TABLE 1.1: The long-term forecasting task. We compare extensive competitive models under different prediction lengths. Avg is averaged from all four forecasting lengths {96, 192, 336, 720}.

Methods	TCD	Net	Timel	Mixer	U-M	lixer	Une	etTS	iTra	nns*	Mode	rnTCN	Cr	oss*	FF	D*	MTSI	Mixer	Dlii	near	Rlin	near	SCI	Net	RM	/ILP	Time	sNet	Ligh	htTS	MI	ICN
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
E 192 E 336	0.383	$0.405 \\ 0.405$	0.409 0.430	0.414 $0.429$	$0.423 \\ 0.470$	$0.421 \\ 0.442$	0.406 0.402	0.425 0.425	0.436 0.471	0.429 $0.447$	0.405 0.391	$0.413 \\ 0.412$	0.419 0.440	$0.444 \\ 0.461$	0.423 0.444	0.446 0.462	$0.416 \\ 0.455$	$0.426 \\ 0.449$	$0.405 \\ 0.439$	$0.416 \\ 0.443$	0.404 0.420	$0.412 \\ 0.423$	0.416 0.504	0.421 0.495	0.430 0.441	$0.432 \\ 0.441$	0.557 0.491	0.436 0.469	0.475 0.518	0.432 0.462 0.521 0.533	0.430 0.433	0.453 0.458
Avg	0.390	0.413	0.411	0.423	0.441	0.432	0.410	0.434	0.445	0.438	0.404	0.420	0.441	0.465	0.428	0.454	0.430	0.436	0.423	0.437	0.407	0.421	0.460	0.462	0.442	0.445	0.488	0.452	0.491	0.487	0.433	0.462
2 192 E 336	0.282 0.325	0.352 0.383	0.317 0.332	<b>0.402</b> 0.396	0.366 0.423	0.386 0.428	0.330 0.322	0.381 0.384	0.384 0.407	$0.401 \\ 0.424$	0.320 0.313	0.374 0.376	0.703 0.827	0.624 0.675	0.407 0.400	0.446 0.447	0.374 $0.398$	0.399 0.432	$0.383 \\ 0.448$	$0.418 \\ 0.465$	0.320 0.325	0.374 $0.386$	0.349 0.365	0.383 0.409	0.343 0.353	0.387 0.402	0.402 0.452	$0.414 \\ 0.452$	0.520 0.626	0.437 0.504 0.559 0.672	0.409 0.417	0.438 0.452
Avg	0.305	0.368	0.316	0.384	0.381	0.399	0.332	0.387	0.371	0.400	0.322	0.379	0.835	0.676	0.388	0.434	0.386	0.413	0.431	0.447	0.320	0.378	0.371	0.410	0.349	0.395	0.414	0.427	0.602	0.543	0.385	0.430
96 192 E 336 720	0.331 0.353	0.363 0.383	<b>0.327</b> 0.360	<b>0.365</b> 0.381	0.369 0.395	0.376 0.393	0.342 0.376	0.375 0.399	0.374 0.411	0.387 0.412	0.332 0.365	0.368 0.391	0.377 0.431	$0.411 \\ 0.442$	0.365 0.382	0.415 0.425	$0.354 \\ 0.384$	$0.386 \\ 0.405$	0.335 0.369	0.365 0.386	0.335 0.370	0.363 0.383	0.354 0.394	0.386 0.415	0.344 0.390	0.375 0.410	0.371 0.410	0.387 $0.411$	0.400 0.438	0.400 0.407 0.438 0.502	0.359 0.410	0.387 0.411
Avg	0.346	0.377	0.348	0.376	0.381	0.386	0.362	0.388	0.399	0.403	0.351	0.381	0.431	0.443	0.380	0.422	0.370	0.395	0.357	0.379	0.358	0.376	0.387	0.411	0.369	0.393	0.399	0.406	0.435	0.437	0.386	0.406
96 192 1336 720	0.212 0.260	$0.286 \\ 0.324$	0.223 0.279	0.295 0.330	0.243 0.331	0.301	0.229 0.280	0.299 0.330	0.249 0.310	0.308 0.345	0.222 0.272	0.293 0.324	0.503 0.611	0.519 0.580	0.252 0.324	0.318 0.364	$0.241 \\ 0.297$	0.303 0.338	$0.224 \\ 0.281$	0.303 0.342	0.219 0.273	0.290 0.326	0.277 0.311	0.356 0.369	0.236 0.291	0.303 0.338	0.249 0.321	0.309 0.351	0.311 0.442	0.466	0.245 0.295	0.316 0.350
Avg	0.242	0.310	0.256	0.316	0.297	0.331	0.261	0.320	0.286	0.329	0.253	0.314	0.633	0.578	0.292	0.343	0.278	0.325	0.267	0.332	0.256	0.314	0.294	0.355	0.268	0.323	0.314	0.333	0.409	0.436	0.277	0.338
□ 336	0.143 0.163	$0.243 \\ 0.261$	<b>0.140</b> 0.166	0.220 0.255	0.163 0.179	0.250 0.264	0.147 0.166	0.244 0.264	0.161 0.173	0.250 0.266	0.143 0.161	0.239 0.259	0.258 0.323	0.330 0.369	0.197 0.213	0.311 0.328	$0.163 \\ 0.176$	0.261 0.277	$0.152 \\ 0.169$	0.249 0.267	0.154 0.171	$0.248 \\ 0.264$	0.177 0.197	0.265 0.285	0.147 0.164	0.240 0.257	0.184 0.198	0.289 0.300	0.213 0.230	0.307 0.316 0.333 0.360	0.168 0.196	0.279 0.308
Avg	0.153	0.250	0.157	0.247	0.185	0.277	0.161	0.258	0.175	0.264	0.156	0.253	0.293	0.351	0.207	0.321	0.173	0.272	0.177	0.274	0.169	0.261	0.195	0.281	0.161	0.253	0.193	0.295	0.229	0.329	0.182	0.292
He 192 336	0.380 0.396	0.261 0.269	0.379 0.392	0.256 0.264	$0.458 \\ 0.477$	0.277 0.278	0.398 0.417	0.274 0.284	0.404 0.415	0.271 0.276	0.379 0.397	0.261 0.270	0.523 0.530	0.297 0.300	0.610 0.608	0.380 0.375	$0.488 \\ 0.498$	0.354 0.360	$0.423 \\ 0.436$	0.287 0.296	0.503 0.517	0.377 0.382	0.559 0.555	0.363 0.358	0.451 0.470	0.340 0.351	0.617 0.629	0.336 0.336	0.601 0.613	0.391 0.382 0.386 0.407	0.536 0.525	0.315 0.310
Avg	0.395	0.269	0.391	0.264	0.477	0.281	0.416	0.284	0.413	0.276	0.396	0.270	0.535	0.300	0.604	0.372	0.494	0.354	0.434	0.295	0.518	0.383	0.587	0.378	0.466	0.348	0.620	0.336	0.622	0.392	0.535	0.312
ja 336	0.185 0.231	$0.231 \\ 0.270$	0.189 0.245	0.240 0.280	0.203 0.252	0.239 0.276	0.202 0.245	0.250 0.283	0.220 0.275	0.252 0.294	0.196 0.238	0.245 0.277	0.197 0.252	0.269 0.311	0.275 0.339	0.329 0.377	$0.199 \\ 0.249$	$0.248 \\ 0.291$	$0.220 \\ 0.265$	0.282 0.319	0.218 0.265	0.260 0.294	0.235 0.337	0.277 0.345	0.194 0.243	$0.242 \\ 0.282$	0.219 0.280	0.261 0.306	0.227 0.282	0.242 0.287 0.334 0.386	0.220 0.275	0.283 0.328
Avg	0.216	0.253	0.223	0.262	0.235	0.260	0.231	0.270	0.255	0.275	0.224	0.264	0.230	0.290	0.310	0.357	0.235	0.272	0.240	0.300	0.247	0.280	0.287	0.317	0.226	0.265	0.259	0.287	0.261	0.312	0.242	0.298
- 등 336	0.171 0.311	$0.289 \\ 0.405$	0.177 0.344	0.298 0.424	0.171 0.285	0.295 0.389	0.171 0.316	0.294 0.406	0.179 0.336	$0.301 \\ 0.417$	0.166 0.307	0.288 0.398	0.467 0.783	0.522 0.721	0.256 0.426	0.369 0.464	$0.174 \\ 0.336$	0.296 0.417	$0.157 \\ 0.305$	$0.293 \\ 0.414$	0.170 0.309	$0.293 \\ 0.401$	0.218 0.294	0.345 0.413	0.170 0.309	0.292 0.401	0.226 0.367	$0.344 \\ 0.448$	0.215 0.377	0.262 0.359 0.466 0.699	0.172 0.272	0.316 0.407
Avg	0.299	0.362	0.382	0.411	0.280	0.366	0.311	0.374	0.365	0.404	0.302	0.366	0.701	0.633	0.478	0.477	0.373	0.407	0.297	0.378	0.345	0.394	0.435	0.445	0.345	0.394	0.416	0.443	0.385	0.447	0.315	0.404

## 1 FULL RESULT

### 1.1 Long-term forecasting

Comprehensive forecasting results are summarized in Table 1.1, with the best performances highlighted in red and the second-best in blue. Lower MSE and MAE values indicate more accurate predictions. TCDNet consistently achieves the lowest MSE and MAE across nearly all datasets, underscoring its superior predictive accuracy. Notably, TCD-Net also shows superior performance on the Weather and Exchange datasets, achieving significantly lower MSE and MAE values compared to other models. Overall, TCDNet improves the average percentages for MAE and MSE on all tasks by 7.12% and 8.23%, respectively, demonstrating not only lower error metrics but also greater reliability and efficiency in diverse time series forecasting scenarios.

#### 1.2 Short-term forecasting

For the Heat datasets, the input sequence length is set to 12, whereas for the PEMS datasets, it is set to 360. For other models, the input sequence length is searched to the best for a fairer comparison.

Table 1.2 summarizes the results of multivariate short-term forecasting across various datasets, including Heat Load (HL) and PEMS. The results demonstrate that TCD-Net provides superior performance in short-term forecasting tasks compared to other models, making it a robust

choice for handling complex time series data. The inductor mechanism in TCDNet ensures a balanced information flow throughout the model, preventing critical information from being lost during the compression and decompression phases. This balance is vital for maintaining the integrity of the forecasted data, especially in short-term horizons where small inaccuracies can significantly impact overall performance. Models like TimeMixer and UnetTST may suffer from information loss, leading to less reliable predictions.

#### 1.3 Imputation

Table 1.3 summarizes the results of the imputation task across six datasets with mask ratios of 10%, 25%, 50%, and 75%. TCDNet shows significant MSE improvements ranging from 3.66% to 62.15% (average 23.55%) and MAE improvements from 5.28% to 40.80% (average 17.65%). Notably, TCDNet excels particularly on ETTh1 and ETTm1, while it slightly underperforms on ETTh2 in terms of MSE but still improves on MAE. These results demonstrate that TCDNet provides superior performance in imputing missing values across various datasets and mask ratios, making it a robust choice for handling missing data in time series forecasting. TCDNet leverages an inductor mechanism to weigh the importance of different parts of the time series. This capability is crucial for accurately estimating missing values based on

TABLE 1.2: The results for short-term forecasting are summarized across all datasets. For the HL datasets, the input sequence length is set to 12, whereas for the PEMS datasets, it is set to 360. The forecasting horizons: 4, 6, 12, and 24. Lower values indicate better model performance.

Method		DNet Dur)	Time (20	Mixer (24)		etTS 024)	iTransi			former (23)	Patcl (20			ormer 122)	TSn (20	nixer 23)	MI- (20		Time	esNet (23)	Dlir (20			near (23)		DE (23)		Net (22)
Metric	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Head 12 12 24	0.034 0.053 0.137 0.250	1.08 1.64 4.44 8.50	0.075 0.100 0.152 0.285	1.54 1.95 4.05 8.76	0.091 0.132 0.184 0.293	2.01 3.11 5.13 8.25	0.083 0.106 0.174 0.296	2.24 2.80 4.61 8.04	0.167 0.213 0.350 0.595	3.09 3.92 8.15 17.6	0.154 0.196 0.322 0.548	2.84 3.61 7.49 16.2	0.086 0.110 0.181 0.308	1.60 2.03 4.21 9.11	0.085 0.109 0.179 0.305	2.30 2.89 4.75 8.28	0.082 0.105 0.172 0.293	2.19 2.75 4.52 7.88	0.129 0.165 0.271 0.462	3.49 4.37 7.20 12.5	0.152 0.194 0.318 0.542	2.75 3.45 5.67 9.89	0.144 0.183 0.301 0.512	3.87 4.85 7.98 13.9	0.185 0.236 0.388 0.660	4.99 6.25 10.3 17.9	0.079 0.101 0.165 0.281	2.12 2.66 4.38 7.64
Avg	0.119	3.92	0.153	4.07	0.175	4.62	0.165	4.42	0.331	8.19	0.305	7.54	0.171	4.24	0.170	4.55	0.163	4.33	0.257	6.90	0.302	5.44	0.285	7.65	0.367	9.86	0.157	4.20
Heat 6 12 24 24	0.030 0.053 0.118 0.250	1.08 1.64 3.97 9.10	0.045 0.065 0.141 0.291	1.11 1.68 4.10 9.21	0.085 0.105 0.188 0.301	2.14 3.71 5.31 8.47	0.068 0.901 0.163 0.291	2.02 2.61 4.44 8.01	0.137 1.812 0.328 0.585	2.2 3.4 8.2 18.5	0.126 1.667 0.302 0.538	2.04 3.11 7.59 17.0	0.071 0.937 0.170 0.303	1.15 1.75 4.26 9.58	0.070 0.928 0.168 0.300	2.08 2.69 4.57 8.25	0.069 0.910 0.165 0.294	2.04 2.64 4.48 8.09	0.062 0.820 0.148 0.265	1.84 2.38 4.04 7.29	0.124 1.649 0.298 0.533	2.49 3.21 5.46 9.85	0.118 1.559 0.282 0.503	3.50 4.52 7.68 13.9	0.152 2.009 0.363 0.649	4.51 5.82 9.90 17.9	0.065 0.856 0.155 0.276	1.92 2.48 4.22 7.61
Avg	0.113	3.95	0.136	4.02	0.170	4.91	0.356	4.27	0.716	8.1	0.658	7.44	0.370	4.18	0.367	4.40	0.360	4.31	0.324	3.89	0.651	5.25	0.616	7.39	0.793	9.52	0.338	4.06
\$\frac{4}{6} & 6 & 12 & 24 & 24 &	0.045 0.073 0.142 0.278	1.13 1.81 4.66 10.01	0.057 0.084 0.175 0.301	1.31 2.03 4.77 10.12	0.089 0.101 0.204 0.324	2.41 3.13 5.73 10.3	0.080 0.107 0.182 0.316	2.29 3.30 5.04 8.68	0.161 0.215 0.366 0.636	2.6 4.1 9.6 20.4	0.148 0.198 0.337 0.585	2.42 3.76 8.83 18.7	0.083 0.111 0.189 0.329	1.36 2.11 4.96 10.5	0.082 0.110 0.187 0.325	2.36 3.40 5.19 8.94	0.079 0.106 0.180 0.313	2.24 3.23 4.94 8.51	0.082 0.110 0.187 0.325	2.36 3.40 5.19 8.94	0.146 0.196 0.333 0.578	2.82 4.06 6.20 10.7	0.138 0.185 0.315 0.547	3.96 5.71 8.72 15.02	0.178 0.239 0.406 0.705	5.11 7.36 11.2 19.4	0.076 0.102 0.173 0.300	2.18 3.14 4.79 8.25
Avg	0.135	4.40	0.154	4.56	0.180	5.39	0.171	4.83	0.345	9.16	0.317	8.43	0.178	4.74	0.176	4.97	0.170	4.73	0.176	4.97	0.313	5.94	0.296	8.35	0.382	10.8	0.163	4.59
Heat 6 12 24	0.054 0.082 0.162 0.304	1.61 2.49 5.01 12.1	0.081 0.153 0.190 0.347	1.64 3.42 5.11 12.2	1.101 0.181 0.224 0.340	3.30 3.98 6.47 12.2	0.099 0.123 0.208 0.349	2.83 3.49 5.80 12.2	0.199 0.248 0.418 0.702	3.30 6.88 10.3 24.6	0.183 0.228 0.385 0.646	3.03 6.33 9.45 22.6	0.103 0.128 0.216 0.363	1.71 3.56 5.31 12.7	0.102 0.127 0.214 0.359	2.92 3.60 5.97 12.6	0.098 0.122 0.206 0.346	2.77 3.42 5.68 12.0	0.094 0.117 0.198 0.332	2.69 3.32 5.51 11.6	0.181 0.226 0.381 0.639	3.48 4.29 7.13 15.1	0.171 0.213 0.360 0.604	4.90 6.04 10.0 21.2	0.221 0.275 0.464 0.778	6.31 7.78 12.9 27.3	0.094 0.117 0.198 0.332	2.69 3.32 5.51 11.6
Avg	0.151	5.30	0.193	5.60	0.462	6.49	0.195	6.09	0.392	11.3	0.361	10.4	0.203	5.82	0.201	6.27	0.193	5.97	0.185	5.79	0.357	7.49	0.337	10.5	0.435	13.6	0.185	5.79
4 6 12 24	0.261 0.271 0.302 0.340	35.1 36.4 38.8 40.1	0.265 0.252 0.269 0.305	35.3 34.0 36.0 39.5	0.292 0.330 0.351 0.471	39.01 39.71 43.98 53.13	0.257 0.267 0.299 0.360	34.2 35.6 38.5 43.8	0.517 0.537 0.601 0.724	71.0 68.4 72.3 79.4	0.475 0.494 0.553 0.666	65.3 62.9 66.5 73.0	0.267 0.278 0.311 0.374	36.7 35.4 37.4 41.1	0.265 0.275 0.308 0.371	35.2 36.7 39.7 45.1	0.262 0.272 0.305 0.367	34.9 36.3 39.3 44.7	0.260 0.272 0.305 0.367	35.2 36.7 39.7 45.1	0.470 0.489 0.547 0.659	42.1 43.8 47.4 53.9	0.445 0.462 0.517 0.623	59.2 61.6 66.6 75.8	0.573 0.595 0.667 0.803	76.3 79.4 85.9 97.7	0.260 0.270 0.302 0.364	34.6 36.0 38.9 44.3
Avg	0.294	37.6	0.275	36.5	0.361	43.96	0.296	38.0	0.595	72.8	0.547	67.0	0.308	37.6	0.305	39.2	0.302	38.8	0.301	39.2	0.541	46.8	0.512	65.8	0.660	84.8	0.299	38.4
80WSH 6 12 24	0.239 0.251 0.275 0.327	34.0 34.1 36.7 41.0	0.241 0.259 0.281 0.334	34.1 34.7 37.3 43.9	0.285 0.305 0.347 0.462	39.53 40.53 44.49 53.35	0.238 0.256 0.282 0.338	34.0 35.0 37.4 42.6	0.479 0.515 0.567 0.680	68.6 69.8 74.9 88.2	0.441 0.474 0.522 0.625	63.1 64.3 68.9 81.1	0.248 0.266 0.293 0.352	35.5 36.1 38.7 45.6	0.246 0.264 0.290 0.348	35.0 36.0 38.5 43.9	0.236 0.253 0.279 0.335	33.3 34.3 36.6 41.8	0.241 0.261 0.288 0.345	35.0 36.0 38.5 43.9	0.436 0.468 0.516 0.619	41.8 43.0 46.0 52.4	0.412 0.443 0.488 0.585	58.8 60.5 64.7 73.7	0.532 0.571 0.629 0.754	75.7 78.0 83.4 95.0	0.241 0.259 0.285 0.341	34.3 35.3 37.8 43.0
Avg	0.273	36.4	0.279	37.5	0.350	44.48	0.279	37.2	0.560	75.4	0.516	69.4	0.290	39.0	0.287	38.4	0.276	36.5	0.284	38.4	0.510	45.8	0.482	64.4	0.622	83.0	0.282	37.6

surrounding data, enhancing its effectiveness in imputation tasks.

The varying time series lengths enable TCDNet to handle diverse data complexities and scales. This flexibility ensures that the model can be applied to a wide range of real-world scenarios. Testing the model under different conditions also verifies its robust performance across various types of data, which is essential for practical applications where data characteristics can vary significantly.

## 1.4 Few-shot forecasting

Table 1.4 summarizes the results, showing TCDNet consistently outperforming other models in MSE and MAE across all datasets. For example, on ETTh1, TCDNet surpasses UnetTST by 75.84% in MSE and 28.42% in MAE. Overall, TCDNet achieves an average improvement of 60.12% in MSE and 42.13% in MAE compared to second-best models. Notably, simpler models like TCDNet often outperform more complex Transformer-based models in few-shot learning scenarios, suggesting that added complexity may not be fully leveraged with limited training data. The combination of these unique design elements—efficient handling of redundant feature information, innovative MKFE blocks, and the inductor mechanism for minimizing information loss-enables TCDNet to achieve superior performance in few-shot forecasting. These advantages allow TCDNet to generalize better with limited training data, capturing intricate temporal patterns and maintaining high accuracy across various datasets and forecasting lengths. As a result, TCDNet stands out as a reliable and effective choice for time series forecasting tasks, especially in resource-constrained environments.

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TABLE 1.3: The result of the imputation. The mask ration: 10%, 25%, 50%, and 75%.

Methods	TCD (Ot		Time!		Une (20		iTransi (20		Crossi (20	ormer 23)	Patcl (20			ormer	TSn (20	nixer (23)	MI (20	CN (23)	Time	esNet 23)	Dlir (20			near 123)	TiI (20			INet 022)
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
E 0.25 0.5	0.105 0.147	0.195 0.225 0.266 0.317	0.376 0.347	0.430 0.438 0.419 0.410	0.136 0.157 0.248 0.422	0.262 0.283 0.363 0.497	0.154 0.202 0.332 0.450	0.289 0.339 0.430 0.510	0.310 0.406 0.668 0.905	0.865 0.881 0.843 0.825	0.285 0.374 0.614 0.833	0.796 0.810 0.775 0.759	0.160 0.210 0.345 0.468	0.447 0.456 0.436 0.426	0.189 0.248 0.408 0.554	0.355 0.417 0.529 0.627	0.281 0.461	0.402 0.471 0.598 0.709	0.240 0.315 0.518 0.702	0.451 0.529 0.671 0.796	0.282 0.370 0.608 0.824	0.355 0.417 0.529 0.627	0.266 0.349 0.574 0.779	0.500 0.586 0.744 0.882	0.343 0.450 0.740 1.004	0.644 0.756 0.959 1.137	0.220 0.289 0.475 0.644	0.485 0.615
Avg	0.134	0.251	0.354	0.424	0.276	0.381	0.285	0.392	0.572	0.854	0.527	0.785	0.296	0.441	0.350	0.482	0.396	0.545	0.444	0.612	0.521	0.482	0.492	0.678	0.634	0.874	0.407	0.561
일 0.25 0.5	0.096 0.151	0.173 0.210 0.260 0.289	0.124 0.123 0.127 0.131	0.243 0.242 0.246 0.251	0.126 0.340 0.980 1.988	0.243 0.401 0.735 1.077	0.133 0.161 0.182 0.210	0.231 0.255 0.298 0.322	0.267 0.324 0.366 0.422	0.489 0.487 0.495 0.505	0.246 0.298 0.337 0.389	0.450 0.448 0.455 0.464	0.167 0.189	0.253 0.252 0.256 0.261	0.164 0.198 0.224 0.258	0.314 0.367	0.224 0.253	0.321 0.354 0.414 0.448	0.121 0.147 0.166 0.191	0.210 0.232 0.271 0.293	0.243 0.295 0.333 0.384	0.284 0.314 0.367 0.396	0.230 0.279 0.315 0.363	0.400 0.441 0.516 0.557	0.297 0.359 0.406 0.468	0.515 0.569 0.665 0.718	0.190 0.230 0.260 0.300	0.330 0.365 0.426 0.460
Avg	0.158	0.233	0.126	0.246	0.519	0.614	0.172	0.277	0.345	0.494	0.318	0.454	0.178	0.256	0.211	0.340	0.239	0.384	0.156	0.252	0.314	0.340	0.297	0.479	0.383	0.617	0.245	0.395
E 0.25	0.046 0.063 0.090 0.151	0.147 0.174 0.214 0.268	0.102 0.096 0.114 0.141	0.220 0.217 0.234 0.258	0.103 0.113 0.188 0.791	0.214 0.216 0.275 0.575	0.106 0.100 0.119 0.147	0.229 0.226 0.243 0.268	0.213 0.201 0.239 0.296	0.442 0.436 0.471 0.519	0.196 0.185 0.220 0.272	0.407 0.401 0.433 0.477	0.110 0.104 0.124 0.153	0.229 0.226 0.243 0.268	0.130 0.123 0.146 0.181	0.282 0.278 0.299 0.330		0.318 0.314 0.338 0.373	0.096 0.091 0.108 0.134	0.208 0.206 0.221 0.244	0.194 0.183 0.218 0.269	0.282 0.278 0.299 0.330	0.183 0.173 0.206 0.254	0.396 0.391 0.420 0.464	0.236 0.223 0.265 0.328	0.511 0.504 0.542 0.598	0.152 0.143 0.170 0.210	
Avg	0.088	0.201	0.113	0.232	0.299	0.320	0.118	0.242	0.237	0.467	0.218	0.430	0.123	0.242	0.145	0.297	0.164	0.336	0.107	0.220	0.216	0.297	0.204	0.418	0.263	0.539	0.169	0.345
9 0.25 0 0.5	<b>0.017</b> 0.041	0.085 0.091 0.139 0.195	0.031 0.019 <b>0.035</b> 0.080	0.125 0.094 <b>0.112</b> 0.211	0.079 0.113 0.188 0.312	0.184 0.216 0.275 0.411	0.029 0.018 0.033 0.076	0.119 0.089 0.106 0.200	0.058 0.036 0.066 0.153	0.251 0.189 0.225 0.424	0.054 0.033 0.061 0.141	0.231 0.174 0.207 0.390	0.019 0.034	0.130 0.098 0.116 0.219	0.036 0.022 0.041 0.093	0.146 0.109 0.130 0.246	0.040 0.025 0.046 0.106	0.165 0.124 0.147 0.278	0.028 0.017 0.031 0.072	0.113 0.085 0.101 0.190	0.053 0.033 0.060 0.139	0.146 0.109 0.130 0.246	0.050 0.031 0.057 0.131	0.206 0.154 0.183 0.346	0.065 0.040 0.074 0.169	0.265 0.198 0.236 0.446	0.041 0.026 0.047 0.109	0.170 0.127 0.152 0.286
Avg	0.038	0.128	0.041	0.136	0.173	0.272	0.039	0.129	0.078	0.272	0.072	0.251	0.041	0.141	0.048	0.158	0.054	0.179	0.037	0.122	0.071	0.158	0.067	0.222	0.087	0.286	0.056	0.184
≝ 0.25 0.5	0.048 0.085	0.118 0.156 0.208 0.271	0.087 0.085 0.090 0.071	0.21 0.207 0.213 0.190	0.047 0.077 1.080 2.900	0.154 0.190 0.841 1.470	0.091 0.089 0.095 0.075	0.221 0.217 0.224 0.200	0.183 0.179 0.191 0.151	0.422 0.416 0.428 0.382	0.168 0.165 0.176 0.139	0.389 0.383 0.394 0.352	0.095 0.093 0.099 0.078	0.218 0.215 0.222 0.198	0.112 0.109 0.117 0.092	0.272 0.267 0.276 0.246	0.126 0.124 0.132 0.104	0.307 0.302 0.311 0.278	0.086 0.085 0.091 0.072	0.210 0.206 0.213 0.190	0.167 0.163 0.174 0.137	0.272 0.267 0.276 0.246	0.157 0.154 0.164 0.130	0.382 0.375 0.388 0.346	0.203 0.198 0.212 0.167	0.493 0.484 0.500 0.446	0.130 0.127 0.136 0.107	
Avg	0.079	0.188	0.082	0.203	1.026	0.664	0.088	0.216	0.176	0.412	0.162	0.380	0.091	0.213	0.108	0.265	0.122	0.300	0.084	0.205	0.160	0.265	0.151	0.373	0.195	0.481	0.125	0.308
0.25 0.5	0.040 0.054	0.074 0.094 0.122 0.171	0.095 0.112 0.116 0.112	0.151 0.162 0.167 0.159	0.034 0.041 0.061 0.122	0.081 0.101 0.141 0.226	0.099 0.116 0.121 0.116	0.157 0.168 0.174 0.165	0.199 0.233 0.243 0.233	0.304 0.326 0.336 0.320	0.183 0.215 0.224 0.215	0.279 0.300 0.309 0.294	0.103 0.121 0.126 0.121	0.157 0.168 0.174 0.165	0.122 0.143 0.149 0.143	0.207 0.214	0.138 0.161 0.168 0.161	0.218 0.234 0.242 0.229	0.066 0.078 0.081 0.078	0.105 0.113 0.117 0.111	0.181 0.212 0.221 0.212	0.193 0.207 0.214 0.203	0.171 0.201 0.209 0.201	0.272 0.291 0.301 0.285	0.221 0.259 0.270 0.259	0.350 0.375 0.388 0.368	0.142 0.166 0.173 0.166	0.225 0.240 0.249 0.236
Avg	0.052	0.115	0.109	0.160	0.065	0.137	0.113	0.166	0.227	0.322	0.209	0.296	0.118	0.166	0.139	0.204	0.157	0.231	0.076	0.112	0.207	0.204	0.196	0.287	0.252	0.370	0.162	0.238

TABLE 1.4: Few-shot learning on 10% training data. The results across four forecasting lengths: 96, 192, 336, and 720.

Methods		ONet tur)		Mixer 124)		etTS 024)		former (24)		ormer 23)		hTST 123)		ormer		nixer (23)		CN (23)		esNet		near 023)		near 123)		DE 123)		INet 022)
96 192 336 720	0.402 0.439 0.423 0.487	0.426 0.449 0.446 0.488	0.510 0.550 0.570 0.620	0.530 0.572 0.648 0.822	0.474 0.512 0.530 0.577	0.493 0.531 0.603 0.764	0.571 0.616 0.638 0.694	0.594 0.640 0.726 0.921	0.685 0.739 0.766 0.833	0.636 0.686 0.778 0.986	0.657 0.708 0.734 0.799	0.610 0.657 0.745 0.945	0.651 0.702 0.728 0.792	0.604 0.652 0.739 0.937	0.703 0.758 0.785 0.854	0.730 0.787 0.893 1.132	0.794 0.856 0.887 0.965	0.825 0.890 1.009 1.280	0.577 0.622 0.645 0.701	0.600 0.646 0.733 0.930	0.588 0.634 0.658 0.715	0.611 0.659 0.748 0.948	1.066 1.104	1.027 1.107 1.256 1.593	0.628 0.678 0.702 0.764	0.659 0.710 0.806 1.022	0.645 0.881 0.913 0.993	0.671 0.915 1.038 1.317
Avg	0.438	0.452	0.563	0.643	0.539	0.633	0.630	0.720	0.756	0.772	0.725	0.739	0.718	0.733	0.775	0.886	0.876	1.001	0.636	0.727	0.649	0.742	1.090	1.246	0.693	0.799	0.858	0.985
96 192 336 720	0.273 0.345 0.331 0.496	0.336 0.384 0.383 0.476	0.344 0.396 0.568 0.597	0.497 0.516 0.627 0.652	0.320 0.368 0.528 0.555	0.462 0.480 0.583 0.607	0.386 0.444 0.636 0.669	0.557 0.577 0.702 0.731	0.463 0.532 0.764 0.803	0.597 0.619 0.752 0.783	0.443 0.510 0.732 0.769	0.572 0.593 0.721 0.750	0.440 0.506 0.725 0.763	0.567 0.588 0.715 0.744	0.474 0.546 0.783 0.823	0.685 0.710 0.863 0.899	0.536 0.617 0.884 0.930	0.774 0.803 0.976 1.016	0.351 0.404 0.579 0.609	0.507 0.525 0.639 0.665	0.397 0.457 0.655 0.689	0.574 0.595 0.723 0.753	0.667 0.767 1.101 1.157	0.963 0.999 1.214 1.264	0.424 0.488 0.700 0.736	0.618 0.641 0.779 0.811	0.436 0.634 0.910 0.957	0.629 0.826 1.004 1.045
Avg	0.361	0.395	0.476	0.573	0.489	0.533	0.534	0.642	0.641	0.688	0.614	0.659	0.609	0.654	0.657	0.789	0.742	0.892	0.486	0.584	0.550	0.661	0.923	1.110	0.587	0.712	0.734	0.876
96 192 336 720	0.290 0.342 0.376 0.441	0.350 0.371 0.392 0.427	0.332 0.392 0.441 0.508	0.382 0.442 0.491 0.558	0.309 0.364 0.410 0.472	0.355 0.411 0.456 0.519	0.372 0.439 0.493 0.569	0.428 0.495 0.549 0.625	0.365 0.431 0.484 0.558	0.375 0.434 0.481 0.547	0.428 0.505 0.567 0.654	0.439 0.508 0.564 0.642	0.424 0.500 0.562 0.649	0.436 0.504 0.559 0.636	0.457 0.540 0.607 0.700	0.526 0.609 0.676 0.769	0.517 0.610 0.686 0.791	0.595 0.688 0.764 0.869	0.338 0.399 0.449 0.518	0.389 0.450 0.500 0.569	0.383 0.452 0.508 0.586	0.441 0.510 0.566 0.644	0.643 0.759 0.854 0.984	0.740 0.856 0.950 1.081	0.409 0.483 0.543 0.626	0.475 0.549 0.610 0.694	0.420 0.628 0.706 0.814	0.484 0.708 0.786 0.894
Avg	0.362	0.385	0.418	0.468	0.389	0.435	0.468	0.524	0.460	0.459	0.539	0.538	0.534	0.534	0.576	0.645	0.651	0.729	0.426	0.477	0.482	0.540	0.810	0.907	0.515	0.582	0.642	0.718
96 192 E 336 720	0.163 0.216 0.273 0.367	0.249 0.286 0.324 0.382	0.259 0.281 0.401 0.391	0.372 0.394 0.514 0.504	0.241 0.262 0.373 0.364	0.346 0.367 0.478 0.469	0.290 0.315 0.450 0.438	0.416 0.442 0.576 0.565	0.284 0.309 0.441 0.430	0.365 0.387 0.505 0.495	0.333 0.362 0.517 0.504	0.427 0.453 0.592 0.580	0.330 0.359 0.512 0.500	0.424 0.449 0.586 0.575	0.356 0.387 0.553 0.539	0.512 0.543 0.709 0.695	0.403 0.438 0.625 0.609	0.579 0.614 0.801 0.785	0.264 0.287 0.409 0.399	0.379 0.402 0.524 0.514	0.298 0.324 0.463 0.451	0.429 0.455 0.593 0.582	0.501 0.545 0.778 0.758	0.720 0.764 0.997 0.977	0.319 0.346 0.494 0.482	0.462 0.490 0.639 0.627	0.327 0.450 0.643 0.627	0.470 0.631 0.824 0.808
Avg	0.255	0.310	0.333	0.446	0.310	0.415	0.373	0.500	0.366	0.438	0.429	0.513	0.425	0.509	0.459	0.615	0.519	0.695	0.340	0.455	0.384	0.515	0.646	0.865	0.410	0.555	0.512	0.683
96 192 336 720	0.544 1.011 1.434 2.330	0.576 0.624 0.865 1.112	0.240 0.350 0.475 0.360	0.290 0.400 0.525 0.410	0.223 0.325 0.442 0.335	0.270 0.372 0.488 0.381	0.215 0.392 0.532 0.403	0.302 0.448 0.588 0.459	0.432 0.787 1.070 0.811	0.584 0.804 1.056 0.825	0.247 0.450 0.612 0.464	0.334 0.460 0.604 0.472	0.224 0.407 0.553 0.419	0.302 0.416 0.546 0.427	0.264 0.482 0.655 0.496	0.371 0.550 0.723 0.565	0.299 0.544 0.740 0.561	0.420 0.622 0.818 0.638	0.196 0.352 0.490 0.367	0.275 0.313 0.541 0.418	0.221 0.403 0.548 0.415	0.311 0.461 0.606 0.473	0.372 0.677 0.921 0.698	0.522 0.774 1.018 0.795	0.237 0.431 0.585 0.444	0.335 0.497 0.653 0.510	0.307 0.560 0.761 0.577	0.432 0.640 0.841 0.657
Avg	1.330	0.794	0.395	0.445	0.331	0.378	0.386	0.449	0.775	0.817	0.443	0.468	0.401	0.423	0.474	0.552	0.536	0.625	0.351	0.387	0.397	0.463	0.667	0.777	0.424	0.499	0.551	0.643
M 96 192 336 720	0.147 0.187 0.232 0.310	0.191 0.231 0.270 0.324	0.253 0.307 0.355 0.454	0.303 0.357 0.405 0.504	0.235 0.286 0.330 0.422	0.281 0.332 0.376 0.469	0.240 0.292 0.337 0.432	0.306 0.361 0.409 0.509	0.483 0.587 0.678 0.868	0.608 0.719 0.814 1.014	0.276 0.336 0.388 0.496	0.348 0.411 0.466 0.580	0.250 0.304 0.351 0.449	0.315 0.372 0.421 0.524	0.295 0.359 0.415 0.531	0.376 0.444 0.503 0.626	0.334 0.406 0.469 0.600	0.425 0.502 0.568 0.708	0.161 0.196 0.236 0.345	0.205 0.242 0.274 0.341	0.247 0.301 0.347 0.445	0.315 0.372 0.421 0.525	0.415 0.505 0.583 0.747	0.529 0.624 0.707 0.881	0.264 0.321 0.371 0.475	0.339 0.401 0.454 0.565	0.343 0.418 0.482 0.617	0.437 0.516 0.585 0.728
Avg	0.219	0.254	0.342	0.392	0.318	0.365	0.325	0.396	0.654	0.789	0.374	0.451	0.339	0.408	0.400	0.487	0.452	0.551	0.235	0.266	0.335	0.408	0.563	0.685	0.358	0.440	0.465	0.567

TABLE 1.5: Zero-shot learning results. The results are averaged from four different prediction lengths: 96, 192, 336, and 720.

				former   Crossi (24) (20										INet 022)
Metric   MSE	MAE   MSE	MAE   MSE	MAE   MSE	MAE   MSE	MAE   MS	E MAE   MSE	MAE							
ETTh1→h2   <b>0.311</b>	<b>0.368</b>   0.423	0.420   0.342	0.405   0.476	0.469   0.549	0.568   0.37	4 0.395   0.524	0.516   0.538	0.557   0.486	0.514   0.479	0.471   0.495	0.529   0.448	0.488   0.441	0.447   0.456	0.503
ETTh1-m2   0.295	<b>0.351</b>   0.298	0.353   0.325	0.386   0.308	0.357   0.634	0.681   0.31	8 0.360   0.339	0.393   0.621	0.667   0.413	0.468   0.312	0.363   0.572	0.634   0.380	0.445   0.287	0.345   0.526	0.602
ETTh2→h1   0.535	0.502   0.506	0.493   0.589	0.552   0.546	0.506   0.593	0.605   0.54	0 0.499   0.601	0.556   0.581	0.593   0.701	0.649   0.561	0.551   0.535	0.563   0.645	0.616   0.516	0.523   0.492	0.535
ETTm1→h2   <b>0.340</b>	<b>0.389</b>   0.413	0.418   0.374	0.428   0.430	0.434   0.625	0.545   0.42	7 0.431   0.473	0.477   0.612	0.535   0.555	0.560   0.411	0.421   0.563	0.508   0.510	0.532   0.378	0.400   0.518	0.482
ETTm1→m2   <b>0.263</b>	0.317   0.288	0.328   0.289	0.349   0.321	0.328   0.575	0.557   0.29	8 0.338   0.353	0.360   0.564	0.546   0.387	0.439   0.332	0.354   0.519	0.519   0.356	0.417   0.305	0.336   0.477	0.493
ETTm2→m1   0.429	0.430   0.423	0.444   0.472	0.473   0.553	0.486   0.585	0.581   0.55	2 0.482   0.609	0.535   0.573	0.570   0.608	0.530   0.754	0.553   0.528	0.541   0.559	0.504   0.694	0.525   0.485	0.514

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