

Tiny Time Mixers (TTMs): Fast Pre-trained Models for Enhanced Zero/Few-Shot Forecasting of Multivariate Time Series

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Abstract

Large pre-trained models for zero/few-shot learning excel in language and vision domains but encounter challenges in multivariate time series (TS) due to the diverse nature and scarcity of publicly available pre-training data. Consequently, there has been a recent surge in utilizing pre-trained large language models (LLMs) with token adaptations for TS forecasting. These approaches employ cross-domain transfer learning and surprisingly yield impressive results. However, these models are typically very slow and large (\sim billion parameters) and do not consider cross-channel correlations. To address this, we present Tiny Time Mixers (TTM), a significantly small model based on the lightweight TSMixer architecture. TTM marks the first success in developing fast and tiny general pre-trained models (≤ 1 M parameters), exclusively trained on public TS datasets, with effective transfer learning capabilities for forecasting. To tackle the complexity of pre-training on multiple datasets with varied temporal resolutions, we introduce several novel enhancements such as adaptive patching, dataset augmentation via down-sampling, and resolution prefix tuning. Moreover, we employ a multi-level modeling strategy to effectively model channel correlations and infuse exogenous signals during fine-tuning, a crucial capability lacking in existing benchmarks. TTM shows significant accuracy gains (12-38%) over popular benchmarks in few/zero-shot forecasting. It also drastically reduces the compute needs as compared to LLM-TS methods, with a 14X cut in learnable parameters, 106X less total parameters, and substantial reductions in fine-tuning (65X) and inference time (54X). In fact, TTM's zero-shot often surpasses the few-shot results in many popular benchmarks, highlighting the efficacy of our approach. Models and source code are available at <https://huggingface.co/ibm/TTM>

1 Introduction

Multivariate time series (TS) forecasting entails predicting future values for multiple interrelated time series based on their historical data. This field has advanced significantly, applying statistical and machine learning (ML) methods [Hyndman and Athanasopoulos, 2021] across domains like weather, traffic, retail, and energy. In general, each time series represents a variable or channel¹. In certain applications, non-forecasting variables, categorized as controllable and uncontrollable external factors, impact the variables to forecast. We term these non-forecasting variables as exogenous, and the variables requiring forecast as target variables.

Related Work: Recent advances in multivariate forecasting have been marked by the advent of transformer-based [Vaswani *et al.*, 2017] approaches, exemplified by models like PatchTST [Nie *et al.*, 2023], Autoformer [Wu *et al.*, 2021], Informer [Zhou *et al.*, 2021], and FEDFormer [Zhou *et al.*, 2022]. These models have demonstrated notable improvements over traditional statistical and ML methods. Furthermore, architectures based on MLP-Mixer [Tolstikhin *et al.*, 2021], such as TSMixer [Ekambaram *et al.*, 2023], have emerged as efficient transformer alternatives, boasting 2-3X reduced compute and memory requirements with no accuracy compromise compared to their transformer counterparts. However, none of these advanced approaches have successfully demonstrated the ability to create general pre-trained models that can successfully transfer the learning to unseen target TS dataset, in a similar way as popularly witnessed in NLP and vision tasks. This is very challenging in the TS domain due to the diverse nature of the datasets across applications and the limited public availability of TS data for pre-training. There are existing self-supervised pre-training TS approaches using masked modeling and contrastive learning techniques such as SimMTM [Dong *et al.*, 2023] and TF-C [Zhang *et al.*, 2022] that offer transfer learning between two datasets when carefully selected based on the dataset properties. However, they fail to provide universal transfer learning capabilities across datasets. Consequently, there has been a recent growing trend to employ pre-trained large language models (LLMs) for TS forecasting, treating it as a cross-domain transfer learning task. These universal

¹“Channel” refers to the individual time series in multivariate data (i.e., a multivariate TS is a multi-channel signal).

cross-transfer approaches, specifically recent works such as LLMTime [Gruver *et al.*, 2023] and GPT4TS [Zhou *et al.*, 2023] yield promising results in few/zero-shot forecasting approaches. These models are bootstrapped from GPT-2/3 or LLAMA-2 with suitable tokenization strategies to adapt to time-series domains.

However, these LLM based TS approaches do not explicitly handle channel correlations and exogenous support in the context of multivariate forecasting. Moreover, these large models, with billions of parameters, demand significant computational resources and runtime. Hence, in this paper, we focus on building pre-trained models from scratch solely using TS data. Unlike language, which has abundant public pre-training data in terabytes, time-series data is relatively scarce, very diverse and publicly limited. Its scarcity leads to overfitting when pre-training “large” models solely on time-series data. This prompts a question: *Can smaller models pre-trained purely on limited public diverse TS datasets give better zero/few-shot forecasting accuracy? Surprisingly, the answer is yes!* Toward this, we propose Multi-level Tiny Time Mixers (TTM), a significantly smaller model ($\leq 1\text{M}$ parameters) based on the lightweight TSMixer architecture, exclusively trained on diverse TS corpora for effective zero/few-shot multivariate TS forecasting via transfer learning.

In particular, TTM is pre-trained using multiple public datasets ($\sim 244\text{M}$ samples) from the Monash data repository² [Godahehwa *et al.*, 2021]. Note that the datasets exhibit considerable diversity in terms of characteristics, such as the different domains, temporal resolution³ (spanning from second to daily), lengths, and number of channels. Pre-training on such heterogeneous datasets cannot be handled directly by TSMixer or existing state-of-the-art (SOTA) models. Hence, TTM proposes the following enhancements to the TSMixer architecture: (i) **Adaptive Patching** across layers, considering the varied suitability of patch lengths for different datasets, (ii) **Dataset Augmentation via Down-sampling** to increase coverage and samples across different resolutions, (iii) **Resolution Prefix Tuning** to explicitly embed resolution information in the first patch, facilitating resolution-conditioned modeling, particularly beneficial in scenarios with short history lengths. Moreover, our approach leverages multi-level modeling, where TTMs are first pre-trained in a channel-independent way and then seamlessly integrate channel mixing during fine-tuning to model target data-specific channel-correlations and exogenous infusion

Below, we outline the paper’s key contributions:

- Amidst the prevalence of large pre-trained models demanding significant compute and training time (in weeks), our work is the first to showcase the efficacy of building **Fast and Tiny Pre-trained models** ($\leq 1\text{M}$ parameters) exclusively trained on Public TS datasets in a flash of just few hours (4-8 hours, 6 A100 GPUs). TTM successfully demonstrates transfer learning to diverse, unseen target datasets for zero/few-shot forecasting, ad-

ressing the data scarcity issues prevalent in time series.

- Pre-training on heterogeneous multi-resolution datasets cannot be handled effectively by TSMixer or other SOTA models. Hence, we propose various **architectural and training enhancements**, such as adaptive patching, data augmentation via downsampling, and (an optional) resolution prefix tuning for robust pre-training.
- TTM employs a **multi-level modeling strategy** to explicitly model channel-correlations, and incorporates exogenous signals – a crucial capability lacking in LLMs-based TS approaches.
- With **extensive evaluation** on 11 datasets, TTM shows significant accuracy gains over popular benchmarks (12-38% in few/zero-shot forecasting). It also drastically reduces the compute needs as compared to LLM-TS methods, with a 14X cut in learnable parameters, 106X less total parameters, and substantial reductions in finetuning (65X), inference time (54X), and memory usage (27X).
- The zero-shot results of TTM often surpass the few-shot results of many SOTA approaches, highlighting the effectiveness of our approach.

2 TTM Components

Let $\mathbf{X} \in \mathbb{R}^{c \times sl}$ be a multivariate time series of length sl and c number of channels. The forecasting task can be formally defined as predicting the future values $\mathbf{Y} \in \mathbb{R}^{c' \times fl}$ given the history \mathbf{X} . Here, fl denotes the forecast horizon and c' denotes number of forecast channels, where $c' \leq c$. The predictions from the model are denoted by $\hat{\mathbf{Y}} \in \mathbb{R}^{c' \times fl}$. In a general multivariate forecasting task, each channel or variable falls into one of the following categories: (a) **Target variables (mandatory)**: corresponding to the channels for which forecasts are required, (b) **Exogenous variables (optional)**: encompassing (i) uncontrolled variables that may influence the forecasts and assumed to be known or estimated for the forecast period (e.g. weather), and (ii) control variables whose future values during the forecast horizon can be manipulated to govern the behavior of the target variables. (e.g. discount in sales forecasting, operator controls in industrial applications). In TTM, uncontrolled and control variables are treated similarly, as both are considered available during forecasting.

2.1 Multi-level Modeling

TTM follows a multi-level architecture consisting of four key components (see Figure 1(a)): (1) The **TTM Backbone** is assembled using building blocks derived from the efficient TSMixer architecture [Ekambaram *et al.*, 2023]. TSMixer is based on simple MLP blocks that enable mixing of features within patches, across patches and channels, surpassing existing transformer-based TS approaches with minimal computational requirements. Since TSMixer is not targeted to handle multi-resolution data, we introduce various novel enhancements to it as explained later. (2) **TTM Decoder** follows the same backbone architecture but is considerably smaller in size, approximately 10-20% of the size of the backbone, (3) **Forecast Head** consists of a linear head designed to produce the forecast output, and (4) Optional **Exogenous Mixer**

² Accessible at <https://forecastingdata.org/>

³ Resolution refers to the sampling rate of the input time series (e.g., hourly, 10 minutes, 15 minutes, etc.)

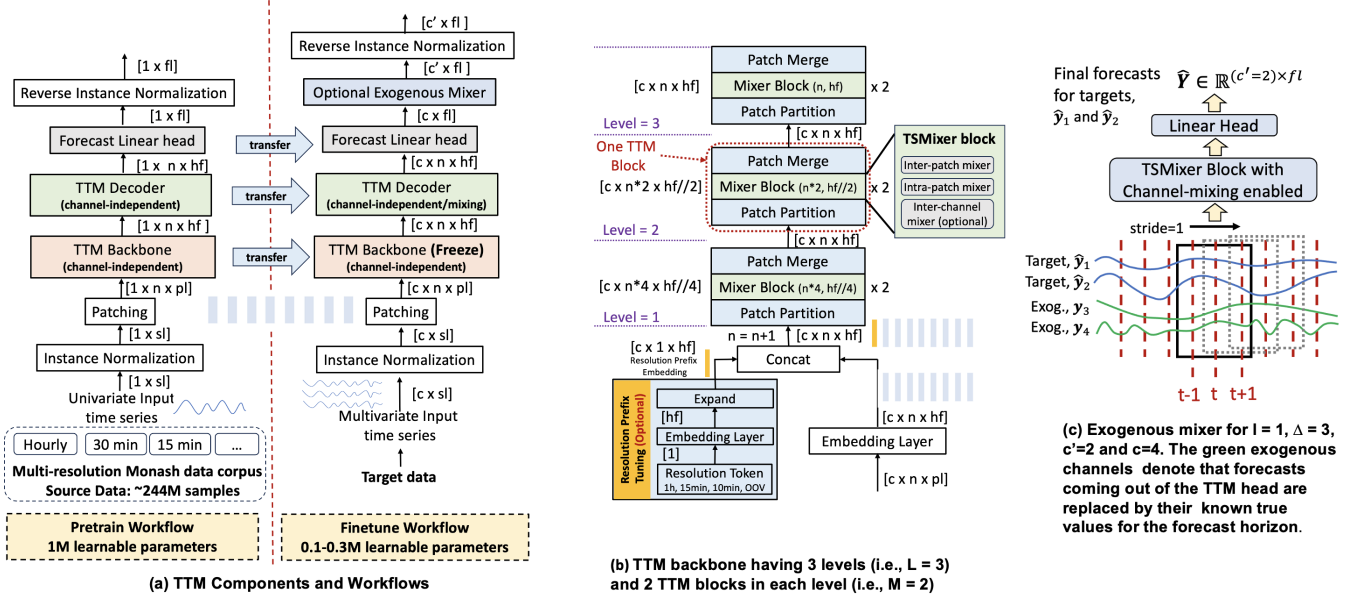


Figure 1: Overview of Multilevel Tiny Time Mixers (TTM): (a) Refer to Section 2 and 3, (b) Refer to Section 3.1, (c) Refer to Section 3.2

serves to fuse exogenous data into the model’s forecasting process. This multi-level model refactoring is required to dynamically change the working behavior of various components based on the workflow type, as explained in Section 3. In addition to the above primary components, we also have a preprocessing component as explained next.

2.2 Pre-processing

As shown in Figure 1(a) with colorless blocks, the historical time series \mathbf{X} is first **normalized** per instance to have zero mean and unit standard deviation for each channel dimension, to tackle any possible distribution shifts [Nie *et al.*, 2023; Ekambaram *et al.*, 2023]. This process is reversed at the end before computing the loss. The normalized data $\bar{\mathbf{X}}$ is subsequently **patched** $\mathbf{X}_p \in \mathbb{R}^{c \times n \times pl}$ into n non-overlapping windows, each of length pl and then, passed to the TTM backbone. Patching, as introduced in [Nie *et al.*, 2023], has proven to be highly valuable for forecasting. Its effectiveness lies in preserving local semantic information, accommodating longer history, and reducing computation.

3 TTM Workflows

TTM works in 2 stages: pre-train and fine-tune (Figure 1(a)).

3.1 Pre-training Workflow

In the pre-training stage, we train the model on a large collection of public datasets from the Monash data repository [Godaheva *et al.*, 2021]. Since the primary focus of TTM is forecasting, pre-training is modeled with a direct forecasting objective. TTM is first pre-trained in a univariate fashion with independent channels on all the existing datasets. Due to varied channel counts in pre-training datasets, modeling multivariate correlations is not feasible here; it is addressed

later during fine-tuning. Multivariate pre-training datasets are initially transformed into independent univariate time series $(\mathbf{X}_1, \dots, \mathbf{X}_N) \in \mathbb{R}^{c(=1) \times sl}$. These are pre-processed (Section 2.2), and subsequently fed into the TTM backbone for multi-resolution pre-training. The output of the backbone $\mathbf{X}_h^L \in \mathbb{R}^{(c=1) \times n \times hf}$ is passed through the decoder and forecast head to produce the forecast $\hat{\mathbf{Y}} \in \mathbb{R}^{(c=1) \times fl}$ which is then reverse-normalized to bring back to the original scale. We pre-train the TTM with mean squared error (MSE) loss function calculated over the forecast horizon: $\mathcal{L} = \|\mathbf{Y} - \hat{\mathbf{Y}}\|_2^2$. Thus for a given input context length sl and forecast length fl , we get a pre-trained model capturing the common temporal forecasting dynamics and seasonal patterns as observed in the overall pre-training data.

Multi-Resolution Pre-training via TTM Backbone

The majority of the pre-training happens in the TTM backbone. The primary challenge with the proposed pre-training technique is that the pre-training data is diverse and has multiple resolutions. There are two main options for pre-training: conducting separate pre-training for each resolution type or pre-training using all resolution data collectively. While it’s common to train a model per resolution type to overcome challenges in learning diverse seasonal patterns, this leads to diminished training data for each resolution due to limited data availability. Consequently, this motivated the exploration of pre-training a single model using datasets from all resolutions. To achieve this, we propose the following 3 enhancements.

Adaptive Patching: The TTM backbone is crafted with an adaptive patching architecture where different layers of the backbone operate at varying patch lengths and numbers of patches. Since each dataset in the pre-training corpora

may perform optimally at a specific patch length, this approach greatly aids in generalization when diverse datasets with different resolutions are introduced. As shown in Figure 1(b), the patched data $\mathbf{X}_p \in \mathbb{R}^{c \times n \times pl}$ is passed through an embedding layer to project it to the patch hidden dimension, $\mathbf{X}_h \in \mathbb{R}^{c \times n \times hf}$. Optionally, if the resolution prefix tuning module is activated (as explained later), the resolution prefix is concatenated with \mathbf{X}_h . For notational simplicity, we denote the concatenated tensor with \mathbf{X}_h as well.

The TTM backbone consists of L levels, each comprising M TTM blocks with identical patch configurations. A TTM block in the i -th level, $i = 1, \dots, L$, receives the processed data $\mathbf{X}_h^{(i-1)} \in \mathbb{R}^{c \times n \times hf}$ from the earlier block. Each TTM block is further comprised of a patch partition model, a vanilla TSMixer block, and a patch merging block. Patch Partition block at every level i increases the number of patches by a factor of K_i and reduces the patch dimension size by the same factor by reshaping $\mathbf{X}_h^{(i-1)} \in \mathbb{R}^{c \times n \times hf}$ to $\mathbf{X}_h^i \in \mathbb{R}^{c \times (n \cdot K_i) \times (hf / K_i)}$, where $K_i = 2^{(L-i)}$. Note that, we set $hf = 2^m$ for some integer $m \geq L$. Then, TSMixer is applied to the adapted data \mathbf{X}_h^i . Finally, the output from TSMixer is again reshaped to its original shape (i.e., $\mathbb{R}^{c \times n \times hf}$) in the patch merging block. Note that, as we go deeper into the network, the number of patches decreases while the patch dimension size increases leading to adaptive patching which helps in better generalization as we pre-train with multiple datasets together. This idea of adaptive patching is popular and very successful in the vision domain (E.g. Swin transformers [Liu *et al.*, 2021]) and we are the first to port it successfully to the time-series domain to resolve multi-resolution issues in pre-training with diverse TS datasets. Figure 1(b) shows the TTM backbone for $L = 3$ and $M = 2$. Please note that adaptive patching is enabled only in the backbone and not in the decoder, which is designed to be very lightweight.

Data Augmentation via Downsampling: A significant challenge in TS pre-training datasets is the scarcity of public datasets at specific resolutions. To overcome this, we employ a downsampling technique for high-resolution datasets, generating multiple datasets at lower resolutions. For example, from a one-second resolution dataset, we derive datasets at minute and hour resolutions. Note that, the original high-resolution dataset remains within the pool of pre-training datasets. This methodology significantly augments the number of datasets for each resolution which greatly improves the model performance (Section 4.5).

Resolution Prefix Tuning: This technique explicitly learns and incorporates a new patch embedding as a prefix into the input data based on the input resolution type (see Figure 1(b)). Similar to the concept of prefix tuning [Li and Liang, 2021], this approach provides an explicit signal to the model about the resolution type for resolution-conditioned modeling. First, we map every resolution to a unique integer, which is then passed through an embedding layer to project it to the hidden dimension, hf . Subsequently, we expand the embedding across all channels to have a representation of shape $c \times 1 \times hf$. This module is optional for the TTM backbone, particularly beneficial when the context length (sl) is short. In these scenarios, automatically detecting the resolu-

tion becomes a challenge for the model. Hence, by explicitly fusing the resolution information as a prefix, we can enhance the model’s ability to learn effectively across resolutions.

3.2 Fine-tuning Workflow

In the fine-tuning workflow, we deal with data from the *target* domain that has no overlap with the pre-training datasets. We have three options here: (a) In **Zero-shot** forecasting, we directly use the pre-trained model to evaluate on the *test* part of the target data, (b) In **Few-shot** forecasting, we utilize only a tiny portion (5-10%) of the *train* part of the target data to quickly update the pre-trained weights of the decoder and head, and subsequently, evaluate it on the *test* part, (c) In **Full-shot** forecasting, we fine-tune the pre-trained weights of the decoder and head on the entire *train* part of the target data, and then, evaluate on the *test* part.

The backbone is completely frozen during fine-tuning, and still operates in a channel-independent univariate fashion. However, the TTM decoder can be fine-tuned via channel-mixing (for multivariate) or a channel-independent (for univariate) way based on the nature of the target data. If pure multivariate modeling is needed, then the channel-mixer block in all the TSMixer components (see Figure 1(b)) in the decoder gets enabled to explicitly capture the channel correlation between the channels. The forecast head and reverse normalization perform similar operations as in the pre-training stage. The fine-tuning also optimizes the forecasting objective with MSE loss. This thoughtful multi-level design choice ensures our backbone excels in channel-independent pre-training, enabling effective temporal correlation modeling across diverse datasets. Simultaneously, the decoder handles target-data-specific tasks like channel-correlation modeling and fine-tuning. In addition, if the target data has exogenous variables, then an exogenous mixer block is applied to the actual forecasts as explained next.

Exogenous Mixer Block: As described in Section 2, the future values of the exogenous channels are known in advance. Let the forecast from the forecast head be $\hat{\mathbf{Y}} \in \mathbb{R}^{c \times fl}$. Let the channels $\mathbf{x}_0, \dots, \mathbf{x}_{c'}$ denote the target variables and $\mathbf{x}_{c'+1}, \dots, \mathbf{x}_c$ denote all exogenous variables with their future values known. First, we replace the forecast values for the exogenous channels with the *true* future values (\mathbf{Y}) and transpose it: $\hat{\mathbf{Y}}_e = [\hat{\mathbf{y}}_0, \dots, \hat{\mathbf{y}}_{c'}, \mathbf{y}_{c'+1}, \dots, \mathbf{y}_c] \in \mathbb{R}^{fl \times c}$. Next, to learn inter-channel *lagged* correlations, we patch $\hat{\mathbf{Y}}_e$ into a series of overlapped windows (i.e., patching with stride= 1) to create a new tensor: $\hat{\mathbf{Y}}_{e,p} \in \mathbb{R}^{fl \times \Delta \times c}$, where $\Delta = 2 \cdot l + 1$ with l being the context length to incorporate on either side of a time point⁴. Subsequently, we pass $\hat{\mathbf{Y}}_{e,p}$ through a vanilla TSMixer block with channel mixing enabled. Thus, the lagged dependency of the forecasts for the target channels on the exogenous channels is seamlessly learned. Finally, we attach a linear head to produce the forecasts for the target channels which is then reshaped as $\hat{\mathbf{Y}} \in \mathbb{R}^{c' \times fl}$. Figure 1(c) depicts this procedure.

⁴This needs padding $\hat{\mathbf{Y}}_e$ with zeros of length l on both sides.

		Zero-shot		Few-shot (5%)						
	fl	TTM	TTM	GPT4TS	PatchTST	TSMixer	TimesNet	DLinear	FEDFormer	Autoformer
ETTH1	96	0.365	0.366	0.543	0.557	0.554	0.892	0.547	0.593	0.681
	192	0.393	0.391	0.748	0.711	0.673	0.940	0.720	0.652	0.725
	336	0.415	0.421	0.754	0.816	0.678	0.945	0.984	0.731	0.761
	720	0.538	-	-	-	-	-	-	-	-
ETTH2	96	0.285	0.282	0.376	0.401	0.348	0.409	0.442	0.390	0.428
	192	0.341	0.338	0.418	0.452	0.419	0.483	0.617	0.457	0.496
	336	0.383	0.383	0.408	0.464	<u>0.389</u>	0.499	1.424	0.477	0.486
	720	0.441	-	-	-	-	-	-	-	-
ETTM1	96	0.413	0.359	0.386	0.399	0.361	0.606	0.332	0.628	0.726
	192	0.476	<u>0.402</u>	0.440	0.441	0.411	0.681	0.358	0.666	0.750
	336	0.553	0.424	0.485	0.499	0.467	0.786	0.402	0.807	0.851
	720	0.737	<u>0.575</u>	0.577	0.767	0.677	0.796	0.511	0.822	0.857
ETTM2	96	0.187	0.174	0.199	0.206	0.200	0.220	0.236	0.229	0.232
	192	0.261	0.240	<u>0.256</u>	0.264	0.265	0.311	0.306	0.394	0.291
	336	0.323	0.299	0.318	0.334	0.314	0.338	0.380	0.378	0.478
	720	0.436	0.407	0.46	0.454	0.410	0.509	0.674	0.523	0.553
Weather	96	0.154	0.152	0.175	0.171	0.188	0.207	0.184	0.229	0.227
	192	0.203	0.198	0.227	0.230	0.234	0.272	0.228	0.265	0.278
	336	<u>0.256</u>	0.250	0.286	0.294	0.287	0.313	0.279	0.353	0.351
	720	0.329	0.326	0.366	0.384	0.365	0.400	0.364	0.391	0.387
Electricity	96	0.169	0.142	<u>0.143</u>	0.145	0.147	0.315	0.150	0.235	0.297
	192	0.196	0.162	0.159	0.163	0.172	0.318	0.163	0.247	0.308
	336	0.209	<u>0.184</u>	0.179	0.175	0.190	0.340	0.175	0.267	0.354
	720	0.264	0.228	0.233	0.219	0.280	0.635	0.219	0.318	0.426
Traffic	96	0.518	0.401	0.419	0.404	0.408	0.854	0.427	0.670	0.795
	192	0.548	0.425	0.434	0.412	0.421	0.894	0.447	0.653	0.837
	336	0.55	0.437	0.449	<u>0.439</u>	0.477	0.853	0.478	0.707	0.867
	720	0.605	-	-	-	-	-	-	-	-
TTM Zero-shot Vs SOTA Few-shot (% IMP)				1%	3%	2%	31%	6%	25%	32%
TTM 5% Few-shot (% IMP)				12%	14%	12%	38%	17%	32%	38%

Table 1: Zero-shot and Few-shot 5% performance (MSE) of TTM and all SOTA models on D1 datasets for varying forecast lengths (fl). Bold and underscore denote the best and the second best. For longer fl (720), some datasets fail to generate fine-tuning samples with just 5% of the data, denoted as ‘-’. The last two rows show relative improvement (IMP) of TTM zero-shot and few-shot w.r.t. SOTA few-shot results. IMP is calculated based on the mean of the percentage improvement of TTM achieved across all rows.

4 Experiments and Results

4.1 Experimental Setting

Datasets: Pre-training employs a subset of the Monash data hub [Godahewa *et al.*, 2021] of size ~ 244 M samples. We specifically exclude datasets (like yearly, monthly) as they do not possess sufficient length for the long-term forecasting task. Moreover, we remove all the datasets that we utilize for evaluation (i.e., weather, electricity, and traffic). For zero/few-shot evaluation we consider seven public datasets (D1): ETTH1, ETTH2, ETTM1, ETTM2, Weather, Electricity & Traffic as popularly used in most prior SOTA works [Zhou *et al.*, 2021; Nie *et al.*, 2023]. Since these datasets do *not* contain any exogenous variables nor exhibit cross-channel correlation benefits, we incorporate four other datasets (D2) for separately validating the efficacy of the decoder channel mixing and exogenous mixer module: bike sharing (BS) [Fanaee-T, 2013], carbon capture plant (CC) [Jablunka *et al.*, 2023], and 2 more datasets from Biz-IT observability domain [ITB, 2023]: Application (APP) and Service (SER). Refer Appendix for full data details.

SOTA Benchmarks: We benchmark TTM with the latest public SOTA forecasting models categorized as follows: (a) **LLM-based TS pre-trained models:** GPT4TS [Zhou

Metric	Data	GPT4TS	TTM (Ours)	IMP (X)
FT	Weather	3.2	0.29	(14X)
	Electricity	3.2	0.29	
	Traffic	5.5	0.29	
TL	Weather	84.3	0.8	(106X)
	Electricity	84.3	0.8	
	Traffic	86.6	0.8	
EPOCH	Weather	37	1	(65X)
	Electricity	241	4	
	Traffic	782	8	
MAX MEMORY (GB)	Weather	21.9	1.06	(27X)
	Electricity	39.7	2.02	
	Traffic	53.7	1.34	
TEST TIME (s)	Weather	52.53	1.66	(54X)
	Electricity	353.4	8.07	
	Traffic	1163.9	13.5	

Table 2: Computational Improvement in few-shot 10% for $fl=96$ using 1 A100 GPU. nX denotes n times average improvement across datasets (IMP).

	10%	25%	50%	75%	100%	IMP
TTM	0.422	0.421	0.413	0.402	0.398	-
SimMTM	0.591	0.535	0.491	0.466	0.415	17%
Ti-MAE	0.660	0.594	0.55	0.475	0.466	24%
TST	0.783	0.641	0.525	0.516	0.469	28%
LaST	0.645	0.610	0.540	0.479	0.443	23%
TF-C	0.799	0.736	0.731	0.697	0.635	43%
CoST	0.784	0.624	0.540	0.494	0.428	26%
TS2Vec	0.655	0.632	0.599	0.577	0.517	31%

Table 3: Cross transfer learning MSE improvement (IMP) for self-supervised pre-training methods in various few-shot settings (10%,25%,50%,75%,100%).

et al., 2023], LLMTime [Gruver *et al.*, 2023] (b) **Self-supervised pre-trained models:** SimMTM [Dong *et al.*, 2023], Ti-MAE [Li *et al.*, 2023], TST [Zerveas *et al.*, 2021], LaST [Wang *et al.*, 2022], TF-C [Zhang *et al.*, 2022], CoST [Woo *et al.*, 2022] and Ts2Vec [Yue *et al.*, 2022] (c) **TS transformer models:** PatchTST [Nie *et al.*, 2023], FEDFormer [Zhou *et al.*, 2022], Autoformer [Wu *et al.*, 2021] (d) **Other SOTA models:** TSMixer [Ekambaram *et al.*, 2023], DLinear [Zeng *et al.*, 2022] and TimesNet [Wu *et al.*, 2022]

TTM Model Details: For our experiments, we build 5 pre-trained models for the following sl, fl configuration: (512,96), (512,192), (512, 336), (512,720) and (96,24). Based on the sl and fl requirement of the target dataset, a suitable pre-trained model is selected to initialize the weights accordingly for fine-tuning. Since our pre-trained models are very small, they can be trained quickly in a few hours (4-8 hrs), as opposed to several days/weeks in standard approaches. Hence, pre-training multiple TTM models is no longer a practical constraint. Pre-training is performed in a distributed fashion with 50 CPUs and 6 A100 GPUs with 40 GB GPU memory while fine-tuning uses only 1 GPU. Other model configurations are as follows: patch length $pl = 64$ (for sl 512) and 8 (for sl 96), stride $s = pl$, number of levels $L = 6$,

	Zero-shot		Few-shot (10%)						
Data	TTM (Ours)	TTM (Ours)	GPT4TS	PatchTST	TSMixer	TimesNet	Dlinear	FEDFormer	Autoformer
ETTH1	0.428	0.422	0.590	0.633	0.578	0.869	0.691	0.639	0.702
ETTH2	<u>0.362</u>	0.360	0.397	0.415	0.370	0.479	0.605	0.466	0.488
ETTM1	0.545	0.458	0.464	0.501	<u>0.441</u>	0.677	0.411	0.722	0.802
ETTM2	0.302	0.278	0.293	0.296	<u>0.282</u>	0.320	0.316	0.463	1.342
Electricity	0.210	<u>0.180</u>	0.176	0.176	<u>0.180</u>	0.323	0.180	0.346	0.431
Traffic	0.555	0.428	0.440	0.430	<u>0.429</u>	0.951	0.446	0.663	0.749
Weather	0.236	0.227	0.238	0.242	<u>0.236</u>	0.279	0.241	0.284	0.300
TTM Zero-shot Vs SOTA Few-shot (% IMP)			-4%	-2%	-7%	27%	2%	27%	39%
TTM 10% Few-shot (% IMP)			7%	9%	4%	34%	13%	34%	45%

Table 4: Zero-shot and Few-shot 10% performance (MSE) of TTM over all SOTA models on D1 datasets, averaged across 4 forecast lengths. The numbers with bold and underscore denote the best and the second best results respectively. The last two rows show relative improvement (IMP) of TTM zero-shot and few-shot w.r.t. SOTA few-shot results. IMP is calculated based on the mean of the percentage improvement of TTM achieved across all rows. The full table is in Appendix.

Data	fl	Zero-shot	
		LLMTime	TTM
Traffic	96	0.340	0.195
	192	0.526	0.367
Weather	96	0.107	0.031
	192	0.062	0.067
Electricity	96	0.609	0.238
	192	0.960	0.488
ETTM2	96	0.167	0.164
	192	0.198	0.228
TTM IMP (%)		29%	

Table 5: TTM vs LLMTime MSE Improvement (IMP) in zero-shot setting.

	BS	CC	APP	SER	% IMP
TTM-CM	0.582	0.250	0.042	0.114	
TTM-Zero-shot	0.992	0.263	0.183	0.238	44%
TTM	0.635	0.261	0.073	0.143	18%
PatchTST	<u>0.735</u>	0.267	0.060	0.119	15%
TSMixer-CC	0.651	0.284	<u>0.053</u>	0.136	15%
TSMixer-CM	0.716	0.303	<u>0.069</u>	0.118	20%
TSMixer	0.664	0.267	0.066	0.134	17%
GPT4TS	0.645	0.254	0.075	0.135	18%

Table 6: Effect of Decoder Mixing and Exog Fusion. MSE Results are reported using (sl , fl) with values of (512, 96) for BS dataset and (96, 24) for other D2 datasets.

Data	Zero-shot		Few-shot (5%)				Few-shot (10%)			
			5 Epochs		50 Epochs		5 Epochs		50 Epochs	
	RI	PT	RI	PT	RI	PT	RI	PT	RI	PT
ETTH1	0.735	0.428	0.687	0.389	0.629	0.393	0.64	0.419	0.552	0.422
ETTH2	0.400	0.362	0.378	0.334	0.379	0.334	0.371	0.357	0.370	0.360
ETTM1	0.722	0.545	0.474	0.483	0.448	0.440	0.421	0.458	0.403	0.458
ETTM2	0.353	0.302	0.296	0.274	0.290	0.280	0.279	0.271	0.274	0.278
Electricity	0.890	0.210	0.356	0.188	0.199	0.179	0.220	0.186	0.178	0.180
Traffic	1.453	0.555	0.593	0.454	0.441	0.421	0.486	0.446	0.430	0.428
Weather	0.321	0.236	0.267	0.233	0.264	0.231	0.240	0.229	0.238	0.227
% IMP	36%		21%		12%		9%		2%	

Table 7: Improvement (IMP) of Pre-Training (PT) over Randomly Initialized (RI) weights. MSE averaged across all fl s.

number of TTM blocks per level $M = 2$, number of decoder layers = 2, batch size $b = 3K$, number of epochs $ep = 20$, and dropout $do = 0.2$. TSMixer specific hyperparameters include feature scaler $fs = 3$, hidden feature size $hf = fs * pl$, expansion feature size $ef = hf * 2$. Resolution prefix tuning is disabled by default and enabled only for shorter context lengths (as explained in Table. 10). Decoder channel-mixing and exogenous mixer blocks are disabled during pre-training and enabled for D2 datasets during fine-tuning. All other model parameters remain the same across pre-training and fine-tuning except for a few parameters like dropout and batch size that can be adjusted based on the target data. Hyperparameters are selected based on the validation performance, and the test results are reported. For full implementation details, refer to the Appendix. MSE is used as the default evaluation metric.

4.2 TTM’s Zero/Few-shot Performance

Table 1 compares the performance of TTM model in zero-shot and few-shot (5%) settings across multiple fl s. Baseline results are reported from [Zhou *et al.*, 2023] as we use the same few-shot data filtering strategy as followed in that paper. Note that for zero-shot performance, the pre-trained TTM model is directly evaluated on the test set. The 5% few-shot TTM outperforms the SOTAs in most of the cases with significant accuracy gains (12-38%). An even more impressive observation is that the TTM in zero-shot setting is also able to outperform most of the SOTAs which are trained on 5% of the target data. This observation establishes the generalization ability of the pre-trained TTM model on the target

datasets. Likewise, Table 4 shows the 10% few-shot performance of the TTM, where we outperform all the existing SOTAs by 4-45% accuracy gains. In addition, TTM zero-shot also beats many SOTAs (not all) with 10% training highlighting the effectiveness of our approach.

Additionally, we conduct a comparison between TTM and the LLMTime model which is explicitly designed for zero-shot setting. Since these models are based on LLaMA and are massive in size, the authors used only the last window of the standard test-set for faster evaluation, as opposed to using all the windows in the full test-set. Hence, we compare them separately in Table 5 based on the same datasets, fl , and test-set as reported in [Gruver *et al.*, 2023]. In this evaluation, we outperform LLMTime by a substantial margin of 29%. In addition, there are alternative pre-training approaches like masked modeling and contrastive learning techniques that may not offer universal transfer learning capabilities across all datasets (like TTM), but they excel in enabling cross-transfer learning between two datasets when carefully selected. Table 3 illustrates the cross-transfer learning from ETTH2 to ETTH1 for these models in various few-shot settings (as reported in [Dong *et al.*, 2023]). Notably, TTM, with no specific cross-data selection, outperforms all popular SOTAs, including the latest SimMTM, by 17-43%. Thus, TTM significantly beats all the existing SOTAs including the recent popular transfer learning benchmarks based on LLMs. Notably, we achieve these accuracy gains with significantly reduced compute requirements, as elaborated next.

Data	Zero-shot		Few-shot (10%)	
	Vanilla	Adaptive Patching	Vanilla	Adaptive Patching
ETTH1	0.501	0.428	0.478	0.422
ETTH2	0.375	0.362	0.372	0.360
ETTM1	0.577	0.545	0.463	0.458
ETTM2	0.310	0.302	0.272	0.278
Electricity	0.215	0.210	0.178	0.180
Traffic	0.556	0.555	0.431	0.428
Weather	0.239	0.236	0.230	0.227
IMP (%)	4%		2%	

Table 8: Effect of adaptive Patching, MSE averaged across 4 values of fl

Data	Zero-shot	
	Original Data	With Downsample
ETTH1	0.603	0.379
ETTH2	0.351	0.313
ETTM1	0.852	0.444
ETTM2	0.261	0.224
Electricity	0.424	0.182
Traffic	0.898	0.533
Weather	0.186	0.178
IMP (%)	30%	

Table 9: Downsampling effect, MSE averaged across fl s: 96, 192

Data	$HL = 96$		$HL = 512$	
	NP	P	NP	P
ETTH1	0.373	0.358	0.365	0.360
ETTH2	0.180	0.179	0.285	0.280
ETTM1	0.559	0.387	0.413	0.384
ETTM2	0.127	0.108	0.187	0.194
Weather	0.103	0.103	0.154	0.160
Electricity	0.208	0.201	0.169	0.175
Traffic	0.754	0.740	0.518	0.518
IMP (%)	8%		0%	

Table 10: Resolution Prefix Tuning: With (P) vs Without (NP). MSE reported

4.3 Computational Benefits of TTM

Table 2 compares the computational benefits of TTM over GPT4TS, the most popular LLM-TS model and the current best SOTA in few-shot setting. For a fair comparison, we run both models with the best-reported parameters in a single A100 GPU with the same setup (Details in Appendix). Since GPT4TS is based on GPT-2, it consumes a huge model footprint and exhibits slow execution. In specific, TTM achieves 14X cut in Fine-tune (FT) parameters (NPARAMS) and a remarkable 106X reduction in Total (TL) parameters. This reduction in model footprint further leads to a significant reduction in fine-tuning EPOCH TIME by 65X, MAX MEMORY usage by 27X, and total inference time on the entire test data (TEST TIME) by 54X. The computational benefits also apply over other LLM-based time series models like LLMTime, built on LLaMA, which is larger than GPT-2. In fact, LLMTime used a very small test set on these datasets as opposed to the standard test set to overcome this slow-execution.

4.4 TTM’s effectiveness in cross-channel and exogenous modeling

Since the datasets ($D1$) used in previous experiments do not have exogenous variables, we evaluate the effectiveness of TTM on 4 other datasets ($D2$, as explained in 4.1) to quantify its benefits. Since these datasets are already very small, we used their full data for fine-tuning. Table 6 shows the performance of the pre-trained TTM model fine-tuned on the target data with exogenous mixer module and decoder channel-mixing enabled (TTM-CM). We compare the performance of TTM-CM with the pre-trained TTM used in zero-shot setting (TTM-Zero-shot), and plain TTM (TTM) and other primary SOTAs (PatchTST, TSMixer variants, and GPT4TS) trained from scratch. Other SOTAs are not reported here, considering their inferior performance and space constraints. Specifically, we compare with TSMixer with channel-mixing enabled (TSMixer-CM) and TSMixer with Cross-Channel reconciliation head (TSMixer-CC) [Ekambaram *et al.*, 2023] as they are the latest SOTAs in channel-correlation modeling. We can see that TTM-CM outperforms all the competitive models with a significant margin (15-44%), thus, demonstrating the power of TTM in capturing inter-channel correlations.

4.5 Ablation Studies

Effect of Pre-training: Table 7 illustrates the advantages of the proposed pre-training (PT) approach in comparison to randomly initialized (RI) model weights. In the case of zero-shot, the pre-trained TTM (PT) exhibits 36% improvement over RI. This outcome is expected, as random weights are directly employed for forecasting with RI. For the 5% few-shot scenario, PT achieves noteworthy improvements of 21% and 12% over RI when fine-tuned for 5 and 50 epochs, respectively. This underscores the utility of pre-trained weights in facilitating quick learning with a limited amount of target data. Even in the case of 10% few-shot, PT continues to demonstrate an improved performance of 9% for 5 epochs and 2% for 50 epochs. Thus, the performance impact of leveraging pre-trained weights greatly increases as the size of the training data and the available time-to-fine-tune reduces.

Effect of Adaptive Patching: The Adaptive patching presented in Section 3.1 is a key component of the TTM backbone. Table 8 demonstrates the relative improvements when we employ adaptive patching with respect to a vanilla TTM backbone without this module. We can see that adaptive patching adds an extra 4% improvement during zero-shot and 2% improvement for 10% few-shot. Performance improvements are observed in almost all datasets which justifies the effectiveness of the adaptive patching module when evaluated on multiple datasets of different resolutions.

Effect of Augmentation via Downsampling: Table 9 compares the zero-shot test performances between the TTM model trained on the original Monash data and the TTM trained on the augmented Monash data after downsampling as described in Section 3.1. There is a significant improvement of 30% for the model pre-trained on the augmented datasets as it adds more data coverage across various resolutions. This observation highlights the strength of the proposed TTM model to learn from diverse datasets together, and increasing the number of datasets for each resolution helps.

Effect of Resolution Prefix Tuning: Since resolution prefix tuning explicitly adds the resolution type as an extra embedding, it greatly helps when the input context length sl is short where it is challenging for the model to derive the resolution type automatically. As observed in Table 10, we observe 8% improvement in zero-shot for shorter context length ($sl = 96$) and no improvement when the context length is longer ($sl = 512$). Hence this component is optional and can

Data	Few-shot (5%)		Few-shot (10%)	
	TTM	Time-LLM	TTM	Time-LLM
ETTH1	0.393	0.627	0.422	0.556
ETTH2	0.334	0.382	0.36	0.37
ETTM1	0.44	0.425	0.458	0.404
ETTM2	0.28	0.274	0.278	0.277
Weather	0.231	0.26	0.227	0.234
Electricity	0.179	0.179	0.18	0.175
Traffic	0.421	0.423	0.428	0.429
TTM IMP(%)	8%		2%	

Table 11: TTM Vs Time-LLM on D1 Datasets averaged across considered 4 forecast lengths. MSE reported.

Data	fl	Zero-shot	
		UniTime	TTM
ETTH2	96	0.306	0.285
	192	0.389	0.341
	336	0.424	0.383
	720	0.434	0.441
Electricity	96	0.409	0.169
	192	0.41	0.196
	336	0.439	0.209
	720	0.487	0.264
Weather	96	0.21	0.154
	192	0.264	0.203
	336	0.326	0.256
	720	0.402	0.329
TTM IMP (%)		27%	

Table 12: TTM vs UniTime
MSE Improvement (IMP)
in zero-shot setting.

be enabled when working with shorter input context length.

4.6 Comparison with recent concurrent works

In this section, we compare the performance of TTM with the very recent concurrent works published in 2024. Time-LLM [Jin *et al.*, 2024] is a recent SOTA that enables successful reprogramming of LLMs for time-series tasks. However, as depicted in Table 11, TTM outperforms Time-LLM by 8% in Fewshot 5% and 2% in Fewshot 10% setting. Likewise, UniTime [Liu *et al.*, 2024] proposes novel techniques towards language-empowered cross-domain time-series forecasting. As indicated in Table 12, TTM’s zero-shot results surpass UniTime’s zero-shot results by 27%. Further, TTM does not need any cross-domain transfer learning and pairwise mapping as our pretraining is enabled on a diverse set of datasets.

5 Conclusions and Future Work

Considering the diversity and limited availability of public TS pre-training data, pre-training large models for effective transfer learning poses several challenges in time series. Hence, we propose TTM, a multi-level Tiny Time Mixer model designed for efficient pre-training on limited diverse multi-resolution datasets. TTM achieves state-of-the-art results in zero/few-shot forecasting, offering significant computational efficiency and supporting cross-channel and exogenous variables — critical features lacking in existing popular

methods. Going forward, we plan to extend our approach to many other downstream tasks beyond forecasting for a purely foundational approach in time series.

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Tiny Time Mixers (TTMs): Fast Pre-trained Models for Enhanced Zero/Few-Shot Forecasting of Multivariate Time Series

Appendix A

The outline of our appendix section is as follows:

- Detailed Literature Survey - **Section A.1**
- TSMixer Background - **Section A.2**
- Details on Pre-training Datasets - **Section A.3**
- Details on Evaluation Datasets - **Section A.4**
- Baseline Implementation Details - **Section A.5**
- TTM *Source Code* and Implementation Details - **Section A.6**
- TTM Computational Benefits: Setup details - **Section A.7**
- Full Tables - **Section A.8**

A.1 Detailed Literature Survey

Multivariate Time Series Forecasting

Statistical approaches for time series forecasting, such as SARIMAX and Exponential Smoothing, generally generate forecasts independently for each time series [Hyndman and Athanasopoulos, 2021]. These methods are essentially univariate and do not build a single model by learning from multiple time series. On the other hand, more advanced models, built upon machine/deep learning techniques, including LightGBM-based models [Makridakis *et al.*, 2022; Jati *et al.*, 2023], N-BEATS [Oreshkin *et al.*, 2020], and DeepAR [Salinas *et al.*, 2020], have the capability to learn from multiple time series. However, these models still follow univariate approaches, thus ignoring any potential cross-channel correlations.

Advanced multivariate forecasting models mostly involve deep neural networks, specifically the transformer [Vaswani *et al.*, 2017] architecture. A series of transformer-based model have been proposed in the last few years including Informer [Zhou *et al.*, 2021], Autoformer [Wu *et al.*, 2021], and FEDFormer [Zhou *et al.*, 2022]. Although these models outperformed all the prior arts, the DLinear [Zeng *et al.*, 2022] model showed that an embarrassingly simple linear model can beat these models by following a few empirically established steps like time series decomposition, normalization, and channel-independent modeling.

PatchTST [Nie *et al.*, 2023] showed that transformers can be effective for forecasting if the input time series is patched or segregated in multiple windows, and subsequently, modeled by a transformer. The patching operation helps preserve local semantic information, accommodates a longer history, and reduces computation time. The PatchTST model outperformed all prior transformer-based models and the DLinear model.

Although PatchTST reinstated faith in transformers for time series modeling, transformer-based models are generally resource-intensive, with slow execution and a high memory footprint. The recently proposed TSMixer model [Ekambaram *et al.*, 2023] addresses these challenges effectively.

TSMixer, built on the MLP Mixer architecture [Tolstikhin *et al.*, 2021], stands out for its exceptional speed and lightweight design. It has attained state-of-the-art (SOTA) performance on benchmark datasets, demonstrating a 2-3X reduction in both execution time and memory usage.

Pre-trained Models for Time Series

One major drawback of all the above models is that they need to be trained in-domain. Hence, none of these models can be transferred to out-of-domain data with zero or minimal training. This approach has been found to be extremely beneficial in the natural language processing (NLP) domain with the invention of BERT [Devlin *et al.*, 2018] and GPT [Radford *et al.*, 2018] models.

However, this is an extremely challenging task in the time series domain because of the unavailability of a publicly accessible large pre-training corpora. There are multiple independent time series datasets, but, unlike in NLP, these datasets differ significantly in important characteristics such as the domain of the data (e.g., retail, sensor data, traffic, etc.), the number of channels, temporal resolution, and length. This makes it hard to train a single model on all the datasets together.

Hence, a few prior works have focused on experimenting with *same-dataset* self-supervised learning for time series [Li *et al.*, 2023; Wang *et al.*, 2022; Woo *et al.*, 2022; Yue *et al.*, 2022]. These methods learn a time series representation from the *train* split of a dataset, build a forecaster on top of the learned representation on the same data, and then evaluate it on the *test* split of the same dataset. Although these approaches have demonstrated promising results, they do not provide evidence of the transfer capability of the model between datasets.

Recent works such as SimMTM [Dong *et al.*, 2023] and TF-C [Zhang *et al.*, 2022] have demonstrated the transfer capabilities of their models between pairs of datasets. These pairs are carefully chosen so that the *source* (the dataset where the model is pre-trained) and *target* (the dataset where the model is fine-tuned and tested) datasets share some matching properties. For instance, SimMTM showcased its few-shot capability by selecting ETTH2 as the source data and ETTH1 as the target data. Both ETTH1 and ETTH2 are collected from Electricity Transformers at two stations, denoting data from a similar domain. TF-C demonstrated the transferability of the model across four different (source, target) pairs, such as (ECG, EMG) and (FD-A, FD-B), where domain-similarity exists in both the source and target datasets.

Pre-trained LLMs for Time Series

To tackle the aforementioned challenges, there has been a notable increase in the adoption of pre-trained large language models (LLMs) for time series tasks. These models are approached as cross-domain transfer learning problems. The LLMTime model [Gruver *et al.*, 2023] feeds the

time series values as text representations and demonstrates promising performance in a zero-shot setting. The GPT4TS model [Zhou *et al.*, 2023] adopts a pre-trained LLM like GPT and fine-tunes only the input embedding layer, normalization layers, and output layer. Specifically, it does not alter the self-attention weights and feed-forward layers. This approach to building a pre-trained model for time series from LLMs is promising, but it does not model cross-channel correlations observed in many multivariate time series datasets. Moreover, these LLMs are very large and exhibit slow execution and a large memory footprint.

A.2 TSMixer Background

We employed TSMixer [Ekambaram *et al.*, 2023] as a building block for the proposed TTM model due to its state-of-the-art performance, faster execution, and significantly lower memory usage. However, as explained in the main paper, vanilla TSMixer cannot be trained on multiple diverse datasets. Therefore, it necessitated the incorporation of the proposed novel components. In this section, we provide a high-level overview of the TSMixer model for a simpler and quicker understanding by the readers.

TSMixer is a lightweight alternative to transformer-based time series models, with no compromise on forecast accuracy. TSMixer adopts some well-established pre-processing steps from the literature, such as normalization and patching. Additionally, it offers the flexibility of enabling or disabling channel mixing. Channel mixing has been found to be beneficial in handling multivariate datasets with cross-channel correlations. For the main learning process, TSMixer employs a series of MLPMixer [Tolstikhin *et al.*, 2021] blocks that perform inter-patch, intra-patch, and inter-channel mixing operations. A mixing operation in TSMixer ensures learning correlations across a specific dimension. For example, inter-channel mixing enables it to learn cross-channel correlations. In the experiments, we employed three different flavors of the TSMixer model: TSMixer vanilla, TSMixer with cross-channel mixing enabled (TSMixer-CM), and TSMixer with cross-channel reconciliation head (TSMixer-CC). We request the authors to refer to [Ekambaram *et al.*, 2023] for further details about these variants.

A.3 List of Pre-training Datasets

We employ a subset of the datasets available in the Monash forecasting data repository [Godahewa *et al.*, 2021] available at <https://forecastingdata.org/>. Since our primary focus in this study is long term forecasting with forecast length ranging from 96 to 720, it is not possible to use yearly, monthly, quarterly, or weekly datasets due to their short lengths. Hence, we skip a few datasets of short lengths. The final list of all pre-training datasets is shown in Table 13.

Temporal cross validation [Jati *et al.*, 2023] is used to chronologically split all the time series into train and validation parts. During pre-training, moving windowing technique is used to create (X, Y) pairs of lengths sl and fl respectively. During pre-training, the total number of train and validation samples (i.e., number of (X, Y) pairs) are 244M and 71M respectively. Please note that, these pre-training datasets have no overlap with the evaluation datasets.

In specific, the `australian_electricity_demand_dataset` and `australian_weather_dataset` used in pre-training are completely different (*w.r.t* location, measured variables, type, resolution, length, etc.) from the standard Electricity (ECL) and Weather dataset used in the evaluation.

A.4 List of Evaluation Datasets

Table 14 illustrates various characteristics of the eleven evaluation datasets. Below, we present the details.

Set D1

For zero/few/full-shot evaluation, we utilize seven multivariate time series datasets that have consistently been employed in the literature. Below, we offer a brief overview of these datasets.

1. **ETT datasets:** The four ETT datasets [Zhou *et al.*, 2021] (ETTH1, ETTH2, ETTM1, ETTM2) contain multivariate time series data collected from electrical transformers at two stations. ETTH1 and ETTH2 are collected at an hourly interval, while ETTM1 and ETTM2 are collected every 15 minutes. All four datasets have 7 channels.
2. **Weather:** The weather dataset consists of 21 channels, which serve as weather indicators. It is collected at 10-minute intervals at the Max Planck Institute of Biogeochemistry weather station.
3. **Electricity (ECL):** The Electricity dataset, also known as the ECL dataset, comprises the hourly electricity consumption data of 321 clients.
4. **Traffic:** This dataset records the hourly rates of road occupancy on the San Francisco Freeways using 862 sensors.

We used the datasets provided in the repository of the Autoformer paper [Wu *et al.*, 2021]⁵. For all the D1 datasets, we execute the same train/validation/test splitting as was performed in the literature [Zhou *et al.*, 2021; Wu *et al.*, 2021; Nie *et al.*, 2023; Ekambaram *et al.*, 2023].

Set D2

To assess the effectiveness of the proposed TTM model in extracting information from exogenous channels, we conduct evaluations on four additional datasets that are known to contain exogenous or control variables.

1. **Bike Sharing (BS):** The Bike Sharing dataset [Fanaee-T, 2013] documents the hourly rental counts of bikes from the Capital Bikeshare system in Washington D.C., USA, spanning the years 2011 to 2012. Rental counts are typically associated with environmental and seasonal conditions. Consequently, this 14-channel dataset encompasses various weather-related features. Our goal was to forecast all three rental counts: “casual”, “registered”, and “cnt” (total count). As the remaining 11 features are consistently available at all future time points, they are treated as exogenous variables in our experiment.

⁵Available at <https://github.com/thuml/Autoformer>

Dataset	Resolution
solar_10_minutes_dataset.tsf	10_minutes
australian_electricity_demand_dataset.tsf	half_hourly
solar_4_seconds_dataset.tsf	4_seconds
wind_4_seconds_dataset.tsf	4_seconds
us_births_dataset.tsf	daily
saugeenday_dataset.tsf	daily
sunspot_dataset_without_missing_values.tsf	daily
australian_weather_dataset.tsf	daily
kdd_cup_2018_dataset_without_missing_values.tsf	hourly
bitcoin_dataset_without_missing_values.tsf	daily
wind_farms_minutely_dataset_without_missing_values.tsf	minutely
australian_electricity_demand_dataset_downsample_2.tsf	hourly
solar_4_seconds_dataset_downsample_225.tsf	15_minutes
wind_4_seconds_dataset_downsample_900.tsf	hourly
london_smart_meters_dataset_without_missing_values_downsample_2.tsf	hourly
solar_4_seconds_dataset_downsample_900.tsf	hourly
wind_farms_minutely_dataset_without_missing_values_downsample_10.tsf	10_minutes
solar_10_minutes_dataset_downsample_6.tsf	hourly
wind_4_seconds_dataset_downsample_150.tsf	10_minutes
wind_farms_minutely_dataset_without_missing_values_downsample_15.tsf	15_minutes
solar_4_seconds_dataset_downsample_150.tsf	10_minutes
wind_4_seconds_dataset_downsample_225.tsf	15_minutes
wind_farms_minutely_dataset_without_missing_values_downsample_60.tsf	hourly

Table 13: List of pre-training datasets. Datasets with “_downsample.X.tsf” suffix denotes an augmented dataset created from the original dataset by downsampling the latter. Please note that, these pre-training datasets have no overlap with the evaluation datasets. Specifically, the `australian_electricity_demand_dataset` and `australian_weather_dataset` used in pre-training are completely different (*w.r.t* location, measured variables, type, resolution, length, etc.) from the standard Electricity (ECL) and Weather dataset used in the evaluation.

2. **Carbon Capture Plant (CC):** The Carbon Capture Plant data [Jablonka *et al.*, 2023] records the emission profiles of “2-amino-2-methyl-1-propanol” (AMP) and “piperazine” (Pz) collected at every 2 minutes interval. We utilize the 8-channel dataset made available in the official repository of [Jablonka *et al.*, 2023]. Among the remaining 6 channels, the following 5 serve as control variables: [“TI-19”, “FI-19”, “TI-3”, “FI-11”, “TI-1213”]. The remaining 1 variable is treated as a conditional variable (as it is neither a target variable nor available during the forecast period to consider it as exogenous). For additional details, please refer to the supplementary materials of [Jablonka *et al.*, 2023].
3. **Service (SER):** This dataset pertains to the cloud-based “Stan’s Robot Shop” application, managed by Instana. It simulates a user’s e-commerce experience, encompassing site access to shipping, utilizing a load generator. Intermittent fault injection introduces diverse IT events. The dataset provides business KPIs for services (e.g., payment, catalog) and IT events tracked by Instana. Sampling occurs every 10 seconds due to high traffic and event frequency. For our experiments, all business KPIs are treated as target variables and IT events are treated as exogenous variables and the goal of our forecasting is to predict the business KPIs given the IT events.
4. **Application (APP):** This dataset is similar to the SER data, but it captures KPIs for the entire application in-

stead of capturing at the service level. Even in this case, all business KPIs are treated as target variables and IT events are treated as exogenous variables and the goal of our forecasting is to predict the business KPIs given the IT events.

A.5 Baseline Implementation Details

We report the implementation details for all the baselines in Table 15.

A.6 TTM Source Code and Implementation Details

Pre-training

For our experiments, we build 5 pre-trained models using the Monash datasets for the following (sl, fl) configurations: (512,96), (512,192), (512, 336), (512,720) and (96,24). Since our pre-trained models are very small, they can be trained quickly in a few hours (4-8 hrs based on fl length), as opposed to several days/weeks in standard approaches. Hence, pre-training multiple TTM models is no longer a practical constraint. Pre-training is performed in a distributed fashion with 50 CPUs and 6 NVIDIA A100 GPUs with 40 GB GPU memory. Based on the sl and fl requirement of the target dataset, a suitable pre-trained model is selected to bootstrap the weights accordingly for fine-tuning. Other model configurations are as follows: patch length $pl = 64$ (when sl is 512) and 8 (when sl is 96), stride $s = pl$ (i.e. non-overlapping

Set	Dataset	Resolution	Length	Total #Channels	#Target variables	#Exog. variables	Source
D1	ETTH1	1 hour	17420	7	7	Not Applicable	https://github.com/zhouhaoyi/ETDataset/tree/main/ETT-small
	ETTH2	1 hour	17420				
	ETTM1	15 minutes	69680				
	ETTM2	15 minutes	69680				
	Weather	10 minutes	52696	21	21		https://www.bgc-jena.mpg.de/wetter/
	ECL	1 hour	26304	321	321		https://archive.ics.uci.edu/dataset/321/electricityloadaddiagrams20112014
	Traffic	1 hour	17544	862	862		https://pems.dot.ca.gov/
D2	BS	1 hour	17379	14	3	11	https://archive.ics.uci.edu/dataset/275/bike+sharing+dataset
	CC	2 minutes	5409	8	2	5	https://github.com/kjappelbaum/aeml/blob/main/paper/20220210_smooth_window_16.pkl
	APP	10 minutes	8834	39	4	35	https://github.com/BizITObs/BizITObservabilityData/tree/main/Complete/Time%20Series/RobotShop
	SER	10 minutes	8835	107	72	35	https://github.com/BizITObs/BizITObservabilityData/tree/main/Complete/Time%20Series/RobotShop

Table 14: Details of the evaluation datasets.

patches), number of patches $n = sl/pl$, number of levels in backbone $L = 6$, number of TTM blocks per level $M = 2$, number of decoder layers = 2, batch size $b = 3000$, number of epochs $ep = 20$, and dropout $do = 0.2$. TSMixer-specific hyperparameters include feature scaler $fs = 3$, hidden feature size $hf = fs * pl$, expansion feature size $ef = hf * 2$. Please note that hf and n will change across TTM blocks based on the adaptive patching strategy. Resolution prefix tuning is disabled by default and enabled only for shorter context lengths (as explained in Table. 10). Decoder channel-mixing and exogenous mixer blocks are disabled during pre-training.

Fine-tuning

We have 2 sets of target datasets: D1 and D2 on which we fine-tune and test our performance. All D1 datasets use $sl = 512$ and fl is varied across $\{96, 192, 336, 720\}$ for zero/few-shot forecasting. Likewise, in D2 datasets, BS data use $sl = 512$ and $fl = 96$ and remaining datasets use $sl = 96$, $fl = 24$. In addition, head dropout is set to 0.7 for smaller ETT datasets and 0.2 for other datasets. Likewise, the batch size is set to 8 for Traffic, 32 for Electricity, and 64 for all other datasets. All other parameters remain the same as used in the pre-training. Also, Decoder channel-mixing and exogenous mixer block are enabled for the D2 datasets. Unlike pre-training, fine-tuning is executed in just 1 A100 GPU as it is a fast process. All these hyperparameters are selected based on the validation performance, and the final test results are reported in the paper.

Source Code

For more implementation details on the TTM model, please refer to the source code of the important classes used in TTM. We have anonymized the important Python class files and shared them in the same technical appendix zip file. Important

modules are listed below. The full project with complete reproducibility will be open-sourced on GitHub after the double-blind review.

- Class *TinyTimeMixerConfig* defines the required configuration.
- Class *TinyTimeMixerBlock* implements the basic TSMixer Block
- Class *ForecastChannelHeadMixer* implements Exogenous Mixer Block
- Class *TinyTimeMixerAdaptivePatchingBlock* implements the Adaptive Patching strategy
- Class *TinyTimeMixerDecoder* implements the TTM Decoder
- Class *TinyTimeMixerForPredictionHead* implements the Forecasting Head
- Class *TinyTimeMixerPreTrainedModel* implements the pretraining model interfaces.
- Class *TinyTimeMixerPatchify* implements the required patching.
- Class *TinyTimeMixerEncoder* implements the TTM Backbone
- Class *TinyTimeMixerModel* implements the TTM Model wrappers.

A.7 Computational Benefits of TTM over GPT4TS: Setup details

Table 2 compares the computational benefits of TTM over GPT4TS, the most popular LLM-TS model and the current

best SOTA in a few-shot setting. This section explains the experimental setup followed to enable this comparison. To execute GPT4TS with the best parameters, we used their official implementation as mentioned in Table 15. For a fair comparison, we run both models with the best-reported parameters in a single A100 GPU environment. Multi-GPU is avoided in this experiment to avoid IPC overheads for precise metric measurements. Since GPT4TS processes data in a purely univariate fashion while TTM fine-tuning processes data in a multi-variate fashion, we set the batch size accordingly to ensure that the number of univariate samples processed in each batch is the same for both models. For example, in TTM, if the batch size is set to 64, it implies processing 64 multi-variate time series in a batch. Consequently, the equivalent batch size for GPT4TS (which process only univariate samples) is $64 \times c$, where c represents the number of channels in the dataset. Additionally, due to GPT4TS encountering out-of-memory (OOM) errors with the default high batch sizes used in TTM, we employed reduced batch sizes for this experiment. The following batch sizes were utilized for TTM: Weather (64), Electricity (8), and Traffic (2). The corresponding batch sizes for GPT4TS can be calculated by multiplying the TTM batch size with the channel counts of the respective dataset. Since Traffic and Electricity have very high number of channels, we had to significantly reduce its batch size for a consistent comparison across models.

A.8 Full tables

Here, we present the complete versions of various tables in the main paper. These full versions essentially include the test results for multiple forecast lengths (fl) across all datasets. Occasionally, these results are averaged across forecast lengths to conserve space in the main paper.

Full table for 10% few-shot experiment

Table 16 shows the 10% few-shot results for all forecast lengths across all D1 datasets.

Full table for validating effect of pre-training

Table 17 shows the effect of pre-training when compared to random initialization of the model weights across all D1 datasets for all forecast lengths.

Full table for validating adaptive patching

Table 18 provides a comprehensive overview, systematically validating the impact of adaptive patching across all D1 datasets and forecast lengths.

Full table for validating effect of downsampling

Table 19 offers a comprehensive summary, systematically validating the influence of dataset augmentation through downsampling across all D1 datasets and forecast lengths (96 and 192).

Category	Baseline	Used in Table	Results Generated From	Link to the used implementation
(a) LLM-based pre-trained TS models	GPT4TS	Few-shot 5% in Table 1	Result from [Zhou <i>et al.</i> , 2023] Table 12	N/A
	GPT4TS	Runtime: Table 2	Ran Official Implementation	GPT4TS Repository: https://github.com/DAMO-DI-ML/NeurIPS2023-One-Fits-All
	GPT4TS	Few-shot 10% in Table 4	Result from [Zhou <i>et al.</i> , 2023] Table 13	N/A
	GPT4TS	Exogeneous in Table 6	Ran Official Implementation	GPT4TS Repository: https://github.com/DAMO-DI-ML/NeurIPS2023-One-Fits-All
	LLMTime	Table 5	Result from LLMTime Repository	LLMTime Repository: https://github.com/ngruver/llmtime Result File: https://github.com/ngruver/llmtime/blob/main/precomputed_outputs/deterministic_csvs/autoformer_comb_results.csv
(b) Self-supervised pre-trained models	SimMTM	Table 3	Directly reported from SimMTM paper	N/A
	Ti-MAE			
	TST			
	LaST			
	TF-C			
	CoST			
	TS2Vec			
(c) TS transformer models	PatchTST	Few-shot 5% and 10% in Table 1 and 4	Result from [Zhou <i>et al.</i> , 2023] Table 12, 13	PatchTST Repository: https://github.com/yuqinie98/PatchTST
	FEDFormer			N/A
	Autoformer			N/A
(d) Other SOTA Models	TSMixer		Used Official Implementation	TSMixer Implementation: https://huggingface.co/docs/transformers/model_doc/patchtsmixer
	DLinear		Result from [Zhou <i>et al.</i> , 2023] Table 12, 13	N/A
	TimesNet		Result from [Zhou <i>et al.</i> , 2023] Table 12, 13	N/A
(e) Concurrent Works	Time-LLM	Table 11	Result from [Jin <i>et al.</i> , 2024] Table 3,4	N/A
	UniTime	Table 12	Results from [Liu <i>et al.</i> , 2024] Table 5	N/A

Table 15: Implementation details for the baseline algorithms.

	Zero-shot		Few-shot (10%)							
	FL	TTM (Ours)	TTM (Ours)	GPT4TS	PatchTST	TSMixer	TimesNet	Dlinear	FEDFormer	Autoformer
ETTH1	96	0.365	<u>0.374</u>	0.458	0.516	0.472	0.861	0.492	0.512	0.613
	192	0.393	0.388	0.570	0.598	0.538	0.797	0.565	0.624	0.722
	336	<u>0.415</u>	0.395	0.608	0.657	0.604	0.941	0.721	0.691	0.750
	720	0.538	0.533	0.725	0.762	0.698	0.877	0.986	0.728	0.721
ETTH2	96	<u>0.285</u>	0.284	0.331	0.353	0.288	0.378	0.357	0.382	0.413
	192	<u>0.341</u>	0.335	0.402	0.403	0.370	0.490	0.569	0.478	0.474
	336	0.383	0.383	0.406	0.426	0.400	0.537	0.671	0.504	0.547
	720	0.441	0.439	0.449	0.477	0.422	0.510	0.824	0.499	0.516
ETTM1	96	0.413	<u>0.377</u>	0.390	0.410	<u>0.373</u>	0.583	0.352	0.578	0.774
	192	0.476	0.424	0.429	0.437	<u>0.413</u>	0.630	0.382	0.617	0.754
	336	0.553	<u>0.424</u>	0.469	0.476	<u>0.451</u>	0.725	0.419	0.998	0.869
	720	0.737	0.606	0.569	0.681	<u>0.527</u>	0.769	0.490	0.693	0.810
ETTM2	96	0.187	0.173	0.188	0.191	<u>0.185</u>	0.212	0.213	0.291	0.352
	192	0.261	0.237	<u>0.251</u>	0.252	<u>0.251</u>	0.270	0.278	0.307	0.694
	336	0.323	<u>0.303</u>	<u>0.307</u>	0.306	0.302	0.323	0.338	0.543	2.408
	720	0.436	0.400	0.426	0.433	0.392	0.474	0.436	0.712	1.913
Weather	96	0.154	0.148	0.163	0.165	0.159	0.184	0.171	0.188	0.221
	192	<u>0.203</u>	0.194	0.210	0.210	0.206	0.245	0.215	0.250	0.270
	336	<u>0.256</u>	0.245	<u>0.256</u>	0.259	<u>0.256</u>	0.305	0.258	0.312	0.320
	720	<u>0.329</u>	0.320	<u>0.321</u>	0.332	<u>0.321</u>	0.381	0.320	0.387	0.390
Electricity	96	0.169	0.139	0.139	<u>0.140</u>	0.141	0.299	0.150	0.231	0.261
	192	0.196	<u>0.157</u>	0.156	0.160	0.158	0.305	0.164	0.261	0.338
	336	0.209	<u>0.179</u>	0.175	0.180	0.182	0.319	0.181	0.360	0.410
	720	0.264	0.244	<u>0.233</u>	0.223	0.238	0.369	0.223	0.530	0.715
Traffic	96	0.518	0.398	0.414	0.403	0.404	0.719	0.419	0.639	0.672
	192	0.548	0.415	0.426	0.415	<u>0.419</u>	0.748	0.434	0.637	0.727
	336	0.550	0.422	0.434	0.426	<u>0.425</u>	0.853	0.449	0.655	0.749
	720	0.605	0.477	0.487	0.474	0.469	1.485	0.484	0.722	0.847

Table 16: Zero-shot and Few-shot 10% performance (MSE) on TTM and all SOTA models on seven datasets for varying forecast lengths (fl). The numbers with bold and underscore denote the best the second best results respectively.

	FL	Zero-shot		Few-shot (5%)				Few-shot (10%)			
		RI	PT	5 Epochs		50 Epochs		5 Epochs		50 Epochs	
		RI	PT	RI	PT	RI	PT	RI	PT	RI	PT
ETTH1	96	0.737	0.365	0.671	0.366	0.548	0.366	0.599	0.372	0.434	0.374
	192	0.737	0.393	0.682	0.392	0.666	0.391	0.626	0.388	0.492	0.388
	336	0.731	0.415	0.708	0.408	0.674	0.421	0.621	0.399	0.588	0.395
	720	0.735	0.538	-	-	-	-	0.716	0.516	0.695	0.533
ETTH2	96	0.380	0.285	0.354	0.283	0.342	0.282	0.293	0.284	0.287	0.284
	192	0.392	0.341	0.391	0.337	0.404	0.338	0.374	0.331	0.368	0.335
	336	0.394	0.383	0.390	0.382	0.390	0.383	0.390	0.380	0.399	0.383
	720	0.432	0.441	-	-	-	-	0.428	0.434	0.424	0.439
ETTM1	96	0.707	0.413	0.367	0.384	0.345	0.359	0.352	0.388	0.354	0.377
	192	0.716	0.476	0.446	0.417	0.378	0.402	0.401	0.408	0.378	0.424
	336	0.726	0.553	0.440	0.463	0.423	0.424	0.425	0.437	0.408	0.424
	720	0.737	0.737	0.641	0.668	0.645	0.575	0.505	0.598	0.471	0.606
ETTM2	96	0.296	0.187	0.203	0.175	0.190	0.174	0.187	0.174	0.178	0.173
	192	0.325	0.261	0.258	0.237	0.247	0.240	0.244	0.231	0.236	0.237
	336	0.360	0.323	0.313	0.295	0.309	0.299	0.297	0.292	0.289	0.303
	720	0.430	0.436	0.411	0.391	0.412	0.407	0.390	0.388	0.392	0.400
Weather	96	0.277	0.154	0.181	0.153	0.179	0.152	0.165	0.150	0.161	0.148
	192	0.302	0.203	0.241	0.201	0.229	0.198	0.209	0.192	0.210	0.194
	336	0.331	0.256	0.280	0.253	0.283	0.250	0.262	0.252	0.258	0.245
	720	0.375	0.329	0.367	0.325	0.367	0.326	0.322	0.321	0.324	0.32
Electricity	96	0.874	0.169	0.212	0.147	0.148	0.142	0.181	0.144	0.141	0.139
	192	0.874	0.196	0.260	0.174	0.174	0.162	0.192	0.164	0.157	0.157
	336	0.893	0.209	0.273	0.187	0.192	0.184	0.225	0.183	0.179	0.179
	720	0.917	0.264	0.678	0.245	0.282	0.228	0.281	0.251	0.237	0.244
Traffic	96	1.434	0.518	0.504	0.421	0.413	0.401	0.432	0.405	0.402	0.398
	192	1.438	0.548	0.539	0.457	0.428	0.425	0.495	0.423	0.420	0.415
	336	1.460	0.550	0.736	0.485	0.482	0.437	0.488	0.435	0.426	0.422
	720	1.481	0.605	-	-	-	-	0.531	0.520	0.471	0.477

Table 17: Effect of pre-training (PT) when compared to random initialization (RI) of model weights. MSE reported.

Data	FL	Zero-shot		Few-shot (10%)	
		Vanilla	Adaptive Patching	Vanilla	Adaptive Patching
ETTH1	96	0.369	0.365	0.367	0.374
	192	0.395	0.393	0.387	0.388
	336	0.457	0.415	0.408	0.395
	720	0.784	0.538	0.751	0.533
ETTH2	96	0.283	0.285	0.282	0.284
	192	0.346	0.341	0.345	0.335
	336	0.400	0.383	0.393	0.383
	720	0.470	0.441	0.469	0.439
ETTM1	96	0.446	0.413	0.38	0.377
	192	0.498	0.476	0.413	0.424
	336	0.598	0.553	0.515	0.424
	720	0.765	0.737	0.544	0.606
ETTM2	96	0.191	0.187	0.171	0.173
	192	0.268	0.261	0.232	0.237
	336	0.333	0.323	0.284	0.303
	720	0.447	0.436	0.400	0.400
Weather	96	0.159	0.154	0.149	0.148
	192	0.204	0.203	0.196	0.194
	336	0.261	0.256	0.249	0.245
	720	0.333	0.329	0.328	0.32
Electricity	96	0.179	0.169	0.138	0.139
	192	0.188	0.196	0.157	0.157
	336	0.220	0.209	0.181	0.179
	720	0.274	0.264	0.238	0.244
Traffic	96	0.521	0.518	0.410	0.398
	192	0.536	0.548	0.416	0.415
	336	0.559	0.550	0.422	0.422
	720	0.609	0.605	0.475	0.477

Table 18: Effect of adapting patching. MSE reported.

Data	FL	Zero-shot	
		Original data	With Downsampling
ETTH1	96	0.501	0.365
	192	0.706	0.393
ETTH2	96	0.309	0.285
	192	0.392	0.341
ETTM1	96	0.829	0.413
	192	0.876	0.476
ETTM2	96	0.222	0.187
	192	0.300	0.261
Weather	96	0.163	0.154
	192	0.208	0.203
Electricity	96	0.334	0.169
	192	0.514	0.196
Traffic	96	0.838	0.518
	192	0.958	0.548

Table 19: Effect of downsampling. MSE reported.