
ESG2Risk: A Deep Learning Framework from ESG News to Stock Volatility Prediction

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Abstract

Incorporating environmental, social, and governance (ESG) considerations into systematic investments has drawn numerous attention recently. In this paper, we focus on the ESG events in financial news flow and exploring the predictive power of ESG related financial news on stock volatility. In particular, we develop a pipeline of ESG news extraction, news representations, and Bayesian inference of deep learning models. Experimental evaluation on real data and different markets demonstrates the superior predicting performance as well as the relation of high volatility prediction to stocks with potential high risk and low return. It also shows the prospect of the proposed pipeline as a flexible predicting framework for various textual data and target variables.

1 Introduction

The widely adopted perspective for judging the sustainability of equity investments is along three pillars, E S G, which stand for **E**nvironmental, **S**ocial and **G**overnance. In this paper we propose a novel approach of volatility forecasting based on ESG newsflow, an original integration of ESG into the investment process. Recently, integrating sustainability into investment strategies are receiving exponentially increasing attention in finance [3, 15]. Environmental metrics cover all aspects of the firm’s interaction with the environment, such as its CO2 emissions, its approach to the climate change transition or its broad strategy in the use of natural resources. The Social dimension encompasses all standards set by companies as they build relationships with employees, suppliers and the communities in which they operate (labor conditions, equality, fairness to suppliers) while Governance would cover leadership elements like executive compensation, diversity of the board and controversies. These ESG inputs are vital to assess the sustainability and the relevant risks of an investment position [16]. Conventionally, ESG related factors are formatted as structured data to facilitate the integration of ESG aspects into quantitative models and the building of expertise in systematic ESG investing.

In our research, we study the predictive power of ESG news on volatility. We develop a pipeline for ESG news extraction and a state-of-the-art transformer based language model to predict stock volatility [18, 4, 9]. This pipeline can be generalized to other predicting targets with ease. As a measure of price fluctuations and market risk, volatility plays an important role in trading strategies, investment decisions and position scaling. In this paper, we focus on predicting Equity realized volatility, which is empirically calculated by the variance of observed returns of an asset. Volatility predictions often rely on predictive models based purely on price/return time-series, from standard

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statistical models of the GARCH family up to more recent deep-learning model based predictions [13].

The input to our models is an alternative source of ESG information: textual financial news-flow. Compared to structured ESG data provided by analysts or data vendors, ESG information from news-flow reflects more timely events of companies, and offers an alternative channel of capturing the relation of ESG events to market dynamics in a timely manner. Numerous research demonstrated that financial news is closely related to market and is becoming a gold mine to analyze market participants' behaviour [12, 7]. An intuitive example is illustrated in Fig.1.

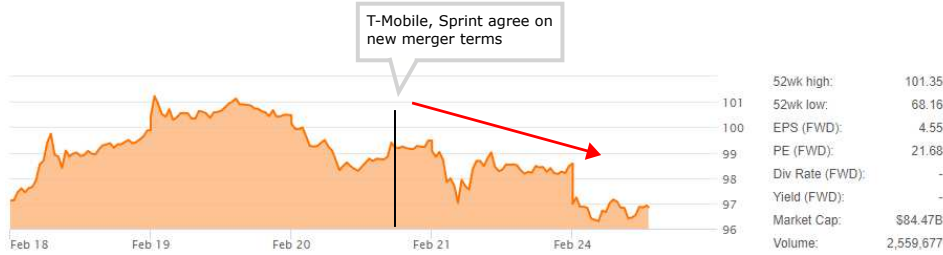


Figure 1: An intuitive example of financial news and stock price movement from T-Mobile.

Though bearing rich information, ESG news is challenging to process for predicting models. Raw textual data is categorical and symbolic represented, which is a hindrance for quantitative models. Financial news is sparse in the sense that it moves in-parallel with real-world events in irregular timings. This is in contrast to the structured and well-formatted market and factor data typically used in conventional quantitative models. Although there are a variety of work studying predicting market behaviours with different data sources [5, 19, 17, 2], how to exploit the predictive power of ESG news on volatility is rarely researched.

To this end, we resort to natural language processing (NLP) and deep learning techniques to explore the predictive power of ESG news. In particular, one key NLP technique, which helps hurdle the challenges above, is language representation (i.e. text embedding) [18, 4, 10]. Deep neural networks, e.g. recurrent neural networks and transformer, trained on large scale text corpus exhibit remarkable success in a variety of NLP applications, such as sentiment analysis, text matching, dialogue systems and so on. This technique transforms text symbols into a numerically high-dimensional dense vectors, while importantly still preserving context and semantic relations.

Contributions. Specifically, the contribution of this paper is as follows:

- We propose a NLP and deep learning based pipeline for ESG news integration.
- We exploit the Transformer based language model to transform textual news into numerical representations including sentiments and semantic-preserving text embedding.
- The predicting model is based on Bayesian inference, in order to enable stable and robust predicting.
- Evaluation on real data and different markets demonstrates the superior predicting performance as well as the efficacy of the volatility prediction in stock selection.

2 ESG2Risk Framework

2.1 Overview

In this part, we give an overview of the proposed ESG2Risk framework and define the notations used throughout the paper.

Pipeline. Fig. 2 illustrates the pipeline mainly consisting of four components: ESG news extraction, transformation, deep learning models, and the strategy. The news flow represents streaming pieces of news, which can be obtained by a variety of tools, e.g. online news feeds, finance data vendors, web crawlers, and so on.

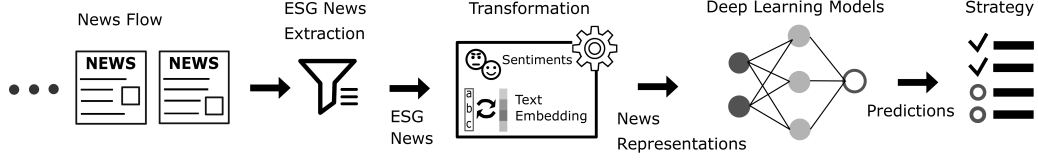


Figure 2: Pipeline of the ESG2Risk Framework.

We first brief the main components of ESG2Risk as follows and then will mainly describe the components of ESG news extraction, transformation, and deep learning models in the next subsection.

- ESG news extraction: generic financial news flow rarely provides labelled ESG news and thus we developed the in-house extraction process. Streaming financial news first go through a filter, which makes use of an ESG vocabulary defined by our domain experts. The output is ESG related news and the corresponding companies mentioned in each piece of news. The mentioned companies are commonly provided as accompanied attributes by data vendors and can also be derived by linking entities in news to a stock dictionary. For instance, Fig. 3 shows the top ESG topics in news within one week period.

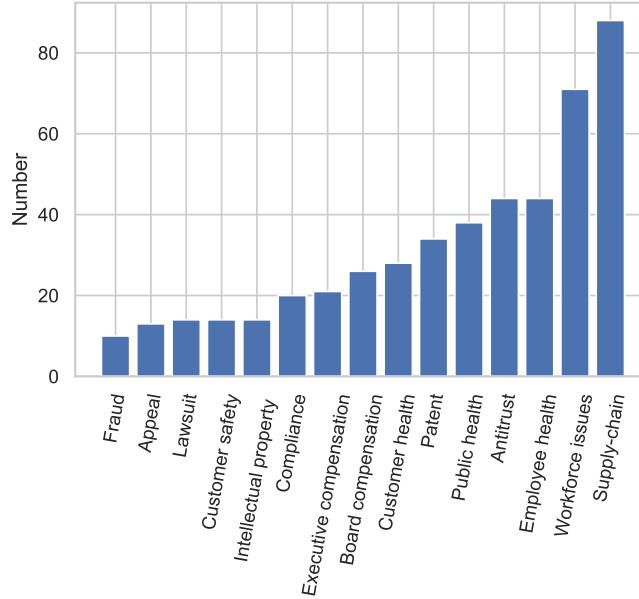


Figure 3: Top-15 ESG topics in the news from an example time period April 06, 2020 to April 12, 2020.

- Transformation: news is represented by symbolic textual data, which is unstructured and infeasible for quantitative models to process. As a results, this step aims to transform news into quantitative representations by transformer based language model and sentiment analysis [18, 1, 4].

Language models or text embedding is a powerful technique in natural language processing (NLP), which is able to transform symbol represented text into numerical dense vectors preserving the semantic relatedness of text in the numerical space. More details will be given in the following.

- Models: in the model training phase, we collect a dataset including pairs of numerical news representations and the volatility of the corresponding companies for supervised training of the predicting model.

In the inference phase of the production system, the newly arriving numerical news representations are fed into the trained models to predict the future volatility of the companies mentioned in the news.

For both training and inference phases, we take advantages of Bayesian inference to enable stable learning and robust predicting [9, 14]. Details will be presented in the next subsection.

- Strategy: by using the volatility predictions from deep learning models, either stand-alone or combined with other signals, we design stock selection strategy.

Problem Definition. We formally define the problem of ESG news based volatility predicting as follows.

Market risk exists because of price changes [13]. The volatility of a stock i is used to characterize the risk and the return fluctuation over time. Let $p_{i,t}$ be the price of stock i at the end of a trading period t with closing returns $r_{i,t}$ given by

$$r_{i,t} = \frac{p_{i,t}}{p_{i,t-1}} - 1 \quad (1)$$

In this paper, we focus on the realized volatility, which is defined as:

$$v_{i,t} = \sqrt{\frac{\sum_j r_{i,j}^2}{K_t}} \quad (2)$$

, where K_t is the number of return samples.

Define the universe of stocks as \mathcal{I} . At time t , a set of stocks $I_t \subseteq \mathcal{I}$ is identified with ESG news in a sliding window w.r.t. t . It means for a stock $i \in I_t$, it has ESG news mentions during time period $[t-w, t]$, where w is the window length. Then, the news mentioning i at time t is represented by $N_{i,t} = \{n_m\}_{m \in M_{i,t}}$, where $M_{i,t}$ is the number of ESG news corresponding to stock i in the time window $[t-w, t]$. n_m denotes the text of one piece of news.

In the inference phase, given observed $N_{i,t}$, we predict the forward volatility $v_{i,t+\Delta}$ by a quantitative model $f(\cdot)$, namely $\hat{v}_{i,t+\Delta} = f(\text{Trm}(N_{i,t}))$, where $\text{Trm}(\cdot)$ is the operation of transforming unstructured news text into model-friendly numerical data and will be described in the next subsection. Δ is the forecasting horizon. Then, based on the set of predictions $\{\hat{v}_{i,t+\Delta}\}_{i \in I_t}$, we can further develop stock selection strategies.

In the learning phase, we collect paired news representations and ground-truth forward volatility, denoted by a dataset $\mathcal{D} = \{(N_{i,t}, v_{i,t+\Delta})\}_{i \in \mathcal{I}, t \in \mathcal{T}}$, to train the predicting model $f(\cdot)$ in the supervised way.

2.2 News Representations

In this part, we describe how to obtain numerical representations of news. It is mainly based on pre-trained language models [18, 4].

Conceptually, the language model is designed to learn the usage of various words, phrases and how the language is written in general. Technically, the typical building blocks in contemporary language models are recurrent neural networks, convolutional neural networks, or the more recently proposed Transformer architecture. A variety of language models are developed by stacking certain types of building blocks with specialized training procedures.

During the training phase of a language model, each token of a text segment is initialized as a numerical dense vector. These numerical vectors are fed into (stacked) building blocks to capture contextual relationships among words. Subsequently, the output vectors of building blocks are used in some language predicting tasks as the training objective, for instance, next word prediction, masked word prediction, next sentence prediction, etc.

A language model is typically pre-trained on a large corpus of text, for instance, the complete Wikipedia dump (2,500 million words), Book Corpus (800 million words), etc. The training process aims to maximize the accuracy of these language predicting tasks, so as to learn vectors representing the semantic relations in large amount of text. This pre-trained language model serves as the Swiss Army Knife for downstream NLP tasks. For instance, sentiment classification is proven to benefit from text embedding by pre-trained language models [1]. Refer to Fig. 4 for an illustration of text embedding.

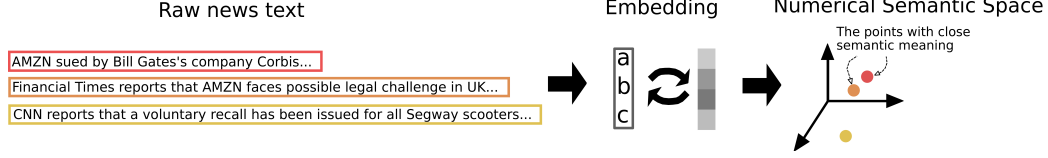


Figure 4: An illustrative example of embedding text into numerical semantic space. Raw news text is transformed into dense vectors in the numerical space. The different colours represent the correspondence between text and vectors (i.e. points) in the space. Texts with semantic closeness are mapped to points close in the semantic space.

In our case, given news $N_{i,t} = \{n_m\}_{m \in M_{i,t}}$, the transformation is defined as follows:

$$\text{Trm}(N_{i,t}) := (\text{pool}_s(\{\mathbf{s}_m\}), \text{pool}_e(\{\mathbf{e}_m\})), \quad (3)$$

where \mathbf{s}_m and \mathbf{e}_m represent the sentiment information and text embedding of one piece of news.

In particular, we use the sentiment analyzer trained on text embedding to extract sentiment scores over segments of news content, which form the fine-grained sentiment vector \mathbf{s}_m for each piece of news. By feeding ESG news text into a pre-trained **Transformer based language model** (e.g. BERT, RoBERTa, etc.) [4, 10], the derived vectors $\{\mathbf{e}_m\}$ are quantitative-model-friendly and conveniently used in the subsequent learning of the volatility predicting model.

Note that different stocks have different number of ESG news over time. **We apply pooling operations to $\{\mathbf{s}_m\}$ and $\{\mathbf{e}_m\}$, in order to format them as structured data across stocks and time instants.** The derived dataset of the uniform shape will be ready for feeding the volatility model. We choose the simple average pooling for $\text{pool}_s(\cdot)$ and $\text{pool}_e(\cdot)$, i.e. $\text{pool}(\{\mathbf{x}_k\}) := \frac{\sum \mathbf{x}_k}{|\{\mathbf{x}_k\}|}$, while it is flexible to use different ones.

2.3 Model Learning and Inference

In this part, we present the architecture of the volatility model and Bayesian learning and inference.

Since we have two types of data, sentiment and text embedding from $\text{Trm}(N_{i,t})$, we design the encoder and information fusion architecture, as is shown in Fig. 5. The idea is to capture data modal specific information by individual encoders and then to perform prediction using fused information from encoders. Different information fusion strategies, e.g. attention mechanism, mixture, etc. can be applied [6]. For encoders, we choose stacked dense layers (with residual connections) [8], though alternative encoders are free to choose.

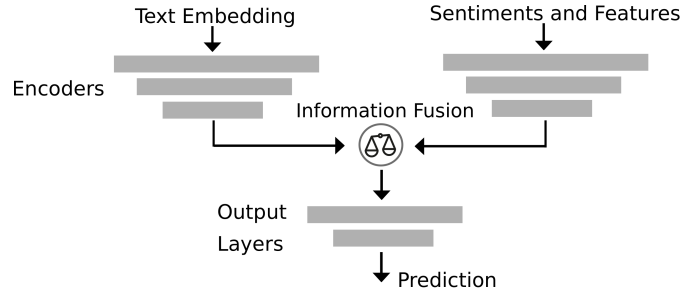


Figure 5: Architecture of the Volatility Model Parameterized by Θ .

Instead of using the conventional squared error loss as the learning objective, we aim to learn the posterior of the model parameter in the Bayesian setting, as is defined below:

$$p(\Theta|\mathcal{D}) \propto \underbrace{\prod_{i,t} p_{\Theta}(v_{i,t+\Delta}|\text{Trm}(N_{i,t}))}_{\text{Likelihood}} \cdot \underbrace{p(\Theta)}_{\text{Prior}}, \quad (4)$$

where the set of parameters of the model to learn from data is denoted by the random variables Θ .

In our task, the target variable volatility is essentially noisy and volatile. More complexly, the sentiment and embedding vectors are high-dimensional, for instance, the embedding derived by BERT is a 768-dimensional vector. These present a great challenge for conventional stochastic gradient descent based training algorithms to learn stable patterns in the data.

On the contrary, Bayesian style learning is probabilistic and theoretically designed to handle the stochasticity inherent in the data [9, 14]. Meanwhile, learning the posterior leads to ensemble inference, which aggregates predictions from a set of model realizations. It has been shown in many applications ensemble inference gives rise to more robust and accurate predicting performance [11, 9, 14]. From the perspective of maximum a posterior probability (MAP) estimate, the prior in Eq. 4 also functions as a regularization term to ensure the generalization ability of the learned model.

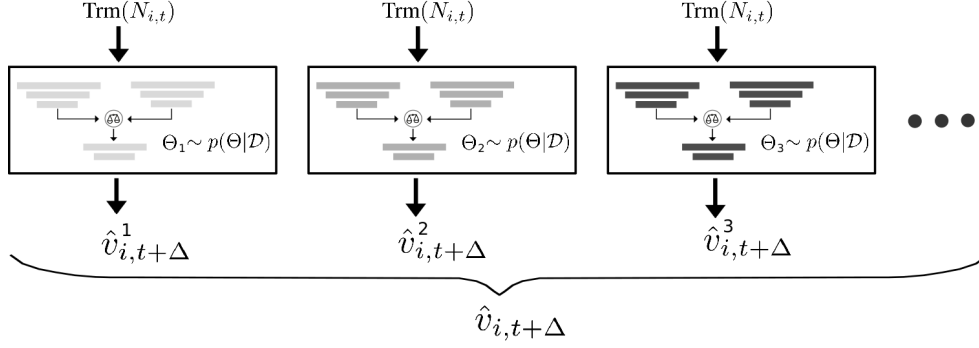


Figure 6: Illustration of Bayesian Model Ensemble. The model in each block represents a realization of the model in Fig. 5 by the parameter sample Θ .

Concretely, we use the modern stochastic gradient based Markov Chain Monte Carlo (SG-MCMC) method to obtain the approximate posterior of $p(\Theta|\mathcal{D})$ in the training phase [11, 9]. Then, in the inference phase, given a testing set of news for stock j , the predictive probabilistic density of the volatility is derived as:

$$p(v_{j,t+\Delta} | \text{Trm}(N_{j,t}), \mathcal{D}) = \int_{\Theta} p_{\Theta}(v_{j,t+\Delta} | \text{Trm}(N_{j,t})) \cdot p(\Theta|\mathcal{D}) d\Theta \quad (5)$$

Empirically, we use Monte Carlo method to sample parameter Θ_c from the posterior, thereby getting a set of model realizations, as is shown in Fig. 6. Each model realization provides the predictive mean of the volatility and the overall prediction is derived as:

$$\hat{v}_{j,t+\Delta} = \frac{1}{C} \sum_{c=1}^C \mathbb{E}[v_{j,t+\Delta} | \text{Trm}(N_{j,t}), \Theta_c], \quad \Theta_c \sim p(\Theta|\mathcal{D}) \quad (6)$$

3 Evaluation

In this part, we report evaluation results to demonstrate the efficacy of our predicting pipeline.

Data. From a collection of financial news in the time period from 2003 to 2019, we extract around 50 thousands ESG related news. We link ESG news to companies from two different markets, i.e. MSCI US and All Cap EU. Then, for each market, we build the training and validation data using the time period from 2003 to 2014, while the rest is used as the out-of-sample testing data. We evaluate the predicting performance of each market independently. The results reported below are from the testing data.

Performance. Table 1 and 2 exhibit the errors on two different predicting horizons, 1 week and 2 weeks. We report the rooted mean squared error (RMSE) and mean absolute error (MAE). For comparison, the performance of the model using solely sentiments, i.e. Senti in the table, and our ESG2Risk, using both sentiment and text embedding, are reported. It is observed that on both markets, ESG2Risk significantly outperforms the Senti method.

Table 1: One Week Forward Volatility Predicting Errors.
Bold values indicate better performance.

Market	RMSE		MAE	
	Senti	ESG2Risk	Senti	ESG2Risk
MSCI-US	0.663	0.289	0.542	0.249
AC-EU	0.630	0.281	0.515	0.241

Table 2: Two Week Forward Volatility Predicting Errors.
Bold values indicate better performance.

Market	RMSE		MAE	
	Senti	ESG2Risk	Senti	ESG2Risk
MSCI-US	0.669	0.289	0.548	0.251
AC-EU	0.624	0.280	0.511	0.240

To assess the possibility to use our ESG2Risk predictions to build more attractive risk-adjusted return portfolios, we split the stocks based on quintiles of volatility predictions and calculate the average return of each quintile with 1 week and 2 weeks holding periods.

The average realized standard deviation of returns and returns of these quintile portfolios are shown in Fig. 7 and 8 and Fig. 9 and 10.

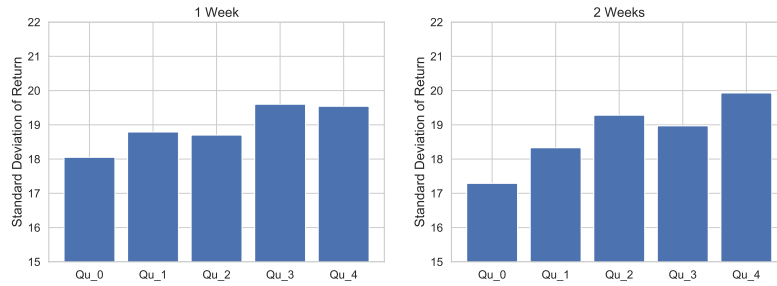


Figure 7: MSCI US Quintile Portfolio Return Standard Deviation based on 1 and 2-week forward volatility predictions.

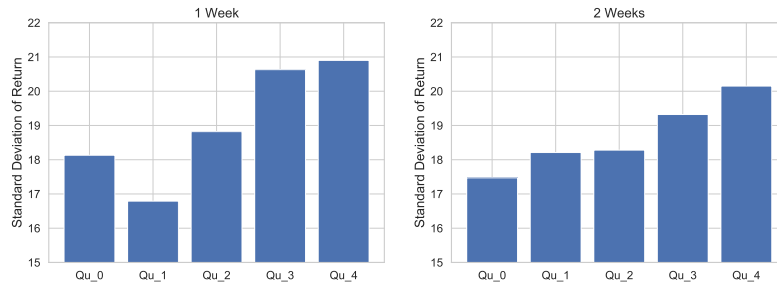


Figure 8: All Cap EU Quintile Portfolio Return Standard Deviation based on 1 and 2 week forward volatility predictions.

Quintile portfolios of stocks with high predicted volatility have significantly higher volatility than low predicted volatility portfolios in our out-of-sample test. The portfolio built with the highest predicted risk names (Qt 4 portfolio) also exhibits significantly lower returns, both in the MSCI US and All Cap Europe investment universes than the other quintile portfolios as shown in Fig. 9 and 10. Extending the findings in existing work on structured ESG rating data [3], integration of ESG news flow data can positively contribute to Equity portfolio returns.

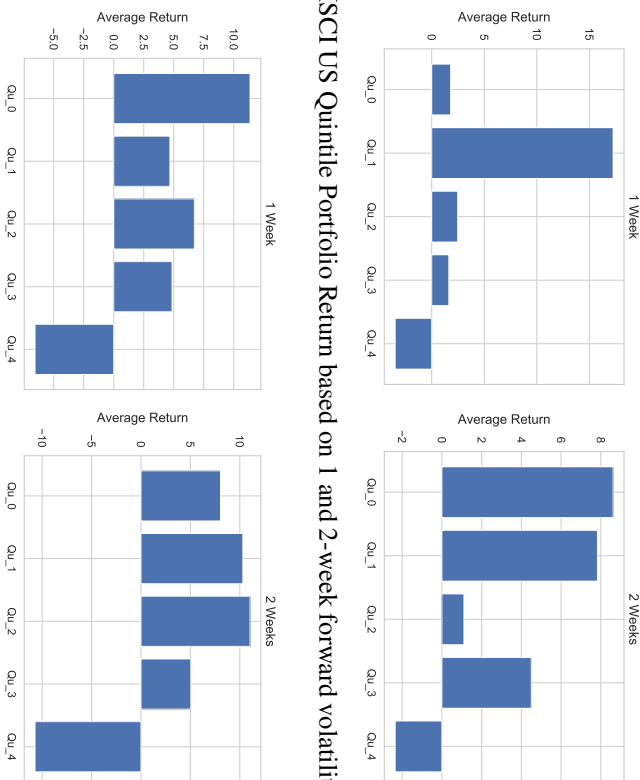


Figure 9: MSCI US Quintile Portfolio Return based on 1 and 2-week forward volatility predictions.



Figure 10: All Cap EU Quintile Portfolio Return based on 1 and 2-week forward volatility predictions.

4 Conclusion

In this paper, we implement a novel deep learning framework, ESG2Risk, to predict future volatility of stock prices. We show that a transformer-based language model successfully manages to extract information from ESG newflow to predict future volatility of stock returns. Predictions of volatility in our model is more accurate when attempting to identify the stocks with the highest volatility risk in the market, hence the worst potential risk contributors to an Equity selection. Our research gives evidence that ESG newflow does significantly impact future return and risk of companies and is a relevant factor for investors to consider when investing. Our findings in different geographies confirm that ESG newflow integration can contribute to build profitable investment strategies, on top of improving the ESG profile of an Equity selection.

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