Supplementary Appendix

This appendix has been provided by the authors to give readers additional information about their work.

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Supplementary Appendix for Adjusting Risk Adjustment: Accounting for Variation in Diagnostic Intensity*

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This appendix details our methodology for obtaining HRR-specific adjustment factors for Medicare Advantage risk scores. Our empirical approach focuses on individuals who move across HRRs. To see the intuition for this approach, imagine a patient who moves from Miami (an area with higher measured risk scores) to Minneapolis (an area with lower measured risk scores). If all of the differences in diagnoses between Miami and Minneapolis arose from supply-side differences like physician practices, we would expect migrant's measured diagnoses to drop immediately following the move, to a level similar to other patients in Minneapolis. On the other hand, if all of the differences in diagnoses between Miami and Minneapolis arose from the demand-side reality that patients in Miami tend to be in worse health, we would expect migrant's utilization to remain constant after the move, at a level similar to other patients in Miami. Where the observed change in measured diagnoses falls between these two extremes identifies the relative importance of place-specific ("supply side") and patient-specific ("demand side") factors.

We use the same data, sample, and definitions of variables as in Finkelstein et al. (2016); these data are a 20 percent random sample of traditional Medicare beneficiaries from 1998-2008. We use the same empirical specification as in Finkelstein et al. (2016) to estimate the "place component" of the risk score. We present considerably more detail on the empirical approach, the identifying assumptions, and our investigation of their validity in Finkelstein et al. (2016) where, we previously estimated that about 50 percent of the geographic variation in measured risk scores is due to place-specific factors.

Here, we first briefly re-describe that specification for estimating risk score "place components." We then outline the empirical Bayes procedure that converts these estimates to our adjustment factors.

Estimating Place Effects

Suppose the measured risk score y_{ijt} for beneficiary i in HRR j and calendar year t has a multiplicative error structure:

$$y_{ijt} = y^*_{it}\xi_{ijt}, \tag{1}$$

where the true log risk score and log measurement error can be written, using α_i to denote beneficiary fixed effects, τ_t to denote year fixed effects, and x_{it} to denote a set of observed time-varying controls,

$$\ln y^*_{it} = \alpha_i + \tau_t + x'_{it}\beta \tag{2}$$

$$\ln \xi_{ijt} = \gamma_j + \epsilon_{ijt}, \tag{3}$$

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where $E[\epsilon_{ijt}|\{i,j,t,x_{it}\}] = 0$. This gives us our main regression specification

$$\ln y_{ijt} = \alpha_i + \gamma_j + \tau_t + x'_{it}\beta + \epsilon_{ijt}, \tag{4}$$

which can be estimated by ordinary least squares (OLS). The place component of this regression, γ_j, represents log measurement error due to the diagnostic intensity of HRR j. With their mean normalized to zero, the γ_j thus reflect average causal effects on log measured risk score from moving a random beneficiary to each HRR j, holding true scores fixed.

We first estimate equation (4) on the main analysis sample of Finkelstein et al. (2016); as discussed in detail there, quasi-experimental variation in beneficiary migration across HRRs identifies the place components. Measured risk scores y_{ijt} come from the model described in Pope et al. (2004), which replicates the community HCC model developed by the Centers for Medicare and Medicaid Services to adjust payments for Medicare Advantage plans. We include in x_{it} indicators for five-year age bins and fixed effects $\rho_{r(i,t)}$ for beneficiaries that move between HRRs in the sample, where $r(i,t) = t - t_i^*$ for a beneficiary who moves during year t_i^*. Standard errors are clustered by beneficiary and $\rho_{r(i,t)}$ is normalized to zero for non-moving beneficiaries. From this regression we obtain 306 place component estimates $\hat{\gamma}_j$, which are noisy but consistent for the place components γ_j. We also observe 306 estimates of HRR-average $\ln y_{ijt}$, denoted μ_j, which are likely-correlated proxies for γ_j. The μ_j are also normalized to be mean-zero; since the sample is so large, we abstract away from estimation error in these proxies.

Constructing Empirical Bayes Posteriors

We now extend our prior work (Finkelstein et al. (2016)) to convert place-specific measurement component estimates to empirical Bayes posterior predictions of place-specific adjustment factors. We use a hierarchical model to combine information from the quasi-experimental estimates $\hat{\gamma}_j$ and the non-experimental proxies μ_j, following Morris (1983) and recent applications in Angrist et al. (forthcoming), Chetty and Hendren (2015), and Hull (2016). Namely, we assume γ_j and μ_j are joint-normally distributed random coefficients, so that

$$\gamma_j = \lambda\mu_j + \eta_j \tag{5}$$

with $\lambda = E[\gamma_j\mu_j]/E[\mu_j^2]$ and independent $\eta_j \sim N(0,\sigma^2)$. Subject to the usual asymptotic approximation, we moreover have

$$\hat{\gamma}_j = \gamma_j + \nu_j \tag{6}$$

where the independent estimation error ν_j is normally-distributed with a covariance structure given by first-order asymptotics of equation (4). Thus,

$$\hat{\gamma}_j = \lambda\mu_j + \eta_j + \nu_j, \tag{7}$$

and we can consistently estimate the hyperparameters λ and σ by OLS:

$$\hat{\lambda}_0 = (\mu'\mu)^{-1}\mu'\hat{\gamma} \tag{8}$$

$$\hat{\sigma}_0^2 = \sum_j w_{0j}\left((\hat{\gamma}_j - \hat{\lambda}_0\mu_j)^2 - \sigma_{\nu j}^2\right), \tag{9}$$

where μ collects observations of μ_j, $\hat{\gamma}$ collects observations of $\hat{\gamma}_j$, the w_{0j} are positive weights with $\sum_j w_{0j} = 1$, and $\sigma_{\nu j}^2$ is the measured variance of ν_j. The initial estimate of σ can then be used to iteratively estimate the hyperparameters by a feasible generalized least squares (FGLS) procedure. The

kth step of this procedure constructs

$$\hat{\lambda}_k = (\mu' \hat{\Omega}_k^{-1} \mu)^{-1} \mu' \hat{\Omega}_k^{-1} \hat{\gamma} \tag{10}$$

$$\hat{\sigma}_k^2 = \sum_j w_{kj} \left((\hat{\gamma}_j - \hat{\lambda}_k \mu_j)^2 - \sigma_{\nu j}^2 \right), \tag{11}$$

where again w_{kj} are positive weights summing to one and

$$\hat{\Omega}_k = \hat{\sigma}_{k-1}^2 I + \Sigma_\nu \tag{12}$$

is the step-k estimate of the variance of $\eta_j + \nu_j$, with I denoting the identity matrix and Σ_ν the variance of the $\hat{\gamma} - \gamma$ vector. In practice we follow Morris (1983) in using inverse-variance weights:

$$w_{0j} = 1/\sigma_{\nu j}^2 \tag{13}$$

$$w_{kj} = 1/(\hat{\sigma}_{k-1}^2 + \sigma_{\nu j}^2). \tag{14}$$

From this we obtain iterated FGLS estimates of $\hat{\lambda} = 0.556$ and $\hat{\sigma} = 0.024$, with heteroskedastic-robust standard errors of 0.028 and 0.001; that $\hat{\lambda}$ is statistically significantly different from zero implies that the proxies μ_j are indeed correlated with the true γ_j, while the significance of $\hat{\sigma}$ reflects additional variation in place components not captured by the proxies.

We then use these estimates to form empirical Bayes posterior predictions of the place effects, noting that under the hierarchical model,

$$\gamma | \hat{\gamma}, \mu \sim N(M, V) \tag{15}$$

where

$$M = \Omega \hat{\gamma} + (I - \Omega) \lambda \mu \tag{16}$$

and

$$V = \sigma^2 (I - \Omega) \tag{17}$$

for $\Omega = \sigma^2(\sigma^2 I + \Sigma_\nu)^{-1}$. With uncorrelated first-step estimation error (i.e. when Σ_ν is diagonal), equations (15)-(17) reduce to equations (1.7)-(1.9) in Morris (1983). Plugging $\hat{\lambda}$ and $\hat{\sigma}$ in to equation (16) yields our posterior mean predictions $\tilde{\gamma}_j$. With the log measurement error residual ϵ_{ijt} unforecastable, $\tilde{\gamma}_j$ reflects the best (minimum mean squared error) prediction of log measurement error $\ln \xi_{ijt}$ given the observed estimates and proxies, and we can adjust observed risk scores y_{ijt} for regional variation in diagnostic intensity by scaling (multiplying) them by a factor of $\exp(-\tilde{\gamma}_j)$. These are the adjustment factors used in the paper.

We report the adjustment factor for each HRR in the table below, along with the average risk score of traditional Medicare beneficiaries before and after adjustment; this table is also available as a separate Excel file.

References

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HRR name	HRR state	HRR ID	Average risk score	Adjustment factor	Adjusted average risk score
Birmingham	AL	1	1.021	1.004	1.026
Dothan	AL	2	0.994	1.010	1.004
Huntsville	AL	5	0.957	1.005	0.962
Mobile	AL	6	0.972	1.020	0.992
Montgomery	AL	7	1.004	1.003	1.007
Tuscaloosa	AL	9	0.999	0.989	0.989
Anchorage	AK	10	0.834	1.081	0.902
Mesa	AZ	11	0.883	1.028	0.908
Phoenix	AZ	12	0.900	1.010	0.909
Sun City	AZ	14	0.951	0.978	0.930
Tucson	AZ	15	0.887	1.032	0.915
Fort Smith	AR	16	0.945	1.025	0.969
Jonesboro	AR	18	0.943	1.025	0.967
Little Rock	AR	19	0.965	1.025	0.989
Springdale	AR	21	0.889	1.003	0.892
Texarkana	AR	22	1.041	1.013	1.054
Orange County	CA	23	1.000	0.942	0.942
Bakersfield	CA	25	1.084	0.938	1.017
Chico	CA	31	0.964	1.004	0.968
Contra Costa County	CA	33	0.961	0.988	0.950
Fresno	CA	43	1.012	0.986	0.998
Los Angeles	CA	56	1.184	0.901	1.067
Modesto	CA	58	1.005	0.961	0.966
Napa	CA	62	1.019	0.968	0.987
Alameda County	CA	65	1.021	0.969	0.989
Palm Springs/Rancho Mirage	CA	69	0.985	0.984	0.969
Redding	CA	73	0.918	1.006	0.923
Sacramento	CA	77	0.951	1.020	0.970
Salinas	CA	78	0.925	0.998	0.923
San Bernardino	CA	79	1.073	0.950	1.019
San Diego	CA	80	1.006	0.983	0.989
San Francisco	CA	81	0.978	0.995	0.973
San Jose	CA	82	0.928	1.007	0.934
San Luis Obispo	CA	83	0.873	1.032	0.901
San Mateo County	CA	85	0.897	1.021	0.915
Santa Barbara	CA	86	0.934	0.988	0.922
Santa Cruz	CA	87	0.921	1.004	0.925
Santa Rosa	CA	89	0.998	1.006	1.005
Stockton	CA	91	1.038	0.983	1.020
Ventura	CA	96	0.994	0.956	0.951
Boulder	CO	101	0.841	1.051	0.884
Colorado Springs	CO	102	0.906	1.010	0.915
Denver	CO	103	0.916	1.013	0.928
Fort Collins	CO	104	0.849	1.055	0.896

Grand Junction	CO	105	0.787	1.084	0.853
Greeley	CO	106	0.909	1.043	0.949
Pueblo	CO	107	0.952	1.003	0.955
Bridgeport	CT	109	1.029	0.967	0.995
Hartford	CT	110	1.037	0.961	0.997
New Haven	CT	111	1.073	0.938	1.006
Wilmington	DE	112	1.039	0.957	0.994
Washington	DC	113	1.005	0.978	0.982
Bradenton	FL	115	0.992	0.967	0.959
Clearwater	FL	116	1.068	0.946	1.010
Fort Lauderdale	FL	118	1.127	0.925	1.042
Fort Myers	FL	119	0.958	0.943	0.904
Gainesville	FL	120	1.008	0.995	1.003
Hudson	FL	122	1.101	0.914	1.006
Jacksonville	FL	123	1.040	0.993	1.033
Lakeland	FL	124	0.945	1.009	0.954
Miami	FL	127	1.342	0.867	1.164
Ocala	FL	129	0.971	0.966	0.938
Orlando	FL	130	1.028	0.950	0.977
Ormond Beach	FL	131	0.997	0.964	0.960
Panama City	FL	133	1.018	0.986	1.005
Pensacola	FL	134	0.990	0.965	0.956
Sarasota	FL	137	0.968	0.962	0.931
St. Petersburg	FL	139	1.103	0.914	1.008
Tallahassee	FL	140	1.015	1.018	1.034
Tampa	FL	141	1.043	0.956	0.997
Albany	GA	142	0.988	1.003	0.991
Atlanta	GA	144	0.947	1.007	0.954
Augusta	GA	145	0.971	1.018	0.988
Columbus	GA	146	1.012	0.998	1.010
Macon	GA	147	1.037	0.979	1.015
Rome	GA	148	0.965	1.007	0.972
Savannah	GA	149	0.980	0.990	0.971
Honolulu	HI	150	0.891	1.016	0.906
Boise	ID	151	0.857	1.064	0.912
Idaho Falls	ID	152	0.828	1.046	0.866
Aurora	IL	154	0.895	1.018	0.910
Blue Island	IL	155	0.986	0.965	0.952
Chicago	IL	156	1.073	1.000	1.072
Elgin	IL	158	0.914	1.001	0.915
Evanston	IL	161	0.920	1.001	0.921
Hinsdale	IL	163	0.887	0.993	0.881
Joliet	IL	164	0.962	0.983	0.946
Melrose Park	IL	166	0.948	0.993	0.942
Peoria	IL	170	0.933	1.023	0.955
Rockford	IL	171	0.900	1.044	0.940
Springfield	IL	172	0.943	1.005	0.947

Urbana	IL	173	0.957	1.006	0.963
Bloomington	IL	175	0.894	1.036	0.927
Evansville	IN	179	0.980	0.999	0.979
Fort Wayne	IN	180	0.943	0.998	0.941
Gary	IN	181	1.050	0.973	1.022
Indianapolis	IN	183	0.975	1.004	0.979
Lafayette	IN	184	0.925	1.022	0.945
Muncie	IN	185	0.974	1.014	0.987
Munster	IN	186	1.026	0.985	1.011
South Bend	IN	187	0.915	1.024	0.937
Terre Haute	IN	188	1.043	0.974	1.016
Cedar Rapids	IA	190	0.882	1.058	0.933
Davenport	IA	191	0.935	1.021	0.954
Des Moines	IA	192	0.907	1.026	0.931
Dubuque	IA	193	0.790	1.092	0.863
Iowa City	IA	194	0.902	1.037	0.935
Mason City	IA	195	0.879	1.052	0.924
Sioux City	IA	196	0.919	1.007	0.926
Waterloo	IA	197	0.941	1.026	0.965
Topeka	KS	200	0.883	1.050	0.927
Wichita	KS	201	0.929	1.035	0.962
Covington	KY	203	1.020	1.005	1.026
Lexington	KY	204	1.038	1.008	1.046
Louisville	KY	205	1.008	1.004	1.012
Owensboro	KY	207	0.991	0.978	0.969
Paducah	KY	208	0.964	1.022	0.985
Alexandria	LA	209	1.065	0.981	1.044
Baton Rouge	LA	210	1.081	0.991	1.072
Houma	LA	212	1.004	0.992	0.996
Lafayette	LA	213	1.069	0.981	1.049
Lake Charles	LA	214	1.042	0.977	1.018
Metairie	LA	216	1.065	0.963	1.025
Monroe	LA	217	1.082	0.948	1.026
New Orleans	LA	218	1.147	0.980	1.124
Shreveport	LA	219	1.068	0.976	1.043
Slidell	LA	220	1.039	0.984	1.022
Bangor	ME	221	0.955	1.017	0.971
Portland	ME	222	0.936	1.033	0.967
Baltimore	MD	223	1.075	0.959	1.030
Salisbury	MD	225	1.026	0.967	0.992
Takoma Park	MD	226	0.976	0.988	0.964
Boston	MA	227	1.070	0.949	1.016
Springfield	MA	230	1.047	0.987	1.033
Worcester	MA	231	1.081	0.953	1.030
Ann Arbor	MI	232	1.015	0.967	0.982
Dearborn	MI	233	1.199	0.887	1.063
Detroit	MI	234	1.208	0.897	1.084

Flint	MI	235	1.124	0.921	1.035
Grand Rapids	MI	236	0.916	1.038	0.950
Kalamazoo	MI	238	0.954	1.039	0.991
Lansing	MI	239	0.983	0.990	0.973
Marquette	MI	240	0.933	1.022	0.954
Muskegon	MI	242	0.944	1.007	0.950
Petoskey	MI	243	0.899	1.030	0.926
Pontiac	MI	244	1.051	0.919	0.966
Royal Oak	MI	245	1.087	0.912	0.991
Saginaw	MI	246	0.979	0.994	0.973
St. Joseph	MI	248	0.968	1.002	0.970
Traverse City	MI	249	0.888	1.037	0.920
Duluth	MN	250	0.856	1.084	0.928
Minneapolis	MN	251	0.822	1.083	0.890
Rochester	MN	253	0.823	1.071	0.881
St. Cloud	MN	254	0.814	1.091	0.889
St. Paul	MN	256	0.836	1.107	0.925
Gulfport	MS	257	0.980	1.009	0.989
Hattiesburg	MS	258	0.960	1.022	0.982
Jackson	MS	259	0.977	1.042	1.017
Meridian	MS	260	1.002	1.022	1.024
Oxford	MS	261	0.967	0.994	0.962
Tupelo	MS	262	0.934	1.040	0.971
Cape Girardeau	MO	263	0.953	1.016	0.968
Columbia	MO	264	0.971	0.995	0.966
Joplin	MO	267	0.980	0.989	0.969
Kansas City	MO	268	0.979	1.002	0.981
Springfield	MO	270	0.906	1.024	0.928
St. Louis	MO	273	1.037	0.975	1.011
Billings	MT	274	0.836	1.080	0.903
Great Falls	MT	275	0.912	1.058	0.965
Missoula	MT	276	0.833	1.086	0.904
Lincoln	NE	277	0.877	1.058	0.928
Omaha	NE	278	0.917	1.033	0.947
Las Vegas	NV	279	1.013	0.956	0.968
Reno	NV	280	0.861	1.051	0.904
Lebanon	NH	281	0.884	1.020	0.901
Manchester	NH	282	0.914	1.031	0.942
Camden	NJ	283	1.135	0.906	1.028
Hackensack	NJ	284	1.109	0.914	1.014
Morristown	NJ	285	1.012	0.939	0.951
New Brunswick	NJ	288	1.093	0.930	1.016
Newark	NJ	289	1.176	0.912	1.072
Paterson	NJ	291	1.104	0.935	1.032
Ridgewood	NJ	292	1.097	0.917	1.006
Albuquerque	NM	293	0.891	1.024	0.912
Albany	NY	295	1.037	0.966	1.002

Binghamton	NY	296	0.941	1.019	0.960
Bronx	NY	297	1.201	0.940	1.129
Buffalo	NY	299	1.043	0.975	1.017
Elmira	NY	300	1.040	0.974	1.012
East Long Island	NY	301	1.152	0.883	1.017
Manhattan	NY	303	1.234	0.901	1.111
Rochester	NY	304	1.040	0.967	1.006
Syracuse	NY	307	0.973	0.987	0.961
White Plains	NY	308	1.084	0.913	0.989
Asheville	NC	309	0.881	1.060	0.934
Charlotte	NC	311	0.953	1.058	1.008
Durham	NC	312	0.964	1.035	0.998
Greensboro	NC	313	0.933	1.033	0.964
Greenville	NC	314	0.945	1.061	1.003
Hickory	NC	315	0.920	1.053	0.968
Raleigh	NC	318	0.971	1.026	0.996
Wilmington	NC	319	0.951	1.035	0.985
Winston-Salem	NC	320	0.956	1.031	0.985
Bismarck	ND	321	0.888	1.043	0.926
Fargo/Moorhead MN	ND	322	0.855	1.057	0.904
Grand Forks	ND	323	0.844	1.050	0.887
Minot	ND	324	0.876	1.040	0.911
Akron	OH	325	1.075	0.960	1.032
Canton	OH	326	0.993	0.987	0.980
Cincinnati	OH	327	1.005	0.987	0.992
Cleveland	OH	328	1.092	0.944	1.032
Columbus	OH	329	1.005	0.985	0.989
Dayton	OH	330	0.992	0.982	0.974
Elyria	OH	331	1.050	0.951	0.998
Kettering	OH	332	0.960	0.982	0.943
Toledo	OH	334	1.037	0.965	1.000
Youngstown	OH	335	1.099	0.954	1.049
Lawton	OK	336	1.001	1.005	1.005
Oklahoma City	OK	339	0.959	1.015	0.973
Tulsa	OK	340	0.942	1.035	0.975
Bend	OR	341	0.820	1.072	0.879
Eugene	OR	342	0.861	1.058	0.910
Medford	OR	343	0.884	1.008	0.891
Portland	OR	344	0.889	1.081	0.962
Salem	OR	345	0.869	1.074	0.933
Allentown	PA	346	1.089	0.933	1.017
Altoona	PA	347	1.028	0.956	0.982
Danville	PA	350	1.035	0.970	1.003
Erie	PA	351	1.019	0.965	0.983
Harrisburg	PA	352	0.992	0.987	0.979
Johnstown	PA	354	1.043	0.965	1.006
Lancaster	PA	355	0.985	0.985	0.970

Philadelphia	PA	356	1.189	0.918	1.092
Pittsburgh	PA	357	1.109	0.960	1.065
Reading	PA	358	1.034	0.985	1.019
Sayre	PA	359	0.933	1.023	0.954
Scranton	PA	360	1.125	0.925	1.041
Wilkes-Barre	PA	362	1.151	0.935	1.076
York	PA	363	0.938	1.028	0.965
Providence	RI	364	1.102	0.948	1.045
Charleston	SC	365	0.951	1.016	0.967
Columbia	SC	366	0.945	1.053	0.995
Florence	SC	367	1.032	0.993	1.025
Greenville	SC	368	0.921	1.041	0.959
Spartanburg	SC	369	0.976	1.017	0.993
Rapid City	SD	370	0.813	1.101	0.895
Sioux Falls	SD	371	0.843	1.054	0.888
Chattanooga	TN	373	0.968	1.018	0.985
Jackson	TN	374	0.984	1.021	1.004
Johnson City	TN	375	0.917	1.011	0.927
Kingsport	TN	376	1.022	1.003	1.024
Knoxville	TN	377	0.998	1.022	1.020
Memphis	TN	379	0.994	1.015	1.008
Nashville	TN	380	0.981	1.022	1.002
Abilene	TX	382	0.955	0.986	0.941
Amarillo	TX	383	0.896	1.036	0.928
Austin	TX	385	0.921	1.001	0.922
Beaumont	TX	386	1.110	0.941	1.044
Bryan	TX	388	0.938	1.035	0.970
Corpus Christi	TX	390	1.149	0.940	1.080
Dallas	TX	391	1.016	0.960	0.975
El Paso	TX	393	0.943	1.005	0.948
Fort Worth	TX	394	0.991	0.991	0.982
Harlingen	TX	396	1.136	0.947	1.076
Houston	TX	397	1.019	0.966	0.985
Longview	TX	399	0.998	0.996	0.995
Lubbock	TX	400	0.975	0.999	0.974
McAllen	TX	402	1.209	0.908	1.098
Odessa	TX	406	0.887	1.054	0.935
San Angelo	TX	411	0.954	1.019	0.972
San Antonio	TX	412	1.008	0.991	0.999
Temple	TX	413	0.959	1.020	0.978
Tyler	TX	416	1.002	0.971	0.973
Victoria	TX	417	1.023	0.982	1.004
Waco	TX	418	0.963	1.026	0.988
Wichita Falls	TX	420	1.016	0.983	0.998
Ogden	UT	421	0.839	1.057	0.887
Provo	UT	422	0.859	1.055	0.906
Salt Lake City	UT	423	0.855	1.021	0.873

Burlington	VT	424	0.927	1.049	0.972
Arlington	VA	426	0.902	0.988	0.891
Charlottesville	VA	427	0.944	1.016	0.959
Lynchburg	VA	428	0.875	1.072	0.938
Newport News	VA	429	0.942	1.040	0.980
Norfolk	VA	430	1.042	0.979	1.020
Richmond	VA	431	0.962	1.035	0.995
Roanoke	VA	432	0.975	1.009	0.984
Winchester	VA	435	0.910	1.020	0.929
Everett	WA	437	0.875	1.049	0.918
Olympia	WA	438	0.912	1.052	0.959
Seattle	WA	439	0.903	1.036	0.935
Spokane	WA	440	0.899	1.055	0.949
Tacoma	WA	441	0.950	1.013	0.962
Yakima	WA	442	0.913	1.025	0.935
Charleston	WV	443	1.034	1.003	1.037
Huntington	WV	444	1.012	0.988	1.000
Morgantown	WV	445	0.994	0.971	0.965
Appleton	WI	446	0.857	1.066	0.914
Green Bay	WI	447	0.865	1.063	0.920
La Crosse	WI	448	0.840	1.068	0.897
Madison	WI	449	0.854	1.086	0.928
Marshfield	WI	450	0.880	1.031	0.906
Milwaukee	WI	451	0.945	1.016	0.960
Neenah	WI	452	0.871	1.071	0.933
Wausau	WI	456	0.863	1.039	0.897
Casper	WY	457	0.804	1.094	0.879