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PRACTITIONER'S DIGEST

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MEASURING THE ECONOMIC AND ACADEMIC IMPACT OF PHILANTHROPIC FUNDING: THE BREAST CANCER RESEARCH FOUNDATION

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Detelina Vasileva, Larry Norton, Marc Hurlbert and Andrew W. Lo

A rapidly growing sector of the impact investment industry is biomedicine and, more specifically, the development of novel therapeutics to treat diseases such as cancer, diabetes, Alzheimer's, and other life-threatening afflictions. One of the pre-requisites for the success of biomedical impact investment funds is the ability to define and measure impact. There is, of course, the traditional measure of return on investment (ROI), but many stakeholders in the healthcare ecosystem would consider this metric inadequate in capturing the full spectrum of impact of funding, especially at the pre-clinical stages of drug discovery where the predominant funding sources are government and philanthropic grants.

In this article, we propose to contribute to the impact investment literature by developing a broader set of measures of commercial and non-commerical impact in the specific area of breast cancer research using survey data we gathered directly from grantees of the non-profit Breast Cancer Research Foundation (BCRF). Founded in 1993, the BCRF has raised and expended over half a billion dollars in breast cancer research at the time of our analysis, and has been awarded the highest grades for commitment, performance, and consistency by groups that monitor charities in the U.S. and worldwide. In 2019–2020, BCRF will award $66 million in annual grants to nearly 275 scientists from top universities and medical institutions around the globe.

Commercially, 19.5% of BCRF grantees filed patents, 35.9% had a project that has reached clinical development, and 12 companies have or will be spun off from existing projects, thus creating 127 new jobs. Non-commercially, 441 graduate students have been trained by 116 grantees, 767 postdoctoral fellows have been trained by 137 grantees, 66% of grantees have used funding for faculty salaries, 93% have achieved collaboration with other researchers, and 42.7% have enacted process improvements in research methodology.

Using survey data from 119 of the BCRF grantees, we identified five significant research outcomes, four of them commercial (filing patents, licensing IP, reaching a clinical development phase, and receiving outside capital for a company started from BCRF-funded work) and one non-commercial (obtaining additional non-BCRF grant funding). By applying logit and probit analysis to this survey data, we show that the key factors associated with research outcomes are the amount of BCRF funding, the number of graduate students and postdocs supported by that funding, the presence of collaboration with other researchers, the support of faculty payroll by BCRF funding, the initiation of process improvements in the project, and the support for graduate students. We also found that the involvement of more than one institution in a collaborative project had a negative impact on subsequent development. This may point to frictions introduced by multi-university interactions.

This last finding illustrates one of the potential implications of our proposed framework, which is to inform policy on how to nurture and accelerate innovation in translational medicine. These policy discussions are becoming more urgent given the increasing rate of commercialization of academic research in the life sciences. Although commercialization is a common endgame of research within the biopharma industry, researchers in academia have started to experience pressure to commercialize their research so as to compete with industry and attract R&D funding and maintain a successful academic career. This pressure will have both negative and positive effects, and at this point it is not possible to determine which will dominate. Measuring this trade-off and developing policies to manage it will require close analysis of the outcomes of funded research, as we have proposed in this case study.

The framework developed in this article can be applied in many fields beyond biomedicine by non-profit and government research funding organizations seeking to optimize their impact on research. In addition, the factors that affect the outcomes of projects in academia funded by nonprofits may also affect the outcomes of projects in industry, since the conditions of the scientific process are similar, and the incentives for innovation are comparably strong. We hope our analysis will serve as a starting point for measuring these relationships and developing more effective ways for investors to maximize the impact of their capital.

EXPONENTIAL GLIDE PATHS PAGE 25

Moshe Levy and Haim Levy

Investors who do not poses genuine ability to time the market are better-off keeping their asset allocation constant over time, rather than changing it over the life-cycle. This statement holds for the investor's total portfolio, which also includes a human-capital component, that is typically considered to be bond-like. As the human capital component diminishes over time, in order to keep the asset allocation in the total portfolio constant, the investor should optimally decrease the allocation to stocks in her financial portfolio over time.

Target-date funds help reduce the variation over the life-cycle for the asset allocation in the total portfolio, by decreasing the allocation to stocks over time. Almost all target-date funds employ a linear glide-path for the reduction in the proportion allocated to stocks. We show that this common practice implies two systematic biases: (i) the optimal glide-path should be exponential, rather than linear, and (ii) the allocation to equities should be adjusted in response to market fluctuations. Both of these biases are easy to fix. The welfare improvement obtained by the suggested corrections is substantial, and we estimate it to be in the range of 5%–22%.

RELEVANCE PAGE 37

Megan Czasonis, Mark Kritzman and David Turkington We introduce a formal statistical procedure for measuring the relevance of observations used in forecasting models. This approach allows us to censor non-relevant observations and, based on a mathematical equivalence, generate forecasts of the dependent variable as relevance-weighted averages of its past values. There are several benefits to measuring the relevance of observations used in a forecasting sample. It aligns with the way we naturally process experiences to contemplate the future. It sheds light on an intriguing feature of linear regression analysis, which is that it places as much importance on non-relevant observations as it does on relevant observations. It therefore raises the question of whether we can produce more reliable forecasts by censoring non-relevant observations. It establishes a unified perspective from which to view regressions, event studies, and machine learning algorithms. And perhaps most important, it enables analysts to produce more reliable forecasts.

HOW WELL DO FACTOR ETFS CAPTURE THE FAMA–FRENCH FACTORS? PAGE 48

Nicholas Apergis, Thomas Poufinas, Alexandros Panagakis and Ioannis Ritsios

The ETF market is expected to be in the spotlight for several reasons. Among the ones we can identify, one is that it attracts the interest of institutional investors. A second one is that investment firms capitalize on the practical and academic experience that they have accumulated over the years in order to launch new ETFs. A third reason is that central banks - starting with the FED—are considering the inclusion of ETDs in their purchase programs. Going to institutional investors, we realize that many asset managers and asset owners on a world-wide basis are seeking the (mix of) investment strategies that will be optimal for their portfolios and customers or beneficiaries to follow. Factor-investing is among the investment approaches followed by a series of institutional investors, among which are pension and sovereign wealth funds, which account potentially for the biggest portion of assets under management. Depending on the size of the portfolio, especially when the portfolio is relatively large, asset managers may choose to pursue factor-investing themselves. However, when the size of the portfolio is smaller, then they may opt to rely on already available Exchange Traded Funds (ETFs), in particular those that claim to follow the factors of interest.

Fama and French (FF) are the pioneers in introducing and testing such factors, extending essentially the Capital Asset Pricing Model, (CAPM) up to a six-factor model in an attempt to better describe the over-performance of securities and portfolios compared to the risk-free rate. These factors are research factors. ETFs in practice are developed so as to replicate smart beta indices. These indices and the replicating ETFs may differ from the corresponding FF factors, as the former may use different construction rules vis-à-vis the FF factors, which are theoretical constructs that capture potential underlying sources of risk and/or return. Combining the quest for the optimal use of ETFs in investment portfolios in practice, along with the FF research factors, it is substantially important to have a model that (i) allows the comparison of the performance of ETFs with the one that they would ideally have if they had copied the Fama-French factor approach, (ii) enables the prediction of the future performance for a given set of FF factor performance outcomes, (iii) explains the contribution of each factor to the performance of the ETF, and (iv) interprets why smart beta indices applied in practice are different from the FF (research) factors.

Ultimately, this study examines how well the factor-ETFs capture the FF factors and attempts to explain their difference from the smart beta indices applied in practice. The findings document that the market factor explains a substantial part of the expected returns, with the remaining factors, except momentum, posting a smaller or no contribution. Style ETFs exhibit mixed results in capturing their referenced style, with almost all of them exhibiting a non-neutral momentum. Even more, momentum seems to improve across all cases the forecasting ability of the model. In summary, the difference between smart beta index ETFs and the FF factors may be attributed to the fact that when ETFs that follow smart beta strategies are formed, there may be a tilt towards SMB and HML stocks, no matter what the orientation of the ETF is, as a result of the incremental returns they offer either in absolute terms, or relative to their contribution to variance. Momentum may be present due to its high incremental returns, as well as its high volatility, considering that the ETFs may not be neutralized for its presence. The findings of this paper can be used by investors, investment managers as well as risk managers and stock exchanges in assessing whether the ETFs indeed follow the factor-investing approach they have opted to adopt, as well as in predicting their future performance.

CHARACTERISTIC-BASED RETURNS: ALPHA OR SMART BETA? PAGE 70

Soohun Kim, Robert A. Korajczyk and Andreas Neuhierl

Many variables have shown some ability to predict the cross section of asset. This predictive power could be due to (1) their ability to predict the cross section of systematic risk (beta); (2) their ability to predict asset mispricing (alpha); and (3) spurious cross-sectional relations due to overfitting (data snooping). A substantive debate exists in the literature about the relative importance of the alpha and beta components. Additionally, variables that predict alpha over one period may fail to do so over subsequent periods as investors arbitrage away the profits from a given strategy.

We develop a procedure that allows us to measure the alpha and beta components consistently with many firm characteristics in samples that have large cross-sections (many assets) and small time series samples. This allows us to let the explanatory power of firm characteristics to ebb and flow, or disappear.

We construct an arbitrage portfolio that has alpha exposure and hedges away exposures to pervasive factors. The explanatory power of any one characteristic (strategy) changes over time. We find the arbitrage portfolio has (statistically and economically) significant alpha and annualized Sharpe ratios ranging from 1.31 to 1.66.