When warm and cold don't mix: The implications of climate for the determinants of homelessness

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Abstract

It is widely understood that climate affects the spatial distribution of homelessness—warm places have on average higher rates of unsheltered homelessness than cold places. A less recognized fact is that variation in rates of unsheltered homelessness is higher in warm places as well. We document this fact using quantile regression techniques and show that it has important implications for estimating the determinants of homelessness across communities. In particular, housing prices, poverty rates and religiosity are much more strongly associated with rates of unsheltered homelessness in warm places than in cold places. As an alternative to splitting the sample, we find that logarithmic transformations of rates of unsheltered homelessness can be reliably used in a pooled sample. Associations between total homelessness and important covariates also vary across warm and cold places, in this case in terms of both rates and logarithms. Ultimately, future research should carefully account for climate when estimating the determinants of homelessness.

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1 Introduction

A mild 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 homeless people, 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. Conventional wisdom among local officials and experts in cities with warm climates is that warm temperatures are major draws for homeless individuals.[1]

Similarly, research has generally affirmed that homelessness, and particularly the unsheltered type, is more common in warmer areas. For example, Appelbaum et al. (1991) find that warmer temperatures are associated with higher rates of total homelessness using some of the earliest cross-sectional estimates of homelessness across select U.S. cities in 1984, as do Quigley et al. (2001) using 1990 U.S. Census counts of homeless populations and Raphael (2010) using more recent homeless counts. Others consider sheltered and unsheltered populations separately and find that warmer temperatures are particularly relevant for unsheltered homelessness (e.g., Grimes and Chressanthis 1997; Early and Olsen 2002). In an extensive review, Byrne et al. (2013) summarize the persistent pattern: "Among 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).

Although it is widely understood that the average rate of unsheltered homelessness is higher in warm places, it is less well recognized that the variation in rates of unsheltered homelessness is much higher in warm places as well. We document this fact using cross-sectional homeless counts

[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).

from communities across the United States, employing quantile regression techniques that allow us to predict the distribution of homelessness rates over temperature when controlling for other factors. In a community where the average daily low temperature in January is 10 degrees, the predicted unsheltered rate is 0.1 per 10,000 for the 10th percentile community and 3.8 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 1.8 and 39.3 per 10,000 people. In other words, while unsheltered homelessness rates are uniformly low in cold climates, there is wide variation in unsheltered homelessness rates in warm communities.[2]

This finding has important implications for studies using cross-sectional data to estimate the determinants of homelessness. Because cold places exhibit little variation in rates of unsheltered homelessness, pooling them with warm places serves to attenuate estimates of the effects of other community characteristics or policy variables in warm places. We suggest two ways in which this model misspecification problem—in which all communities are pooled in regressions explaining variation in rates of unsheltered homelessness—can be addressed. First, determinants of rates of unsheltered homelessness can be estimated separately for cold and warm places. Using cross-sectional data, we find that housing prices, poverty rates and religiosity have stronger associations with rates of unsheltered homelessness in the subset of communities with above-median January temperatures than when a single estimate is generated for the pooled sample. Second, a pooled sample can be used when taking the logarithmic transformation of the rate of unsheltered homelessness. Based on a quantile regression, we show that the distribution of the natural logarithm of unsheltered rates is relatively constant over January temperature.

There are important implications for studying cross-sectional variation in total homelessness as well. Housing prices, poverty rates and religiosity are more strongly associated with rates of total homelessness in warm places than cold places. And in this case, heterogeneity in associations across warm and cold places carries over for logarithmic transformations of rates of total home-

[2] In an appendix, we use panel data on homeless counts within communities over time to provide evidence that non-persistent multiplicative measurement error cannot explain this fact. However, we cannot rule out persistent measurement error within particular communities as an explanation.

lessness. Thus, using logarithmic transformations of rates of total homelessness in a pooled sample may continue to mask heterogeneity in the determinants of total homelessness across warm and cold places. Splitting the sample by climate will help researchers investigating the determinants of total homelessness identify any such effects.

In addition to their methodological value, the results that account for the role of climate provide new insights into the determinants of homelessness. Based on the full sample logarithmic specification, a one percent increase in median rent is associated with a 3.7 percent increase in the rate of unsheltered homelessness, and a one percentage point increase in the poverty rate is associated with a 20 percent increase. When including a set of variables capturing the religiosity of the community's population, we find that a one percentage point increase in the population that is an adherent to Catholic churches is associated with a statistically significant 2.8 percent decrease in the rate of unsheltered homelessness. The magnitude for Protestants is similar but not statistically significant, while that for Mormons and Evangelicals are smaller. Given that adherence to Catholic churches is associated with fewer homeless assistance beds, it is unclear whether this result is driven by more effective services despite fewer beds, or by broader cultural factors in the population.

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—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). We contribute to this literature by documenting the much wider variation in rates of unsheltered homelessness in warm places and its implications for estimating the determinants of homelessness in cross-sectional data. We also provide new evidence on the importance of religiosity.

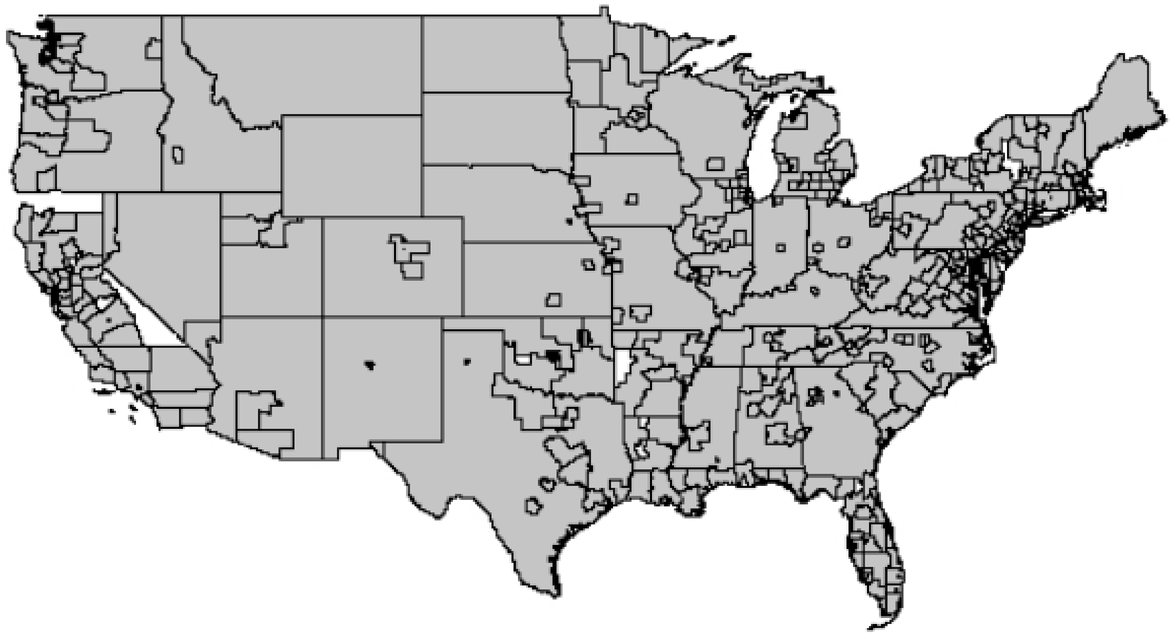
The paper proceeds as follows. We discuss our data and methodology in section 2. We present our results in section 3. We discuss our findings with implications for policy and future research in section 4. Section 5 concludes.

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).

Figure 1: Map of Continuum of Care Boundaries, 2013



Source: HUD CoC 2013 Shapefile.

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 25 years ending in 2013. For precipitation, we use the average monthly precipitation in January over the same 25-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.[3] 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. 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 homelessness, accounting for the climate patterns observed, we sometimes include additional explanatory variables. Rates of adherents of

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

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, Protestant and Church of Jesus Christ of Latter-day Saints (Mormon) adherence; other denominations and religions have few or no adherents documented in a number of counties. Some of our specifications predict inventories of emergency shelter, transitional housing, and permanent supportive housing beds. These data are obtained from HUD's annual inventory of homeless assistance beds.[4] Summary statistics for all variables are provided in Table 1.

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

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

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 25 years, and X is a vector of control variables. We estimate equation (1) with the unsheltered, sheltered and total homelessness rate per 10,000 population 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 measurement error. While an additive error that has constant variance over rates of un-

[4]One other important factor is the degree to which communities pass and enforce ordinances that affect the ability to sleep unhindered in unsheltered locations. Unfortunately, quality community level data on these ordinances are not available. For example, 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 is included 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.

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
Total homeless per 10,000 residents	13.91	19.71	21.12
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
Permanent supportive housing 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
Percent Mormon	.007	.018	.065

Note: All variables are based on the year 2013, with the exception of January temperature and precipitation which are based on 25-year averages ending in 2013. Homeless variables come from the 2013 HUD PIT counts, climate variables come from the United States Historical Climate Network, 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.

sheltered 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.[5] The methodology for estimating an upper bound of the impact of non-persistent 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, non-persistent 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 non-persistent measurement error), we assess the cross-sectional determinants of unsheltered homelessness in ways that 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 con-

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

trol variables used previously, we also include religious adherents of particular denominations of the population. Finally, we use the same exercise to show that climate has important implications for estimating the determinants of total homelessness as well.

3 Results

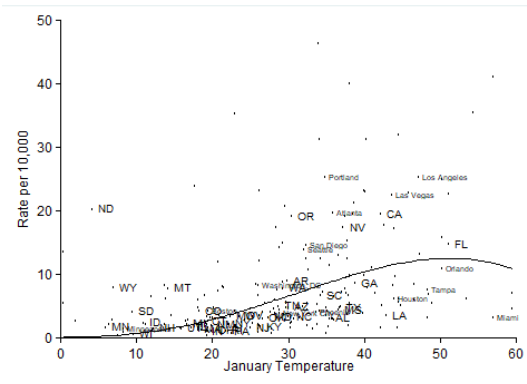
3.1 Documenting variation in homelessness over climate

Figure 2 shows histograms of homelessness rates (unsheltered, sheltered and total) 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.[6] 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. Meanwhile, sheltered homelessness rates display 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.[7]

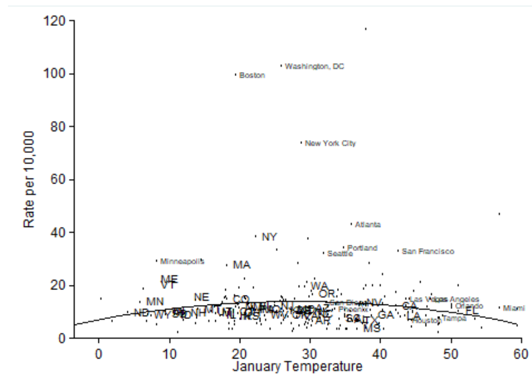
Quantile regression estimates are presented in Table 2, including estimates of the effect of temperature at the 10th percentile, 25th percentile, 50th percentile, 75th percentile and 90th percentile. Specifications with and without controls are shown, as are specifications with the unsheltered, sheltered and total homelessness rate as dependent variables. All specifications include precipitation, and they exclude higher order polynomial terms in temperature. Estimated temperature effects for

[6] A notable exception is the state of North Dakota (which has only one CoC), which despite a January temperature of 4 degrees Fahrenheit, reported 1,395 unsheltered homeless individuals in 2013. However, the state reported only 53 unsheltered individuals in 2012, and 464 in 2014, suggesting the 2013 count may be unreliable. Wyoming similarly has reported substantial variation in unsheltered counts, ranging from 64 in 2009 to 1,338 in 2012 (and 452 in 2013). Alternatively, elevated unsheltered homeless populations in North Dakota and Wyoming could be due to economic booms from the oil industry (see for example, Ellis (2013) and Healy (2013)).

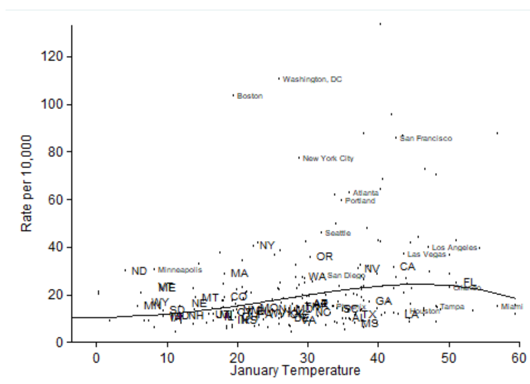
[7] Leopold (2014) identifies Washington DC, New York City, Columbus, OH, Hennepin County, MN, Montgomery County, MD and the state of Massachusetts as those with a legal right to shelter.



(a) Unsheltered homelessness



(b) Sheltered homelessness



(c) Total homelessness

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

Note: Temperature is average daily low in January for the 25-year period ending 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.

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 0.06, 0.09, 0.16, 0.42 and 0.76 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. These estimates imply that for rates sheltered homelessness, there is less variation in warm places than in cold places. This suggests that variation in unsheltered homelessness rates in warm places is unlikely to be explained by communities with much higher rates of unsheltered homelessness simply sheltering their homeless population. This could be due to greater difficulty in coaxing unsheltered individuals into shelters when the climate is milder (without raising shelter quality to a point where many otherwise housed individuals seek out shelter as well), and thus, less investment in shelter quality and lower equilibrium quantities of shelters in warm places.[8] It is notable that this relationship only emerges when controlling for other community-level factors, suggesting that some warm places tend to have observable characteristics that make them more likely have higher sheltered homeless populations (e.g., higher incomes that boost the supply of shelter). Finally, effects of temperature on total homelessness rates are larger at the upper ends of the distribution, reflecting the especially stark pattern for unsheltered homelessness. When controlling for other factors, this relationship weakens given the stronger temperature effects for sheltered homelessness in this case that partially mute the temperature effects for the unsheltered population.

Incorporating a squared temperature term to allow for a nonlinear relationship between temperature and the homelessness rate presents a similar pattern of results. Figure 3 shows how estimates translate into predicted homelessness rates. 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.

[8]See O'Flaherty (2003) for a model of how shelter quality plays the role of price in the market for homeless shelters.

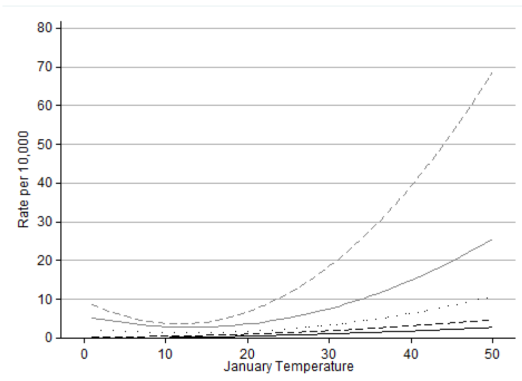
Table 2: Quantile Regression Estimates: Distribution of Temperature Effects on Rate of Homelessness

	Unsheltered rate	Unsheltered rate	Sheltered rate	Sheltered rate	Total rate	Total rate
10th percentile	0.0388***	0.0582***	-0.0170	-0.0684	0.0930*	0.0157
	(0.00873)	(0.0202)	(0.0305)	(0.0436)	(0.0542)	(0.0561)
25th percentile	0.0973***	0.0937***	-0.0301	-0.104**	0.132***	-0.0312
	(0.0190)	(0.0175)	(0.0226)	(0.0432)	(0.0327)	(0.0573)
50th percentile	0.171***	0.160***	0.00789	-0.166**	0.189**	0.0169
	(0.0173)	(0.0378)	(0.0366)	(0.0641)	(0.0759)	(0.0747)
75th percentile	0.346***	0.422***	-0.0869**	-0.279***	0.346***	0.0806
	(0.0656)	(0.0939)	(0.0438)	(0.0817)	(0.0656)	(0.164)
90th percentile	0.698***	0.758***	-0.0523	-0.435***	0.991***	0.383
	(0.149)	(0.261)	(0.152)	(0.139)	(0.330)	(0.375)
Controls		X		X		X
Observations	379	379	379	379	379	379

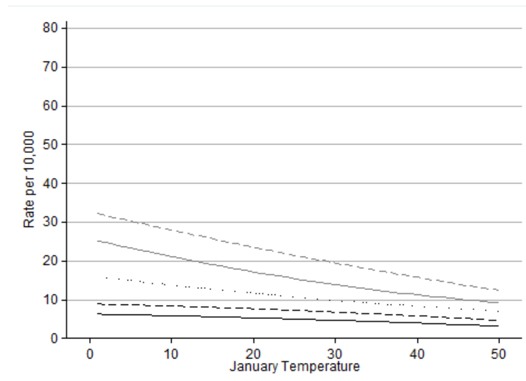
Note: Dependent variable is homeless persons (either unsheltered, sheltered, or total) per 10,000 residents. Estimates shown are for average daily low temperature in January for the 25-year period ending in 2013. Control variables include the 25-year average of precipitation, logarithm of median rent, poverty rate, rural score indicator variables, percent black, and percent Hispanic. Bootstrapped standard errors are shown in parentheses. * indicates significance at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Higher temperatures lead to lower rates of sheltered homelessness, particularly at the upper ends of the distribution. Effects for total homelessness are a combination of unsheltered and sheltered rates, with more variation in predicted rates of homelessness at the low and high ends of temperature. Figures based on higher order polynomials in temperature are shown in the appendix, with these same basic patterns. Table 3 summarizes predicted rates of unsheltered homelessness at various points in the distribution based on the specification incorporating both a linear and squared temperature term. Sizable differences between the highest and lowest percentiles are observed across the distribution, and these differences persist with the inclusion of relevant covariates.

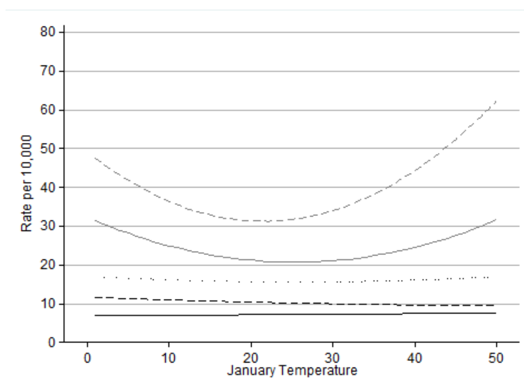
One potential explanation for wide variation in unsheltered homelessness rates in warm climates is measurement error. CoCs with higher unsheltered rates may plausibly have larger measurement error, and given that higher temperatures are associated with higher unsheltered rates, this could explain the variation we observe. We use panel data on homeless counts between 2007 and 2014 to bound the extent to which non-persistent measurement error can explain these results. We find that non-persistent measurement error can explain at most 40 percent of the gap between



(a) Unsheltered homelessness



(b) Sheltered homelessness



(c) Total homelessness

Figure 3: Predicted Homeless Rate per 10,000 Residents by Temperature (with controls)

Note: Predicted homelessness rates are based on quantile regression estimates including all control variables listed in Table 2, along with a squared temperature term. Average values of controls are assumed. Plotted are the 10th, 25th, 50th, 75th and 90th percentiles.

Table 3: 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	0.23	0.31	0.83	2.44	5.41	2.12	5.18
Controls	0.10	0.48	1.39	2.95	3.77	2.47	3.67
Temperature = 25							
No controls	0.39	1.08	1.93	3.91	8.80	2.84	8.41
Controls	0.77	1.41	2.35	5.18	11.53	3.77	10.77
Temperature = 40							
No controls	1.29	3.19	6.46	15.56	39.40	12.38	38.11
Controls	1.81	3.16	6.40	14.91	39.29	11.75	37.48

Note: Temperature is measured in degrees Fahrenheit. Predicted homelessness rates are based on quantile regression estimates including all control variables listed in Table 2, along with a squared temperature term. Average values of controls are assumed.

the 90th and 10th percentile community when the temperature is 40 degrees Fahrenheit (including controls). Details and results are included in the appendix.

3.2 Implications for the determinants of homelessness

We have shown 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 effective approach may be to account for nonlinearity by using the logarithm of unsheltered homeless rates. Table 4 shows quantile regression estimates predicting the logarithm of homelessness rates. Temperature effects across the distribution are much more condensed than when the dependent variable is expressed as a rate.

Table 4: Quantile Regression Estimates: Distribution of Temperature Effects on Logarithm of Rate of Homelessness

	Unsheltered rate	Unsheltered rate	Sheltered rate	Sheltered rate	Total rate	Total rate
10th percentile	0.0652***	0.0479***	-0.00407	-0.0159**	0.0134*	-0.00230
	(0.00973)	(0.0118)	(0.00669)	(0.00625)	(0.00791)	(0.00512)
25th percentile	0.0648***	0.0481***	-0.00507	-0.0176***	0.0152***	-0.00437
	(0.00859)	(0.00911)	(0.00451)	(0.00437)	(0.00301)	(0.00427)
50th percentile	0.0735***	0.0657***	0.000800	-0.0161*	0.0140**	-0.000334
	(0.00822)	(0.0138)	(0.00361)	(0.00839)	(0.00601)	(0.00678)
75th percentile	0.0686***	0.0607***	-0.00613**	-0.0182***	0.0172***	0.00115
	(0.00431)	(0.0130)	(0.00282)	(0.00560)	(0.00395)	(0.00588)
90th percentile	0.0698***	0.0825***	-0.00255	-0.0252***	0.0282***	0.00509
	(0.0136)	(0.0161)	(0.00740)	(0.00669)	(0.00490)	(0.00879)
Controls		X		X		X
Observations	377	377	379	379	379	379

Note: Dependent variable is homeless persons, either unsheltered, sheltered or total, as indicated in column headings, per 10,000 residents. Estimates shown are for average daily low temperature in January for the 25-year period ending in 2013. Control variables include 25-year average precipitation, logarithm of median rent, poverty rate, rural score indicator variables, percent black, and percent Hispanic. Bootstrapped standard errors are shown in parentheses. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table 5 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.[9] We find that splitting the sample is important when the dependent variable is expressed as a rate—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. For example, a one percent increase in median rent is associated with a 3.9 percent increase in the rate of unsheltered homelessness in cold places, and a 3.2 percent increase in warm places.[10] Another notable result is that precipitation is inversely related to unsheltered homelessness in cold communities but is unrelated in warm ones, in both the rate and log specifications. This is consistent with the fact that precipitation is more likely to yield snow and

[9]Two observations are dropped when using logarithms due to zero counted unsheltered homeless individuals. A potential remedy for this issue is to use the "inverse hyperbolic sine" (IHS) transformation of the unsheltered homelessness rate that approximates the logarithm but allows for zero values. See Lucas (2017) for an application.

[10]Table A3 in the appendix shows results excluding "balance of state" CoCs, which tend to be geographically large areas and that can vary in important ways from other regions. Results are similar.

ice in colder places, which is plausibly more problematic for outdoor living and sleeping than rain.

Table 5: OLS Estimates of the Determinants of Unsheltered Homelessness (Split Sample)

	Unsheltered rate	Unsheltered rate	Unsheltered rate	Log unsheltered rate	Log unsheltered rate	Log unsheltered rate
Temperature	0.102	0.667***	0.490***	0.0466***	0.0497***	0.0584***
	(0.0737)	(0.204)	(0.116)	(0.0176)	(0.0121)	(0.00734)
Log precipitation	-1.441***	4.261	-0.322	-0.782***	0.134	-0.380***
	(0.551)	(3.874)	(1.704)	(0.149)	(0.160)	(0.119)
Log median rent	8.235***	40.39***	29.49***	3.908***	3.203***	3.716***
	(2.903)	(9.600)	(5.930)	(0.817)	(0.597)	(0.485)
Poverty rate	50.47**	168.1***	144.2***	18.36***	18.96***	19.98***
	(23.69)	(51.84)	(32.21)	(4.306)	(3.855)	(2.729)
Percent black	-7.391	-41.10***	-40.30***	-1.432	-3.705***	-3.389***
	(7.409)	(10.07)	(8.621)	(1.519)	(0.811)	(0.740)
Percent Hispanic	-10.69***	-17.59	-22.01***	-4.496***	-1.942**	-2.962***
	(3.952)	(12.67)	(8.134)	(1.223)	(0.858)	(0.703)
Sample above/below median temperature	Below	Above	All	Below	Above	All
Observations	189	190	379	187	190	377
R^2	0.198	0.275	0.279	0.270	0.365	0.434

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. Rural indicator variables are included. 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 6 shows regression estimates for total homelessness, splitting the sample based on temperature and using both rates of total homelessness and its logarithm. For rates of total homelessness, associations are similarly much larger in warm than in cold places. However, associations are also substantially larger for key covariates when using logarithmic transformations as well. A one percent increase in median rent is associated with a 1.3 percent higher total homelessness rate in cold places, and a 2.4 percent higher rate in warm places.

Finally, we explore whether other factors can help explain the variation in the logarithm of unsheltered homelessness. Table 7 includes the religious adherence of the population. The percent of the population that are adherents of the Catholic Church is significantly and negatively associated with unsheltered homelessness. A one percentage point increase in Catholic adherents is associ-

Table 6: OLS Estimates of the Determinants of Total Homelessness (Split Sample)

	Homeless rate	Homeless rate	Homeless rate	Log homeless rate	Log homeless rate	Log homeless rate
Temperature	-0.154	0.335	0.178	-0.00711	0.00713	0.00462
	(0.149)	(0.257)	(0.149)	(0.00950)	(0.00778)	(0.00481)
Log precipitation	-1.485	3.699	-0.803	-0.166*	-0.00307	-0.148**
	(1.613)	(4.487)	(2.204)	(0.0927)	(0.112)	(0.0703)
Log median rent	28.42**	70.87***	56.12***	1.343***	2.372***	2.120***
	(12.20)	(15.71)	(9.972)	(0.509)	(0.431)	(0.311)
Poverty rate	182.5***	335.0***	298.8***	8.404***	13.22***	12.36***
	(65.37)	(92.30)	(53.48)	(2.608)	(2.815)	(1.743)
Percent black	4.390	-44.85***	-41.41***	0.790	-1.847***	-1.496***
	(13.55)	(13.75)	(11.76)	(0.784)	(0.426)	(0.377)
Percent Hispanic	-9.937	-34.42*	-34.27***	-0.531	-1.610***	-1.486***
	(14.56)	(19.15)	(12.87)	(0.778)	(0.573)	(0.438)
Sample above/below median temperature	Below	Above	All	Below	Above	All
Observations	189	190	379	189	190	379
R^2	0.278	0.232	0.242	0.307	0.309	0.309

Note: Dependent variable is rate or logarithm of total 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. Rural indicator variables are included. Robust standard errors are shown in parentheses. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

ated with a 2.8 percent reduction in the unsheltered homelessness rate. Evangelical, Protestant and Mormon adherents are also negatively associated with unsheltered homelessness, although none are statistically significant. In order to provide insight into whether this result is driven by more services or broader cultural factors, we test whether religiosity is associated with additional homeless assistance beds in Table 8. Catholic adherence is negatively associated with emergency shelter, transitional housing, and permanent supportive housing beds for otherwise homeless individuals. This does not support the possibility that Catholics are more likely to provide additional services, although it is nonetheless possible that the services they do provide are more effective in reducing unsheltered homelessness or that they provide services not captured by inventories of shelter beds.

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 implies an increase in the rate of unsheltered population per 10,000 people from 1.8 to 39.3.

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 are much larger in warm places than cold places. We also provide new evidence that religiosity is significantly associated with unsheltered homelessness. Future research should explore whether this is attributable to differences in efforts to assist the homeless, different expectations and possibly ordinances surrounding sleeping outdoors, or other factors.

Table 7: OLS Estimates of the Determinants of Unsheltered Homelessness (Including Religiosity)

	Unsheltered rate	Unsheltered rate	Unsheltered rate	Log unsheltered rate	Log unsheltered rate	Log unsheltered rate
Temperature	0.0396	0.624***	0.518***	0.0305	0.0468***	0.0460***
	(0.0576)	(0.208)	(0.129)	(0.0214)	(0.0132)	(0.00808)
Log precipitation	-1.081	6.183	0.254	-0.665***	0.173	-0.284**
	(0.905)	(4.003)	(1.798)	(0.191)	(0.158)	(0.119)
Log median rent	8.422**	25.09**	23.72***	3.420***	2.960***	3.361***
	(3.774)	(11.50)	(6.498)	(0.962)	(0.731)	(0.558)
Poverty rate	46.85**	116.5**	126.8***	14.99***	15.72***	16.73***
	(23.00)	(51.34)	(33.63)	(4.832)	(3.591)	(2.831)
Percent black	-6.983	-32.78***	-35.43***	-0.949	-2.528***	-3.095***
	(6.902)	(11.24)	(8.094)	(1.518)	(0.845)	(0.734)
Percent Hispanic	-9.993**	2.315	-15.51*	-3.842**	-1.023	-1.736**
	(4.289)	(16.31)	(9.293)	(1.491)	(0.963)	(0.777)
Percent Evangelical	6.778	-47.77*	-21.99**	0.592	-0.701	-0.578
	(8.639)	(25.79)	(10.03)	(1.182)	(1.251)	(0.788)
Percent Protestant	-4.389	-17.57	1.823	-2.866*	-4.552	-2.654
	(5.579)	(63.87)	(15.66)	(1.632)	(4.251)	(1.699)
Percent Catholic	-0.104	-46.42*	-13.79*	-1.025	-3.062**	-2.826***
	(3.658)	(26.13)	(7.987)	(1.097)	(1.389)	(0.718)
Percent Mormon	-0.782	-88.62	-7.675	-0.0984	13.97	-0.463
	(2.228)	(186.7)	(5.653)	(0.540)	(9.959)	(0.543)
Sample above/below median temperature	Below	Above	All	Below	Above	All
Observations	189	190	379	187	190	377
R^2	0.212	0.302	0.289	0.287	0.416	0.460

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. Rural indicator variables are included. Robust standard errors are shown in parentheses. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table 8: OLS Estimates of the Determinants of Homeless Assistance Beds

	Log emergency shelter rate	Log transitional housing rate	Log perm. supp. housing rate
Temperature	-0.0168***	-0.00125	-0.0158**
	(0.00553)	(0.00495)	(0.00617)
Log precipitation	-0.117	-0.133*	0.0375
	(0.0802)	(0.0747)	(0.0943)
Log median rent	0.969**	0.707*	0.932*
	(0.406)	(0.383)	(0.522)
Poverty rate	8.690***	7.447***	13.77***
	(2.038)	(2.153)	(2.753)
Percent black	-0.0937	-0.214	0.305
	(0.429)	(0.473)	(0.539)
Percent Hispanic	-0.445	-0.582	-1.556**
	(0.513)	(0.488)	(0.747)
Percent Evangelical	0.171	-1.051*	-3.399***
	(0.542)	(0.573)	(0.732)
Percent Protestant	0.194	1.369	2.664**
	(0.970)	(0.997)	(1.287)
Percent Catholic	-0.190	-0.528	-0.190
	(0.493)	(0.440)	(0.608)
Percent Mormon	-0.451	-0.530	-0.192
	(0.737)	(0.842)	(0.626)
Observations	379	373	372
R^2	0.191	0.167	0.355

Note: Dependent variable is expressed as the logarithm of homeless assistance beds per 10,000 residents. Rural indicator variables are included. Robust standard errors are shown in parentheses. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

This paper also has important implications for cross-sectional studies of total homeless populations. As with unsheltered homelessness, associations of median rent and poverty rates with rates of total homelessness are much larger in warm places than cold places. However, logarithmic transformations of total homelessness rates do not necessarily resolve this issue. Future research on the determinants of homelessness should be cautious in combining unsheltered and sheltered homelessness, in addition to combining warm and cold places. Our finding that unsheltered populations vary more in warm places while sheltered populations vary more in cold places suggests that the underlying drivers of these populations may vary.

While we do not identify the impact of policies on unsheltered homelessness, the results 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 tighter in warm places and rates are lower. 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 15.8 at the 90th percentile. This suggests that communities with low rates of unsheltered homeless people are not simply sheltering otherwise unsheltered people.

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 the 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.[11] 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

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

(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 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.

It is important to emphasize that the focus of this paper is on climate and the implications for cross-sectional variation in unsheltered and total homelessness. Thus, we do not 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, nationwide 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 an appendix to 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 help ascertain the importance of non-persistent 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.

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. Non-persistent 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 and total homelessness. We also find that measures of religiosity can help explain significant variation in unsheltered homelessness in warm places, suggesting that culture or variation in service delivery may play an important role.

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A Bounding non-persistent measurement error

This section estimates an upper bound on the extent to which non-persistent measurement error in homeless counts can explain greater variation in rates of homelessness in warm places than in cold places.

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 (A1) and (A2) and 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. Table A1 shows estimates from the fixed effects regression, and Table A2 shows estimates of the association between unsheltered rates and squared residuals.

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.

Figure A3 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 37.5 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 40 percent of the gap. Since many other factors beyond measurement error likely drive within-CoC variation in unsheltered rates over time, measurement error is likely less important than this implies. 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. At the same time, however, persistent measurement error cannot be ruled out as an important explanation.

B Supplemental tables and figures

Table A1: Fixed Effects Regression Estimates

	Unsheltered rate
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 parentheses. * 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

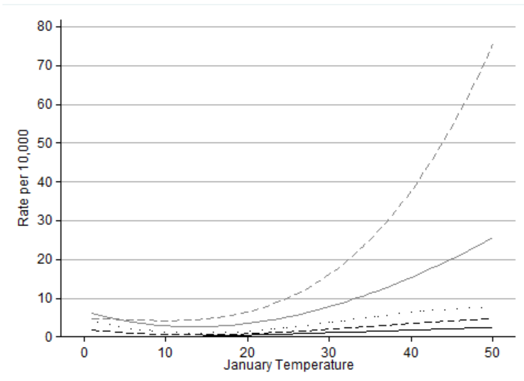
	Squared residuals
Unsheltered homeless per 10,000 residents	2.817***
	(0.534)
(Unsheltered homeless per 10,000 residents)^2	0.0407***
	(0.00536)
Observations	2,367
R^2	0.243

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 parentheses. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

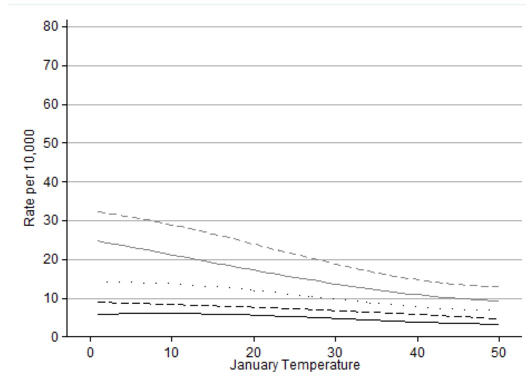
Table A3: OLS Estimates of the Determinants of Unsheltered Homelessness (Excluding "Balance of State" CoCs)

	Unsheltered rate	Unsheltered rate	Unsheltered rate	Log unsheltered rate	Log unsheltered rate	Log unsheltered rate
Temperature	0.105	0.665***	0.483***	0.0494***	0.0494***	0.0593***
	(0.0759)	(0.207)	(0.117)	(0.0189)	(0.0127)	(0.00772)
Log precipitation	-1.485**	4.797	-0.283	-0.840***	0.196	-0.336**
	(0.712)	(3.880)	(2.025)	(0.167)	(0.159)	(0.132)
Log median rent	7.211***	40.99***	29.76***	3.573***	3.311***	3.589***
	(2.678)	(9.986)	(6.300)	(0.792)	(0.627)	(0.497)
Poverty rate	45.03*	176.1***	145.6***	16.40***	19.34***	19.46***
	(23.07)	(58.44)	(33.72)	(4.183)	(4.243)	(2.765)
Percent black	-6.359	-40.36***	-39.57***	-0.903	-3.698***	-3.282***
	(7.583)	(10.45)	(8.701)	(1.480)	(0.847)	(0.761)
Percent Hispanic	-10.11***	-18.27	-21.39**	-4.505***	-2.018**	-2.905***
	(3.479)	(13.08)	(8.382)	(1.177)	(0.891)	(0.707)
Sample above/below median temperature	Below	Above	All	Below	Above	All
Observations	173	175	348	171	175	346
R^2	0.201	0.283	0.286	0.265	0.367	0.436

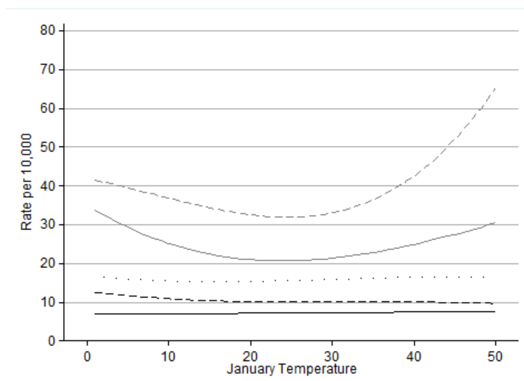
Note: Dependent variable is rate or logarithm of unsheltered homeless persons per 10,000 residents. Cold places are those with temperature below the median and warm places are those with temperatures above the median. Rural indicator variables are included. Robust standard errors are shown in parentheses.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



(a) Unsheltered homelessness



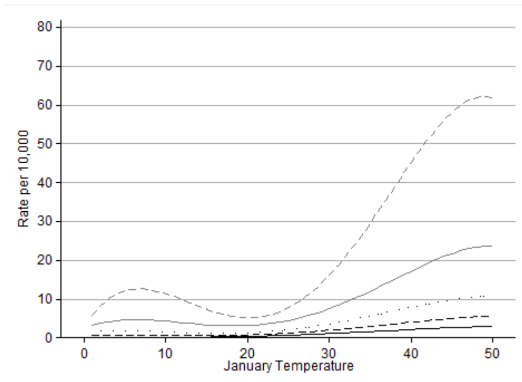
(b) Sheltered homelessness



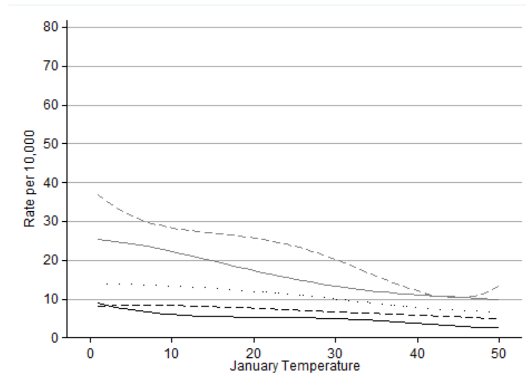
(c) Total homelessness

Figure A1: Predicted Homeless Rate per 10,000 Residents by Temperature (with controls): Polynomial of degree 3

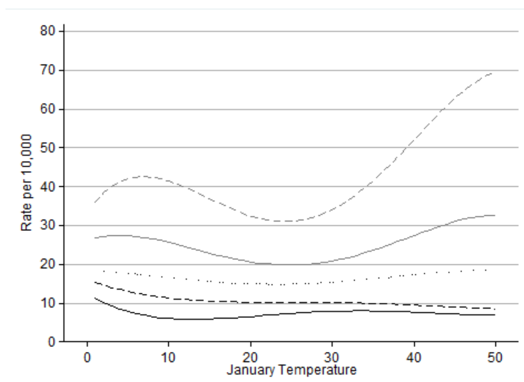
Note: Predicted homelessness rates are based on quantile regression estimates. Estimates available by request from authors. Plotted are the 10th, 25th, 50th, 75th and 90th percentiles.



(a) Unsheltered homelessness



(b) Sheltered homelessness

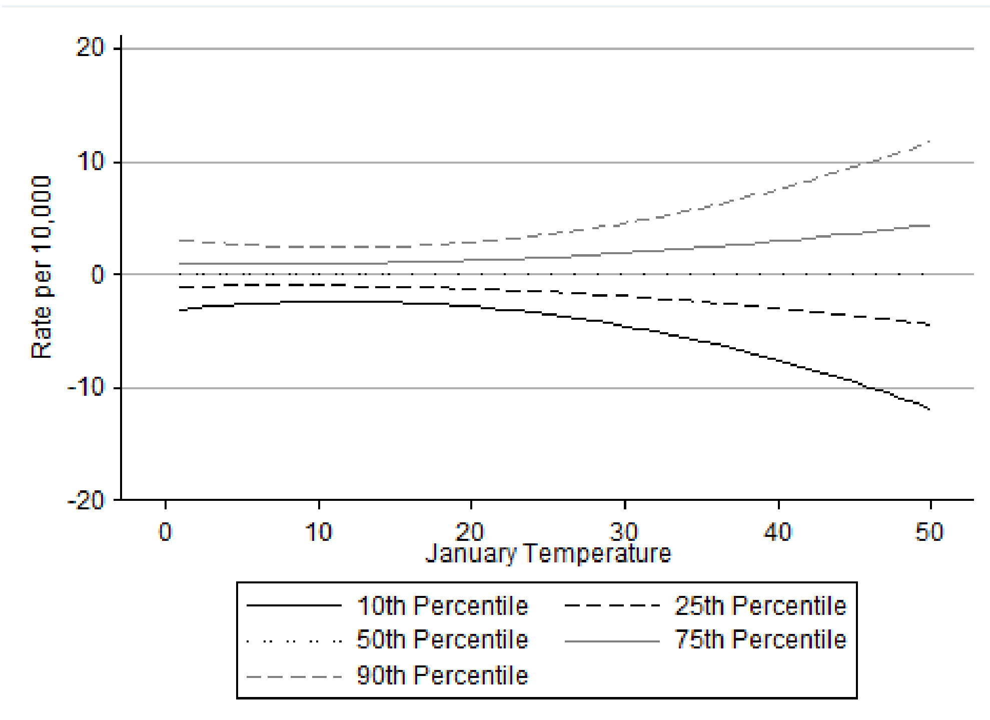


(c) Total homelessness

Figure A2: Predicted 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. Plotted are the 10th, 25th, 50th, 75th and 90th percentiles.

Figure A3: 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.