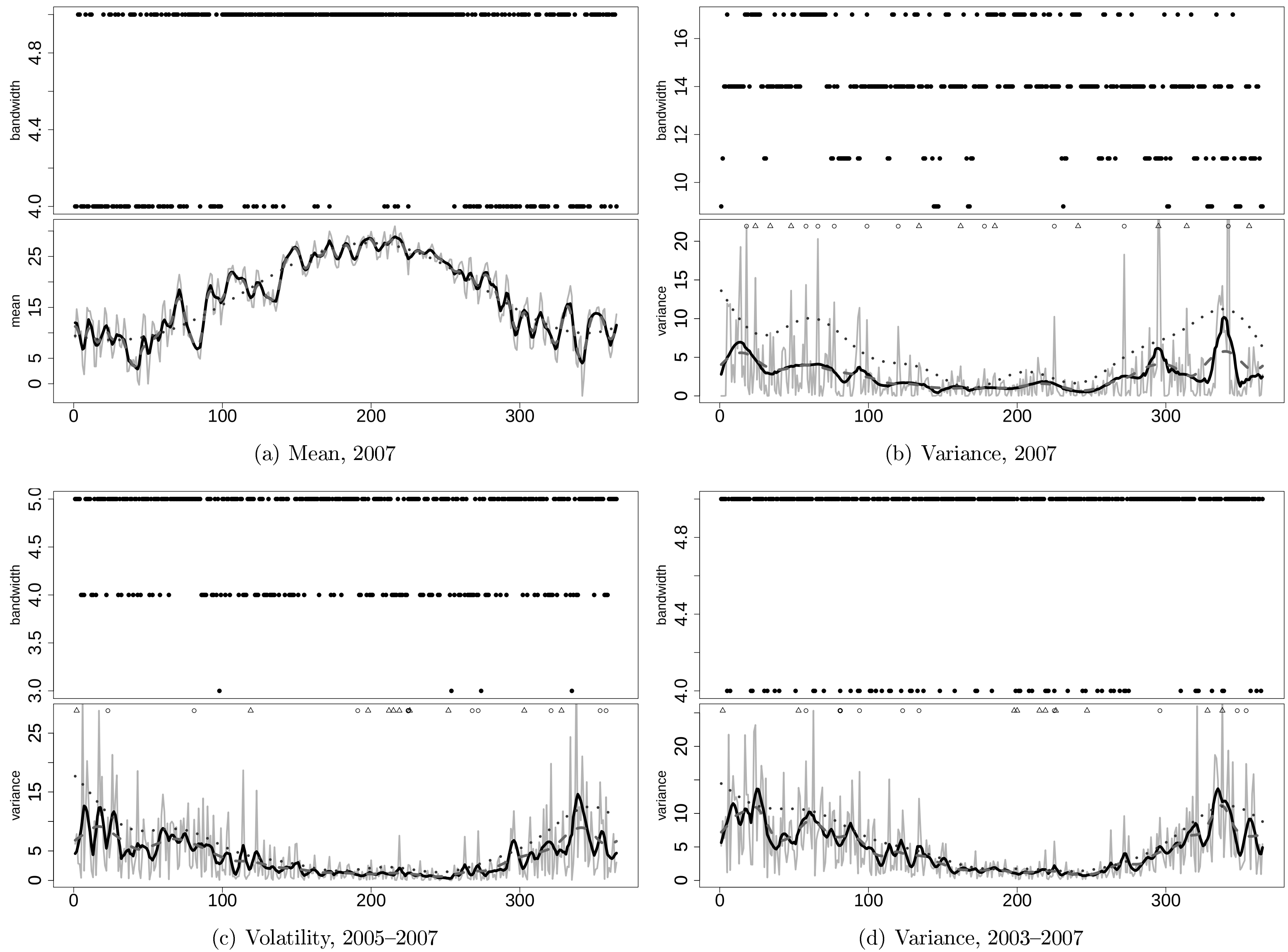
Localising temperature risk: Supplementary Material*

October 23, 2015

*Data is available from Risk Data Center (RDC) of the CRC 649 "Ökonomisches Risiko" (http://sfb649.wiwi.hu-berlin.de/)



(a) Mean, 2007

(b) Variance, 2007

(c) Volatility, 2005–2007

(d) Variance, 2003–2007

Figure 1: Estimation of mean and variance for Atlanta. In each figure sequence of bandwidths (upper panel), nonparametric function estimation (solid grey line), with fixed bandwidth (dashed grey line), adaptive bandwidth (solid black line) and Fourier (dotted line) (bottom panel of each figure).

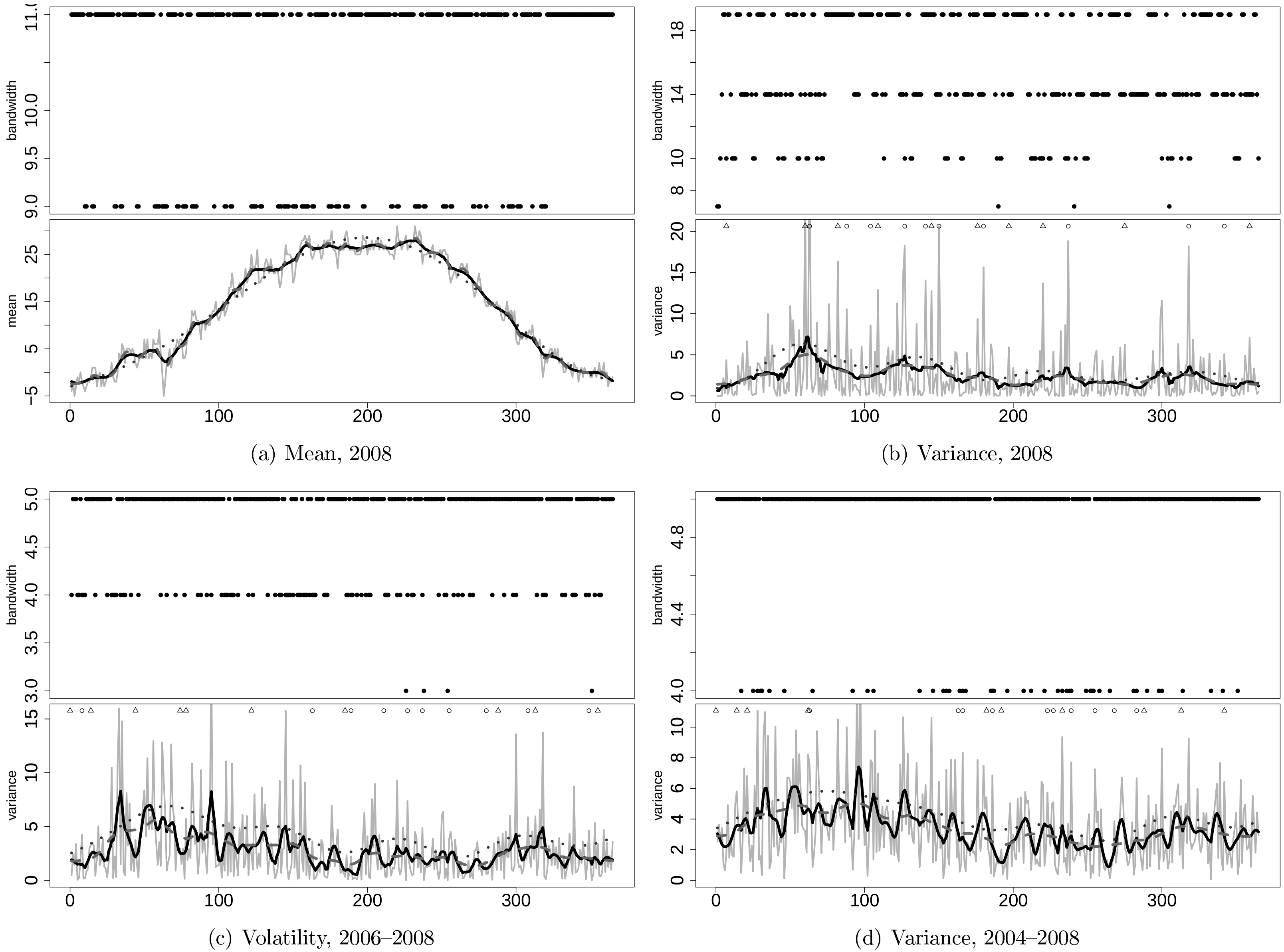
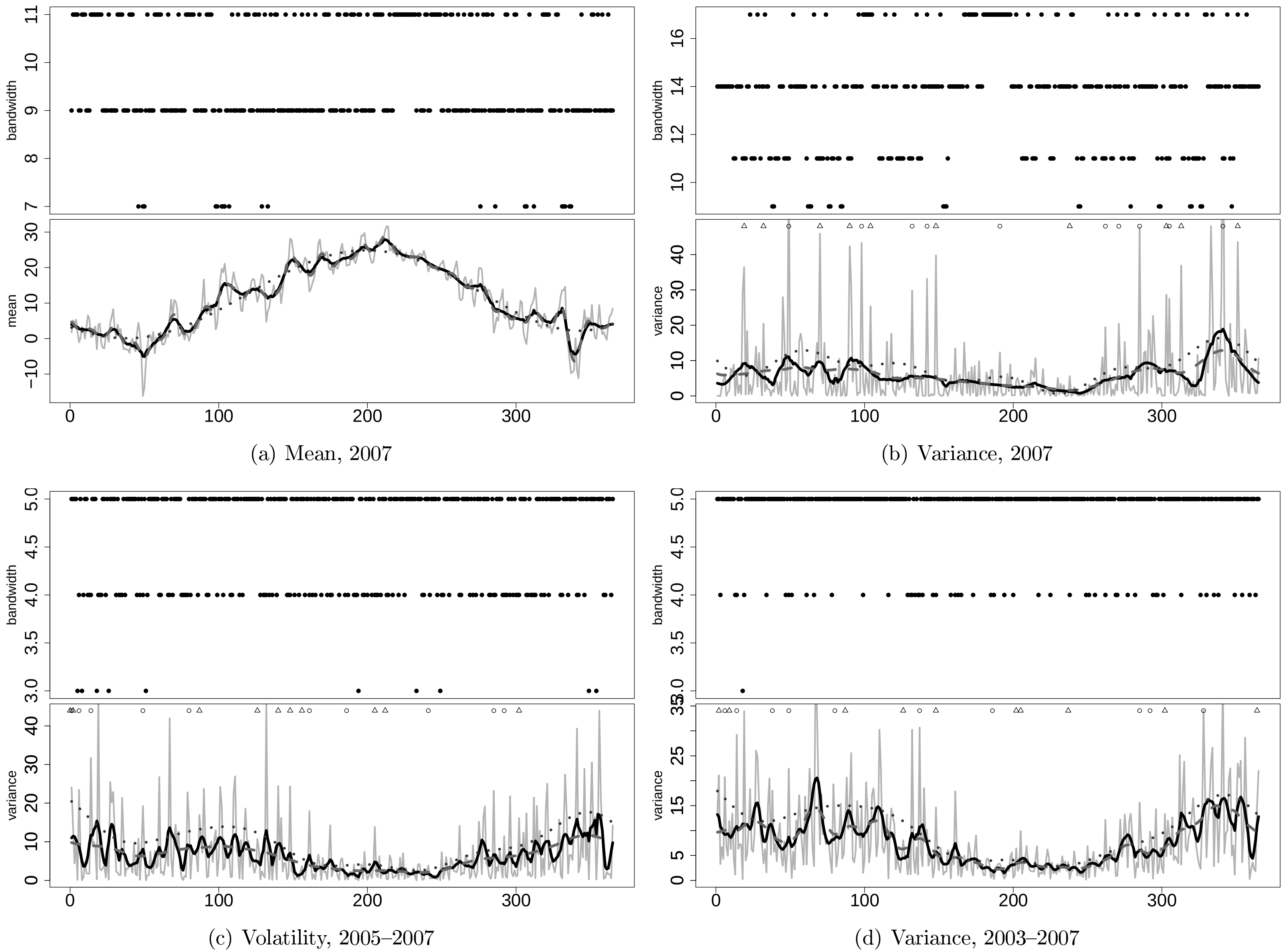


Figure 2: Estimation of mean and variance for Beijing. In each figure sequence of bandwidths (upper panel), nonparametric function estimation (solid grey line), with fixed bandwidth (dashed grey line), adaptive bandwidth (solid black line) and Fourier (dotted line) (bottom panel of each figure).



(a) Mean, 2007

(b) Variance, 2007

(c) Volatility, 2005–2007

(d) Variance, 2003–2007

Figure 3: Estimation of mean and variance for Chicago. In each figure sequence of bandwidths (upper panel), nonparametric function estimation (solid grey line), with fixed bandwidth (dashed grey line), adaptive bandwidth (solid black line) and Fourier (dotted line) (bottom panel of each figure).

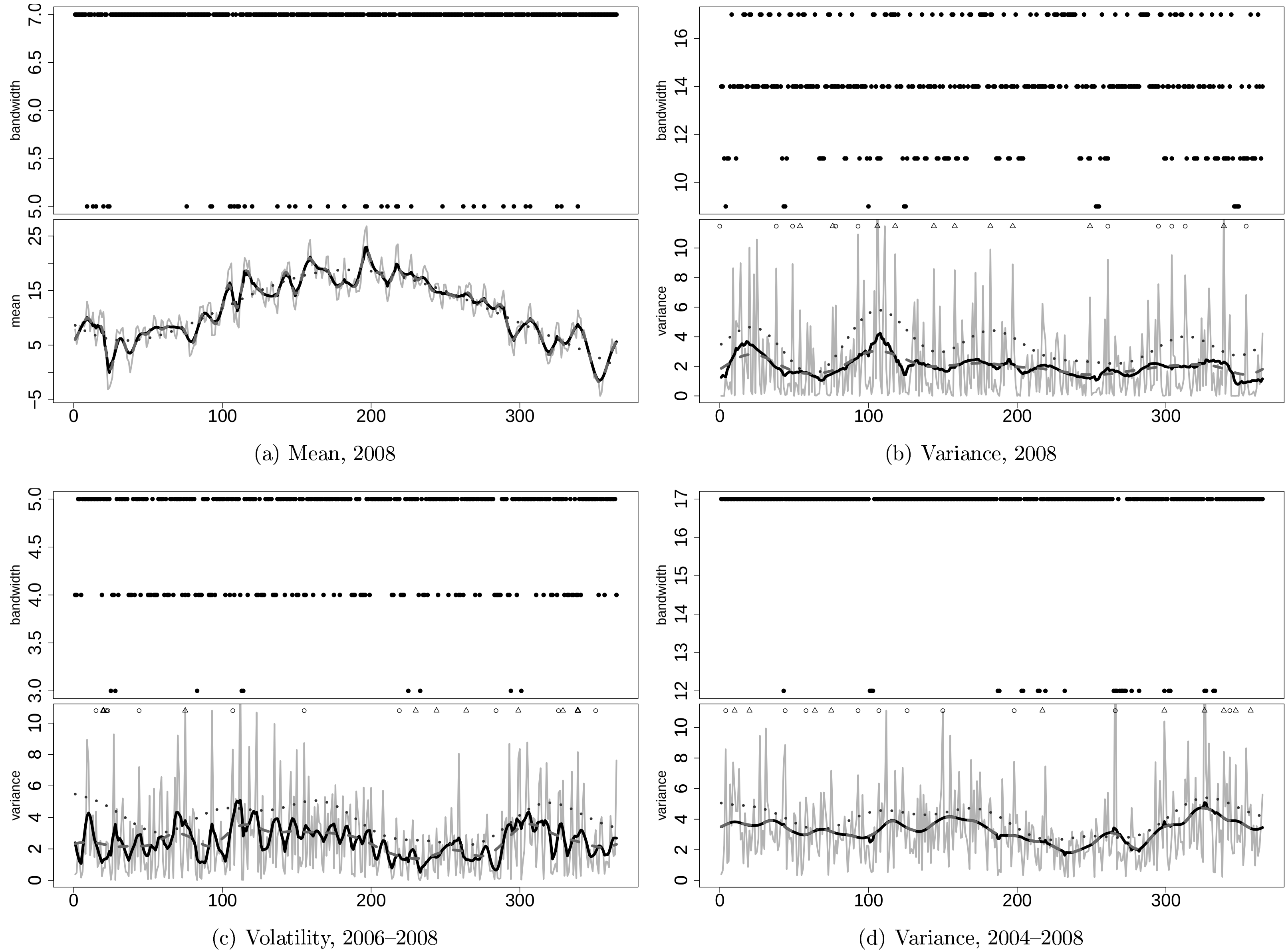


Figure 4: Estimation of mean and variance for Essen. In each figure sequence of bandwidths (upper panel), nonparametric function estimation (solid grey line), with fixed bandwidth (dashed grey line), adaptive bandwidth (solid black line) and Fourier (dotted line) (bottom panel of each figure).

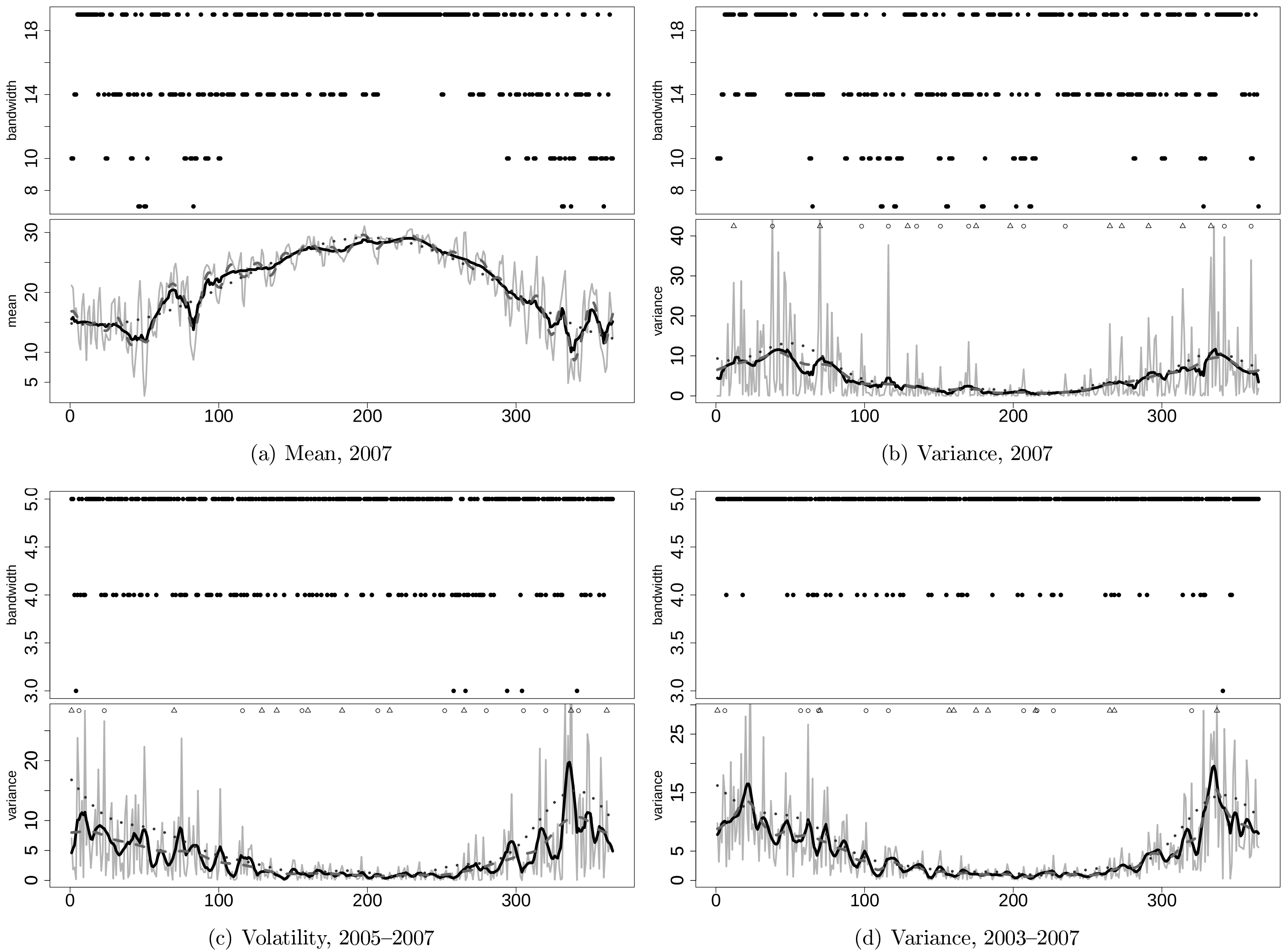
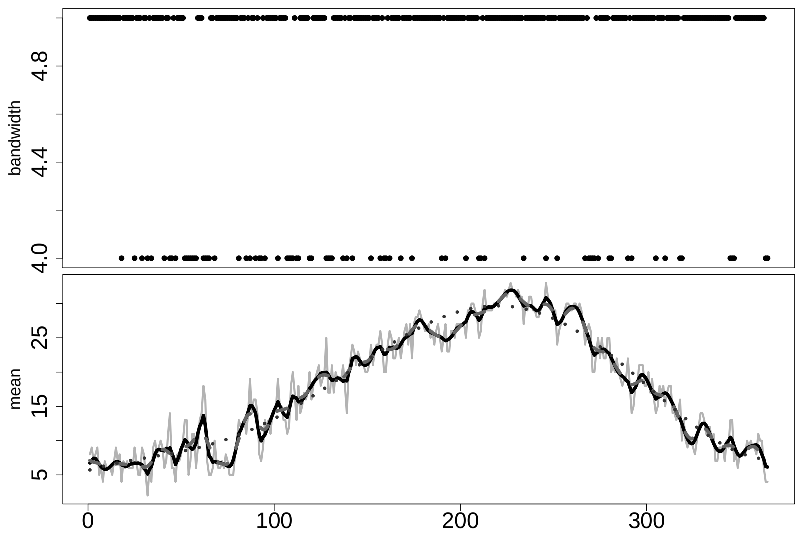
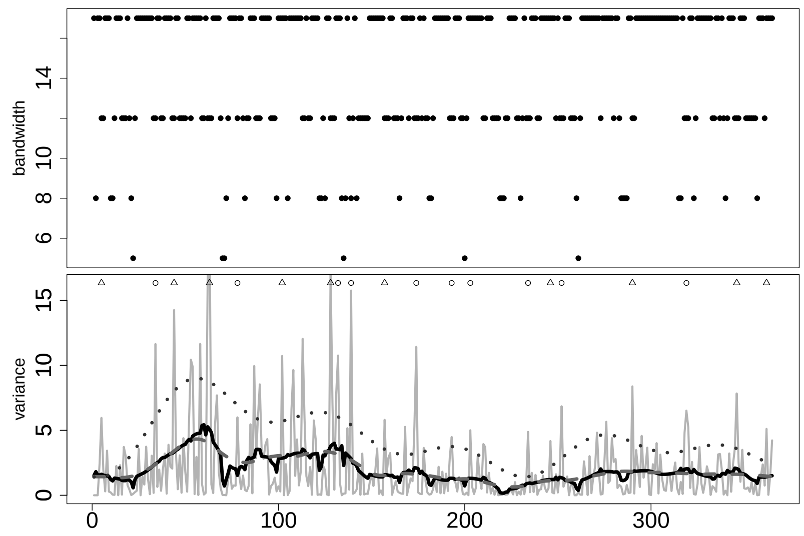


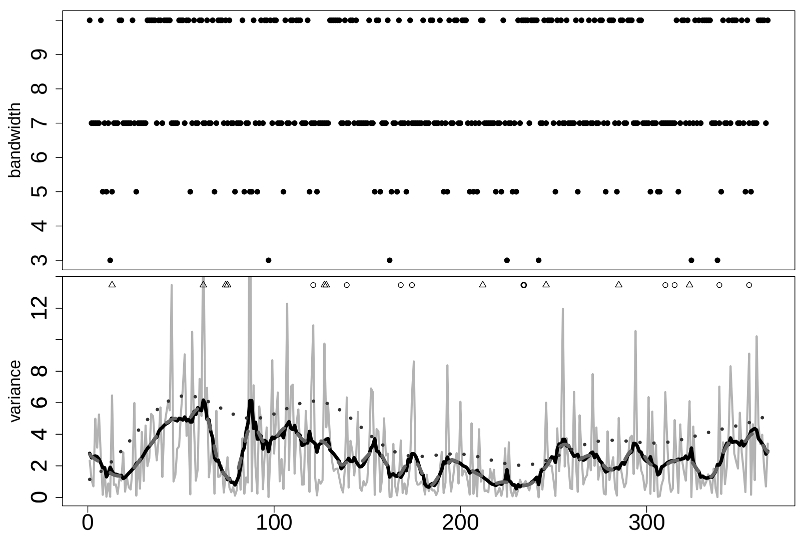
Figure 5: Estimation of mean and variance for Houston. In each figure sequence of bandwidths (upper panel), nonparametric function estimation (solid grey line), with fixed bandwidth (dashed grey line), adaptive bandwidth (solid black line) and Fourier (dotted line) (bottom panel of each figure).



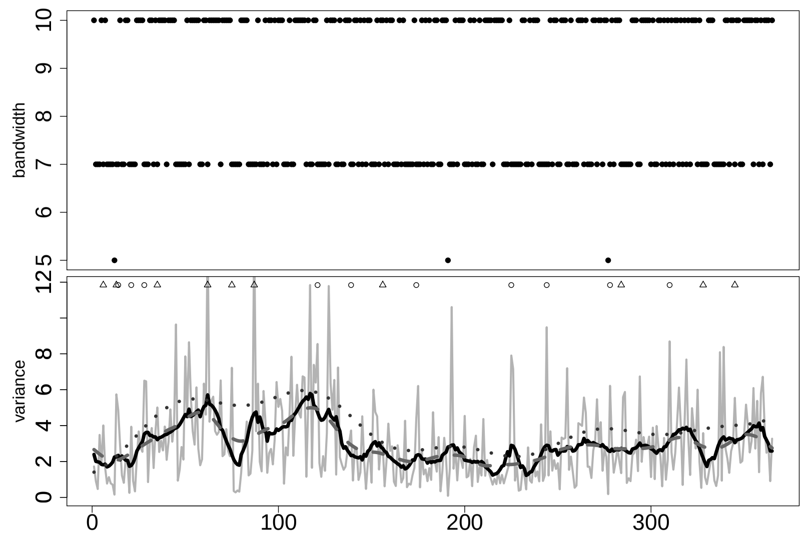
(a) Mean, 2008



(b) Variance, 2008

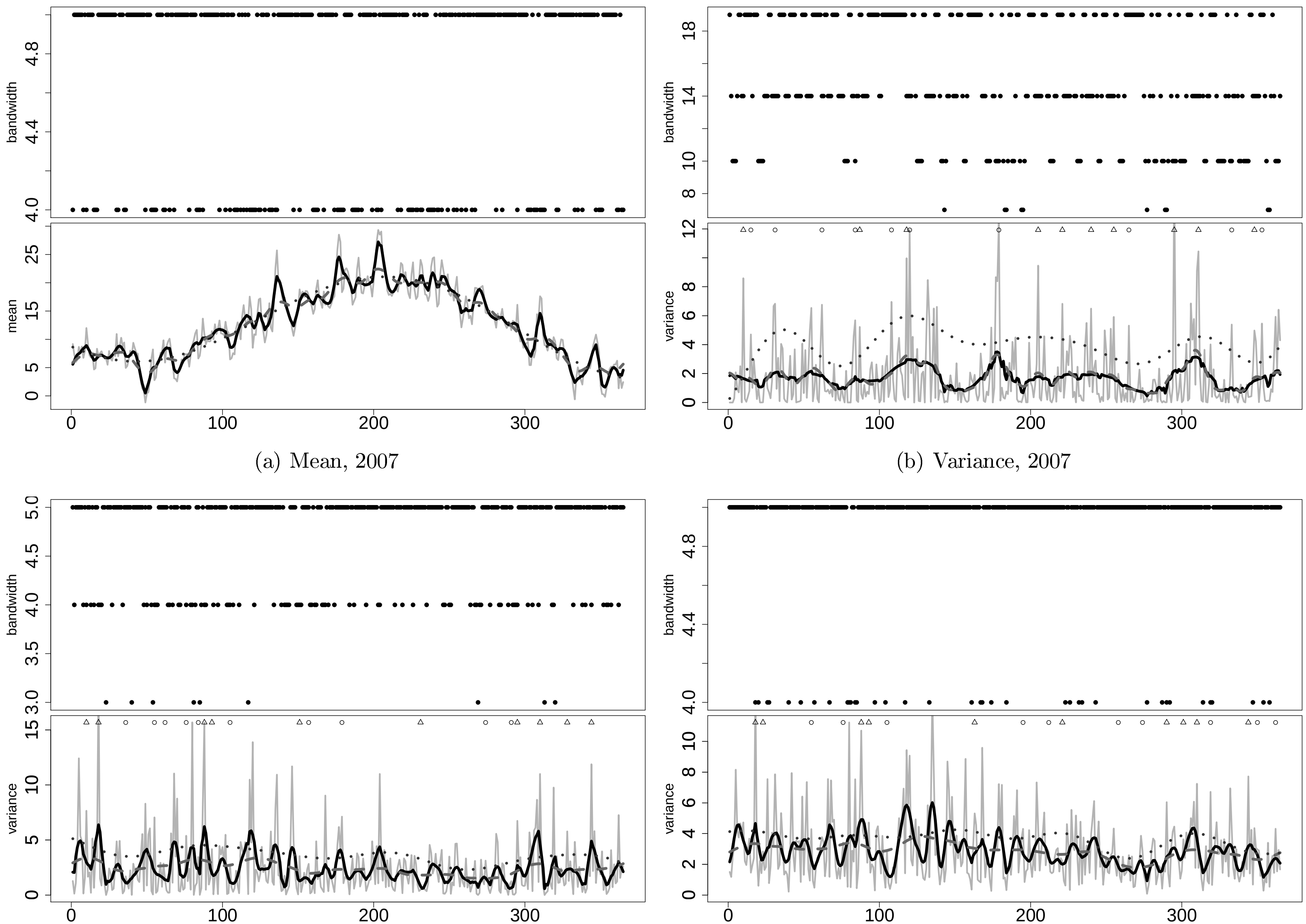


(c) Volatility, 2006–2008



(d) Variance, 2004–2008

Figure 6: Estimation of mean and variance for Osaka. In each figure sequence of bandwidths (upper panel), nonparametric function estimation (solid grey line), with fixed bandwidth (dashed grey line), adaptive bandwidth (solid black line) and Fourier (dotted line) (bottom panel of each figure).



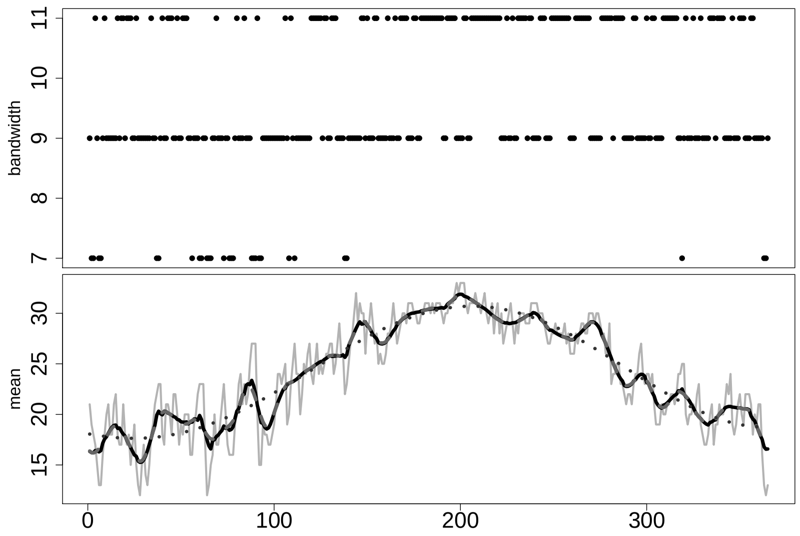
(a) Mean, 2007

(b) Variance, 2007

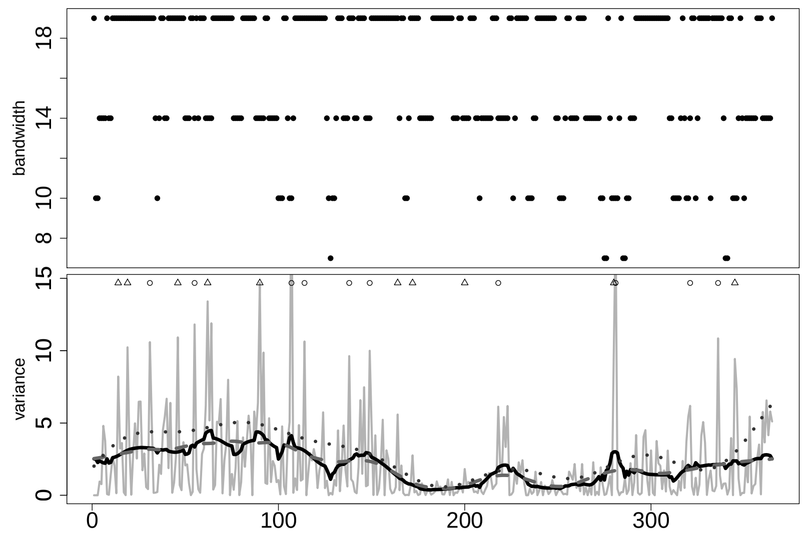
(c) Volatility, 2005–2007

(d) Variance, 2003–2007

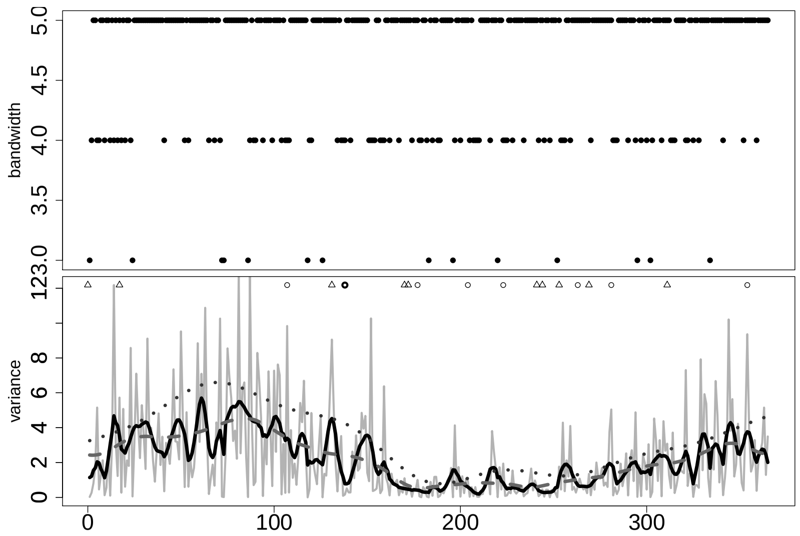
Figure 7: Estimation of mean and variance for Portland. In each figure sequence of bandwidths (upper panel), nonparametric function estimation (solid grey line), with fixed bandwidth (dashed grey line), adaptive bandwidth (solid black line) and Fourier (dotted line) (bottom panel of each figure).



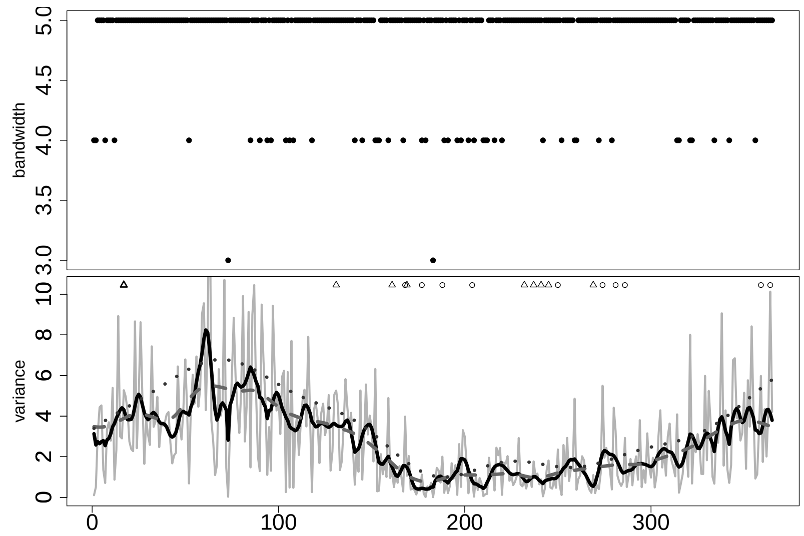
(a) Mean, 2008



(b) Variance, 2008



(c) Volatility, 2006–2008



(d) Variance, 2004–2008

Figure 8: Estimation of mean and variance for Taipei. In each figure sequence of bandwidths (upper panel), nonparametric function estimation (solid grey line), with fixed bandwidth (dashed grey line), adaptive bandwidth (solid black line) and Fourier (dotted line) (bottom panel of each figure).

		1 year			2 years			3 years			4 years			5 years		
		KS	JB	AD	KS	JB	AD	KS	JB	AD	KS	JB	AD	KS	JB	AD
Atlanta	JoMe adMe adVa	0.20	0.01	2.75e-04	2.00e-07	5.35e-04	1.29e-05	2.91e-08	2.69e-10	9.60e-15	5.81e-09	4.08e-14	5.33e-21	8.61e-10	0.00e+00	9.68e-26
	JoMe fiMe fiVa	0.05	0.00	3.93e-04	1.96e-04	8.80e-07	4.77e-08	1.15e-06	0.00e+00	1.57e-16	7.02e-07	0.00e+00	6.56e-22	1.05e-07	0.00e+00	1.95e-28
	SeMe adMe adVa				9.28e-08	3.10e-02	6.41e-04	2.23e-04	4.71e-05	1.18e-05	1.60e-04	6.66e-06	6.91e-09	2.41e-04	1.46e-06	2.61e-09
	SeMe fiMe fiVa				2.61e-05	9.72e-04	8.46e-04	1.52e-04	1.28e-07	6.55e-06	8.22e-05	2.91e-10	2.91e-09	8.03e-05	2.04e-13	6.78e-11
	Locave				9.84e-02	1.85e-02	2.51e-04	4.94e-02	3.82e-04	2.24e-05	7.55e-03	2.73e-05	1.60e-08	2.50e-03	7.15e-07	5.30e-09
	Locsep				9.84e-02	1.85e-02	2.51e-04	4.94e-02	3.83e-04	2.24e-05	7.55e-03	2.72e-05	1.60e-08	2.50e-03	7.15e-07	5.30e-09
	Locmax				1.18e-01	1.22e-01	2.73e-04	8.34e-02	1.85e-03	3.66e-05	9.28e-03	4.30e-05	1.93e-08	2.43e-03	2.21e-07	5.01e-09
	Fourier	0.05	0.00	4.80e-05	1.96e-03	2.29e-07	4.33e-09	5.27e-05	0.00e+00	6.39e-17	1.75e-06	0.00e+00	6.72e-23	7.63e-08	0.00e+00	2.41e-30
	Diebold	0.19	0.00	2.96e-04	1.60e-09	3.07e-10	6.27e-09	0.00e+00	0.00e+00	1.24e-15	0.00e+00	0.00e+00	7.07e-24	0.00e+00	0.00e+00	4.55e-29
Beijing	JoMe adMe adVa	0.92	0.31	0.69	5.76e-07	0.30	0.11	0.00	8.24e-03	0.02	0.01	2.06e-02	0.04	0.03	2.85e-04	1.16e-03
	JoMe fiMe fiVa	0.94	0.87	0.52	4.28e-04	0.01	0.02	0.02	3.03e-03	0.00	0.10	2.17e-04	0.00	0.04	7.50e-06	4.36e-05
	SeMe adMe adVa				2.32e-05	0.73	0.74	0.00	6.36e-01	0.44	0.04	4.29e-01	0.41	0.15	1.73e-01	1.27e-01
	SeMe fiMe fiVa				1.35e-05	0.58	0.41	0.01	7.69e-01	0.21	0.08	5.88e-01	0.10	0.23	6.56e-01	6.95e-02
	Locave				6.37e-01	0.23	0.45	0.90	4.84e-01	0.57	0.86	4.02e-01	0.15	0.41	3.33e-01	3.18e-02
	Locsep				6.37e-01	0.23	0.45	0.90	4.84e-01	0.57	0.86	4.02e-01	0.15	0.41	3.33e-01	3.18e-02
	Locmax				5.97e-01	0.52	0.51	0.98	8.18e-01	0.82	0.81	5.32e-01	0.19	0.41	2.68e-01	4.00e-02
	Fourier	0.46	0.08	0.22	1.20e-01	0.00	0.00	0.15	6.42e-05	0.00	0.30	8.47e-05	0.00	0.05	1.41e-06	3.54e-06
	Diebold	0.40	0.00	0.07	4.62e-06	0.00	0.00	0.00	4.05e-04	0.00	0.00	2.79e-04	0.00	0.00	1.21e-05	4.11e-06
Berlin	JoMe adMe adVa	0.99	7.15e-01	0.99	5.06e-06	1.91e-01	0.55	0.01	2.41e-01	0.56	0.03	2.45e-01	0.18	0.13	2.17e-01	2.33e-01
	JoMe fiMe fiVa	0.87	3.71e-01	0.53	3.49e-03	1.81e-10	0.06	0.09	6.55e-08	0.13	0.06	7.29e-13	0.00	0.37	9.59e-14	8.22e-03
	SeMe adMe adVa				8.15e-06	1.52e-01	0.85	0.00	3.42e-01	0.90	0.02	4.18e-01	0.81	0.22	3.72e-01	7.85e-01
	SeMe fiMe fiVa				5.16e-04	2.89e-03	0.04	0.01	1.59e-05	0.01	0.11	3.88e-05	0.01	0.11	7.08e-05	3.52e-02
	Locave				8.48e-01	3.09e-01	0.88	0.93	1.47e-02	0.44	0.89	6.05e-04	0.31	0.68	1.27e-05	9.56e-02
	Locsep				8.48e-01	3.09e-01	0.88	0.93	1.47e-02	0.44	0.89	6.06e-04	0.31	0.68	1.27e-05	9.55e-02
	Locmax				9.79e-01	3.30e-01	0.94	0.87	1.60e-02	0.47	0.77	4.85e-04	0.35	0.47	3.85e-06	1.52e-01
	Fourier	0.77	8.04e-11	0.00	3.14e-01	0.00e+00	0.01	0.60	2.22e-16	0.01	0.66	2.88e-15	0.00	0.72	2.14e-12	1.16e-02
	CD	0.54	7.94e-11	0.01	4.94e-07	0.00e+00	0.00	0.00	0.00e+00	0.01	0.00	0.00e+00	0.00	0.00	0.00e+00	1.72e-06
Chicago	JoMe adMe adVa	0.95	6.04e-01	0.96	3.34e-05	5.89e-01	1.25e-01	0.00	1.20e-02	1.64e-01	0.00	1.12e-02	5.19e-02	0.01	1.69e-02	3.19e-02
	JoMe fiMe fiVa	0.95	9.59e-01	0.78	5.44e-04	6.18e-07	5.74e-03	0.02	1.14e-05	3.60e-04	0.03	1.88e-05	2.90e-04	0.07	7.59e-05	4.02e-04
	SeMe adMe adVa				6.98e-07	1.61e-01	8.49e-01	0.00	6.64e-01	9.66e-01	0.00	9.77e-01	7.70e-01	0.01	9.76e-01	6.78e-01
	SeMe fiMe fiVa				5.57e-07	2.29e-01	2.14e-01	0.00	4.95e-02	1.77e-02	0.00	2.77e-03	1.11e-04	0.00	6.68e-04	3.85e-05
	Locave				9.94e-01	7.72e-01	9.63e-01	0.97	6.83e-01	7.66e-01	0.79	7.50e-01	4.34e-01	0.75	9.48e-01	5.30e-01
	Locsep				9.94e-01	7.72e-01	9.63e-01	0.97	6.83e-01	7.66e-01	0.79	7.50e-01	4.35e-01	0.75	9.48e-01	5.30e-01
	Locmax				9.41e-01	9.49e-01	9.92e-01	0.99	4.58e-01	8.34e-01	0.88	7.45e-01	5.04e-01	0.92	8.25e-01	5.74e-01
	Fourier	0.28	5.22e-03	0.00	1.62e-01	9.96e-07	2.36e-04	0.12	1.53e-05	1.31e-04	0.13	3.60e-05	2.42e-04	0.04	3.25e-05	1.22e-04
	Diebold	0.15	5.51e-07	0.00	2.80e-04	1.86e-09	4.03e-05	0.00	0.00e+00	2.14e-13	0.00	0.00e+00	7.47e-19	0.00	0.00e+00	1.76e-09

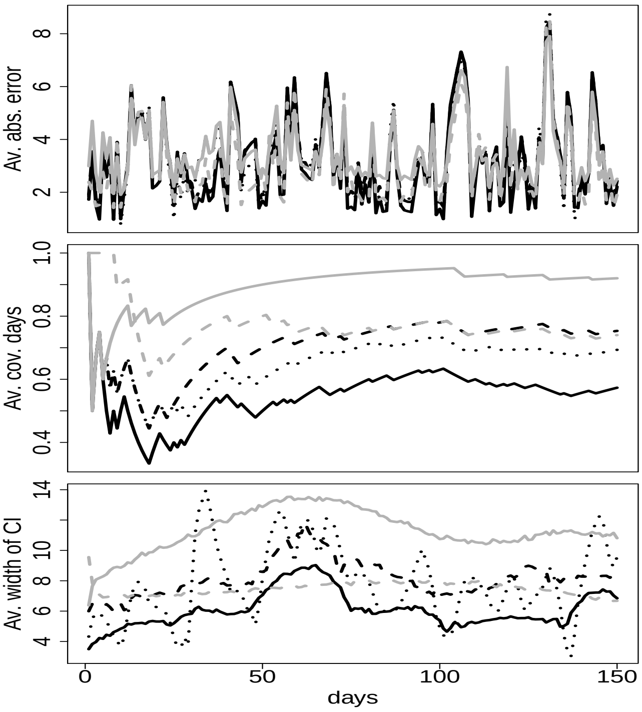
Table 1: p-values for different models, cities and goodness-of-fit tests.

		1 year			2 years			3 years			4 years			5 years		
		KS	JB	AD	KS	JB	AD	KS	JB	AD	KS	JB	AD	KS	JB	AD
Essen	JoMe adMe adVa	0.95	0.17	0.52	3.70e-06	0.98	0.82	1.70e-03	0.99	0.95	0.12	5.29e-01	0.88	0.15	0.41	0.90
	JoMe fiMe fiVa	0.90	0.24	0.53	1.82e-04	0.96	0.38	1.87e-02	0.93	0.79	0.10	6.25e-01	0.75	0.19	0.08	0.84
	SeMe adMe adVa				2.44e-06	0.59	0.96	6.18e-04	0.54	0.69	0.01	1.11e-01	0.46	0.00	0.13	0.31
	SeMe fiMe fiVa				5.51e-06	0.00	0.08	1.59e-03	0.00	0.01	0.02	7.56e-05	0.00	0.09	0.00	0.01
	Locave				9.98e-01	0.40	0.92	7.59e-01	0.82	0.57	0.62	1.22e-01	0.40	0.48	0.22	0.26
	Locsep				9.98e-01	0.40	0.92	7.59e-01	0.82	0.57	0.62	1.22e-01	0.40	0.48	0.22	0.26
	Locmax				9.97e-01	0.32	0.97	7.98e-01	0.71	0.61	0.79	1.14e-01	0.52	0.44	0.30	0.36
	Fourier	0.86	0.98	0.48	7.86e-01	0.85	0.29	5.63e-01	0.70	0.35	0.90	9.21e-01	0.71	0.96	0.00	0.91
	Diebold	0.89	0.75	0.66	2.11e-05	0.98	0.49	1.11e-16	0.69	0.50	0.00	9.23e-01	0.73	0.00	0.00	0.92
Houston	JoMe adMe adVa	0.92	0.16	0.29	9.19e-06	5.08e-04	3.26e-03	0.00	3.52e-04	8.73e-06	0.00	3.88e-06	1.05e-08	1.67e-05	7.86e-12	3.96e-14
	JoMe fiMe fiVa	0.91	0.14	0.46	1.00e-03	2.89e-04	1.79e-03	0.00	8.94e-08	2.21e-08	0.00	1.32e-11	2.46e-11	2.31e-04	0.00e+00	8.63e-17
	SeMe adMe adVa				1.30e-09	1.02e-02	1.53e-01	0.00	5.56e-01	2.71e-01	0.00	1.67e-01	2.60e-01	5.07e-02	6.19e-03	8.88e-03
	SeMe fiMe fiVa				5.25e-05	2.03e-01	2.30e-01	0.02	5.08e-02	3.55e-02	0.04	1.00e-02	2.51e-02	4.18e-02	1.09e-05	1.91e-04
	Locave				4.68e-01	1.37e-01	9.57e-02	0.23	1.38e-02	1.78e-02	0.20	2.48e-03	1.19e-02	2.70e-02	3.12e-06	5.47e-05
	Locsep				4.68e-01	1.37e-01	9.57e-02	0.23	1.38e-02	1.78e-02	0.20	2.48e-03	1.19e-02	2.70e-02	3.12e-06	5.47e-05
	Locmax				1.22e-01	5.48e-02	9.29e-02	0.17	1.80e-02	1.82e-02	0.13	3.51e-03	1.40e-02	2.29e-02	2.80e-06	7.16e-05
	Fourier	0.58	0.03	0.13	2.68e-01	4.55e-06	3.94e-05	0.01	1.40e-11	3.76e-10	0.00	0.00e+00	3.95e-15	3.56e-04	0.00e+00	5.37e-20
	Diebold	0.82	0.02	0.06	1.84e-08	0.00e+00	0.00e-00	0.00	0.00e+00	0.00e-00	0.00	0.00e+00	0.00e-00	0.00e+00	0.00e+00	1.74e-21
Kaohsiung	JoMe adMe adVa	0.32	1.11e-02	1.82e-03	1.55e-07	9.90e-03	1.78e-02	2.38e-05	1.04e-11	1.57e-07	0.00	8.88e-16	6.88e-12	8.85e-06	0.00e+00	1.69e-15
	JoMe fiMe fiVa	0.54	2.97e-04	5.26e-04	1.83e-05	0.00e+00	2.76e-09	2.25e-03	0.00e+00	1.13e-14	0.00	0.00e+00	5.74e-19	4.80e-05	0.00e+00	8.87e-22
	SeMe adMe adVa				1.59e-07	1.62e-01	1.55e-02	8.61e-04	3.39e-05	6.71e-05	0.01	5.98e-07	5.00e-07	1.01e-02	4.61e-06	1.33e-05
	SeMe fiMe fiVa				6.29e-06	3.10e-07	9.60e-05	1.12e-03	1.26e-08	4.93e-06	0.02	2.88e-15	1.42e-09	9.87e-03	8.32e-15	3.55e-10
	Locave				6.18e-02	1.36e-04	8.55e-05	1.15e-02	1.56e-06	1.16e-06	0.01	2.29e-10	4.23e-09	2.14e-02	8.35e-10	2.56e-07
	Locsep				6.18e-02	1.36e-04	8.55e-05	1.15e-02	1.56e-06	1.16e-06	0.01	2.29e-10	4.24e-09	2.14e-02	8.39e-10	2.56e-07
	Locmax				5.92e-02	1.11e-04	4.44e-04	9.05e-03	1.57e-05	4.46e-06	0.00	3.58e-09	1.24e-08	7.30e-03	1.00e-07	9.03e-07
	Fourier	0.08	6.75e-09	6.12e-05	6.29e-03	0.00e+00	3.03e-10	3.89e-04	0.00e+00	2.01e-14	0.00	0.00e+00	2.15e-19	1.09e-05	0.00e+00	9.86e-23
	CD	0.12	3.80e-08	3.18e-05	1.49e-05	0.00e+00	1.95e-10	0.00e+00	0.00e+00	6.72e-20	0.00	0.00e+00	1.19e-24	0.00e+00	0.00e+00	3.84e-36
New-York	JoMe adMe adVa	0.51	0.02	0.02	3.45e-05	0.46	0.40	0.00	1.77e-01	0.26	0.08	0.08	0.30	0.06	3.09e-02	0.05
	JoMe fiMe fiVa	0.56	0.20	0.02	4.28e-04	0.01	0.11	0.01	2.77e-03	0.01	0.10	0.00	0.02	0.06	6.42e-04	0.00
	SeMe adMe adVa				1.83e-07	0.08	0.90	0.00	9.72e-01	0.70	0.00	0.50	0.61	0.00	4.48e-01	0.35
	SeMe fiMe fiVa				1.27e-06	0.03	0.02	0.00	5.50e-01	0.05	0.00	0.13	0.01	0.02	2.25e-03	0.00
	Locave				9.92e-01	0.57	0.74	0.97	5.83e-01	0.61	0.94	0.84	0.51	0.54	6.55e-01	0.15
	Locsep				9.92e-01	0.57	0.74	0.97	5.83e-01	0.61	0.94	0.84	0.51	0.54	6.55e-01	0.15
	Locmax				7.56e-01	0.82	0.97	0.95	6.37e-01	0.81	0.94	0.82	0.53	0.76	4.57e-01	0.24
	Fourier	0.99	0.42	0.81	7.97e-01	0.01	0.12	0.52	3.94e-03	0.01	0.23	0.00	0.00	0.18	2.45e-04	0.00
	CD	0.98	0.26	0.87	1.68e-05	0.06	0.03	0.00	8.64e-06	0.00	0.00	0.00	0.00	0.00	2.56e-05	0.00

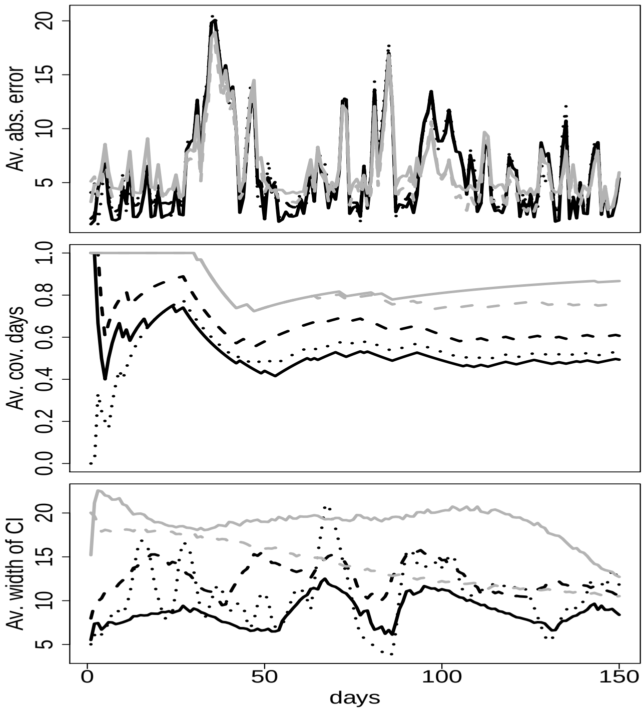
Table 2: p-values for different models, cities and goodness-of-fit tests.

		1 year			2 years			3 years			4 years			5 years		
		KS	JB	AD	KS	JB	AD	KS	JB	AD	KS	JB	AD	KS	JB	AD
Osaka	JoMe adMe adVa	0.92	0.06	0.19	6.69e-07	0.21	0.13	2.35e-03	0.04	0.10	0.01	1.39e-02	0.02	0.04	2.52e-03	4.80e-03
	JoMe fiMe fiVa	0.65	0.29	0.42	6.95e-06	0.01	0.07	5.94e-04	0.06	0.09	0.01	2.85e-04	0.00	0.02	9.41e-06	1.81e-03
	SeMe adMe adVa				1.60e-07	0.27	0.23	1.79e-04	0.62	0.60	0.00	8.89e-01	0.94	0.02	1.33e-01	8.84e-01
	SeMe fiMe fiVa				2.28e-06	0.15	0.60	1.56e-04	0.40	0.50	0.01	3.53e-02	0.33	0.03	3.19e-02	6.56e-01
	Locave				7.49e-01	0.15	0.14	9.95e-01	0.51	0.70	0.90	3.89e-01	0.84	0.91	2.13e-01	8.41e-01
	Locsep				7.50e-01	0.15	0.14	9.95e-01	0.51	0.70	0.90	3.89e-01	0.84	0.91	2.13e-01	8.41e-01
	Locmax				1.92e-01	0.14	0.54	4.74e-01	0.15	0.94	0.96	1.59e-01	0.87	0.90	1.86e-01	9.26e-01
	Fourier	0.34	0.06	0.00	3.08e-01	0.06	0.01	4.70e-01	0.08	0.06	0.21	1.97e-04	0.00	0.13	6.36e-06	4.79e-05
	Diebold	0.33	0.02	0.01	8.33e-06	0.05	0.01	1.11e-16	0.03	0.06	0.00	1.57e-07	0.00	0.00	3.47e-07	1.50e-05
Portland	JoMe adMe adVa	0.92	0.04	0.08	3.65e-05	0.94	0.30	1.83e-03	8.18e-01	0.27	0.01	5.99e-01	0.24	0.06	4.23e-01	0.46
	JoMe fiMe fiVa	0.78	0.05	0.05	1.46e-04	0.55	0.18	2.32e-02	2.48e-03	0.00	0.05	2.30e-03	0.01	0.13	9.76e-04	0.00
	SeMe adMe adVa				1.74e-07	0.41	0.48	1.40e-05	2.15e-01	0.19	0.00	1.95e-01	0.20	0.01	1.59e-01	0.16
	SeMe fiMe fiVa				1.04e-07	0.13	0.05	9.18e-04	4.88e-05	0.01	0.01	1.18e-02	0.00	0.08	7.97e-07	0.00
	Locave				8.40e-01	0.09	0.07	7.49e-01	1.72e-01	0.29	0.26	1.35e-02	0.05	0.14	2.11e-03	0.01
	Locsep				8.40e-01	0.09	0.07	7.49e-01	1.72e-01	0.29	0.26	1.35e-02	0.05	0.14	2.11e-03	0.01
	Locmax				1.26e-01	0.33	0.22	6.45e-01	3.08e-02	0.32	0.32	5.21e-03	0.07	0.15	1.55e-03	0.02
	Fourier	0.70	0.93	0.63	7.98e-01	0.08	0.61	1.79e-01	6.41e-05	0.01	0.19	1.12e-03	0.01	0.33	4.85e-04	0.01
	Diebold	0.72	0.84	0.59	1.42e-05	0.00	0.30	7.11e-14	6.00e-09	0.00	0.00	1.28e-05	0.01	0.00	1.45e-09	0.00
Taipei	JoMe adMe adVa	0.30	0.01	2.25e-03	3.77e-10	2.15e-02	5.87e-04	4.39e-08	6.77e-06	2.85e-08	2.81e-07	1.73e-05	2.02e-08	4.24e-05	3.01e-09	4.93e-11
	JoMe fiMe fiVa	0.72	0.12	4.40e-02	1.36e-07	5.24e-03	4.69e-05	4.47e-06	1.39e-06	9.67e-09	4.49e-05	7.09e-10	7.66e-11	1.65e-04	2.58e-12	3.48e-12
	SeMe adMe adVa				1.40e-07	5.82e-01	7.16e-01	7.03e-06	1.28e-01	1.18e-01	9.02e-05	6.93e-01	2.84e-01	1.82e-03	3.64e-01	1.30e-01
	SeMe fiMe fiVa				1.12e-07	5.02e-01	3.94e-01	1.56e-05	7.14e-02	6.01e-02	4.66e-04	5.83e-02	4.57e-02	4.79e-04	1.10e-03	9.74e-04
	Locave				8.19e-01	3.84e-02	2.87e-02	5.02e-01	5.53e-02	4.64e-02	7.41e-01	3.59e-01	1.91e-01	5.93e-01	3.01e-01	7.89e-02
	Locsep				8.19e-01	3.84e-02	2.87e-02	5.02e-01	5.53e-02	4.64e-02	7.40e-01	3.59e-01	1.91e-01	5.93e-01	3.01e-01	7.89e-02
	Locmax				8.85e-01	3.19e-01	1.25e-01	7.17e-01	4.03e-01	2.79e-01	2.13e-01	6.62e-01	4.36e-01	6.11e-02	3.06e-02	4.38e-01
	Fourier	0.08	0.00	8.44e-05	4.72e-03	5.42e-05	1.32e-05	6.75e-03	7.50e-08	5.49e-09	1.59e-03	1.30e-11	1.16e-11	5.51e-05	2.51e-13	2.81e-14
	Diebold	0.10	0.00	1.85e-05	2.21e-08	3.10e-09	4.38e-07	0.00e+00	5.02e-08	5.25e-09	0.00e+00	3.91e-12	9.91e-12	0.00e+00	8.10e-14	3.66e-15
Tokyo	JoMe adMe adVa	0.90	0.66	0.74	7.50e-03	2.62e-01	0.58	3.17e-02	3.24e-01	0.29	0.21	3.30e-01	3.44e-01	0.35	1.21e-01	7.33e-02
	JoMe fiMe fiVa	0.33	0.00	0.06	1.25e-02	1.77e-04	0.05	1.23e-01	2.45e-06	0.01	0.21	5.42e-07	1.13e-03	0.33	1.15e-08	1.50e-04
	SeMe adMe adVa				2.19e-06	8.69e-01	0.93	5.03e-04	7.82e-01	0.42	0.06	3.99e-01	2.74e-01	0.11	1.13e-01	1.60e-01
	SeMe fiMe fiVa				8.85e-04	5.22e-08	0.00	9.99e-02	0.00e+00	0.00	0.18	7.20e-13	2.80e-05	0.34	1.36e-14	1.23e-05
	Locave				4.56e-01	2.86e-02	0.17	1.96e-01	3.65e-03	0.07	0.17	6.48e-04	1.68e-02	0.38	2.22e-05	1.84e-02
	Locsep				4.56e-01	2.86e-02	0.17	1.96e-01	3.65e-03	0.07	0.17	6.48e-04	1.68e-02	0.38	2.21e-05	1.84e-02
	Locmax				3.32e-01	6.40e-02	0.18	1.55e-01	3.00e-03	0.08	0.22	1.65e-04	2.09e-02	0.44	1.17e-05	2.02e-02
	Fourier	0.62	0.00	0.00	3.71e-01	8.27e-07	0.00	2.21e-01	2.58e-10	0.00	0.15	3.47e-10	3.89e-04	0.29	4.15e-12	2.30e-04
	CD	0.18	0.00	0.00	7.11e-05	3.93e-13	0.00	3.33e-16	3.99e-13	0.00	0.00	2.22e-15	2.43e-05	0.00	8.34e-13	5.94e-05

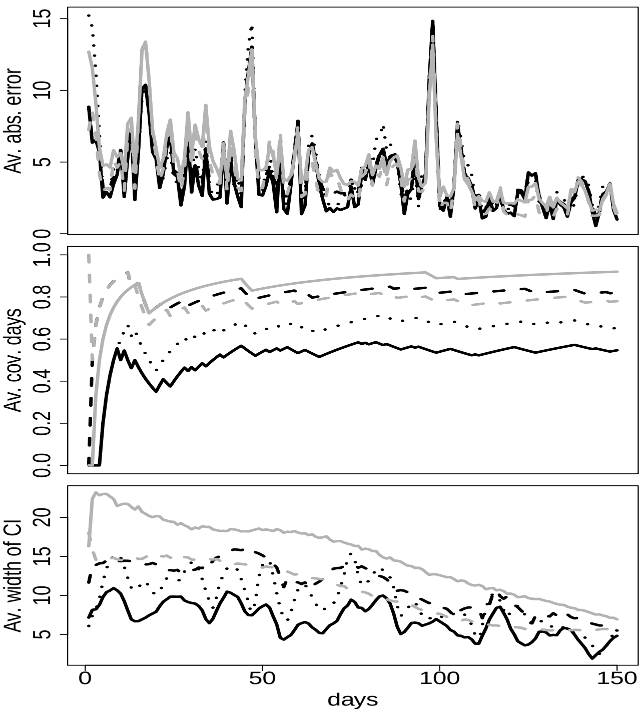
Table 3: p-values for different models, cities and goodness-of-fit tests.



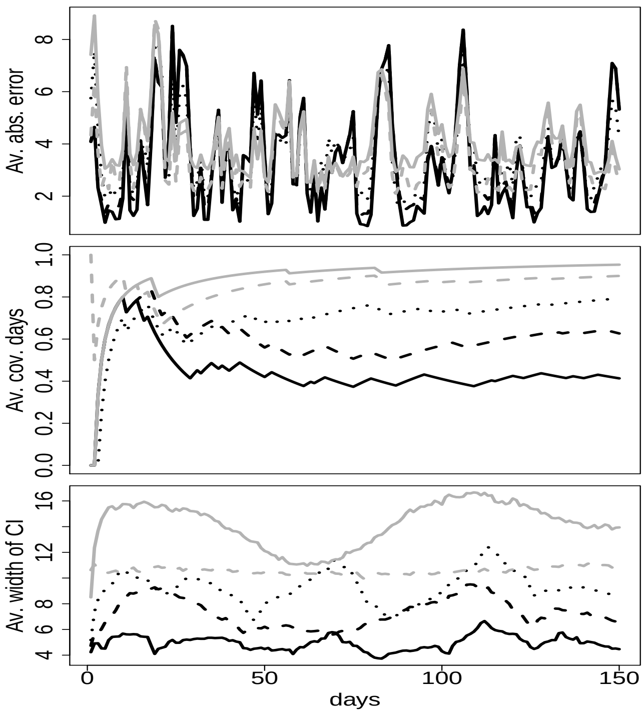
(a) Beijing (2007-2008)



(b) Chicago (2006-2007)

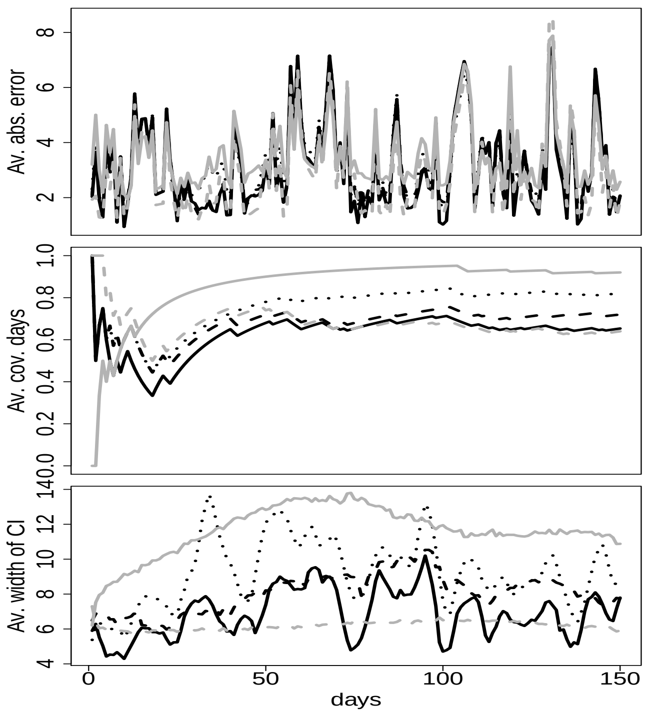


(c) Houston (2006-2007)

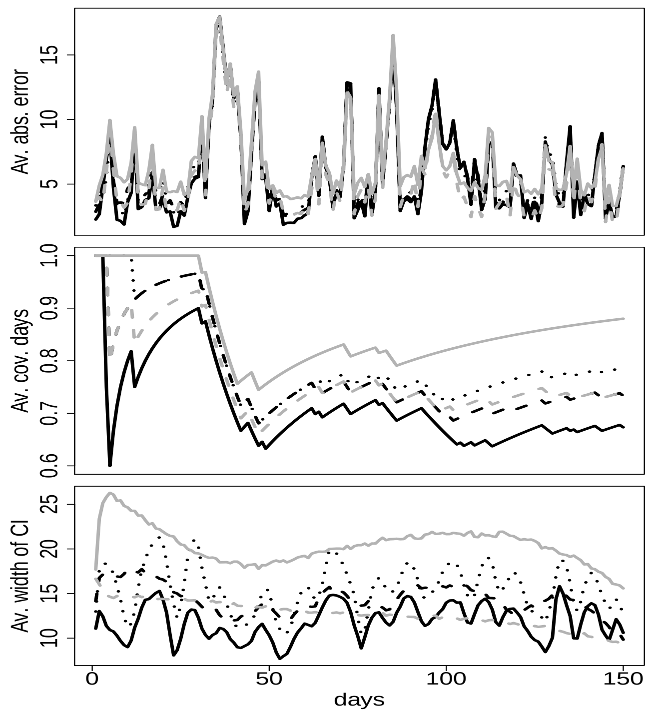


(d) Essen (2007-2008)

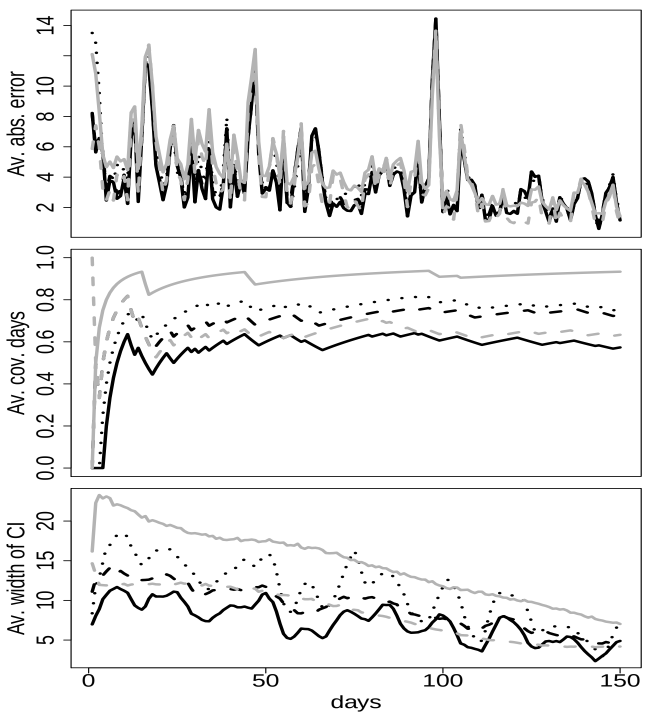
Figure 9: $h = 1, \ldots, 150$ days (OX axis) ahead forecast for Beijing, Chicago, Houston and Essen (left to right, top to bottom); averaged absolute error (Y axis, upper panel), averaged coverage days (Y axis, middle panel), averaged width of the confidence 95% intervals (Y axis, lower panel), SeMe adMe adVo (solid black), Locmax (dashed grey), JoMe adMe adVo (dotted black), truncated Fourier (solid grey), CD (dashed black), fitted using 2 years of historical data and 10000 samples.



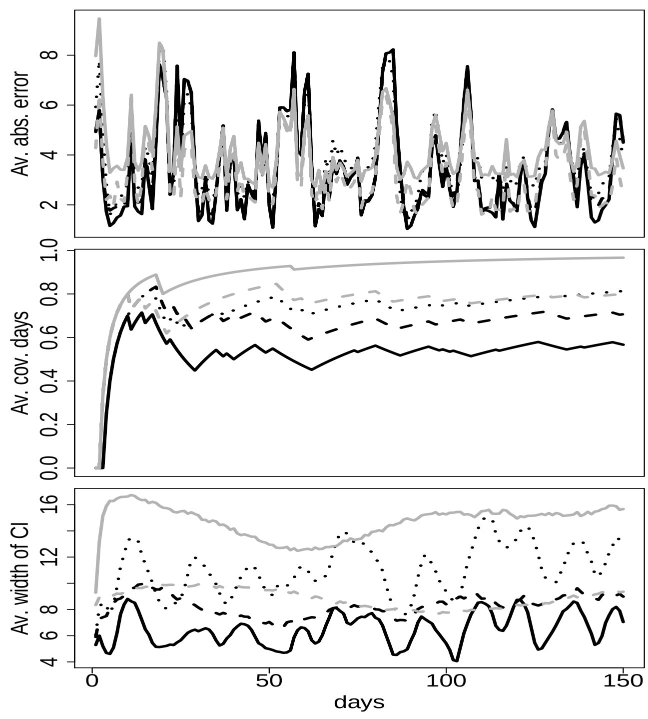
(a) Beijing (2006-2008)



(b) Chicago (2005-2007)

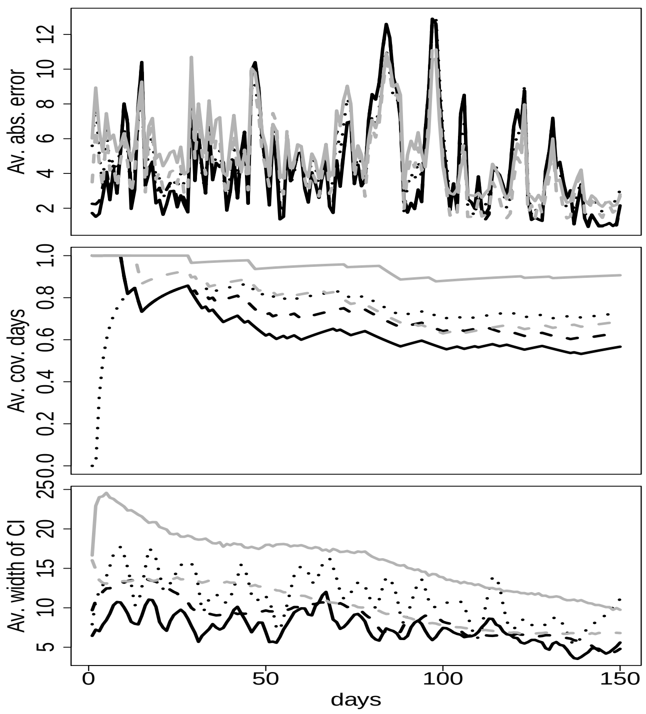


(c) Houston (2005-2007)

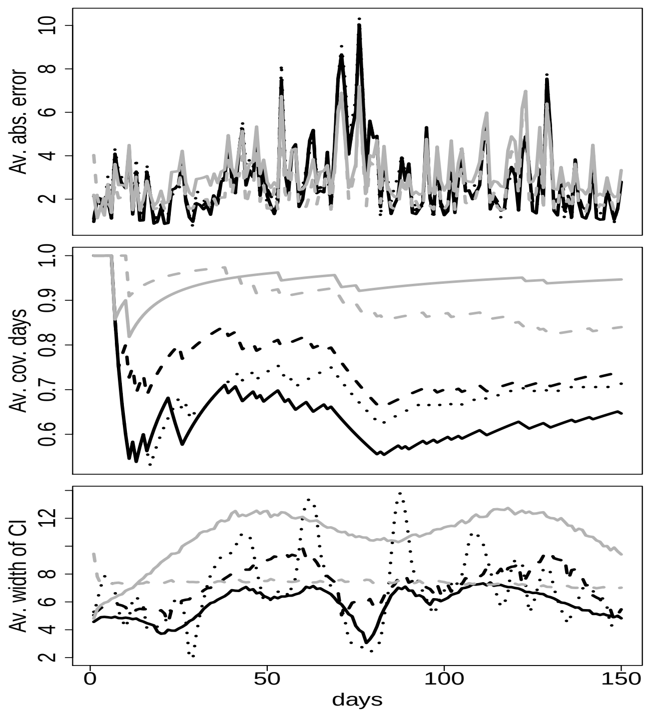


(d) Essen (2006-2008)

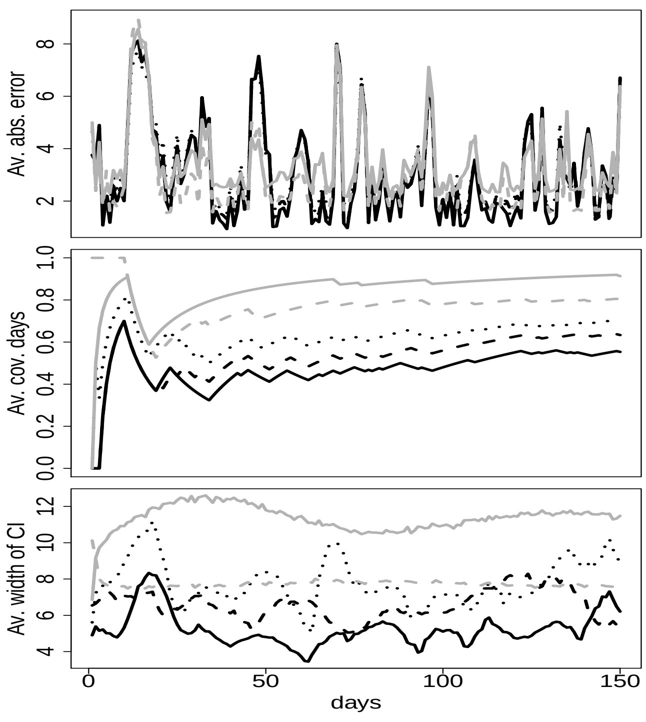
Figure 10: $h = 1, \ldots, 150$ days (OX axis) ahead forecast for Beijing, Chicago, Houston and Essen (left to right, top to bottom); averaged absolute error (Y axis, upper panel), averaged coverage days (Y axis, middle panel), averaged width of the confidence 95% intervals (Y axis, lower panel), SeMe adMe adVo (solid black), Locmax (dashed grey), JoMe adMe adVo (dotted black), truncated Fourier (solid grey), CD (dashed black), fitted using 3 years of historical data and 10000 samples.



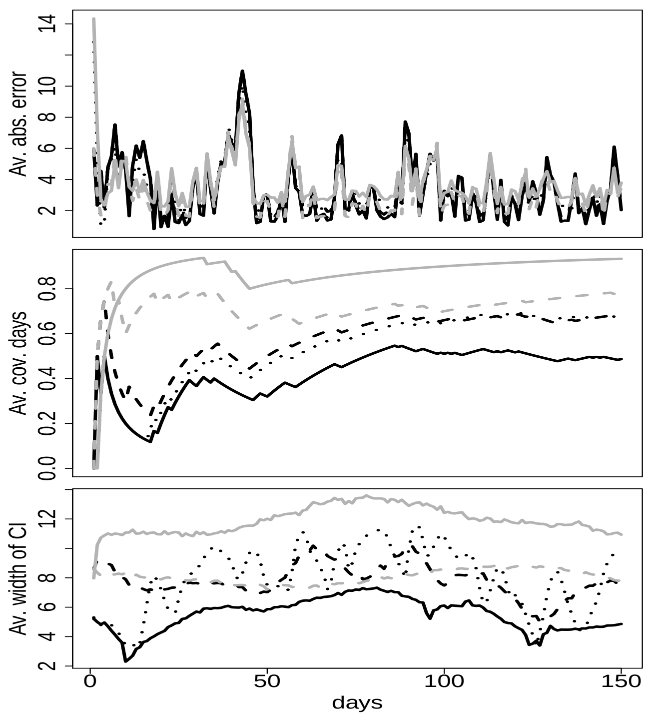
(a) Atlanta (2006-2007)



(b) Osaka (2007-2008)

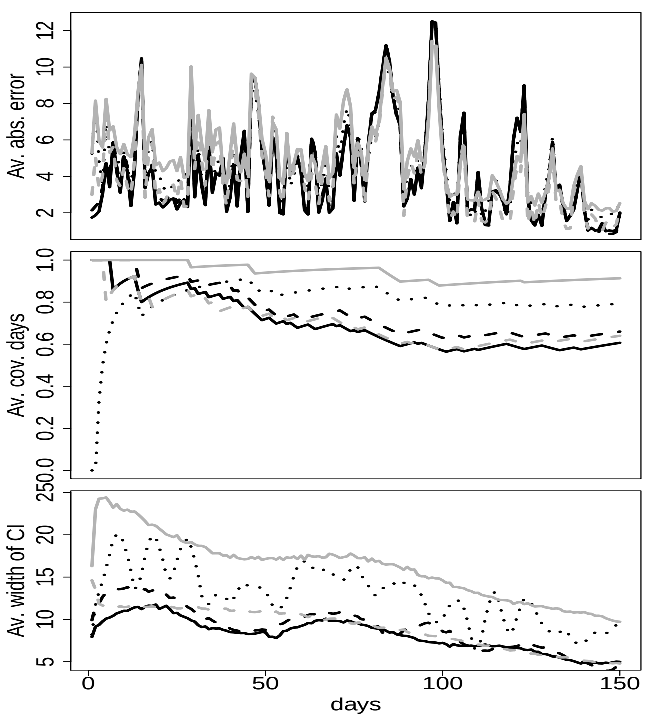


(c) Portland (2006-2007)

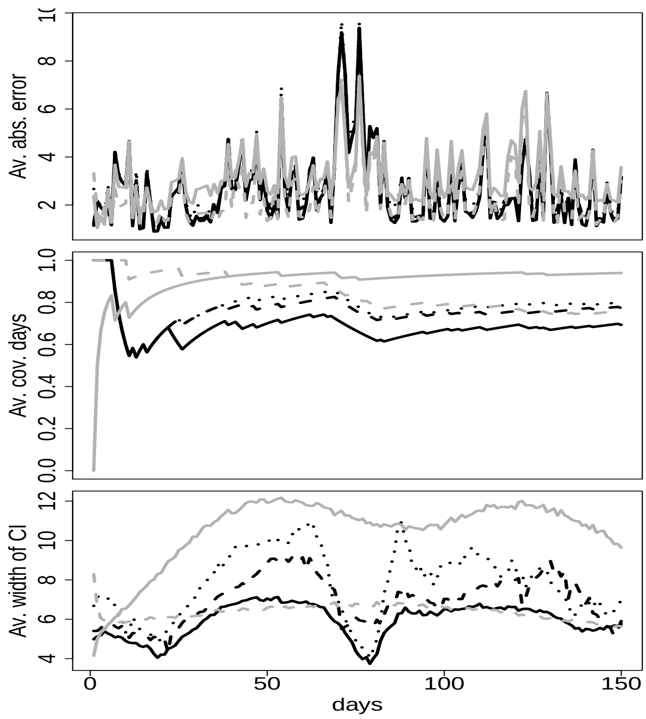


(d) Taipei (2007-2008)

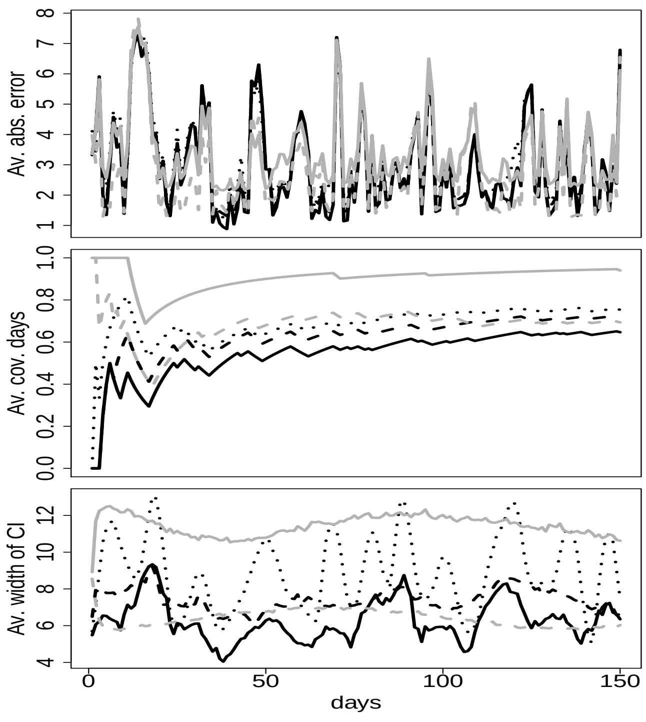
Figure 11: $h = 1, \ldots, 150$ days (OX axis) ahead forecast for Atlanta, Osaka, Portland and Taipei (left to right, top to bottom); averaged absolute error (Y axis, upper panel), averaged coverage days (Y axis, middle panel), averaged width of the confidence 95% intervals (Y axis, lower panel), SeMe adMe adVo (solid black), Locmax (dashed grey), JoMe adMe adVo (dotted black), truncated Fourier (solid grey), CD (dashed black), fitted using 2 years of historical data and 10000 samples.



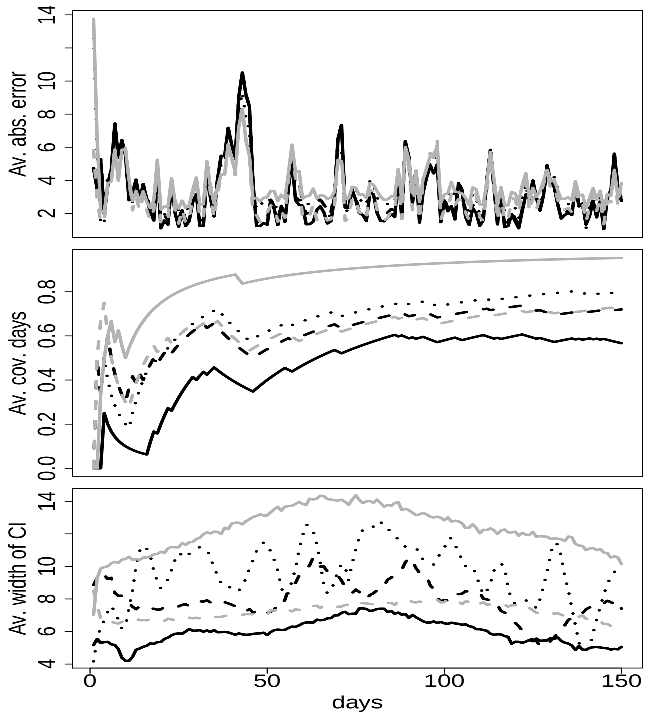
(a) Atlanta (2005-2007)



(b) Osaka (2006-2008)



(c) Portland (2005-2007)



(d) Taipei (2006-2008)

Figure 12: $h = 1, \ldots, 150$ days (OX axis) ahead forecast for Atlanta, Osaka, Portland and Taipei (left to right, top to bottom); averaged absolute error (Y axis, upper panel), averaged coverage days (Y axis, middle panel), averaged width of the confidence 95% intervals (Y axis, lower panel), SeMe adMe adVo (solid black), Locmax (dashed grey), JoMe adMe adVo (dotted black), truncated Fourier (solid grey), CD (dashed black), fitted using 3 years of historical data and 10000 samples.

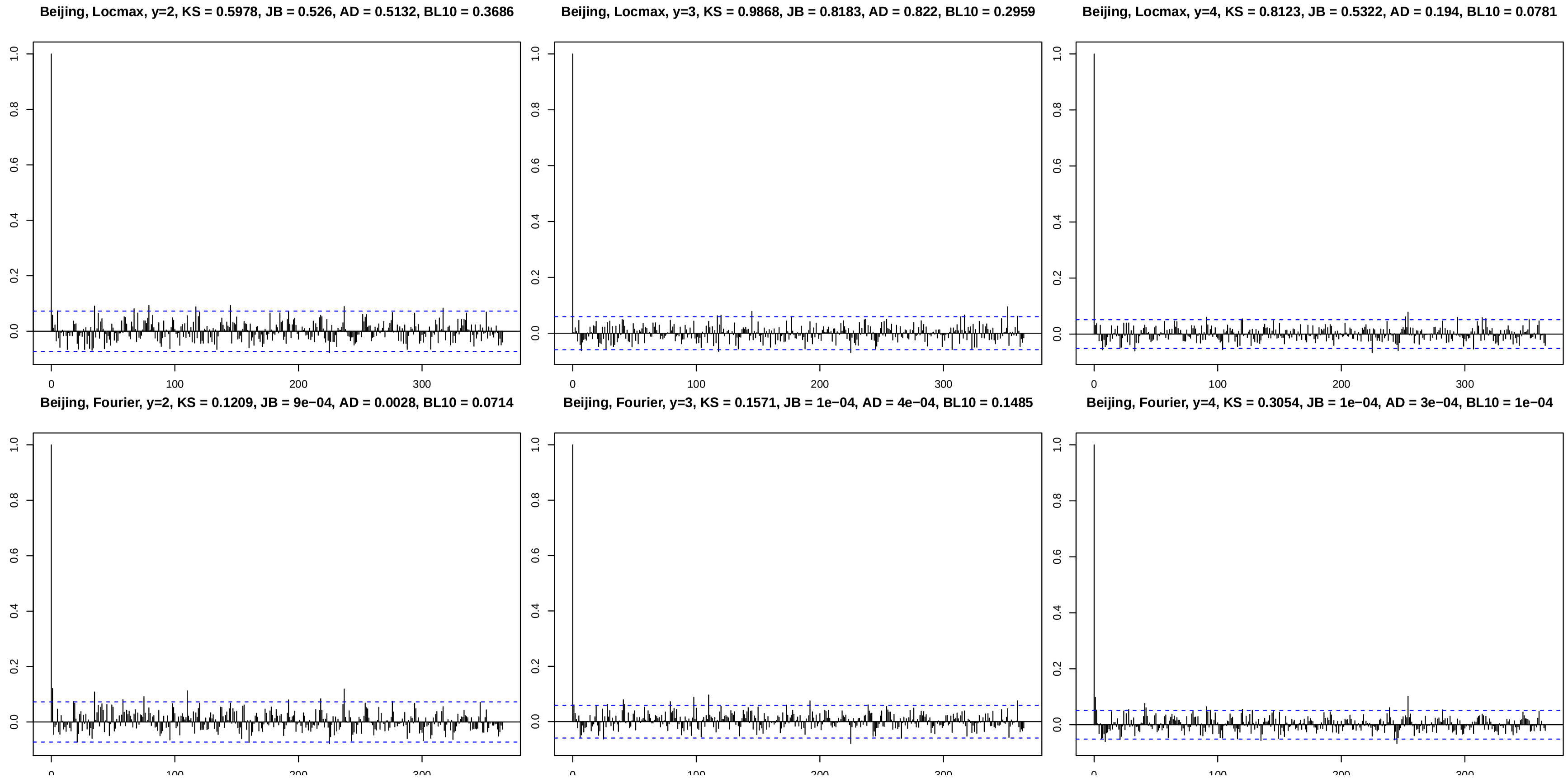


Figure 13: ACF for the squared residuals for Beijing from Locmax (first row) and Fourier method (second row) with 2, 3 and 4 years of history (first, second and third columns correspondingly). Caption of each figure represent also p-values for tests of KS, JB and AD tests, as well as Box-Ljung test with 10 lags.

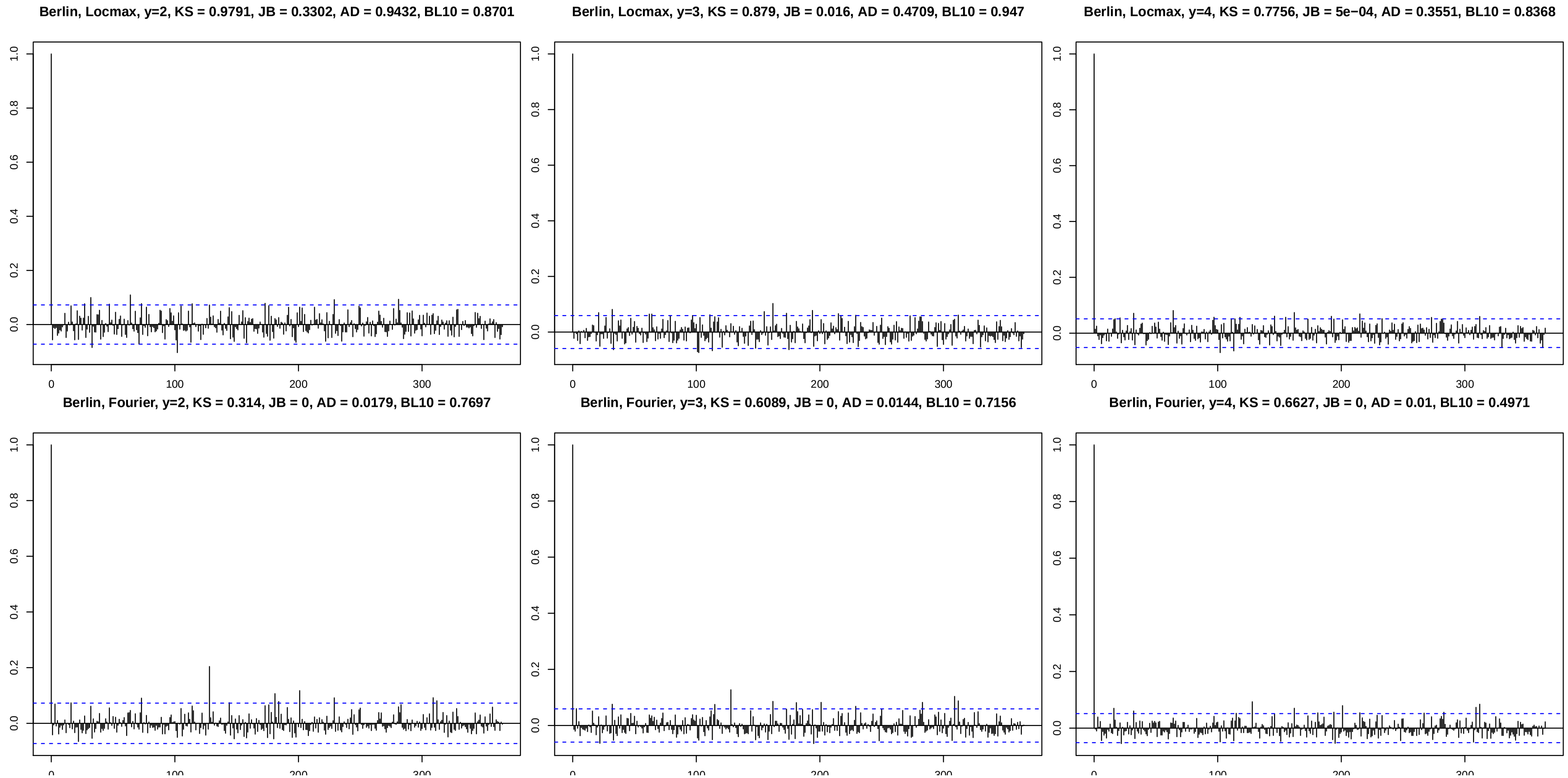


Figure 14: ACF for the squared residuals for Berlin from Locmax (first row) and Fourier method (second row) with 2, 3 and 4 years of history (first, second and third columns correspondingly). Caption of each figure represent also p-values for tests of KS, JB and AD tests, as well as Box-Ljung test with 10 lags.

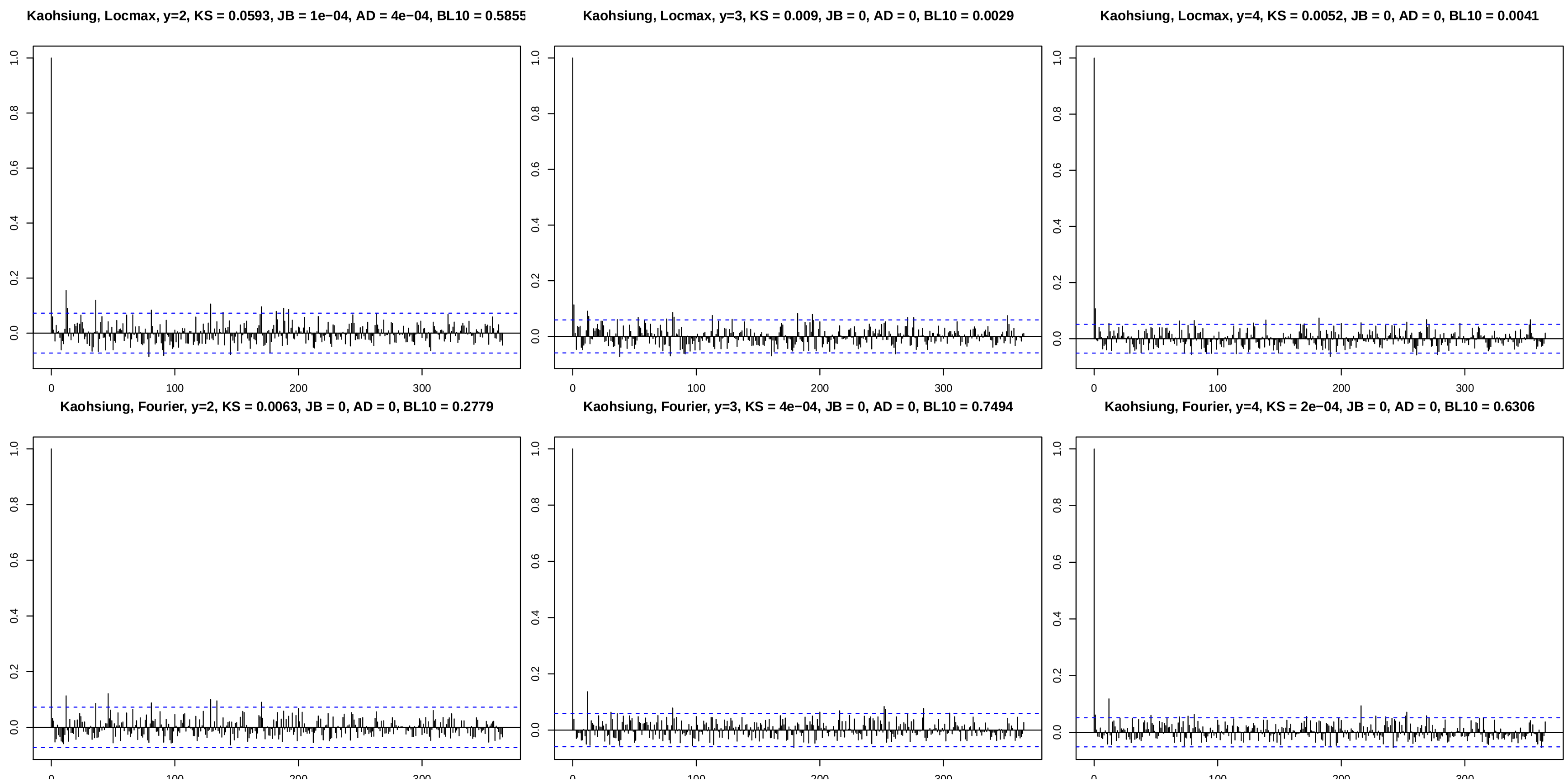


Figure 15: ACF for the squared residuals for Kaohsiung from Locmax (first row) and Fourier method (second row) with 2, 3 and 4 years of history (first, second and third columns correspondingly). Caption of each figure represent also p-values for tests of KS, JB and AD tests, as well as Box-Ljung test with 10 lags.

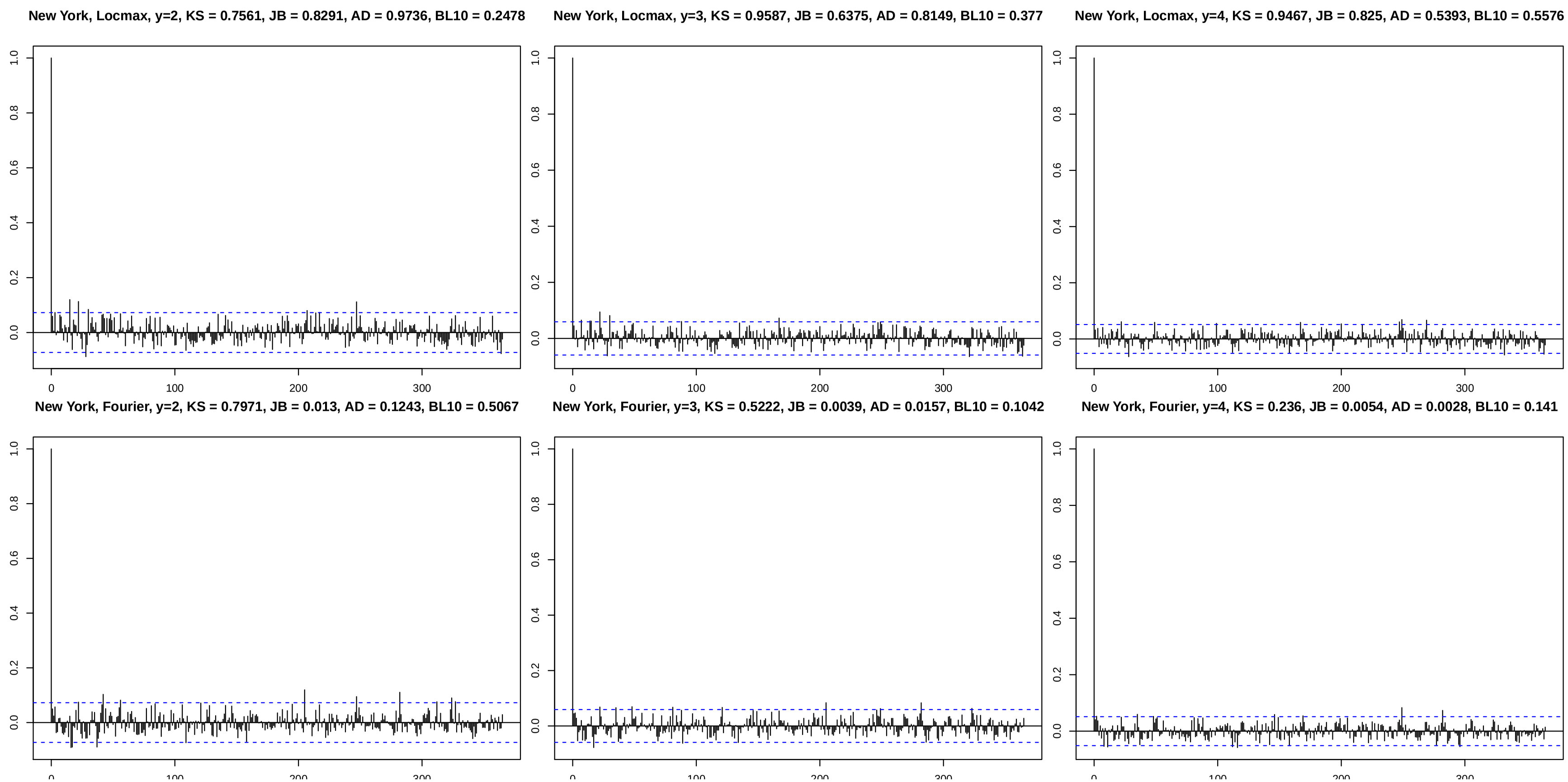


Figure 16: ACF for the squared residuals for New York from Locmax (first row) and Fourier method (second row) with 2, 3 and 4 years of history (first, second and third columns correspondingly). Caption of each figure represent also p-values for tests of KS, JB and AD tests, as well as Box-Ljung test with 10 lags.

	Method	KS	JB	AD		KS	JB	AD
1 Year	JoMe adMe adVa	0.000	0.416	*0.333*				
	JoMe fiMe fiVa	0.000	*0.250*	*0.333*				
	Fourier	0.000	0.583	0.583				
	CD	0.000	0.750	0.583		KS	JB	AD
2 Years	JoMe adMe adVa	1.000	0.333	0.333	3 Years	1.000	0.583	0.416
	JoMe fiMe fiVa	1.000	0.833	0.500		0.833	0.833	0.750
	SeMe adMe adVa	1.000	0.166	*0.166*		1.000	*0.166*	*0.166*
	SeMe fiMe fiVa	1.000	0.500	0.416		0.916	0.583	0.666
	Locave	*0.000*	0.333	0.250		0.166	0.416	0.333
	Locsep	*0.000*	0.333	0.250		0.166	0.416	0.333
	Locmax	*0.000*	*0.083*	*0.166*		*0.083*	0.500	0.250
	Fourier	0.250	0.750	0.750		0.333	0.833	0.833
	CD	1.000	0.750	0.833		1.000	0.916	0.833
4 Years	JoMe adMe adVa	0.750	0.583	0.500	5 Years	0.583	0.667	0.583
	JoMe fiMe fiVa	0.500	0.916	0.916		0.500	0.916	0.916
	SeMe adMe adVa	0.916	*0.166*	*0.166*		0.666	*0.250*	*0.250*
	SeMe fiMe fiVa	0.750	0.750	0.833		0.583	0.916	0.833
	Locave	*0.166*	0.500	0.333		*0.250*	0.500	0.500
	Locsep	*0.166*	0.500	0.333		*0.250*	0.500	0.500
	Locmax	*0.166*	0.500	0.333		*0.250*	0.583	0.500
	Fourier	0.333	0.916	0.916		0.416	1.000	0.916
	CD	1.000	0.916	0.916		1.000	1.000	0.916

Table 4: Rejection rates of the normality at 5% level for original 12 cities with different history, methods of estimation and normality tests. Tests for normality are Kolmogorov–Smirnov (KS), Jarque–Bera (JB) and AD. Methods used: joint/separate mean (JoMe/SeMe) with fixed/adaptive (fi/ad) bandwidth for the mean/variance (Me/Va), Locave, Locsep, Locmax, truncated Fourier (Fourier) and CD model. Highlighted with italic are models with smallest rejection rate for each GoF test and each history.

Localising temperature risk

Wolfgang Karl Härdle[*], Brenda López Cabrera[†], Ostap Okhrin [‡], Weining Wang[§]

October 5, 2016

1 Appendix

1.1 Theoretical Background

We now briefly introduce the theoretical background for the adaptation procedure. For $\ell < k$, the accuracy of the estimation is measured by the fitted likelihood ratio (LR):

$$L(W^{\ell}, \tilde{\theta}_{\ell}, \tilde{\theta}_{k}) \stackrel{\text{def}}{=} L(W^{\ell}, \tilde{\theta}_{\ell}) - L(W^{\ell}, \tilde{\theta}_{k}). \tag{1}$$

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For the Gaussian risk factor situation the variance σ_t^2 (or trend Λ_t) estimation is carried out within an exponential family framework, so the LR can be written in a closed form:

$$\begin{aligned} L(W^k, \tilde{\theta}_k, \theta^*) &\stackrel{\text{def}}{=} N_k \mathcal{K}(\tilde{\theta}_k, \theta^*) \\ &= -\{\log(\tilde{\theta}_k/\theta^*) + 1 - \theta^*/\tilde{\theta}_k\}/2, \end{aligned} \tag{2}$$

where $N_k = J \sum_{t=1}^{365} w(s, t, h_k)$ and $\mathcal{K}(\tilde{\theta}_k, \theta^*)$ is the Kullback-Leibler divergence (3) between two normal distributions with variances $\tilde{\theta}_k$ and θ^*. Note that (2) is the divergence for exactly this case. For trend Λ_t estimation, it has to be replaced by $(\tilde{\theta}_k - \theta^*)^2/(2\sigma^2)$.

Recall that the Kullback-Leibler divergence of two distributions with densities $p(x)$ and $q(x)$ is

$$\mathcal{K}\{p(x), q(x)\} \stackrel{\text{def}}{=} \mathsf{E}_{p(.)} \log \frac{p(x)}{q(x)} \quad . \tag{3}$$

To guarantee the feasibility of the tests, we need moment bounds and confidence sets for the LR that will guarantee that the MLE is concentrated in the level set of the likelihood ratio process (indexed by the number of observations) around the true parameter, see Polzehl and Spokoiny (2006) and Mercurio and Spokoiny (2004). Below we state a result along this line for the variance (a similar bound can be derived for the mean).

Theorem 1.1 *[Spokoiny (2009)] Assuming that* $\theta(t) = \theta^*$ *for any* $t \in [1, 365]$*, then for* $\mathfrak{z} > 0$ *and* $k \in 1, \ldots, K, r > 0$*, denote by* $\mathrm{P}_{\theta^*}(.)$ *the measure corresponding to (9) (main text). We obtain*

$$\mathrm{P}_{\theta^*}\left\{L(W^k, \tilde{\theta}_k, \theta^*) > \mathfrak{z}\right\} \leq 2\exp(-\mathfrak{z}) \tag{4}$$

and a risk bound for a power loss function:

$$\mathsf{E}_{\theta^*}|L(W^k, \tilde{\theta}_k, \theta^*)|^r \leq \mathfrak{r}_r, \tag{5}$$

where $\mathfrak{r}_r = 2r \int_{\mathfrak{z} \geq 0} \mathfrak{z}^{r-1} \exp(-\mathfrak{z}) d\mathfrak{z}$. *This polynomial bound applies to all localising schemes* W^k *simultaneously.*

The risk bound (5) allows us to define likelihood based confidence sets since together with (4) it tells us that the likelihood process is stochastically bounded. The confidence sets are therefore defined with critical values $\mathfrak{z}_k$ to level α as shown in (10) (main text).

The LMS algorithm is illustrated in Figure 1. For every estimate $\tilde{\theta}_k$ the corresponding confidence set is shown. If the horizontal line originating in $\tilde{\theta}_k$ does not cross all the preceding intervals then the selection algorithm terminates.

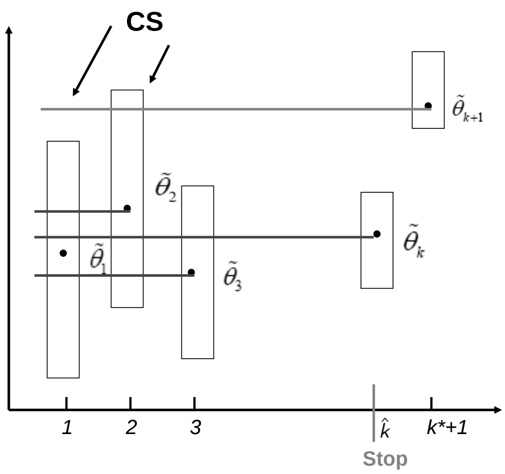

Figure 1: Illustration of the LMS

A further integrated approach is to consider an iterative algorithm, which iterates between estimating the seasonal component and the variance $\theta(t) = \{\Lambda_t, \sigma_t^2\}$. This algorithm can further cope with heteroscedasticity in the corrected residuals after seasonality in mean and variance components. The procedure is:

Step 1. Estimate $\hat{\beta}$ in an initial Λ_t^0 using a truncated Fourier series or any other deterministic function;

Step 2. For fixed $\hat{\Lambda}_{s,\nu} = \{\hat{\Lambda}'_{s,\nu}, \hat{\Lambda}''_{s,\nu}\}^\top, s = \{1, \dots, 365\}$ from last step ν, and fixed $\hat{\beta}$, get $\hat{\sigma}^2_{s,\nu+1}$ by

$$\begin{aligned} \hat{\sigma}^2_{s,\nu+1} &= \arg\min_{\sigma^2} \sum_{t=1}^{365} \sum_{j=0}^{J} [\{T_{365j+t} - \hat{\Lambda}'_{s,\nu} - \hat{\Lambda}''_{s,\nu}(t-s) \\ &- \sum_{l=1}^{L} \hat{\beta}_l X_{365j+t-l}\}^2/2\sigma^2 + \log(2\pi\sigma^2)/2] w(s,t,h'_k); \end{aligned}$$

Step 3. For fixed $\hat{\sigma}^2_{s,\nu+1}$ and $\hat{\beta}$, we estimate $\hat{\Lambda}_{s,\nu+1}, s = \{1, \dots, 365\}$ via another local adaptive procedure:

$$\hat{\Lambda}_{s,\nu+1} = \arg\min_{\{\Lambda',\Lambda''\}^\top} \sum_{t=1}^{365} \sum_{j=0}^{J} \left\{T_{365j+t} - \Lambda' - \Lambda''(t-s) - \sum_{l=1}^{L} \hat{\beta}_l X_{365j+t-l}\right\}^2 w(s,t,h'_k)/2\hat{\sigma}^2_{s,\nu+1},$$

where $\{h'_1, h'_2, h'_3, \dots, h'_{K'}\}$ is a sequence of bandwidths;

Step 4. Repeat steps 2 and 3 until both $|\hat{\Lambda}_{t,\nu+1} - \hat{\Lambda}_{t,\nu}| < \pi_1$ and $|\hat{\sigma}^2_{t,\nu+1} - \hat{\sigma}^2_{t,\nu}| < \pi_2$ for some constants π_1 and π_2.

Our empirical implementation suggests that one iteration is enough. The LMS methods require Critical Values $\mathfrak{z}_k$, which define the significance for the LR statistics $L(W^\ell, \tilde{\theta}_\ell, \tilde{\theta}_k)$ or alternatively the length of the confidence interval (see (4)) at each step. As can be seen from above, the Critical Values are calibrated from the "propagation condition" below which ensures a desired level of type one error. To be more specific, for every step k, define $\hat{\theta}_k$ as the "survived estimator" after the kth step (if the estimator is not rejected up to step k, then $\hat{\theta}_k = \tilde{\theta}_k$, else if the estimator has been rejected at step $l < k$, then $\hat{\theta}_k = \tilde{\theta}_l$). Measure the closeness of $\tilde{\theta}_k$ and $\hat{\theta}_k$ by

$$\mathsf{E}_{\theta^*}|L(W^k, \tilde{\theta}_k, \hat{\theta}_k)|^r \leq \alpha \mathfrak{r}_r \tag{6}$$

for $k = 1, \ldots, K$ with $\mathfrak{r}_r$ the parametric risk bound in (5) and α a control parameter corresponding to the type one error. In fact

$$\mathsf{E}_{\theta^*}|L(W^k, \tilde{\theta}_k, \hat{\theta}_k)|^r \to \mathrm{P}_{\theta^*}(\tilde{\theta}_k \neq \hat{\theta}_k)$$

for $r \to 0$, therefore α can be interpreted as a false alarm probability.

More precisely, if step k is accepted as described in Figure 1, then $\tilde{\theta}_k = \hat{\theta}_k$ and a non-zero loss $\mathsf{E}_{\theta^*} L(W^k, \tilde{\theta}_k, \hat{\theta}_k)$ can only occur if the estimator has been rejected before or at step k, which under the homogeneous parametric model case, is denoted as a "false alarm".

A risk bound for a constant model ($\theta(t) = \theta^*$) has been given in (6). In order to expand this to a nonparametric $\theta(t)$, the "Small Modeling Bias (SMB)" condition is employed:

$$\Delta(\theta) \stackrel{\text{def}}{=} \sum_{t=1}^{365} \mathcal{K}\{\theta(t), \theta\} \, \mathbf{I}\{w(s, t, h_k) > 0\} \leq \Delta, \forall k < k^*, \tag{7}$$

where k^* is the maximum k satisfying (7), also called "oracle". Consequently the estimation risk for $\theta(t)$ is described for $k \leq k^*$ by the "propagation" property:

$$\mathsf{E}_{\theta(\cdot)} \log\{1 + |L(W^k, \tilde{\theta}_k, \hat{\theta}_k)|^r / \mathfrak{r}_r\} \leq \Delta + \alpha. \tag{8}$$

An estimate for the oracle k^* is given via the adaptive estimate $\hat{\theta}_{\hat{k}}$. The estimate $\hat{\theta}_{\hat{k}}$ behaves similarly to the oracle estimate $\tilde{\theta}_{k^*}$ since it is "stable" in the sense that even if the described selection scheme (12) (main text), (13) (main text) overshoots k^*, the resulting estimate $\hat{\theta}_{\hat{k}}$ is still close to the oracle $\tilde{\theta}_{k^*}$. In fact the attained quality of estimation during "propagation" is not lost at further steps:

$$L(W^{k^*}, \tilde{\theta}_{k^*}, \hat{\theta}_{\hat{k}}) \, \mathbf{I}\{\hat{k} > k^*\} \leq \mathfrak{z}_{k^*}$$

In other words, $\hat{\theta}_{\hat{k}}$ lies in the confidence set of $\tilde{\theta}_{k^*}$. A combination of the propagation and stability property leads to the "oracle" property:

$$\mathsf{E}_{\theta(\cdot)} \log\left\{1+\frac{|L(W^{k^*},\tilde{\theta}_{k^*},\theta)|^r}{\mathfrak{r}_r}\right\} \le \Delta+1,$$
$$\mathsf{E}_{\theta(\cdot)} \log\left\{1+\frac{|L(W^{k^*},\tilde{\theta}_{k^*},\hat{\theta}_{\hat{k}})|^r}{\mathfrak{r}_r}\right\} \le \Delta+\alpha+\log\left\{1+\frac{\mathfrak{z}_{k^*}}{\mathfrak{r}_r}\right\},$$

for θ with $\Delta(W^k,\theta) \le \Delta$ and $k \le k^*$. These bounds show that the risk of estimating adaptively is composed into three parts: the SMB, the false alarm rate, and a small term corresponding to the risk of overshooting.

1.2 Discretization

We now prove the connection of the discrete $AR(3)$ model in (2)(main text) and the $CAR(3)$ model in (1) (main text) is proved by deriving an analytical link between $X_{k(t)}$ and the lagged deseasonalised temperatures up to time $t-L$. $X_{k(t+L)}$ is approximated by Euler discretization. For example, the step length to be Δ, and observation number to be $N(\Delta)$, for $L=3\Delta$, let $e_t \stackrel{\text{def}}{=} B_{t+\Delta}-B_t$ and a time step of length one $\Delta_t \stackrel{\text{def}}{=} (t+\Delta)-t=\Delta$, $X_{1(t+3\Delta)}$ is obtained by iteratively substituting $X_{3(t)}$ from the following discretization:

$$\begin{aligned}
X_{1(t+\Delta)}-X_{1(t)} &= X_{2(t)}\Delta \\
X_{2(t+\Delta)}-X_{2(t)} &= X_{3(t)}\Delta \\
X_{3(t+\Delta)}-X_{3(t)} &= -\alpha_3(\Delta)X_{1(t)}\Delta-\alpha_2(\Delta)X_{2(t)}\Delta-\alpha_1(\Delta)X_{3(t)}\Delta+\sigma_t(\Delta)e_t \\
&\cdots \\
X_{1(t+3\Delta)}-X_{1(t+2\Delta)} &= X_{2(t+2\Delta)}\Delta \\
X_{2(t+3\Delta)}-X_{2(t+2\Delta)} &= X_{3(t+2\Delta)}\Delta \\
X_{3(t+3\Delta)}-X_{3(t+2\Delta)} &= -\alpha_3(\Delta)X_{1(t+2\Delta)}\Delta-\alpha_2(\Delta)X_{2(t+2\Delta)}\Delta-\alpha_1(\Delta)X_{3(t+2\Delta)}\Delta \\
&+ \sigma_{t+2\Delta}(\Delta)e_{t+2\Delta}. \qquad (9)
\end{aligned}$$

Rearranging the above equations, we have a $AR(3)$ discrete time model that is linked to (2) (main text):

$$\begin{aligned} X_{1(t+3\Delta)} &= \underbrace{\{3-\alpha_1(\Delta)\}}_{\beta_1(\Delta)} X_{1(t+2\Delta)} + \underbrace{\{2\alpha_1(\Delta)-\alpha_2(\Delta)-3\}}_{\beta_2(\Delta)} X_{1(t+\Delta)} \\ &+ \underbrace{\{-\alpha_1(\Delta)+\alpha_2(\Delta)-\alpha_3(\Delta)+1\}}_{\beta_3(\Delta)} X_{1(t)} + \sigma_{t+2\Delta}(\Delta)e_t. \end{aligned} \tag{10}$$

Let us define $\mathbf{\Gamma}(\Delta) \stackrel{\text{def}}{=} \{\alpha_1(\Delta), \alpha_2(\Delta), \alpha_3(\Delta), \sigma_t(\Delta)\}^\top$. According to Pedersen (1995), Broze, Scaillet and Zakoian (1998), under some regularity assumption, the estimated parameter in discrete time $\hat{\mathbf{\Gamma}}(\Delta)$ converge to the continuous time parameter $\mathbf{\Gamma}$ as $\Delta \to 0$:

$$\lim_{\Delta\to 0} \lim_{N(\Delta)\to\infty} |\hat{\mathbf{\Gamma}}(\Delta) - \mathbf{\Gamma}| = 0 \qquad \text{a.s.}$$

The continuous time process (1) (main text) is Markov and therefore allows standard applications of pricing tools. The last three columns of Table 4 (main text) display the $CAR(3)$ parameters $\hat{\alpha}(1)$. Note that in (1) (main text) changes in the deseasonalized temperature are regressed against the deseasonalized temperatures itself. This leads to the fact, that the temperature tends toward a seasonal function, which is not the case in the CD model.

References

Benth, F. E. and Benth, S. (2011). Weather derivatives and stochastic modelling of temperature, *International Journal of Stochastic Analysis* **2011**: 1–21.

Benth, F. E. and Benth, S. (2012). A critical view on temperature modelling for application in weather derivatives markets, *Energy Economics* **34**: 592–602.

Benth, F. E., Benth, S. and Koekebakker, S. (2007). Putting a price on temperature, *Scandinavian Journal of Statistics* **34**: 746–767.

Benth, F. E., Härdle, W. K. and López Cabrera, B. (2011). Pricing asian temperature risk, *in* P. Cizek, W. K. Härdle and R. Weron (eds), *Statistical Tools for Finance and Insurance*, 2 edn, Springer Verlag Heidelberg.

Broze, L., Scaillet, O. and Zakoian, J.-M. (1998). Quasi-indirect inference for diffusion processes, *Econometric Theory* **14**(02): 161–186.

Campbell, S. and Diebold, F. X. (2005). Weather forecasting for weather derivatives, *Journal of the American Statistical Association* **100(469)**: 6–16.

Chen, Y., Härdle, W. K. and Pigorsch, U. (2010). Localized realized volatility modelling, *Journal of the American Statistical Association* **105(492)**: 1376–1393.

Cízek, P., Härdle, W. K. and Spokoiny, V. (2009). Adaptive pointwise estimation in time-inhomogeneous conditional heteroschedasticity models, *The Econometrics Journal* **12**: 248–271.

Davis, M. (2001). Pricing weather derivatives by marginal value, *Quantitative Finance* **1**: 305–308.

Granger, C. W. J. and Hyung, N. (2004). Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns, *Journal of Empirical Finance* **11**: 399–421.

Härdle, W. K. and López Cabrera, B. (2012). The implied market price of weather risk, *Applied Mathematical Finance* **19(1)**: 59–95.

Horst, U. and Mueller, M. (2007). On the spanning property of risk bonds priced by equilibrium, *Mathematics of Operation Research* **32(4)**: 784–807.

Karatzas, I. and Shreve, S. (2001). *Methods of Mathematical Finance*, Springer Verlag, New York.

Mercurio, D. and Spokoiny, V. (2004). Statistical inference for time-inhomogeneous volatility models, *The Annals of Statistics* **32(2)**: 577–602.

Pedersen, A. R. (1995). Consistency and asymptotic normality of an approximate maximum likelihood estimator for discretely observed diffusion processes, *Bernoulli* pp. 257–279.

Polzehl, J. and Spokoiny, V. (2006). Propagation-separation approach for local likelihood estimation, *Probability Theory and Realated Fields* **135**: 335–362.

Spokoiny, V. (2009). Multiscale local change point detection with applications to value at risk, *The Annals of Statistics* **37**(3): 1405–1436.