Pesquisa Operacional (2021) 41: e232555 p.1-13
doi: 10.1590/0101-7438.2021.041.00232555

Printed version ISSN 0101-7438 / Online version ISSN 1678-5142
www.scielo.br/pope
ARTICLES

ASSESSING THE VALUE OF SUBJECTIVE VIEWS ON MACROECONOMIC FACTORS VIA BLACK-LITTERMAN BASED PORTFOLIO OPTIMIZATION

Camillo Cantini[1*], Davi Valladão[2] and Betina Fernandes[3]

Received December 26, 2019 / Accepted April 26, 2021

ABSTRACT. Black and Litterman proposed a portfolio selection model that blends investor's views on asset returns with market equilibrium concepts to construct optimal portfolios. However, the model efficiency relies on the performance of investors' views regarding tradable assets, which is challenging in practice. Venturing to improve Black-Litterman practical application, this work provides new insights based on views about macroeconomic factors, which are largely available, though not directly tradable. The main advantage is that market players usually provide predictions on these factors publicly. We present a case study based on the information disclosed by the Brazilian Central Bank to validate the proposed framework. The out-of-sample, risk-adjusted returns obtained incorporating the players' macroeconomic expectations applying the proposed framework outperformed the traditional mean-variance model as well as the Brazilian stock index benchmark.

Keywords: portfolio optimization, Black-Litterman, factor investment, macroeconomic subjective views.

1 INTRODUCTION

The goal of a portfolio manager is to pursue maximum returns while minimizing risks. Despite presenting an intuitive framework for handling the risk-return relationship, the model proposed by Markowitz (1952) is often avoided in practice due to estimation errors (Michaud (1989), Michaud et al. (2013) and Idzorek (2002)). Robust optimization (Soyster, 1973; Ben-Tal & Nemirovski, 1998, 1999; Bertsimas & Sim, 2004; Fernandes et al., 2016) and Black Litterman

*Corresponding author

[1] Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Industrial Engineering Department, Rua Marquês de São Vicente, 225, Gávea, 22451-900, Rio de Janeiro, RJ, Brazil– E-mail: camillo.cantini@gmail.com – https://orcid.org/0000-0002-9161-5523

[2] Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Industrial Engineering Department, Rua Marquês de São Vicente, 225, Gávea, 22451-900, Rio de Janeiro, RJ, Brazil– E-mail: davimv@puc-rio.br – https://orcid.org/0000-0002-1084-6881

[3] Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Electrical Engineering Department, Rua Marquês de São Vicente, 225, Gávea, 22451-900, Rio de Janeiro, RJ, Brazil– E-mail: bdmfernandes@gmail.com – https://orcid.org/0000-0002-5879-7337

(Michaud, 1989; Michaud et al., 2013) are different alternatives to handle estimation errors on selecting a reliable portfolio. In particular, the Black-Litterman approach is very appealing for practitioners since it incorporates the subjective views into the optimal allocation; i.e., it selects a portfolio that conjugates investors' beliefs with the risk-return tradeoff characterized by historical returns.

The Black-Litterman framework (Black & Litterman, 1992) makes it possible for investors to blend their subjective views on securities returns with market equilibrium returns using a simple formula to achieve balanced portfolios, see Cheung (2009)) and Meucci (2010) for further details. Avramov & Zhou (2010) interprets the model as a Bayesian portfolio allocation since the investor's view is a posterior update to the market information. Fabozzi et al. (2010); Stefanescu (2016); Kim et al. (2017) point out its robust characteristics due to shrinkage, which is further explored in the extension proposed by Bertsimas et al. (2012). Bessler et al. (2017) presents a case study where the Black-Litterman model stands out compared to other allocation approaches.

Notwithstanding the simplicity and practical appeal of the Black-Litterman model, the literature raises critical issues for its practical usage: (i) being insensitive to historical data; and (ii) lacking an organized framework for setting the investors' views, in particular, to handle views on non-tradable factors. To address (i), Zhou (2009) proposes mixing historical returns with Black-Litterman while Michaud et al. (2013) proposes an alternative model to reduce estimation errors. To partially address the issue (ii), Fernandes et al. (2018) proposes the use of historical returns and fundamentalist data to set securities views, and Cheung (2013) proposes views derived from a linear factor model that explains securities returns. To the best of our knowledge, no previous works propose a framework to select the optimal portfolio based on subjective views over non-tradable factors.

In this paper, we propose novel a Macrofactor Black-Litterman model (MBL) that enables the use of subjective views on non-tradable factors to tilt optimal allocation of tradable assets. This novel approach is broadly applicable since there exist an abundance of subjective views (opinions) on future values of non-tradable macro-eonomic factors (e.g., inflation, GDP, etc) that can be harnessed to enhance portfolio performance. Our approach completely bypasses a factor modeling step since we use the Black-Litterman (Bayesian) update to directly compute the expectation vector and covariance matrix as functions of the subjective views on non-tradable factors. Additionally, circumvents the absence of non-tradable market values by avoiding the use of Black-Litterman traditional parameters τ and δ[1]. Following the work of Zhou (2009) we use historical averages to estimate prior expected returns for both factors and tradable securities, which enables us to avoid the use of δ, τ. We summarize the three main contributions of this paper:

1. A novel framework to directly incorporate views on (non-tradable) macroeconomic factors into the portfolio optimization via factor-assets correlations;

[1] τ is the constant of proportionality between assets returns covariance matrix and assets expected returns covariance matrix and δ is the risk aversion parameter defined in the CAPM.

2. The setup of views based on macroeconomic indicators available on the Brazilian Central Bank (BCB) database.

3. An empirical backtesting study for the Brazilian financial market. The results suggest that the MBL model generates greater out-of-sample risk-adjusted returns when compared to the selected benchmarks.

We organize the paper as follows. In Section 2 we describe the proposed model. In Section 3 we present a case study using Brazilian financial market data, where we set views using BCB information. We present the conclusion in Section 4.

2 THE PROPOSED MBL MODEL

Throughout this paper, we use capital boldface to indicate matrices $(\Sigma, \Omega, \ldots)$, boldface to indicate vectors $(\mu, \pi, \ldots)$ and regular text for scalars numbers $(\tau, n, \ldots)$. Vectors and matrices dimensions are shown in brackets $([n \times 1], [n \times n], \ldots)$. We use the accents hat and tilde to denote estimates and random variables, respectively. We use Black-Litterman notation presented in Satchell & Scowcroft (2000) and Cheung (2009), where the subscript t indicates time. We assume the portfolio investment decision is taken before knowing the values taken by uncertain parameters. For instance, let $\hat{m}_t$ denote the vector of expected returns of the securities on the investment universe between step time t and $t+1$; it is based on the information available up to time t.

We consider a daily allocation on one-period step in a rolling horizon scheme. Let w_t denote the allocation vector made at the beginning of day t. Let us consider $\hat{m}_t$ (which is a one-step ahead forecast) for maximizing the portfolio return $w_t^T \hat{m}_t$. Afterwards, we test this allocation in a one-step-ahead out-of-sample analysis. Let also r_t denote the realized return on time step t. Figure 1 shows the time frame diagram.

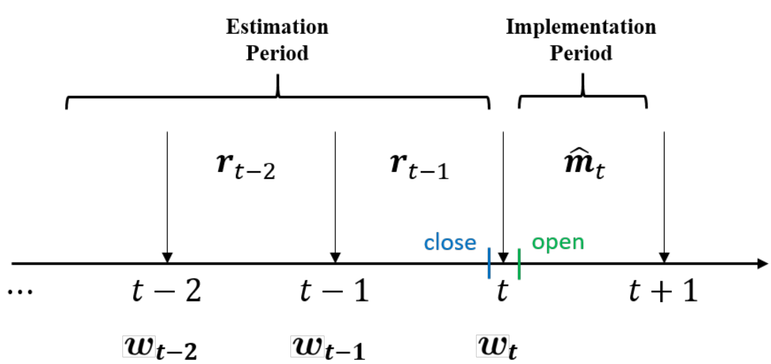

Figure 1 – Time frame diagram.

2.1 Incorporating Macroeconomic Views

We propose an MBL model where investors' views on factors affect securities' expected returns and covariance matrix due to its intrinsic relation with such securities, even when those factors are not explicitly linked to the securities by any factor model.

Let us split the n securities within the views' universe in s tradable securities and f factors, such that $n = s + f$. Let $\tilde{y}_{t\,[n\times 1]}$ denote the returns of our views' universe, where

$$\tilde{y}_t = \begin{bmatrix} \tilde{r}_t^S \\ \tilde{r}_t^F \end{bmatrix} \tag{1}$$

Considering separate views for tradable securities and non-tradable factors[2], we could sort the model inputs: $\hat{\Sigma}_{t\,[n\times n]}$, $\hat{\pi}_{t\,[n\times 1]}$, $P_{t\,[k\times n]}$, $\hat{q}_{t\,[k\times 1]}$ and $\Omega_{t\,[k\times k]}$ in tradable and non-tradable components

$$\hat{\Sigma}_t = \begin{bmatrix} \hat{\Sigma}_t^S & \hat{\Sigma}_t^{SF} \\ \hat{\Sigma}_t^{FS} & \hat{\Sigma}_t^F \end{bmatrix} \tag{2}$$

$$\hat{\pi}_t = \begin{bmatrix} \hat{\pi}_t^S \\ \hat{\pi}_t^F \end{bmatrix} \tag{3}$$

$$P_t = \begin{bmatrix} P_t^S & 0 \\ 0 & P_t^F \end{bmatrix} \tag{4}$$

$$\hat{q}_t = \begin{bmatrix} \hat{q}_t^S \\ \hat{q}_t^F \end{bmatrix} \tag{5}$$

$$\Omega_t = \begin{bmatrix} \Omega_t^S & 0 \\ 0 & \Omega_t^F \end{bmatrix} \tag{6}$$

where k is the total number of views and $k = k_S + k_F$.

Using equilibrium and views for both securities and factors, we devise the Black-Litterman output estimates

$$\hat{m}_t = \left[\hat{\Sigma}_t^{-1} + P_t^T \Omega_t^{-1} P_t\right]^{-1} \left[\hat{\Sigma}_t^{-1} \hat{\pi}_t + P_t^T \Omega_t^{-1} \hat{q}_t\right], \tag{7}$$

and

$$\hat{V}_t = \left[\hat{\Sigma}_t^{-1} + P_t^T \Omega_t^{-1} P_t\right]^{-1}, \tag{8}$$

[2] The model also allows the use of combined security/factor views, but it is more practical for investors to set separate views.

to extract posterior means and covariances for the tradable securities. For that, the mean vector

$$\hat{m}_t = \begin{bmatrix} \hat{m}_t^S \\ \hat{m}_t^F \end{bmatrix} \tag{9}$$

and covariance matrix

$$\hat{V}_t = \begin{bmatrix} \hat{V}_t^S & \hat{V}_t^{SF} \\ \hat{V}_t^{FS} & \hat{V}_t^F \end{bmatrix} \tag{10}$$

are decomposed into their securities and factor counterparts. Finally, we set a volatility target σ^2 and solve the optimization model

$$\max_{w_t} \quad w_t^T \hat{m}_t^S \tag{11}$$

$$\text{s.t.} \quad w_t^T \hat{V}_t^S w_t \leq \sigma^2 \tag{12}$$

$$w_t^T 1 = 1 \tag{13}$$

$$w_t \geq 0 \tag{14}$$

build upon the posterior (Black-Litterman) mean vector $\hat{m}_t^S$ and coveriance matrix $\hat{V}_t^S$, associated only with tradable securities. By using $\hat{m}_t^S$ and $\hat{V}_t^S$, as opposed to $\hat{\pi}_t^S$ and $\hat{\Sigma}_t^S$, we ensure that w_t is a product of investors' views. The conceptual workflow is:

1. Choose the tradable securities and obtain prior parameters;
2. Select the macroeconomic factors related to tradable securities;
3. Set views regarding the macroeconomic factors returns (may include views on securities returns);
4. Set further model parameters and obtain posterior assets parameter;
5. Run optimization; and
6. Compare the out of sample risk adjusted returns results to selected benchmarks.

2.2 Assessing Performance Using Historical Data

Following the work of Zhou (2009) we use historical averages to estimate prior expected returns for both factors and tradable securities, which enables us to avoid the use of δ, τ. By using public survey we avoid the heuristic that estimates Ω. These are the issues most criticized on Black-Litterman literature (see Fusai & Meucci (2003) and Michaud et al. (2013)).

It is important to estimate an appropriate length for the rolling window estimation, weighting the tradeoff between using a bigger sample to reduce the estimation error, and avoiding using older data as the distribution changes over time. Thus, these optimal lenghts may be different for mean and variance estimation (Luenberger (2014)). We achieve the proper window length for mean and variance estimation through successive out-of-sample evaluations, using different combinations for expected returns estimation length l_r and covariance matrix estimation length l_c. We understand that using different windows is important since the effect of estimation errors in covariances might be greater than the ones in expected values (see Chopra & Ziemba (2013)). Figure 2 is the flowchart used to optimize the estimation window's lengths.

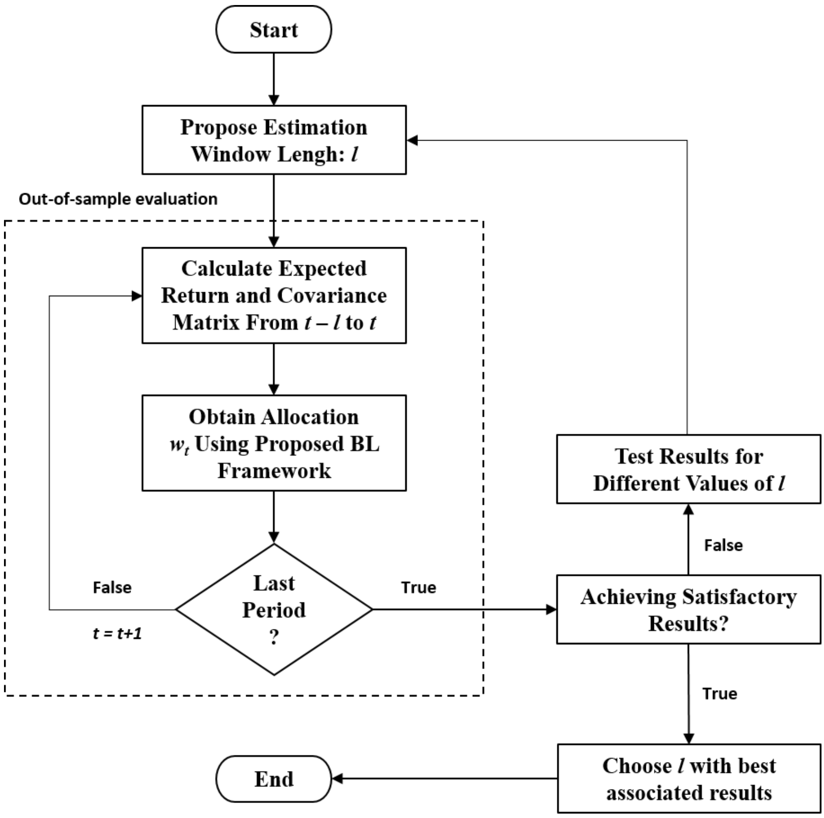

Figure 2 – Flowchart for backtesting and optimizing estimation windows lengths.

3 CASE STUDY

We analyze the performance of the MBL model in a daily investment strategy that sets views using data collected from BCB[3]. We perform the study with daily data from March 2010 to October 2018 (due to data availability).

BCB has on its system predictions of several factors from many institutions. Aiming to improve the results, we use predictions available from the Top 5 predictors (which is also disclosed in the system). The views are set using the median of these Top 5 predictors estimates for: (i) The Brazilian monthly inflation rate (BIR); (ii) The Real to US Dollar exchange rate, end of the

[3]Brazilian Central Bank holds a system called Market Expectations System to gather data from market players.

month (BRLUS) and; (iii) The target Brazilian interest rate (Selic). These factors are chosen for the impact they have on asset returns. The works of Bernanke & Kuttner (2005) and Jiménez et al. (2014) are examples of empirical studies that show how macroeconomic factors and monetary policies have a strong influence on asset prices and returns. With this information we set P_t and $\hat{q}_t$. We use the variances of the predictions to set Ω_t. Table 1 shows the securities available for investment, Table 2 presents their correlations and Figure 3 presents their cumulative return.

Table 1 – List of available investment securities.

Security	Ticker
US Dollar	BRLUS
Brazilian stock index	IBOV
Interbank deposit rate	CDI
Brazilian inflation-linked bonds with constant duration of 3 years	iDkA I3
Brazilian fixed income bonds with constant duration of 3 years	iDkA P3

Table 2 – Securities correlation (full sample period).

	CDI	BRLUS	IBOV	iDkA I3	iDkA P3
CDI	1.000	-0.009	0.001	0.040	0.030
BRLUS	-0.009	1.000	-0.340	-0.232	-0.330
IBOV	0.001	-0.340	1.000	0.256	0.313
iDkA I3	0.040	-0.232	0.257	1.000	0.831
iDkA P3	0.030	-0.330	0.313	0.831	1.000

As discussed, in the absence of market weights for the securities or macroeconomic factors, we use historical averages (instead of using CAPM to estimate the value of $\hat{\pi}_t$). The windows lengths for mean ($\hat{\pi}_t$) and covariance ($\hat{\Sigma}_t$) estimation were 60 and 90 business days, chosen as presented on Section 2.

Once with $\hat{\Sigma}_t$, $\hat{\pi}_t$, $\hat{\Sigma}_{\pi,t}$, P_t, $\hat{q}_t$ and Ω_t, we could use the Black-Litterman formulas (Cheung (2009)) to obtain $\hat{m}_t$ and $\hat{V}_t$ and then, with $\hat{m}_{s,t}$ and $\hat{V}_{s,t}$, run the optimizer. The optimization given by (11) is carried out setting a 5% target for annualized portfolio volatility. This value represents a common benchmark for Brazilian hedge funds[4]. The constraint $w_{i,t} \geq 0$ was used to avoid short selling.

We consider six portfolios as described below[5]:

1. Mean-variance optimization using historical data (MVO);
2. MBL model considering BCB views on **BRLUS**, **BIR** and **Selic** (MBL BCB);

[4]This portfolio volatility is standard deviation of a portfolio consisting of 20% IBOV and 80% CDI

[5]Perfect t+1 views mean we set the views at time t predicting the return of the security as the t+1 return of the security, for all the time interval.

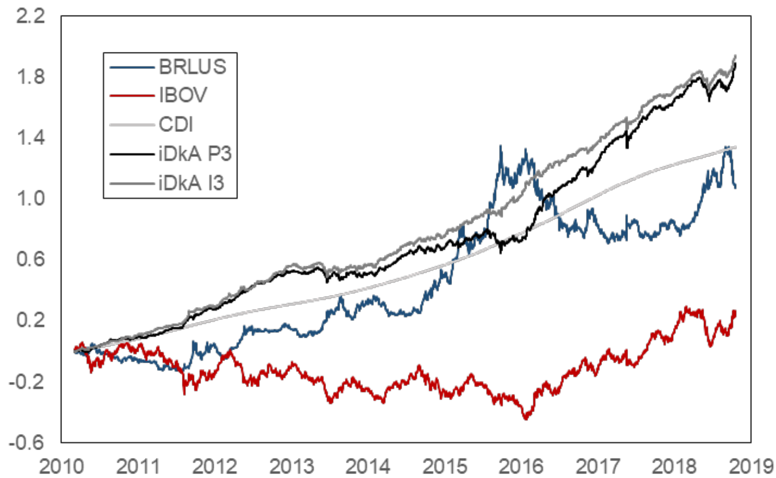

Figure 3 – Securities cumulative returns (March 2010 to October 2018).

3. MBL model considering perfect t+1 views on **BRLUS**, **BIR** and **Selic** (MBL PV), used to evaluate the effect of perfect views on the returns;

4. MBL model considering perfect t+1 views on **BIR** and **Selic** (MBL PV -BRLUS), used to evaluate the effect of perfect views on macroeconomic factors on the returns as **BRLUS** is also a security available for investment;

5. MBL model considering BCB views on **BIR** and **Selic** (MBL PV -BRLUS), used to compare the effects of BCB views only on macroeconomic factors;

6. Invested in interbank deposit rate (CDI).

Table 3 shows the out-of-sample results for the optimized portfolios, its annualized returns, annualized volatility, maximum drawdown and Sharpe ratio, from July 2010 to October 2018.

Table 3 – Out-of-sample portfolios returns, volatility and maximum drawdown.

Ticker	Ann. Ret.	Ann. σ	Max. Drawdown	Sharpe Ratio
1. MVO	14.70%	6.99%	6.24%	0,63
2. MBL BCB	17.02%	6.92%	6.11%	0,97
3. MBL PV	40.41%	6.71%	6.21%	4,49
4. MBL PV -BRLUS	16.33%	6.86%	5.72%	0,88
5. MBL BCB -BRLUS	16.54%	6.86%	5.34%	0,91
6. CDI	10.31%	0.14%	0.02%	0.00

The higher cumulative returns for MBL PV reflect the use of the perfect view for the BRLUS, which is a security in the investment universe. Although its results are not useful to validate the

MBL model, the results show the impact of a perfect view of a security on the out-of-sample cumulative portfolio returns.

All portfolios surpass the 5% target for annualized standard deviation, which is expected given that results are out-of-sample and the covariances' estimates change over time. As covariances in $\hat{V}_t$ are greater than covariances in $\hat{\Sigma}_t$ due to the model correction, the MVO portfolio which is the only one that uses $\hat{\Sigma}_t$ in its risk constraint has a higher standard deviation.

The use of perfect views on BIR and Selic[6] (MBL PV -BRLUS) increases the return and lowers the risk, compared to MVO even though there are not any known factor model that relates the securities' returns to such factors. The use of BIR and Selic views from BCB (MBL BCB - BRLUS) provides very similar returns and using BRLUS views (MBL BCB) further increases the overall outcome. Figure 4 presents the cumulative returns for the portfolios, compared to the CDI.

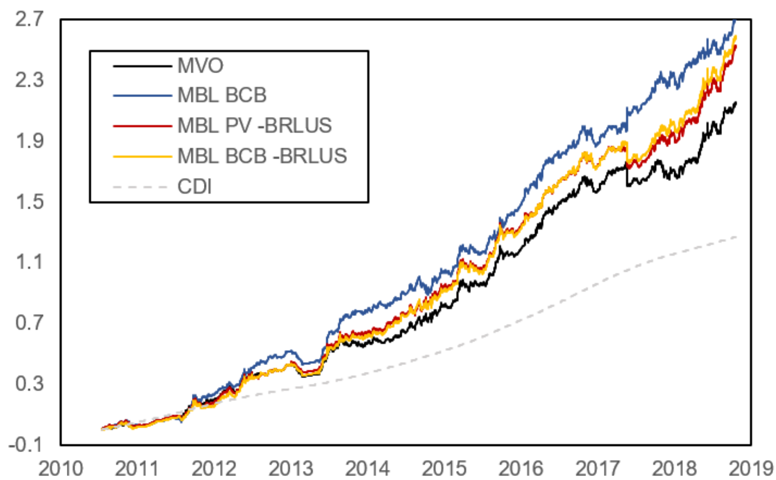

Figure 4 – Cumulative returns of studied strategies.

One can notice that portfolios MVO, MBL PV -BRLUS and MBL BCB -BRLUS have a similar profile and that portfolio MBL BCB, outperforms other portfolios on downfalls, implying that BCB views on BRLUS are effective to avoid downfalls. The proposed model enhances regular MVO using not only good views on the factors but also BCB views.

Figure 5[7] and Figure 6 present the dynamic asset allocation and cumulative returns for portfolios MVO and MBL BCB respectively.

The MBL is more dynamic, since the views on returns and the views' variances, which are relevant, may change across time. For instance, the change in BRLUS view variance in May 2017 enabled the MBL BCB portfolio to avoid a downfall (Figure 7).

[6] The two macroeconomic factors considered in this study.

[7] RHS means the right hand side axis

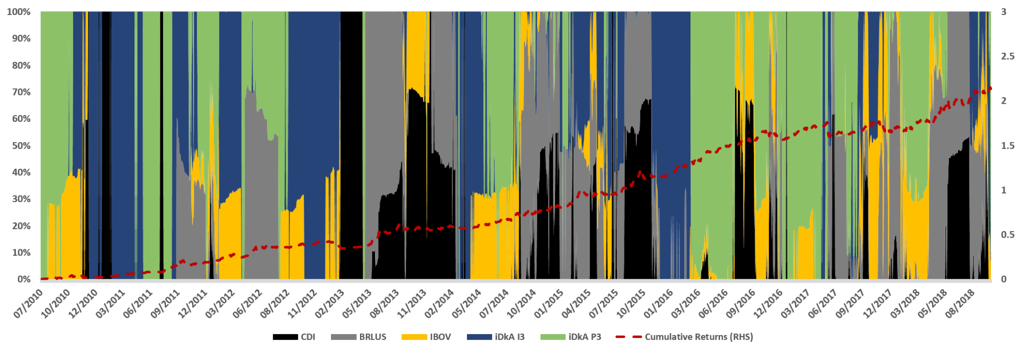

Figure 5 – Allocations and cumulative return for Portfolio MVO.

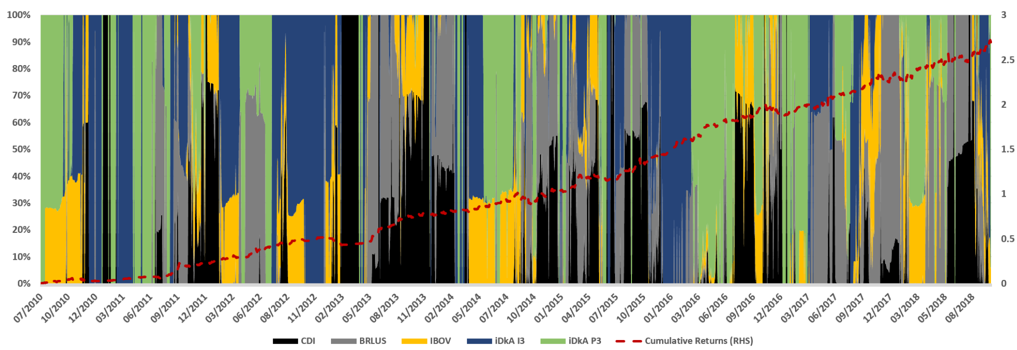

Figure 6 – Allocations and cumulative return for Portfolio MBL BCB.

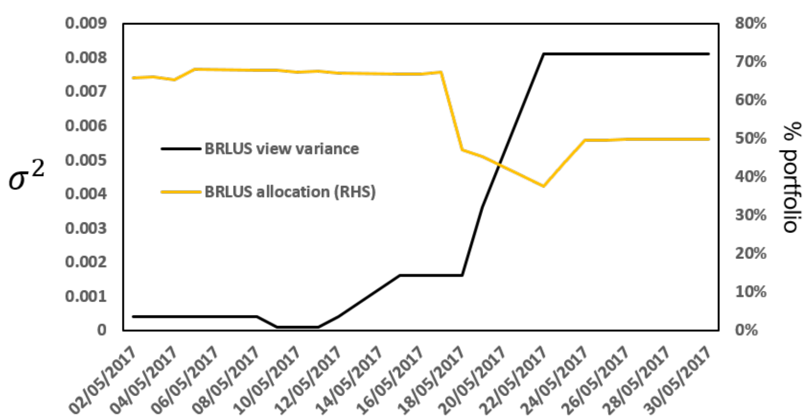

Figure 7 – BRLUS view risk May 2017.

4 CONCLUSIONS

Our proposed Macrofactor Black-Litterman model enables investors to improve their investments using their views on macroeconomic factors while eliminating parameters (τ and δ) and the heuristic procedure for estimating Ω from the original model. Also, our framework does not require investors to model securities returns. Finally, we developed a framework for setting views on returns based on the information disclosed by BCB, which can be adapted to many other sources of macroeconomic predictions.

Within the case study presented, using historical data, we blended BCB views on macroeconomic factors and securities. As a result, the optimized portfolios outperformed the MVO portfolio on every studied scenario, implying that the proposed model using macroeconomic factors views generates superior outcomes.

Possible future extensions for the study could be: to incorporate transaction costs on the optimization, to use more than the one-step-ahead prediction for the macroeconomic factors and to consider a broader range of macroeconomic factors and securities.

Acknowledgements

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

References

[1] AVRAMOV D & ZHOU G. 2010. Bayesian Portfolio Analysis. *Annual Review of Financial Economics*, **2**: 25–47.

[2] BEN-TAL A & NEMIROVSKI A. 1998. Robust Convex Optimization. *Mathematics of Operations Research*, **23**(4): 769–805.

[3] BEN-TAL A & NEMIROVSKI A. 1999. Robust solutions of uncertain linear programs. *Operational Research Letter*, **25**: 1–13.

[4] BERNANKE BS & KUTTNER KN. 2005. What Explains the Stock Market's Reaction to Federal Reserve Policy? *The Journal of Finance*, **60**(3): 1221–1257.

[5] BERTSIMAS D, GUPTA V & PASCHALIDIS IC. 2012. Inverse Optimization: A New Perspective on the Black-Litterman Model. *Operations Research*, **60**(6): 1389–1403. Available at: https://doi.org/10.1287/opre.1120.1115.

[6] BERTSIMAS D & SIM M. 2004. The Price of Robustness. *Operations Research*, **52**: 35–53.

[7] BESSLER W, OPFER H & WOLFF D. 2017. Multi-asset portfolio optimization and out-of-sample performance: an evaluation of Black–Litterman, mean-variance, and naïve di-

versification approaches. *The European Journal of Finance*, **23**(1): 1–30. Available at: https://doi.org/10.1080/1351847X.2014.953699.

[8] BLACK F & LITTERMAN R. 1992. Global Portfolio Optimization. *Financial Analysts Journal*, **48**(5): 28–43.

[9] CHEUNG W. 2009. The Black-Litterman model explained. *Journal of Asset Management*, **11**.

[10] CHEUNG W. 2013. The augmented Black-Litterman model: a ranking-free approach to factor-based portfolio construction and beyond. *Quantitative Finance*, **13**(2): 301–316. Available at: https://doi.org/10.1080/14697688.2012.714902.

[11] CHOPRA VK & ZIEMBA WT. 2013. The Effect of Errors in Means, Variances, and Covariances on Optimal Portfolio Choice. In: *Handbook of the Fundamentals of Financial Decision Making*. chap. 21.

[12] FABOZZI FJ, HUANG D & ZHOU G. 2010. Robust portfolios: contributions from operations research and finance. *Annals of Operations Research*, **176**: 191–220.

[13] FERNANDES B, FERNANDES C, STREET A & VALLADÃO D. 2018. On an Adaptive Black-Litterman Investment Strategy using Conditional Fundamentalist Information: A Brazilian Case Study. *Finance Research Letters*, **27**. Available at: https://doi.org/10.1016/j.frl.2018.03.006.

[14] FERNANDES B, STREET A, VALLADÃO D & FERNANDES C. 2016. An adaptive robust portfolio optimization model with loss constraints based on data-driven polyhedral uncertainty sets. *European Journal of Operational Research*, **255**.

[15] FUSAI G & MEUCCI A. 2003. *Assessing Views*. Università degli studi del Piemonte orientale, Facoltà di economia. Available at: https://books.google.com.br/books?id=Ura1AQAACAAJ.

[16] IDZOREK T. 2002. *A step-by-step guide to the Black-Litterman model: Incorporating user-specified confidence levels. Forecasting Expected Returns in the Financial Markets*. Academic Press. 17-38 pp.. Available at: https://doi.org/10.1016/B978-075068321-0.50003-0.

[17] JIMÉNEZ G, ONGENA S, PEYDRÓ JL & SAURINA J. 2014. Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking? *Econometrica*, **82**(2): 463–505. Available at: https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA10104.

[18] KIM JH, KIM WC & FABOZZI FJ. 2017. Robust Factor-Based Investing. *The Journal of Portfolio Management*, **43**(5): 157–164. Available at: https://jpm.pm-research.com/content/43/5/157.

[19] LUENBERGER D. 2014. *Investment Science*. Oxford University Press. Available at: https://books.google.com.br/books?id=YMSeDAEACAAJ.

[20] MARKOWITZ H. 1952. Portfolio Selection. *The Journal of Finance*, **7**: 77–91.

[21] MEUCCI A. 2010. Black–Litterman Approach. In: *Encyclopedia of Quantitative Finance*. American Cancer Society. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470061602.eqf14009.

[22] MICHAUD R. 1989. The Markowitz Optimization Enigma: Is 'Optimized' Optimal? *Financial Analysts Journal*, **45**: 31–42.

[23] MICHAUD R, ESCH D & MICHAUD R. 2013. Deconstructing Black-Litterman: How to Get the Portfolio You Already Knew You Wanted. *Journal of Investment Management*, **Vol 11**: 6 – 20.

[24] SATCHELL S & SCOWCROFT A. 2000. A demystification of the Black–Litterman model: Managing quantitative and traditional portfolio construction. *Journal of Asset Management*, **1**(2): 138–150. Available at: https://doi.org/10.1057.

[25] SOYSTER AL. 1973. Technical Note—Convex Programming with Set-Inclusive Constraints and Applications to Inexact Linear Programming. *Operations Research*, **21**(5): 1154–1157.

[26] STEFANESCU R. 2016. Optimal Asset Allocation Strategies. *SSRN Electronic Journal*, Available at: http://dx.doi.org/10.2139/ssrn.2800815.

[27] ZHOU G. 2009. Beyond Black-Litterman: Letting the Data Speak. *The Journal of Portfolio Management*, **36**(1): 36–45. Available at: https://jpm.iijournals.com/content/36/1/36.

How to cite

CANTINI C, VALLADÃO D & FERNANDES B. 2021. Assessing the value of subjective views on macroeconomic factors via Black-Litterman based portfolio optimization. *Pesquisa Operacional*, **41**: e232555. doi: 10.1590/0101-7438.2021.041.00232555.