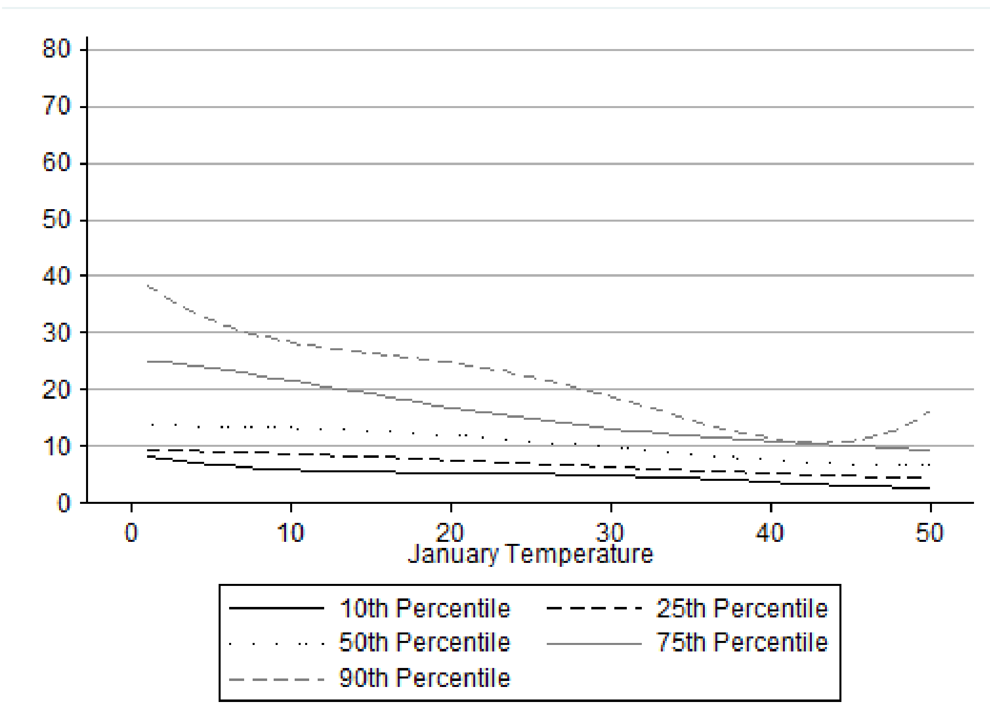
Note: Predicted homelessness rates are based on quantile regression estimates. Estimates available by request from authors.

Figure A3: Predicted Sheltered Homeless Rate per 10,000 Residents by Temperature (With Controls): Polynomial of degree 3



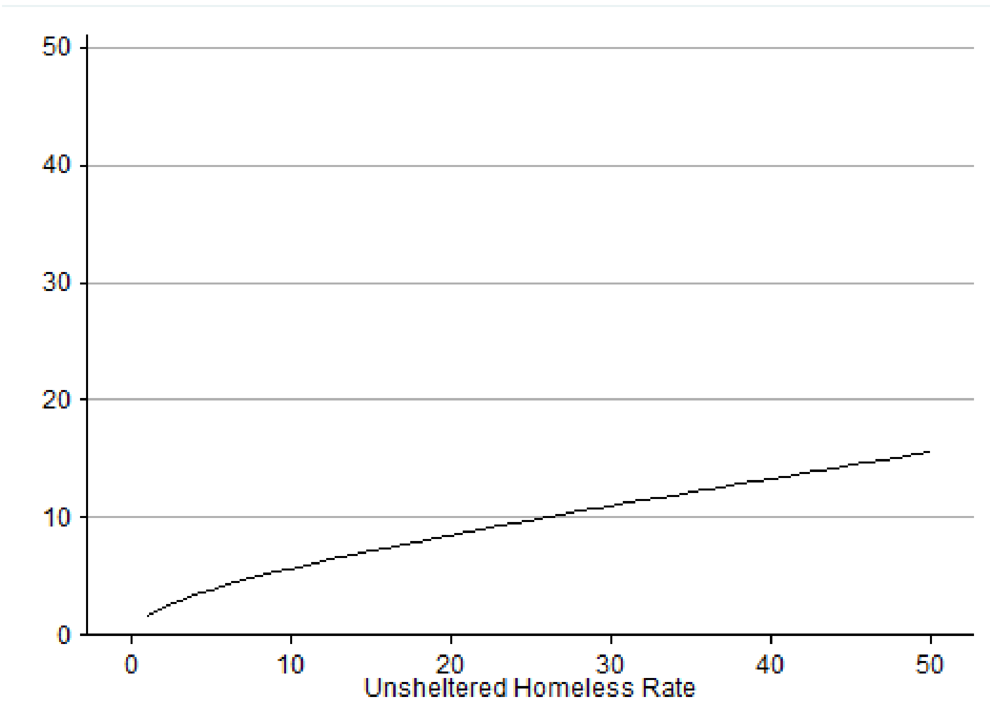
Note: Predicted homelessness rates are based on quantile regression estimates. Estimates available by request from authors.

Figure A4: Predicted Sheltered Homeless Rate per 10,000 Residents by Temperature (With Controls): Polynomial of degree 4



Note: Predicted homelessness rates are based on quantile regression estimates. Estimates available by request from authors.

Figure A5: Predicted standard deviation in homeless counts by unsheltered homeless rate



Note: Standard deviations are predicted on the basis of residual from a fixed effects regression using CoC panel data between 2007 and 2014. Table A2 shows estimates of the association between unsheltered rates and squared residuals.