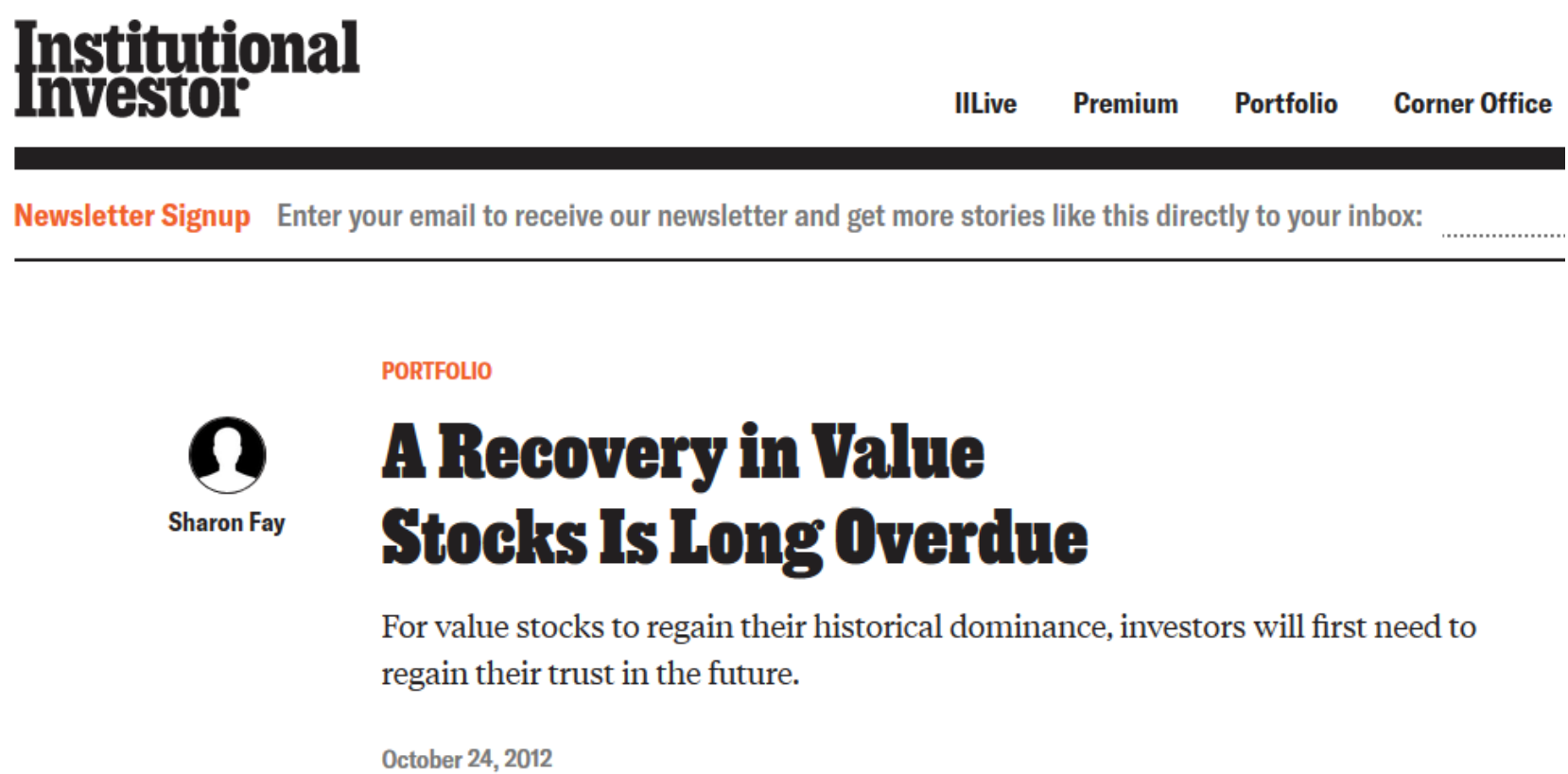


Abstract

Since 2017, the number of listed indices has exceeded the number of listed firms in the US markets. Exchange traded funds have grown in popularity and represent a liquid way to get exposure to equity style investing. This situation raises some concerns regarding investors’ limitations in processing information. Whereas investors benefit from financial research for individual listed firms, no channel of information covers style or factor investing. We examine the informational role of financial media targeting institutional investors with regard to style investing. We extract equity style coverage and sentiment from news targeting institutional investors. We further investigate news style coverage implication on mutual fund managers trading behavior and holdings. Our work extends the literature on investor attention to news with a special emphasis to equity style investments.

News Analytics

Style information in Institutional Media



We identify magazines whose mission statement includes the production of trusted information targeting financial decision makers, i.e. **Institutional Media**. Those magazines provides information and strategic advises from a portfolio management perspective. Related news contain information covering different asset classes (equity, fixed income, hedge funds and private equity). We intend to identify news covering small-cap, large-cap, value and growth equity investments, i.e. **Style information**. Detecting style information represents some challenge :

- Style information is disseminated among a broad range of topics.
- News main topic isn’t necessarily related to style information.

Textual analysis methodology

- We test two different approaches :
- **dictionary-based method** : we use list of terms to directly detect style information.  
→ [smallcap, midcap, small cap, mid cap] and [large cap]  
→ [value stocks, value funds] and [growth stock, growth funds]
  - **Machine Learning methods** : we use a sub-sample of manually annotated news to train Naïve Bayes (NB) and Support Vector Machine (SVM) algorithms. Trained algorithms sparse institutional media to classify news in two main categories : news with and without style information.

Performance Assessment

Table 1 : Performance of different classification methods

	Performance scores		
	Precision	Recall	F1_score
Panel A : Small style classification			
Lexicon	1.00	0.68	0.81
Naive Bayes	0.28	0.88	0.42
Support Vector Machine	0.31	0.47	0.37
Panel B : Large style classification			
Lexicon	1.00	0.55	0.71
Naive Bayes	0.23	0.90	0.37
Support Vector Machine	0.29	0.84	0.43

- **Small and large styles** : Dictionary-based method exhibits strong performance : all news detected contains style information (Precision = 1). The method fail to detect some news due to restricted term lists (low recall)  
→ We suggest enlarged dictionaries to improve recall performance
- Failed detection : “Fidelity Investments has announced the availability of the Fidelity Advisor **Mega Cap** Stock Fund, providing financial advisers and their clients access to a fund with dedicated mega cap exposure.”
- **Value and growth styles** : Dictionary-based method fail to correctly detect style information due to false detection (low precision) and absence of detection (low recall). Machine learning methods could be the solution but require large set of annotated news, i.e. large **training sample**.

False detection : “Bond funds experienced (net) outflows of USD89 million while GIC/ **stable value funds** had USD49 million in outflows, Aon Hewitt reported.”

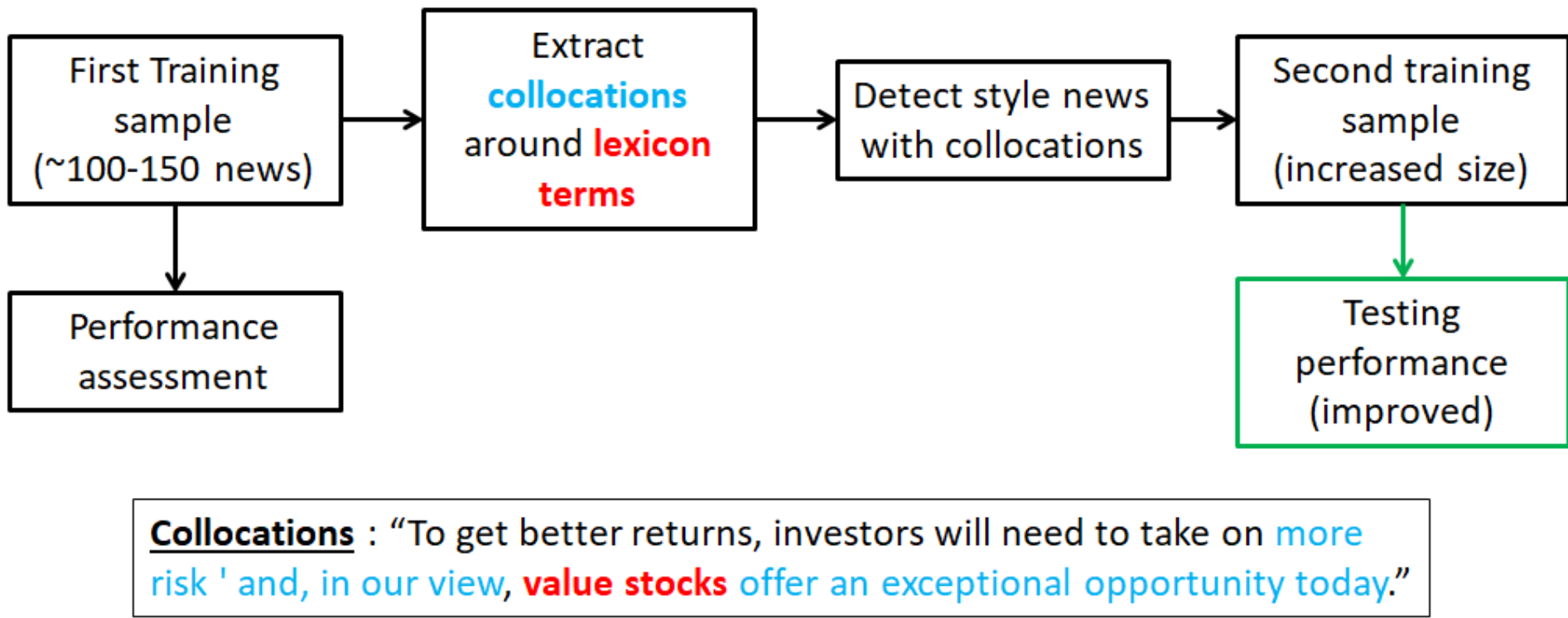


Figure 1: Improving performance by increasing training sample size

Motivation

- We investigate how Institutional Media could influence the information channel towards investors. We intend to :
- Clarify the relation between media content and the turn-of-the-year effect.
  - Investigate the potential relation between media content and shifts in investors preferences (across style investments).
  - Explore the impact of Institutional Media on ETFs performance and flows.
- We contribute to the literature on seasonal effects in market anomalies and dynamic style preferences of investors :
- **Revisiting the Turn-of-the year effect** : **Sikes (2014)** concludes that institutional investors contribute to the turn-of-the-year effect whatever their incentives (window-dressing or tax-loss-selling).
  - **Preference shifts across style investments** : **Kumar (2009)** shows that bullish and bearish signals to investment styles of individual investors is significantly related to the information content of expert newsletters in the previous month.
  - **Media Coverage and ETFs performance** : **Fang and Peress (2009)** find that stocks with no media coverage outperformed stocks with high media coverage. In another paper, **Fang and Peress (2014)** find that mutual fund exhibiting high propensity to buy high coverage stocks underperformed their peers.

Data and Methodology

- We classify style coverage of more than 80000 news from our institutional media database (from 2009 to 2017).
- We estimate monthly style coverage dividing the total news covering one style by the total news released during the month.
  - We categorize sentiment in news using **Loughran and McDonald (2011)** dictionary. A news is positive if it contains more positive words than negative words and vice-versa.
- We collect monthly data from Thomson Reuters Eikon database for Exchange-Traded-Funds with US geographical focus and whose mutual fund classification belongs to the following categories : small, mid and large capitalization ETFs.
- Monthly variable : Total Net Asset (TAN), Past Returns (Return) and aggregate flows (Flow).
- For each ETF and month, we estimate the following cross-sectional regressions :

$$\frac{Flow_{f,t}}{TNA_{f,t-1}} = constant + \beta_1 StyleCoverage_{t-1} + \beta_2 R_{f,t-1} + e_{f,t}$$

(1)

Coverage and sentiment

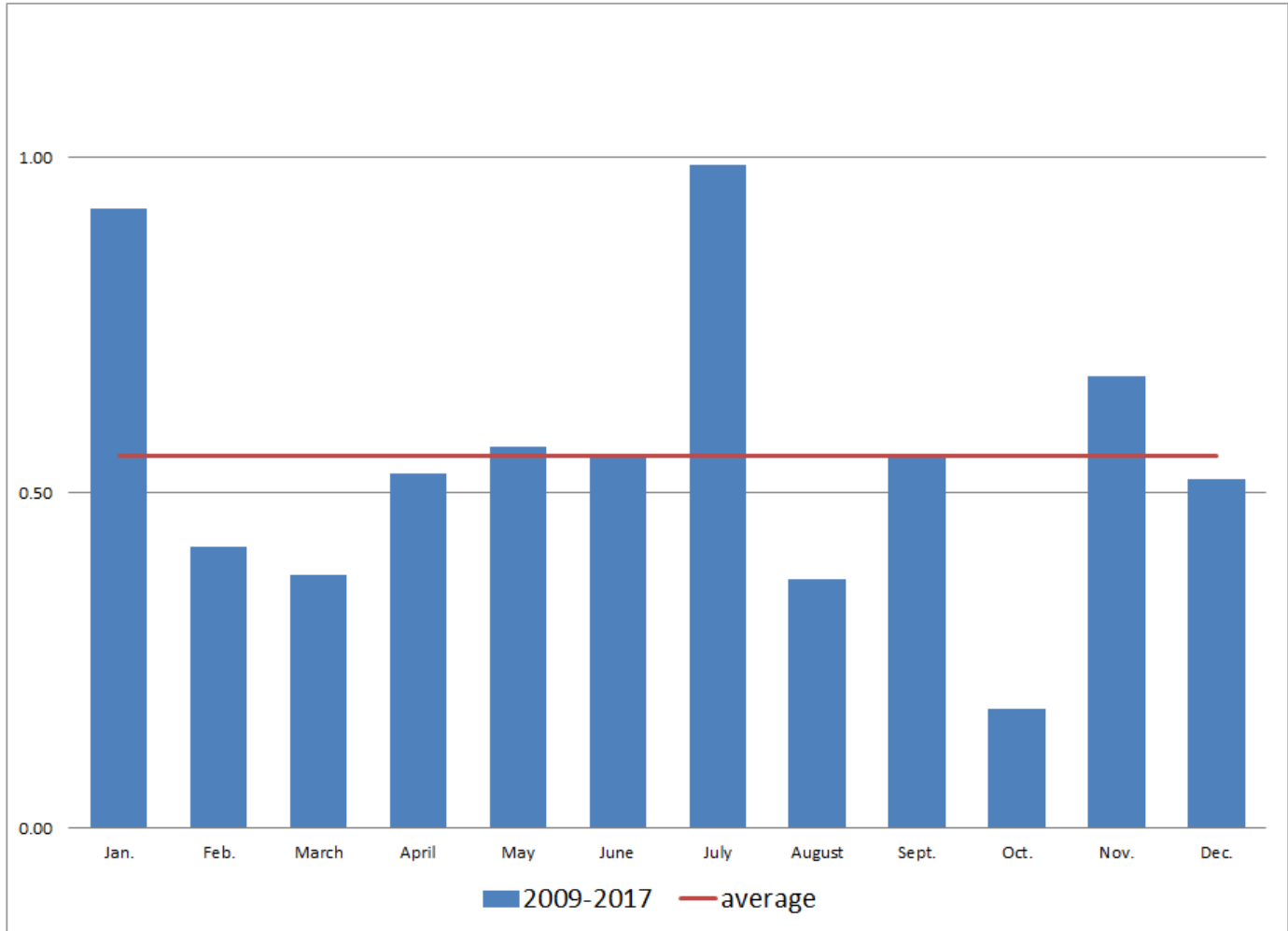


Figure 2: Spread of coverage between small and large style

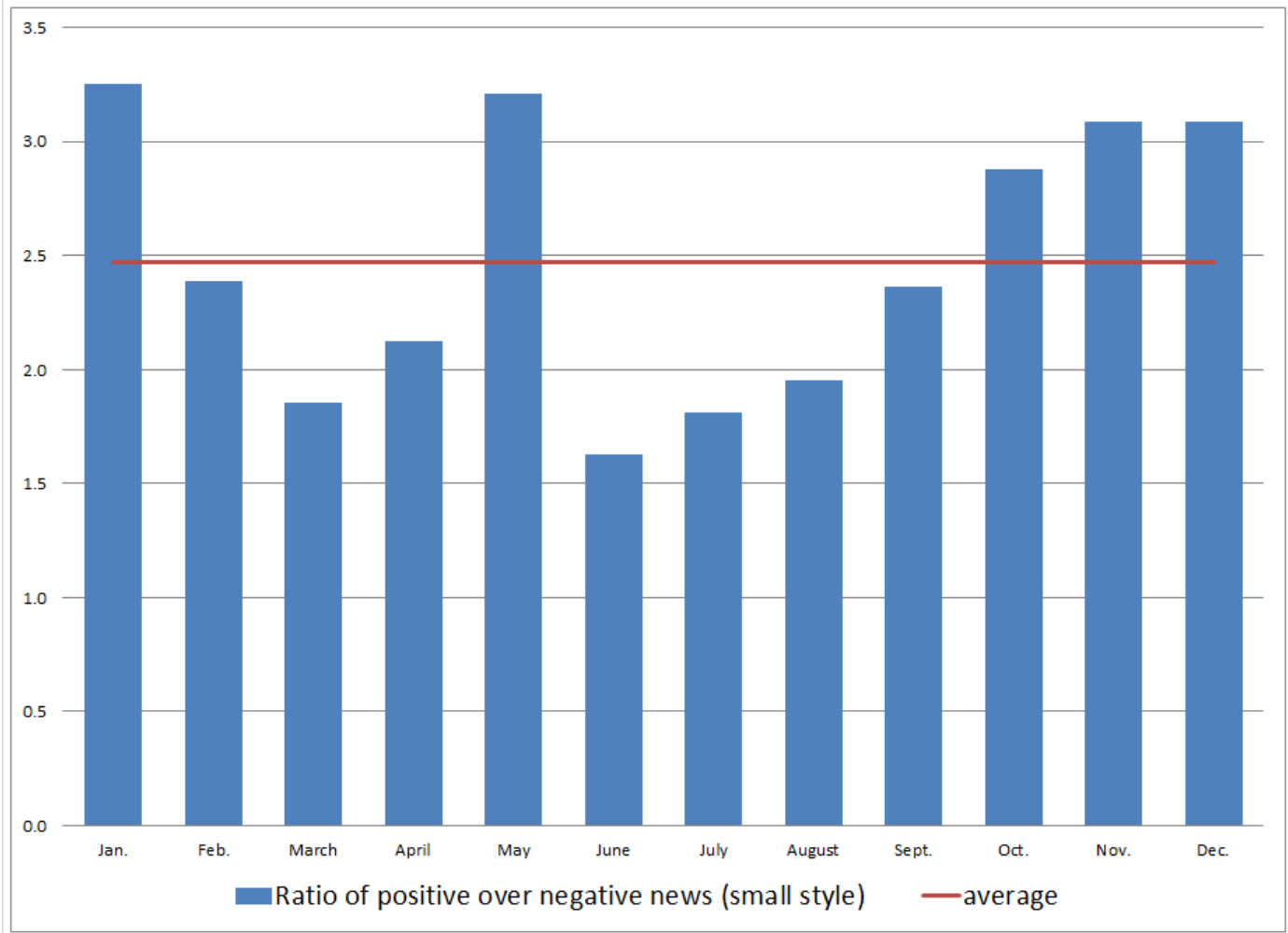


Figure 3: Ratio of positive over negative news (small style)

Exchange-Traded-Funds sample

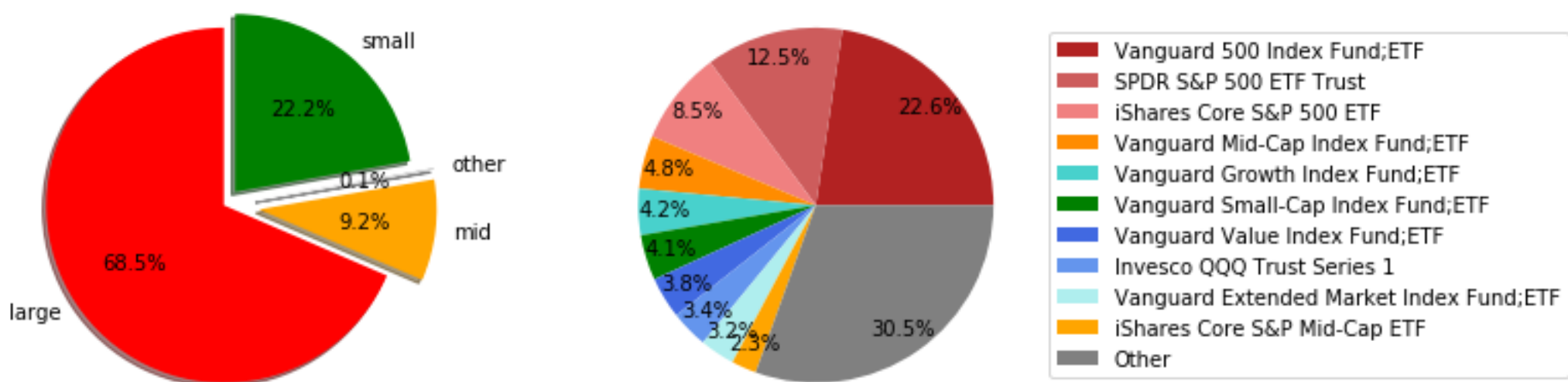


Figure 4: Total Net Asset value