Using Time Series Foundation Models for Atmospheric CO_2 Concentration Forecasting

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Abstract

Recent advancements in foundation models for time series forecasting have outperformed traditional statistical and ML methods. In this study, we approach the problem of CO_2 concentration forecasting using time series foundation models (TSFMs). We extensively evaluate the performance of TSFMs under zero-shot and fine-tuned settings against popular traditional forecasting baselines and discuss the spatial transfer learning capability of TSFMs across diverse geographic locations.

1 Introduction

Accurate forecasting of atmospheric CO_2 is vital for informing climate policy, guiding emissions reduction strategies, and anticipating societal responses to future climate scenarios. Multiple measurements using ground sensors such as NOAA NOAA (2025), TCCON, etc. and satellite based observations such as GOSAT, GOSAT-2, OCO-2, OCO-3, Tansat etc. provide rich CO_2 concentration time series (TS) spanning diverse regions. Studies such as M. et al. (2024); Zhong et al. (2024) have used traditional autoregressive methods such as ARIMA and seasonal-ARIMA Kotu & Deshpande (2019) for forecasting CO_2 emissions. CO_2 forecasting at city and country scales using machine learning techniques are detailed in Li & Sun (2021); Li & Zhang (2023). Comparative analysis of CO_2 emission forecasting using various models concludes that ML and DL models outperform statistical models Ajala et al. (2025). However, these are bespoke models trained on CO_2 and correlated exogenous data for CO_2 forecasting.

In contrast, time series foundation models (TSFMs) pre-trained on public TS data have demonstrated generalizability in forecasting across multiple domains Ansari et al. (2024); Woo et al. (2024); Darlow et al. (2024); Goswami et al. (2024); Gao et al. (2024). They rely on the strengths of architecture to learn generalized representations of time-series data Ekambaram et al. (2024). While PRESTO Tseng et al. (2023) is a pretrained model for remote sensing TS, it is designed for representation learning rather than forecasting. We are unaware of prior work applying TSFMs to air quality or CO_2 forecasting. Building on this gap, TSFMs can leverage transfer learning capabilities to forecast in diverse locations by fine-tuning on data from just one location, thus enabling scalable and accurate CO_2 forecasting.

Key contributions of this paper are:

- Evaluating TSFMs to forecast CO_2 data from NOAA sensor in zero-shot & fine-tuned settings.
- Comparing TSFMs against traditional forecasting models, namely - Prophet, ThetaForecaster, and the Seasonal Naive model to assess their performance on CO_2 concentration forecasting.
- Evaluating the spatial transfer learning capability of TSFMs by using fine-tuned models (trained on NOAA sensor data) to forecast XCO_2 concentrations from satellite-based timeseries (OCO-2 and OCO-3 NASA (2025)) across various geographic regions.

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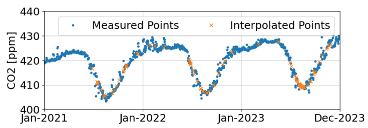
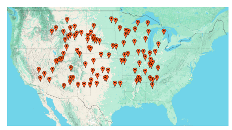
2 Methodology

2.1 Data

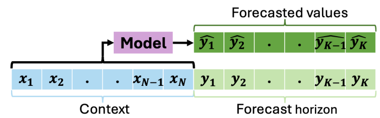
Ground-Based Observations: The CO_2 concentration data (unit: parts per million (ppm)) used is measured at the NOAA/GML atmospheric baseline observatories located at Barrow, Alaska, US Thoning et al. (2024). At the time of writing this paper, the data was available from January-1974 to April-2024. In this paper, we used daily averaged CO_2 concentration. This dataset has around 10% missing values which were filled using interpolation to ensure data continuity for modeling as shown in Figure 1a.



(a) Sensor data at Barrow, Alaska



(b) 100 random points in USA.



(c) TSFMs use context $x_1, \ldots x_N$, to forecast $y_1, \ldots y_K$ as $\widehat{y_1}, \ldots, \widehat{y_K}$

Figure 1: Sensor data at Barrow observatory; Locations points chosen in USA; Working of TSFMs

Satellite-Based Data: We utilized daily XCO_2 data from Jan-2019 to Dec-2023, derived from a model based on OCO-2 & OCO-3 observations Das et al. (2023), covering continental USA. This model uses satellite observations with meteorological covariates to produce daily gridded XCO_2 estimates at 10×10 km resolution Das et al. (2023). Since the available data was considerably less than the NOAA observations, we used this to assess the transfer learning capabilities of TSFMs. We randomly used 100 locations from USA to evaluate the fine-tuned models (Figure 1b).

Data Preparation: To prepare data for modeling, CO_2 concentration data is divided into chunks of context and forecast windows as illustrated in Figure 1c. The context is the initial sequence of data given to a TSFM to generate forecasts. Specifically, context length of 1024 daily observations and a forecast horizon of 365 days is used. This setup enables the model to generate forecasts for one full year and provides sufficient number of data points to generate statistically significant results.

Training Setup: The chunks of data are split into training, validation, and test sets. A common training set of daily observations from 1974 to 2013 is used in the fine-tuning setting to train the TSFMs while the next five years' data is used to evaluate the performance during training. The test set, from 2019 to 2023, is used for forecasting and remains unseen by the models during training. In the zero-shot setting, a pretrained model directly forecasts on the test set without any fine-tuning. All reported error metrics and visualizations in this study are based on the test set performance.

2.2 Models

In this study, we primarily focus on the pre-trained TSFM - Tiny Time Mixer (TTM) Ekambaram et al. (2024) for CO_2 concentration forecasting. TTM is a compact model with only 1M parameters based on the light-weight TSMixer Chen et al. (2023) architecture. It has been pre-trained exclusively on public TS datasets and shows excellent transfer learning capabilities.

The forecasting performance of TTM is evaluated against other state-of-the-art TSFMs - Chronos Ansari et al. (2024) and TimesFM Das et al. (2024). Additionally, we use the Seasonal Naive Forecaster, ThetaForecaster Assimakopoulos & Nikolopoulos (2000), and Prophet Taylor & Letham (2018) as baselines for forecasting.

2.3 Experiments

Our experimental setup is designed to evaluate the performance of both traditional forecasting models and TSFMs under various settings. We also explore how well the TSFMs generalize across spatial domains and assess the benefits of transfer learning.

Traditional Models: We evaluated widely-used traditional TS forecasting models — ThetaForecaster, Seasonal Naive, and Prophet — on the NOAA sensor data. These models were trained and tested

Table 1: Experimental setup for atmospheric CO_2 forecasting

Dataset	Model		Parameters	Transfer Learning
CO_2 data from NOAA ground sensor, Barrows, Alaska, USA for 1974 to 2023	TTM	TSFMs are evaluated in two settings for Alaska location: 1. Zero-Shot (ZS) 2. Fine-Tuning (FT)	Context: 1024, Forecast: 365	Fine-tuned model on Alaska data is evaluated on CO_2 derived from satellite for 2019-2023 for 100 locations in USA
	Chronos			
	TimesFM			
	Prophet forecaster		Default params	Transfer learning is not applicable for traditional machine learning models
	Theta forecaster		`sp = 365`	
	Seasonal naive forecaster			

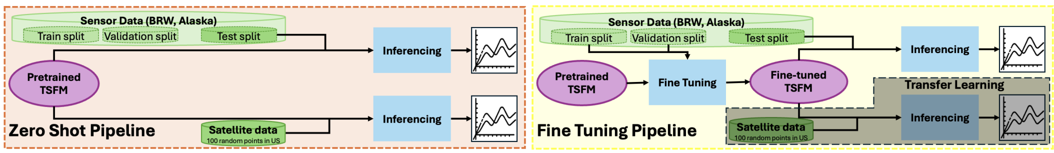


Figure 2: Pipelines for zero-shot forecasting, model fine-tuning and transfer learning

solely on this dataset to establish baseline performance in the same-region and same-distribution setting. We used `sktime` Löning et al. (2019), a Python-based unified framework for machine learning with TS, to implement the baselines and TTM. While Chronos and TimesFM were implemented using their respective github repositories as detailed in Table A1 (Appendix).

TSFM Pipelines: We adopt two evaluation pipelines for TSFMs: zero-shot & fine-tuning (Figure 2).

- **Zero-Shot (ZS) Evaluation:** In this setting, we directly evaluate pre-trained (raw) TSFMs without any task-specific training. This evaluation is performed on the NOAA sensor data to assess the models' generalization capabilities to a new domain, that is, CO_2 forecasting.
- **Fine-Tuning (FT) and Transfer Learning:** In this pipeline, TSFMs are fine-tuned using the train split of NOAA sensor data. We then evaluate performance on:
  1. Test split of NOAA data to quantify improvements through fine-tuning on in-domain data.
  2. OCO-2/OCO-3 derived XCO_2 data Das et al. (2023), to evaluate transfer learning effectiveness – the ability of models fine-tuned on one region to generalize across diverse locations.

For each of the TSFMs we choose 1024 as the context length and 365 as the forecast horizon as mentioned in Sec. 2.1. Summary of the experimental setup is provided in Table 1.

2.4 Evaluation Metrics

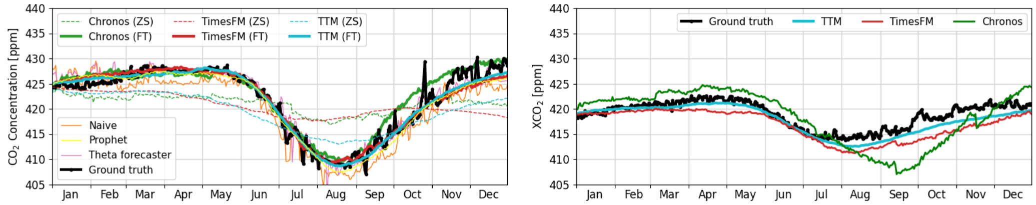
To evaluate model performance, we report widely used error metrics for TS forecasting (1) Root Mean Squared Error (RMSE), (2) Mean Absolute Error (MAE) and (3) Mean Absolute Scaled Error (MASE) Hyndman & Koehler (2006). Equations A1 define these metrics, using the same notations as illustrated earlier in Fig. 1c. For MASE, s is the seasonality of the data. This is set to be the same as the `sp=365` parameter shown in Table 1, since the data follows a yearly seasonal cycle.

3 Results

Tables 2 and Figure 3 present the results obtained using the experimental setup described in Sec. 2.3. We now discuss the results in more details.

3.1 Traditional Machine Learning Models vs. Time Series Foundation Models

We compare the performance of traditional time series models (Seasonal Naive, ThetaForecaster, and Prophet) with TSFMs, namely, TTM, Chronos, and TimesFM under both zero-shot and fine-tuned configurations in Table 2 (*Left*). Among the traditional models, Prophet achieves the lowest MASE error of 46%. This may be attributed to its capacity to model both linear trends and strong yearly seasonality, which are characteristic of the NOAA CO_2 dataset. In comparison, the ThetaForecaster,



(a) CO_2 for NOAA sensor data, Alaska (b) Transfer learning: XCO_2 for OCO-2/3 derived data

Figure 3: Comparison of forecast of CO_2 concentration [ppm] from different experiments for 2023.

Table 2: *Left:* Traditional ML and TSFMs (zero-shot & fine-tune) for NOAA data, *Right:* Inference of fine-tuned TSFM model on XCO_2 from OCO2/3 data. (**best score**, second-best scores)

	Baselines			**Chronos**		**TimesFM**		**TTM**	
	Theta	Naive	Prophet	ZS	FT	ZS	FT	ZS	FT
RMSE	1.85	2.84	1.72	5.16	2.04	5.65	1.55	4.36	**1.37**
MAE	1.33	2.40	1.31	4.59	1.54	4.91	1.09	3.81	**0.95**
MASE	0.47	0.84	0.46	1.61	0.54	1.72	0.38	1.34	**0.34**

	Transfer Learning		
	Chronos	TimesFM	TTM
RMSE	3.63	2.49	**1.46**
MAE	2.93	2.13	**1.19**
MASE	1.20	0.87	**0.49**

while robust and computationally efficient, provides limited adaptability to complex seasonal patterns. The Seasonal Naive model, which simply repeats values from the previous year, serves as a baseline and performs worst among the traditional approaches. When evaluating the TSFMs, TTM consistently outperforms other TSFMs in both fine-tuned and zero-shot settings. Fine-tuned TTM achieves the overall lowest MASE of 34% among all models, including traditional models. In the zero-shot setting, TTM's performance drops but still outperforms other TSFMs in zero-shot setting.

3.2 Zero-shot vs. Fine-tuned TSFM Performance

We assess the forecasting capabilities of TSFMs in both zero-shot and fine-tuned configurations on the NOAA sensor data, with results shown in Figure 3a and Table 2 (Left). Importantly, this dataset was not part of the pretraining corpus for any of the evaluated TSFMs, allowing us to assess their ability to generalize to new domains. Across the TSFMs, fine-tuning significantly improves forecasting over zero-shot with TTM achieving least MASE of 34%. The performance gap between zero-shot and fine-tuned models reflects the role of domain adaptation in improving forecasting accuracy.

3.3 Generalization Across 100 Random Locations Through Transfer Learning

TTM, fine-tuned on the NOAA sensor data, demonstrates strong generalization ability over the satellite-derived data. It consistently outperforms other foundation models across all metrics for 99 out of 100 randomly selected locations from continental USA, suggesting robustness to domain shifts and the effectiveness of its learned temporal representations. As shown in Figure 3b and Table 2 (*Right*), for one of the locations, it achieves 1.46 ppm as RMSE, 1.19 ppm as MAE, and a MASE of 49%. Transfer learning results for all 100 location is presented in Table A2 (Appendix).

4 Conclusion

In this study, we have evaluated the zero-shot and fine-tuned performance of several pre-trained time series foundation models: TTM, Chronos, and TimesFM against traditional baselines for the task of CO_2 concentration forecasting using data from ground sensors as well as satellite-based models. Overall, TTM achieves the best performance across all metrics, followed by TimesFM. We also demonstrate TTM's ability to learn effective temporal representations making it robust to domain shifts across different geographies. We illustrate the strong potential of TSFMs in the fields of climate monitoring and remote sensing. As future work, we plan to include relevant exogenous variables to augment the fine-tuning performance, thereby, enabling comprehensive learning.

References

Adewole Adetoro Ajala, Oluwatosin Lawrence Adeoye, Olawale Moshood Salami, and Ayoola Yusuf Jimoh. An examination of daily co2 emissions prediction through a comparative analysis of machine learning, deep learning, and statistical models. Environ Sci Pollut Res, 2025. URL `https://doi.org/10.1007/s11356-024-35764-8`.

Abdul Fatir Ansari, Lorenzo Stella, Caner Turkmen, Xiyuan Zhang, Pedro Mercado, Huibin Shen, Oleksandr Shchur, Syama Sundar Rangapuram, Sebastian Pineda Arango, Shubham Kapoor, et al. Chronos: Learning the language of time series. arXiv preprint arXiv:2403.07815, 2024.

Vassilis Assimakopoulos and Konstantinos Nikolopoulos. The theta model: a decomposition approach to forecasting. International journal of forecasting, 16(4):521–530, 2000.

Si-An Chen, Chun-Liang Li, Nate Yoder, Sercan O. Arik, and Tomas Pfister. Tsmixer: An all-mlp architecture for time series forecasting, 2023. URL `https://arxiv.org/abs/2303.06053`.

Luke Darlow, Qiwen Deng, Ahmed Hassan, Martin Asenov, Rajkarn Singh, Artjom Joosen, Adam Barker, and Amos Storkey. Dam: Towards a foundation model for time series forecasting. arXiv preprint arXiv:2407.17880, 2024.

Abhimanyu Das, Weihao Kong, Rajat Sen, and Yichen Zhou. A decoder-only foundation model for time-series forecasting. In Forty-first International Conference on Machine Learning, 2024.

Kamal Das, Ranjini Guruprasad, and Manikandan Padmanaban. Machine learning based estimation of column averaged co2 from oco-2 satellite data. In IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, pp. 1444–1447, 2023. doi: 10.1109/IGARSS52108.2023.10283342.

Vijay Ekambaram, Arindam Jati, Pankaj Dayama, Sumanta Mukherjee, Nam H Nguyen, Wesley M Gifford, Chandra Reddy, and Jayant Kalagnanam. Tiny time mixers (ttms): Fast pre-trained models for enhanced zero/few-shot forecasting of multivariate time series. CoRR, 2024.

Shanghua Gao, Teddy Koker, Owen Queen, Thomas Hartvigsen, Theodoros Tsiligkaridis, and Marinka Zitnik. Units: Building a unified time series model. arXiv preprint arXiv:2403.00131, 2024.

Mononito Goswami, Konrad Szafer, Arjun Choudhry, Yifu Cai, Shuo Li, and Artur Dubrawski. Moment: A family of open time-series foundation models. arXiv preprint arXiv:2402.03885, 2024.

Rob J Hyndman and Anne B Koehler. Another look at measures of forecast accuracy. International journal of forecasting, 22(4):679–688, 2006.

Vijay Kotu and Bala Deshpande. Chapter 12 - time series forecasting. In Vijay Kotu and Bala Deshpande (eds.), Data Science (Second Edition), pp. 395–445. Morgan Kaufmann, second edition edition, 2019. ISBN 978-0-12-814761-0. URL `https://www.sciencedirect.com/science/article/pii/B9780128147610000125`.

Xiangqian Li and Xiaoxiao Zhang. A comparative study of statistical and machine learning models on carbon dioxide emissions prediction of china. Environ Sci Pollut Res, 30:19260–19271, 2023. URL `https://doi.org/10.1007/s11356-023-30428-5`.

Ying Li and Yanwei Sun. Modeling and predicting city-level co2 emissions using open access data and machine learning. Environ Sci Pollut Res, 28:19260–19271, 2021. URL `https://link.springer.com/article/10.1007/s11356-020-12294-7`.

Markus Löning, Anthony Bagnall, Sajaysurya Ganesh, Viktor Kazakov, Jason Lines, and Franz J Király. sktime: A unified interface for machine learning with time series. arXiv preprint arXiv:1909.07872, 2019.

Hrithik P. M., Mohd Ziaur Rehman, Amir Ahmad Dar, and Tashi Wangmo A. Forecasting co2 emissions in india: A time series analysis using arima. Processes, 12(12), 2024. ISSN 2227-9717. URL `https://www.mdpi.com/2227-9717/12/12/2699`.

NASA. Measuring co2 concentration, 2025. URL `https://earth.jpl.nasa.gov/resources/259/oco-2-oco-3/`.

NOAA. Co2 in-situ measurements, 2025. URL `https://gml.noaa.gov/obop/mlo/programs/esrl/co2/co2.html`.

Sean J Taylor and Benjamin Letham. Forecasting at scale. The American Statistician, 72(1):37–45, 2018.

K.W. Thoning, A.M. Crotwell, and J.W. Mund. Atmospheric carbon dioxide dry air mole fractions from continuous measurements at Mauna Loa, Hawaii, Barrow, Alaska, American Samoa and South Pole, 1973–present. version 2024-08-15. National Oceanic and Atmospheric Administration (NOAA), Global Monitoring Laboratory (GML), Boulder, Colorado, USA, 2024.

Gabriel Tseng, Ruben Cartuyvels, Ivan Zvonkov, Mirali Purohit, David Rolnick, and Hannah Kerner. Lightweight, pre-trained transformers for remote sensing timeseries. arXiv preprint arXiv:2304.14065, 2023.

Gerald Woo, Chenghao Liu, Akshat Kumar, Caiming Xiong, Silvio Savarese, and Doyen Sahoo. Unified training of universal time series forecasting transformers. arXiv preprint arXiv:2402.02592, 2024.

Weiyi Zhong, Dengshuai Zhai, Wenran Xu, Wenwen Gong, Chao Yan, Yang Zhang, and Lianyong Qi. Accurate and efficient daily carbon emission forecasting based on improved arima. Applied Energy, 376:124232, 2024. ISSN 0306-2619. URL https://www.sciencedirect.com/science/article/pii/S0306261924016155.

Appendix

Table A1: Details of TSFMs evaluated.

Model	**Model Source**	**Implementation Source**	**Params (M)**	**Input Length**
TimesFM	HuggingFace	Github	500	1024
TTM	HuggingFace	sktime	1	1024
Chronos	HuggingFace	Github	46	1024

$$\text{RMSE} = \sqrt{\sum_{k=1}^{K} \frac{\left(\widehat{y_k} - y_k\right)^2}{K}} \quad \text{MAE} = \sum_{k=1}^{K} \frac{\left|\widehat{y_k} - y_k\right|}{K} \quad \text{MASE} = \frac{\sum_{k=1}^{K} \frac{|y_k - \hat{y}_k|}{K}}{\sum_{n=s+1}^{N} \frac{|x_n - x_{n-s}|}{N-s}} \tag{A1}$$

Table A2: Transfer learning results for 100 locations selected in Figure 1b (**bold face: best results**)

	RMSE			**MAE**			**MASE**		
location ID	TTM	TimesFM	Chronos	TTM	TimesFM	Chronos	TTM	TimesFM	Chronos
mean ± std	2.15±0.27	3.02±0.34	4.42±1.35	1.92±0.31	2.72±0.39	3.30±0.61	0.75±0.12	1.07±0.15	1.30±0.24
1	**2.28**	3.42	4.41	**2.10**	3.21	3.12	**0.83**	1.27	1.24
2	**1.93**	2.57	4.51	**1.60**	2.19	3.31	**0.63**	0.86	1.30
3	**1.83**	2.57	3.72	**1.55**	2.19	2.50	**0.60**	0.84	0.96
4	**2.36**	3.43	4.71	**2.22**	3.28	3.47	**0.89**	1.31	1.38
5	**2.33**	3.42	4.52	**2.18**	3.16	3.43	**0.85**	1.23	1.33
6	**2.33**	3.29	4.13	**2.16**	3.06	3.22	**0.84**	1.19	1.25
7	**2.18**	3.10	4.84	**1.89**	2.67	3.89	**0.71**	1.01	1.47
8	**2.42**	3.47	3.65	**2.25**	3.21	2.88	**0.85**	1.22	1.10
9	**1.61**	2.65	4.57	**1.32**	2.25	3.32	**0.53**	0.90	1.32
10	**2.27**	3.19	15.65	**2.04**	2.94	3.69	**0.81**	1.17	1.46
11	**1.99**	2.57	3.94	**1.68**	2.19	2.75	**0.65**	0.85	1.07
12	**2.02**	2.78	4.05	**1.71**	2.36	3.10	**0.65**	0.90	1.18
13	**1.93**	2.69	4.68	**1.63**	2.30	3.43	**0.62**	0.87	1.30
14	**2.66**	3.37	4.32	**2.49**	3.18	3.18	**1.03**	1.31	1.31
15	**2.04**	2.81	4.10	**1.75**	2.40	3.22	**0.67**	0.92	1.23
16	**2.19**	3.05	5.01	**1.96**	2.72	3.70	**0.78**	1.08	1.47
17	**2.35**	3.26	4.83	**2.19**	3.01	3.44	**0.85**	1.16	1.33
18	**1.94**	2.67	5.82	**1.66**	2.36	4.58	**0.67**	0.95	1.85
19	**2.33**	3.06	5.06	**2.07**	2.74	3.59	**0.81**	1.08	1.41
20	**1.70**	2.25	3.78	**1.38**	1.94	2.87	**0.56**	0.78	1.16
21	**2.29**	3.34	4.47	**2.15**	3.12	3.28	**0.82**	1.19	1.25
22 (presented in table 2)	**1.46**	2.49	3.63	**1.19**	2.13	2.93	**0.49**	0.87	1.20
23	**1.81**	2.59	3.73	**1.49**	2.29	2.94	**0.61**	0.94	1.21
24	**2.39**	3.15	5.90	**2.18**	2.86	5.07	**0.85**	1.11	1.97
25	2.50	3.44	**2.45**	2.28	3.18	**2.01**	0.90	1.26	**0.80**
26	**1.81**	2.40	4.89	**1.53**	2.07	3.75	**0.62**	0.84	1.51
27	**1.97**	2.76	4.77	**1.67**	2.35	3.63	**0.64**	0.90	1.40
28	**1.85**	2.56	4.05	**1.58**	2.23	2.95	**0.63**	0.89	1.18
29	**2.15**	3.28	4.51	**2.01**	3.08	3.43	**0.80**	1.23	1.37
30	**2.48**	3.17	5.31	**2.35**	2.94	4.24	**0.90**	1.12	1.61
31	**2.54**	3.71	4.37	**2.40**	3.48	3.41	**0.92**	1.34	1.31
32	**2.09**	2.92	4.72	**1.81**	2.48	3.43	**0.69**	0.95	1.31
33	**1.73**	2.36	4.52	**1.43**	2.03	3.28	**0.58**	0.83	1.33
34	**1.72**	2.40	4.12	**1.42**	2.04	3.06	**0.58**	0.83	1.25
35	**2.36**	3.31	4.08	**2.19**	3.09	3.32	**0.86**	1.21	1.30
36	**2.59**	3.37	5.00	**2.43**	3.17	3.73	**0.99**	1.29	1.52
37	**2.25**	3.19	3.57	**2.04**	2.96	2.81	**0.81**	1.17	1.11
38	**2.25**	3.08	4.33	**1.99**	2.80	3.24	**0.79**	1.11	1.28
39	**2.23**	3.14	5.88	**1.93**	2.77	4.77	**0.73**	1.04	1.80
40	**1.83**	2.41	4.49	**1.51**	2.04	3.75	**0.61**	0.82	1.50
41	**2.29**	3.23	3.80	**2.01**	2.94	2.95	**0.81**	1.18	1.19
42	**1.61**	2.49	4.16	**1.32**	2.09	3.19	**0.53**	0.84	1.28
43	**2.27**	3.10	4.84	**2.10**	2.84	3.65	**0.84**	1.14	1.46
44	**1.99**	2.83	4.11	**1.65**	2.49	3.28	**0.67**	1.01	1.33
45	**2.20**	3.19	3.48	**2.06**	3.00	2.76	**0.84**	1.22	1.12
46	**1.88**	2.56	4.99	**1.59**	2.21	3.77	**0.62**	0.86	1.47
47	**2.32**	2.90	3.56	**2.04**	2.64	2.83	**0.81**	1.04	1.12
48	**2.44**	3.33	3.56	**2.30**	3.14	2.71	**0.89**	1.22	1.05
49	**2.54**	3.35	3.33	**2.39**	3.17	2.64	**0.97**	1.28	1.07
50	**2.20**	3.06	4.75	**1.95**	2.66	3.69	**0.78**	1.06	1.47
51	**1.99**	2.69	3.48	**1.69**	2.30	2.74	**0.66**	0.89	1.06
52	**2.40**	3.58	4.94	**2.24**	3.42	3.72	**0.91**	1.39	1.51
53	**2.48**	3.25	4.50	**2.33**	3.05	3.40	**0.94**	1.22	1.37
54	**2.22**	3.20	4.42	**1.94**	2.84	3.23	**0.73**	1.07	1.22
55	**2.09**	3.11	4.80	**1.83**	2.84	3.65	**0.72**	1.12	1.43
56	**2.16**	3.14	3.95	**1.89**	2.76	3.03	**0.71**	1.04	1.14
57	**2.29**	3.25	4.35	**2.03**	2.89	3.32	**0.78**	1.10	1.27
58	**2.15**	3.11	3.70	**1.96**	2.80	3.11	**0.78**	1.12	1.24
59	**2.08**	2.93	3.49	**1.79**	2.55	2.81	**0.69**	0.97	1.08
60	**2.29**	3.18	4.48	**2.06**	2.94	3.47	**0.79**	1.12	1.33
61	**2.33**	3.39	4.63	**2.20**	3.18	3.41	**0.83**	1.20	1.28
62	**2.41**	3.12	4.35	**2.18**	2.87	3.28	**0.85**	1.12	1.27
63	**2.35**	3.07	4.40	**2.12**	2.78	3.20	**0.83**	1.09	1.25
64	**2.01**	3.08	6.40	**1.73**	2.69	5.62	**0.67**	1.04	2.17
65	**1.60**	2.43	5.16	**1.35**	2.06	3.80	**0.53**	0.81	1.49
66	**1.90**	2.73	4.10	**1.61**	2.36	2.99	**0.61**	0.90	1.14
67	**2.31**	3.27	4.54	**2.13**	3.04	3.45	**0.84**	1.20	1.36
68	**2.15**	3.00	3.65	**1.88**	2.66	2.86	**0.72**	1.02	1.09
69	**2.36**	3.29	5.03	**2.19**	3.09	3.74	**0.88**	1.24	1.50
70	**2.40**	3.37	5.04	**2.23**	3.16	4.02	**0.88**	1.25	1.58
71	**2.30**	3.25	4.14	**2.12**	3.05	2.97	**0.83**	1.19	1.17
72	**1.77**	2.48	5.13	**1.44**	2.15	4.12	**0.59**	0.88	1.68
73	**2.48**	3.08	3.82	**2.26**	2.83	3.26	**0.86**	1.08	1.24
74	**2.31**	3.33	3.47	**2.13**	3.13	3.07	**0.86**	1.26	1.23
75	**1.90**	2.85	3.90	**1.60**	2.39	3.01	**0.61**	0.91	1.15
76	**1.84**	2.52	3.84	**1.55**	2.15	2.66	**0.60**	0.83	1.02
77	**1.58**	2.32	3.56	**1.30**	2.03	2.73	**0.53**	0.82	1.11
78	**2.22**	3.21	3.29	**1.96**	2.92	2.43	**0.78**	1.16	0.97
79	**2.32**	3.23	4.58	**2.08**	2.92	3.51	**0.79**	1.11	1.34
80	**2.14**	2.86	2.96	**1.90**	2.61	2.35	**0.72**	0.99	0.89
81	**2.06**	2.97	4.54	**1.78**	2.55	3.45	**0.71**	1.02	1.39
82	**2.31**	3.05	3.72	**2.04**	2.73	2.77	**0.78**	1.04	1.05
83	**2.12**	2.98	4.37	**1.80**	2.55	3.29	**0.68**	0.96	1.24
84	**2.45**	3.16	3.34	**2.24**	2.87	2.69	**0.88**	1.13	1.06
85	**2.17**	3.11	3.94	**2.02**	2.91	2.90	**0.80**	1.14	1.14
86	**2.16**	3.22	3.28	**2.03**	3.04	2.47	**0.80**	1.19	0.97
87	**2.28**	3.32	3.94	**2.12**	3.13	3.51	**0.82**	1.20	1.35
88	**2.05**	3.16	5.45	**1.82**	2.92	4.54	**0.72**	1.15	1.78
89	**2.17**	2.98	4.53	**1.90**	2.61	3.31	**0.73**	1.00	1.27
90	**2.29**	3.27	4.82	**2.12**	3.00	3.45	**0.83**	1.18	1.36
91	**2.32**	3.31	5.02	**2.11**	3.07	3.53	**0.79**	1.15	1.32
92	**2.01**	2.54	6.58	**1.69**	2.20	5.52	**0.65**	0.85	2.13
93	**1.47**	2.41	4.18	**1.22**	2.09	3.11	**0.50**	0.86	1.28
94	**2.30**	3.34	5.14	**2.12**	3.17	3.55	**0.86**	1.30	1.45
95	**2.43**	3.34	4.28	**2.18**	3.07	3.24	**0.85**	1.20	1.26
96	**2.33**	3.19	3.45	**2.10**	2.86	2.76	**0.81**	1.11	1.07
97	**2.46**	3.20	3.00	**2.20**	2.91	2.08	**0.84**	1.12	0.80
98	**2.41**	3.45	3.58	**2.30**	3.26	2.77	**0.90**	1.27	1.08
99	**2.50**	3.34	3.30	**2.30**	3.07	2.55	**0.90**	1.20	1.00
100	**1.55**	2.69	3.50	**1.27**	2.24	2.72	**0.51**	0.91	1.11