

Factor Investing Using Capital Market Assumptions



Overview

In [*Factor Investing Using Capital Market Assumptions*](#), from the January 2022 quantitative special issue of *The Journal of Portfolio Management*, three Canadian researchers—**Redouane Elkamhi** and **Marco Salerno** of the **Rotman School of Management** at the University of Toronto and **Jacky Lee** of the **Healthcare of Ontario Trust Plan**—present a factor investing methodology far less complicated and expensive than existing practices by making use of publicly available capital market assumption reports.

Most factor investing strategies require access to large databases and use costly proprietary mathematical models. In the hope of making factor investing possible for a wider range of investors, the team identified three macroeconomic factors that appear to be embedded in publicly available reports on capital market assumptions (CMAs): the rate of economic growth, the real interest rate, and the rate of inflation. Using these macroeconomic factors, they calculate asset class returns closely aligned to those in the CMAs. They then devised a formula to calculate the factor sensitivity of a sizable group of publicly traded asset subclasses, as well as a separate formula to price private assets. In addition, they developed a formula to reconcile their target factor weights with a portfolio that is built with constraints on diversification and risk.

Practical Applications

- **Capital market assumptions, which embed key macroeconomic factors, provide a framework for portfolio construction based on those factors.** The three key macroeconomic factors are the rate of economic growth, the real interest rate, and the rate of inflation. They can be used to price asset class returns, and the implied CMA's factor model can be computed with much less expense and complexity than widely used factor models.

Authors: Redouane Elkamhi, Jacky S. H. Lee, and Marco Salerno
Source: *The Journal of Portfolio Management*, Vol. 48, No. 2
Date of Article: January 2022
Report Written By: Frank Beck
Date of Report: Jun 15, 2022
Keywords: factor investing, capital market assumptions, excess returns, risk premia



Key Definitions

Capital market assumptions (CMAs)

Capital market assumptions are forecasts of the long-term expected return and risk (expressed as the standard deviation of returns) for individual asset classes. The forecasts implicitly embody assumptions about macroeconomic variables such as economic growth, real interest rates, and inflation. Many firms publish capital market assumptions (e.g., JPMorgan Chase, BlackRock, Northern Trust). Some firms survey market participants and publish results showing the range of views. The CMA survey reports published by Horizon Actuarial Services are an example (<https://www.horizonactuarial.com/blog/category/publications>).

Factor investing

Factor investing is an investment strategy in which securities are chosen based on attributes (factors) that are associated with higher returns, lower risk, or both. Such factors might include style (growth and value), size (large cap and small cap), risk (volatility and momentum), and fundamentals (profitability, investment, and dividends).

Covariance

Covariance is a statistical measure of the degree to which two random variables tend to move in the same or opposite directions. The formula for the

- **In many cases, the CMA-based approach can be implemented using publicly available data, and the authors provide a closed-form formula that enables investors to build asset portfolios with the desired exposures to those factors.** The method can be implemented in Excel. Adding an additional factor allows including private assets as well (e.g., hedge funds, real estate, private equity, etc.).
- **The CMA-based approach can be tailored to take into account a portfolio's existing constraints regarding diversification and risk.**

Discussion

Factor investing seeks to identify the drivers of risk and return and to determine the sensitivity of an asset class or an individual security to those drivers. Across the asset classes, factor sensitivity is typically calculated using various macroeconomic data, such as changes in the rate of economic growth or of the real interest rate; within an asset class, sensitivity is generally calculated using a characteristic such as quality, style (growth or value), or momentum. Factor strategies have greatly grown in popularity in recent years: Black Rock estimates that by the end of 2022 they will be used to manage \$3.2 trillion in assets.

Most factor strategies, however, rely on access to large databases and employ expensive mathematical modeling that can be complicated to use.

The authors address the cost and complexity of most strategies involving macroeconomic factors, using a method for identifying three macroeconomic factors that are apparently embedded in widely used capital market assumptions. They showed how those can be used to generate factor sensitivity values for the major asset classes and a sizable group of subasset classes, using a closed-form formula, and how the factor sensitivity values can then be employed in portfolio construction.

UNPACKING THE FACTORS IN CAPITAL MARKET ASSUMPTIONS

Factor investing usually relies on large databases, using complex mathematical modeling to identify drivers of risk and return. This expensive process is out of reach for many investors. The obvious solution would be to identify factors that can be derived relatively



sample covariance of random variables X and Y is

$$\begin{aligned}\text{cov}(X, Y) &= \sigma_{x,y} \\ &= \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}),\end{aligned}$$

where n is the number of observations, x_i is the i^{th} observation of X , y_i is the i^{th} observation of Y , \bar{x} is the sample mean of X , and \bar{y} is the sample mean of Y . Covariance is closely related to the concept of correlation, which expresses the degree to which two variables tend to move in the same or opposite direction on a scale from -1 to 1 . The correlation of two random variables X and Y can be calculated from their covariance as follows:

$$\text{corr}(X, Y) = \rho_{x,y} = \frac{\text{cov}(X, Y)}{\sigma_x \sigma_y},$$

where σ_x is the sample standard deviation of X and σ_y is the sample standard deviation of Y .

Covariance matrix

A covariance matrix is a matrix that contains the covariances between pairs of random variables within a list of random variables. The element in the i^{th} row and j^{th} column of the matrix indicates the covariance between the i^{th} and j^{th} random variables in the list. The elements along the diagonal of the matrix are the variances of the random variables.

easily, using publicly available information. Redouane Elkamhi is one of the team of three researchers who set out to find such factors.

“Our goal,” Redouane Elkamhi told us, “was to develop a framework that could be used by practitioners to guide their investment decisions, while being guided by a thorough analysis based on the latest academic research. We wanted to bridge the gap between academic and industry by making it easier for investors to use a factor framework.”

“We looked for factors that satisfied two conditions: 1) they were known drivers of asset returns and 2) they were widely recognized among practitioners. The latter was important, to ensure that our framework could be easily accepted. We used the capital market assumption reports issued by Horizon Actuarial Services, which represent a consensus from dozens of investment advisors. Specifically, we looked at the 10-year assumptions in annual surveys published between 2013 and 2020.”

“The three things we chose to use were the rate of economic growth, the real interest rate, and the rate of inflation. We picked these three factors because evidence has shown that they affect asset prices (for example, Campbell and Viceira 2001 and Bansal and Shaliastovich 2013) and because they are already widely used in the industry.”

“First we had to see if these macroeconomic factors could accurately price the asset class returns produced by CMAs. When we found they did, we were very excited. We believed we could investigate further and come up with something useful.”

“Our approach is truly accessible to anyone—even retail investors—and we are excited about that.”

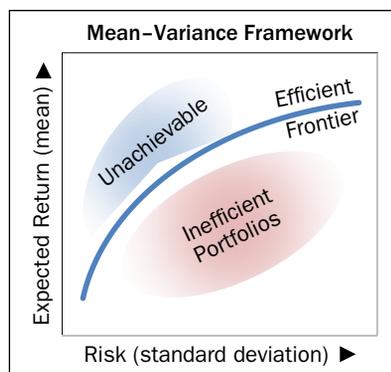
—Jacky Lee

No one had proved this before, but the team found that these three factors held the key to much of an asset’s excess returns—the difference between the returns of the asset class and those of a risk-free investment for the same period—reported in CMAs. In fact, the differences between the excess returns predicted by their three factors and those shown in the CMAs were negligible.

“The pricing errors were minimal,” Marco Salerno explained. “For example, the average pricing error for large-cap US equities was

Mean-variance framework

The mean-variance framework is a way to assess portfolios in terms of their expected return (mean) and their variability of returns (expressed in terms of variance or standard deviation). The mean-variance framework is an expression of modern portfolio theory (MPT), for which Harry Markowitz received the 1990 Nobel Prize in economics. MPT is an approach to constructing efficient portfolios based on the assumption that investors seek to maximize expected returns while minimizing variability (i.e., risk). For a given level of risk, the portfolio with the highest return is an efficient portfolio. For a given level of expected return, the portfolio with the lowest risk is an efficient portfolio. The “efficient frontier” comprises the efficient portfolios at each level of risk. Diversification is a key concept in MPT because it reduces risk when returns on individual assets have less than perfect correlation. Mean-variance analysis is an implicit cornerstone of financial regulations that require advisors to understand, and to base their recommendations on, a client’s overall risk tolerance.



approximately 0.1%—very small, considering that the average excess return of that asset subclass was 4.42%. Overall, pricing errors were small across all public asset classes, suggesting that the factors we identified are indeed the main drivers of equities, corporate bonds (both core and high-yield), inflation-protected bonds, and commodities.”

The next task was to calculate factor loadings for each of the publicly traded asset subclasses their study focused on.

“Factor loadings represent the sensitivity of an asset class or a subasset class to a factor,” Marco Salerno told us. “Traditionally, analysts have time series of both assets and factors and can calculate factor loadings using a linear regression. However, with CMAs, we have only a snapshot of the data at a given point in time.”

“Here our paper makes a very practical contribution: We provide a formula to estimate factor loadings, solely using information from the CMAs. As we show in the paper, after some math, the estimated factor loadings are a function of the covariance matrix of the assets and the chosen definitions of factors. That is, the CMAs provide the assets’ standard deviation and correlations that can then be used to calculate the covariance. Since (1) the CMAs give us the covariance matrix of the assets and (2) we defined our factors as mimicking tradable portfolios, we were able to derive a simple, closed-form formula for estimating the factor loadings.”

“This allows more investors to consider factor investing, because our proposed framework is considerably simpler than traditional methods. Our framework requires only the definition of the factors, with the rest of the information provided by a simple, plug-in formula. Furthermore, many CMAs are publicly available. That means anyone can potentially use our approach to build portfolios with factors.”

What about private assets, which the team defined as commercial real estate, infrastructure, and private equity and short public subasset classes?

“When we priced private assets using only three factors (economic growth, the real interest rate, and the rate of inflation),” Jacky Lee said, “we found that there were sizable, unexplained premia. These means that, while these three factors price public assets well, they are not enough to price private assets. So we created a portfolio that was long private assets and short public assets, in order to create a private-asset factor that would be idiosyncratic to the factors for public



assets. We believed it would enable us to capture a large portion of the unexplained premia.”

How did the team prove that their private-asset calculations were sound?

“In fact,” Lee replied, “we were unable to test our private-asset factor using the CMAs from Horizon Actuarial, because they have only three private asset subclasses. That’s too few for a robust analysis. So we turned to the JPMorgan CMAs, which have seven private asset subclasses, and found that our private-asset factor could price the risks specific to private assets, based on a cross-sectional regression analysis that matched our estimates with those of JPMorgan.”

PUTTING THE TEAM’S METHODS TO WORK

In practice, how would an asset manager put the team’s methods to work? How time-consuming are they?

“We gave investors a ‘turn-key’ solution,” Jacky Lee pointed out, “provided that they have CMAs for all the asset classes they manage. They can obtain the CMAs from Horizon Actuarial or another firm, such as JPMorgan—these are available to the public. Or they can obtain CMAs through a private arrangement with a CMA provider.”

“Typically a CMA’s covariance matrix is stable year-over-year, unless the CMA producer switches to a different model. Even if they switch models, that would likely affect only the private assets, while the public assets would remain fairly the same, because research in the public markets is more mature. So, factor loadings for public markets, too, are fairly stable, as we have shown in our paper. Nonetheless, factor loadings calculated with our methodology should be updated so they are consistent with the latest CMAs. Some are published annually; some are more frequent.”

“You asked how time-consuming this process is. The math is straightforward, and it is in closed-form. Even for a large CMA matrix involving 50 to 100 asset classes and subasset classes, the math can readily be done in Microsoft Excel, using only its native functions. Our approach is truly accessible to anyone—even retail investors—and we are excited about that.”

One challenge in factor investing is reconciling the portfolio weights dictated by the factor loadings with any portfolio built using



traditional portfolio construction methodologies. The team proposed a solution for that.

“The literature has developed various ways of applying factor exposures to asset weights,” Marco Salerno explained. “For example, Greenberg, Babu, and Ang (2016) proposed a method of translating factors based on investor preferences and constraints such as leverage, minimum and maximum asset class positions, etc.”

“We set out a new methodology of translating factors that can be expressed in a closed-form solution. We demonstrate its use with an inverse volatility portfolio—one in which assets are weighted in inverse proportion to their risk. The resulting portfolio achieves a trade-off between two components: 1) having the most risk-diversified portfolio and 2) achieving a particular factor exposure risk.”

While the team’s method focuses on asset classes and subclasses, most factor investing operates on a security-by-security basis. A typical factor strategy might assess the earnings quality of each stock in the Russell 3000 Index. The team hopes to develop their methods further so they be used in security selection.

“We would like to elaborate on our research,” Redouane Elkamhi said. “While we think that explaining the differences in returns at the individual security level is important, our paper has strategic asset allocation in mind. It is well known that this affects a portfolio’s return more than security selection or market timing.”

The team’s next step is to do some back-testing to determine whether their methods would have generated superior performance in past market cycles.

“In our paper, we showed that our methodology would generate stable Sharpe ratios. We would have liked to include more, but adding more material would have made it too long for publication.”

“Would this method generate robust performance? The answer is ‘yes,’ on the condition that the chosen factors can accurately price asset class returns. The intuition is simple: if returns are driven by our chosen factors—the rate of economic growth, the real interest rate, and the rate of inflation—our methods provide a framework to achieve diversification and control risk across these fundamental drivers of performance.”



“Were you to use an alternative method, such as mean–variance alone, you might achieve the same degree of diversification but, more likely, a lesser degree, as a result of loading up more on an individual factor. A proper backtest is something we are considering as a future research project. We hope to be sharing some new projects with you soon.”

References

Bansal, R., and I. Shaliastovich. 2013. “A Long-Run Risks Explanation of Predictability Puzzles in Bond and Currency Markets.” *The Review of Financial Studies* 26 (1): 1–33.

Campbell, J. Y., and L. Viceira. 2001. “Who Should Buy Long-Term Bonds?” *American Economic Review* 91 (1): 99–127.

Greenberg, D., A. Babu, and A. Ang. 2016. “Factors to Assets: Mapping Factor Exposures to Asset Allocations.” *The Journal of Portfolio Management* 42 (5): 18–27.

The content is made available for your general information and use and is not intended for trading or other specific investment advice purposes or to address your particular requirements. We do not represent or endorse the accuracy or reliability of any advice, opinion, statement, or other information provided by any user of this publication. Reliance upon any opinion, advice, statement, or other information shall also be at your own risk. Independent advice should be obtained before making any such decision. Any arrangements made between you and any third party named in this publication are at your sole risk.



Redouane Elkamhi

redouane.elkamhi@rotman.toronto.ca

Redouane Elkamhi is an associate professor of finance at the University of Toronto. His research has been published in leading finance journals and presented at major conferences; its topics span investment strategies, portfolio construction, corporate finance, and risk management, including risk budgeting. Both his research and teaching have received multiple awards. Prof. Elkamhi also has extensive experience in the financial industry through his participation in advisory roles at pension funds, investment and commercial banks, and global asset management firms. He received his PhD from McGill University, his MBA from École Nationale des Ponts et Chaussées, and his degree in electrical engineering from École Hassania des Travaux Publics.



Jacky S. H. Lee

jlee5@hoopp.com

Jacky Lee is a vice president of total portfolio at the Healthcare of Ontario Pension Plan in Toronto. He oversees asset-liability management, portfolio construction and asset allocation, factor frameworks, research, and advanced analytics. In his previous position as a managing director at the Ontario Teachers' Pension Plan, he led many operations, including total fund asset allocation, risk management, advanced analytics, and the use of investment factors. He is a recipient of the International Centre for Pension Management (ICPM) Research Award and earned his MASc and MMF from the University of Toronto.



Marco Salerno

marco.salerno@rotman.utoronto.ca

Marco Salerno is completing his PhD studies in finance at the University of Toronto's Rotman School of Management. He is focusing on empirical theoretical asset pricing, with a concentration on portfolio allocation. He has presented papers at the American Finance Association and the European Financial Association. Prior to his studies, he served for five years as a senior research associate at the BMO Financial Group's Finance Research and Trading Lab.